Sensory Substitution:
Situational Awareness and Resilience
using Available Sensors

by

Luke Russell

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Department of Systems and Computer Engineering
Carleton University

Ottawa, Ontario, Canada

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Abstract

This thesis proposes 1) the concept of sensory substitution to provide data extraction from multiple sensors, 2) data analytics approaches in scenarios, and 3) response vectors where rapidly deployable fixed and mobile sensors (such as Unmanned Aerial Vehicles [UAVs] as a flying sensor platform) and emerging human-in-the-loop sensing are used. A “resilience feedback loop” is used throughout to improve each of these approaches. This data can provide actionable intelligence for public safety and critical infrastructure systems.

This thesis presents an algorithm called sensory substitution and resilience feedback, which improves situational awareness by solving two key design challenges – limitations on deployment of new infrastructure (sensors), and limited response vectors – using sensors in-place as a source of new information.

In Internet of Things (IoT) environments, numerous sensors may be available – although required sensors may not. Sensory substitution can be a solution. To make a system resilient, any smart environment or system should provide redundancies. Sometimes adding hardware/sensors is not possible, so software must simulate other sensors, creating a multi-sensory approach, with a single sensor type. A commonly found measurement system for an application is to use a sensor designed to measure Quantity X. In many real-world applications, modification constraints may limit the ability to deploy new hardware. In many cases, a sensor for X is present, though the measurement need is Quantity Y. How can a sensor for X act as a substitute for Sensor Y to provide some of the missing information? An agile IoT approach can be a solution.

In an effort for additional improvement for increasingly deeper situational awareness, a system called sensory substitution is developed for multiple sensing systems and generalized as part of an Agile IoT approach. However, an Agile IoT system can present privacy and security concerns. With such ubiquitous sensing, seemingly innocuous data could actually “leak” information. Since additional data can be collected with sensors already in-situ, relevant privacy and security implications are discussed.

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1 Introduction

1.1 Problem Statement: Need for Sensory Substitution

The problem addressed in this thesis is that frequently, we need information about Quantity or Parameter Y, but we are unable to deploy a sensor to measure Y and instead, have access to a sensor designed to measure X.

A commonly found measurement system for most applications is to deploy, then use a sensor designed to measure Quantity X. In many real-world applications, modification constraints may limit the ability to deploy new hardware. Sometimes, a sensor measuring X is present, though the measurement need is Quantity Y. How can a sensor designed to measure Y instead act as a substitute sensor to provide Parameter X, thus providing some of the missing information?

In Chapter 2, we introduce Internet of Things (IoT), ICS/SCADA (Industrial Control Systems / Supervisory Control and Data Acquisition), control loops, and a sample scenario of our approach, but in short - sensory substitution can also include other IoT layers such as data analytical algorithms and communication channels. Sensory substitution, algorithmic substitution, and communication channel substitution can lead to a larger Agile IoT approach. In an effort to obtain additional improvement for increasingly deeper situational awareness, a system and technique called sensory substitution is developed for multiple sensing systems and generalized.

1.2 Context

The context of this thesis is that there is a need for additional information in modification constrained environments, and this is an important step towards increasing situational awareness to improve resilience. This may require using available sensing.

Situational awareness can be defined as “information gathered from a variety of sources that [...] can form the basis for incident management decision-making” [1], and an increase in situational awareness has a direct impact on resilience.

For improving situational awareness, an agile, multi-sensory approach is needed, though sometimes only one sensor type is pre-existing in a given scenario. As IoT proliferates, sensors are sometimes deployed in an ad-hoc manner, so this results in the reality that many sensors are already installed in operating environments and available for repurposing.

This thesis proposes a three-layer framework for using existing sensors with analytics to increase situational awareness and improve resilience. Sensory substitution is a key pillar of a “resilience feedback loop” where augmented information can be provided with alternative sensing sources, and key issues include deriving increased situational awareness with whatever equipment and sensors are already there, using already-deployed sensors to provide actionable intelligence, quickly augmenting data, examining what sensor data can reveal, and exploring security implications.

The hypothesis of this thesis is:

Situational Awareness Can be Increased Using Available Sensors and Algorithms, and this Agile IoT Approach can Enable Resilience With Informed Intervention.

By increasing sensor modalities, situational awareness can increase, and lead to better resilience. For increased resilience, not only is better situational awareness important, but also is the response. Though all routes lead to some form of intervention (including a decision that no action is necessary), increased information to key decision-makers—algorithms or people—can improve the effectiveness of the response.

1.3 Thesis Objectives

The objective of this thesis is to present, describe, and validate the method of sensory substitution, in which a sensor designed to measure X is instead used to measure Y, and the resilience feedback loop.

The goal of doing so is to increase resilience of critical systems by using already present IoT sensors and algorithms in a new modality: provide additional information with the same hardware - increasing situational awareness, then using “resilience feedback” to inform responses.

For the purposes of this work, we define “resilience feedback” as using information gathered to improve sensing techniques and responses with the goals of either increasing sensing confidence, adding orthogonal sensor modalities, increasing situational awareness, or increasing resilience overall.

This work focuses on aspects for improving sensing confidence: bringing sensing capability to an area where a sensor does not exist thus increasing confidence from zero to a nonzero value. By using orthogonal sensing modalities, the confidence of sensing can be further increased, along with the resilience of sensing. Thus, the work in this thesis brings sensing to an area where the required sensor does not exist increasing sensor confidence from zero using other sensor modalities.

1.4 Areas of Focus - Effective Intervention

Overcoming time and modification constraints (e.g. political, process, regulatory, etc) are essential to improving situational awareness – using available sensing. The high level Agile sensing approach contrasts with traditional sensor systems, where there are no modifications constraints, and the “ideal” sensor can be deployed as needed.

Improving analytics approaches when modification constraints are present is important for increasing resilience. Three scenarios addressed are Sensory Validation, Classification and Adaptation, and Multi-Sensory Fusion. This thesis focuses primarily on the sensors and analytics aspects as opposed to the control loop or related aspects.

Also addressed is use of Agile IoT sensing to provide information feedback and response vectors for situational awareness. Action vectors include flying sensor platforms, human-in-the-loop sensing, and Agile IoT. Resilience feedback is used throughout this research to improve techniques, and is described in Chapter Six.

1.5 Motivation for Research

Increase Resilience and Sensing Ability with Existing Hardware

Common to all critical infrastructure sectors (in addition to general physical infrastructure, sectors include health, energy, information/communication, food, banking, etc) is the need for improved situational awareness. Critical infrastructure is infrastructure that is essential to day-to-day operations and functions. Whether we are discussing transportation, for example the control tower at a major airport, the flight deck of a passenger airliner, the control room of a nuclear facility, or the inside of a hospital, most critical infrastructure facilities suffer from varying degrees of a lack of situational awareness. Many accidents and problems relate to situational awareness shortfalls. For example, company employees may be unaware of a robbery in progress (whether physical, or cyber). In the event of an adverse event in a healthcare facility, often the employees involved do not have a full picture of the patient they are dealing with, their history, and all possible cases of action. When talking about a physical facility, situational awareness can be provided in many ways including cameras, reports from guards and staff members or delivery persons, reports from neighbours, passers-by, other sensors, etc. Even when information is available, it is not always in a form of actionable intelligence that directly could improve public safety. Had more information been available, adverse events could be better prevented rather than simply providing a response after the event has taken place.

Increase Awareness about Privacy and Security

Throughout this thesis, analytic approaches are shown that increase information without increasing hardware. Security and privacy concerns are important, as well as the ethics of pervasive sensing. This is also addressed throughout the thesis. For example, there is an area of study called OpenData, where much data is being made publicly available. The sharing of data provides great benefits, but before opening data, it is important to know that the concept of sensory substitution can be used to derive personal information that should perhaps be protected. Smart homes and smart, connected environments also are important and useful good, but sometimes aspects can be exploited. This does not mean open data is a problem, but rather that the impact of information that an outsider could gain, needs to be evaluated in terms of risk. For example, one consideration is that the

Heating, Ventilation, and Air Conditioning (HVAC) data for a building could be made available using an Application Programming Interface (API, a programmable stream of data). This sounds innocuous as it could facilitate very useful building automation studies, but it could also provide unwanted leakage of information - for example, occupancy or personnel movement (guards) within the building. Why look at this consideration? HVAC systems are designed to tell one thing - room conditions, but not to derive other personal information. As new standards on what is confidential and what is OpenData are enacted, one must consider through deeper analysis, “Can Sensor X also provide Y and Z, and are Y and Z also innocuous”? Will it result in a privacy breach of some sort? Will it result in an unwanted leakage of data?

1.6 Contributions

The contributions of this thesis are development of algorithms, methodologies, and prototype cases to provide some answers to the hypothesis using a multi-sensor approach that uses the sensory substitution approach, Agile IoT methods, analytical approaches, and resilience feedback responses. Note that resulting Journal Papers and peer-reviewed conference papers are presented in Chapter seven.

1. Data Capture - Sensory Substitution [2], [3]: Proposed an approach for sensor substitution / cross-modal sensing and designed a framework and techniques for Agile IoT as part of a situational awareness approach. Also designed a method of using sensor modality shifting with temperature sensors to measure other non-temperature data .
2. Data Analytics [4], [5], [6], [7], [8], [9], [10]:
 - A) Sensory Validation: Designed a method of validating sensor inputs: ambient physical sensors for AI camera analytic validation and performed an analysis of sensing security implications.
 - B) Classification and Adaptation: Proposed an urban sensing method using imaging analytics with acoustic signals for UAV signature classification and designed an environmental and physical sensor system for smart environments to perform human detection and develop personalization in an IoT environment.
 - C) Multi-sensory Fusion: Designed smart environments, infrastructure and person security using sound and multi-sensory situational awareness algorithms: LMS and acoustic-based approaches to enable sensory substitution for posture detection and

analytics in smart environments .

3. Response Mechanism [11], [12], [13], [14], [15]: Proposed rapid situational awareness using mobile and fixed sensor nodes, computer vision, human-in-the loop measurements, and low-cost, rapid-deployment sensing instrumentation for critical IoT systems; and proposed a “Resilience Feedback-Loop” that constantly improves sensory substitution approaches for increasing resiliency .

The mapping of the thesis contributions can be found below in Figure 2.1, with locations of contribution on the map shown. These numbers co-respond to the contribution numbers above.

1.7 Organization of Thesis

This document begins with the current chapter.

Immediately following the introduction is an overview of the case for Sensory Substitution in Chapter 2. Related work in the field is presented in Chapter 3, and this is some of the work built upon throughout this thesis.

Subsequent chapters are focused on the technical details: Chapter 4 covers the general technique developed and used as a component of the remaining parts of the thesis: Sensory Substitution. Though sensory substitution can stand alone and provide output data, its data can be enhanced with various data analytics and applications. So, Chapter 5 discusses Data Analytics: Approaches in Scenarios. Sometimes, the data from the analytical responses is sufficient intelligence, but this data can be used to enhance resilience in critical infrastructure systems. With this in mind, Chapter 6 covers Response Mechanism and Resilience Feedback, showing how the methods from Chapter 4 and Chapter 5 increases situational awareness and supports decision making with available sensors.

Following the discussion of each contribution, a list of peer-reviewed technical publications stemming from this work is presented in Chapter 7 of the Impact of Research: Resulting Publications.

2 Thesis Contextualization and Background

“Critical infrastructure refers to processes, systems, facilities, technologies, networks, assets and services essential to the health, safety, security or economic well-being of [citizens] and the effective functioning of government. Critical infrastructure can be stand-alone or interconnected and interdependent [...] Disruptions of critical infrastructure could result in catastrophic loss of life, adverse economic effects, and significant harm to public confidence.” - National Strategy for Critical Infrastructure [16]

Situational awareness is important and provides a key input into resilient systems, and when applied to critical infrastructure, resilience feedback can improve public safety.

This chapter begins with a discussion of the context and background in section 2.1 and then discusses relevant related work in chapter 3. The overview of the thesis can be found in Figure 2.1.

2.1 Background: Thesis Context and Application Scenarios

Situational awareness can be defined as “information gathered from a variety of sources that [...] can form the basis for incident management decision-making” [1], and an increase in situational awareness has a direct impact on resilience.

One of the most consequential applications of distributed computing in society is to provide relevant data to key decision-makers in critical infrastructure sectors as is needed. Demand and societal expectations for resilient systems may increase as the paradigm shifts further and further into real-time cyber-physical sensing.

Figure 2.1: Thesis Contribution Mapping

Continuous, evolving data gathering needs must be rapidly addressed to enable decision-makers to facilitate resilient systems.

Critical infrastructure (CI) is that on which modern society relies [16]. Resilience is the approach to quickly resolve any problems and recover to full capacity. For example in the energy sector, the outages of electricity can cause ripple effects across all critical sectors from banking to transportation. Therefore, it is of utmost importance to quickly resolve any type of outage, and a key is situational awareness. The concept of resilience feedback acknowledges that improving resilience is not just about developing a particular system for a particular location, but rather adapting what is already there to improve resilience, or adding whatever is needed at the time to provide the information needed to quickly resolve an issue and to monitor over the longer term. Increasing resilience of CI can then increase public safety. In section 2.3, an End-To-End Usage Case, Triggers, and 3-Layered Approach is discussed to illustrate the three layers clearly.

The developed Resilience Feedback Loop approach of informed responses is presented for distributed sensing, enabled by sensory substitution. Resilience feedback is the use of information gathered to improve sensing techniques and responses with the goals of either increasing sensing confidence, adding orthogonal sensor modalities, increasing situational awareness, or increasing resilience overall.

2.1.1 3-Layer Architecture

We propose a three-layer architecture to be organized as seen in Figure 2.1. The entire approach focuses outside normal instrumentation systems and normal control loops, and focuses on what information can be derived from existing sensors.

Surrounded by a light green frame in Figure 2.1, is Layer 1 - Data Capture: Sensory Substitution. In this layer, Agile IoT is presented, which can enable sensing a different output than for which a sensor was originally designed. For example, a temperature sensor can measure mechanical events. As shown with black output arrows, sensory substitution in Agile IoT can then enable additional modalities of sensing. This data then must have analytics applied to it, and the output of this layer is an input to the data analytics approaches layer of our framework. The approach can be tuned using information gained with the resilience feedback loop.

Again in Figure 2.1, surrounded by a dark green frame, Layer 2, which is the Data Analytics approaches layer, takes the input of sensed data from the Data Collection: Sensory

Substitution an Agile IoT layer, and performs additional analytics. These approaches include sensory validation, classification and adaptation, and multi-sensory fusion. The outputs from these approaches, indicated with an arrow, can be used as the response mechanism and the algorithms and techniques can be further tuned with the resilience feedback loop.

The third frame in Figure 2.1 represents Layer 3, and is circled in blue as the response mechanism. This methodology can stand alone to provide an output to resolve issues, or can take inputs from the sensory substitution in Agile IoT layer, and from the analytics layer. The resilience feedback layer then can output data to directly resolve an issue, or combined with data from the sensory substitution and Agile IoT layer and the analytics layers, can then produce an output of situational awareness and intelligence.

This research is organized in three specific areas of work. The first area is sensory substitution and Agile IoT discussed in chapter 4. The second part are analytical approaches of sensory validation, classification and adaptation, and multi-sensory fusion, which are discussed in chapter 5. Finally this information then enables a response mechanism and resilience feedback techniques which are discussed in chapter 6.

2.1.2 Layer 1 - Sensory Substitution and Agile IoT

The first layer of our research presents a new approach to sensing: sensory substitution, as indicated in Part 1 of Figure 2.1. In chapter 4, Sensory Substitution is presented, which is an Agile IoT approach to measure data with available sensors rather than task-specific sensors.

Given the design requirement of getting new information, a step becomes to increase situational awareness by collecting a new type of information without installing anything further. Traditional engineering techniques often involve trade-offs between time and money. Sensory substitution addresses a problem separate from time and money – though related – and is a real problem in critical infrastructure applications. The problem to address is modification constraints, therefore modifying the physical environment is out of the question [3, 2]. Modification constraints can be realistic constraints like time and money, or in some operational environments, process constraints, policy constraints, legal/code constraints, or other constraints. This can be exemplified and overcome particularly with common temperature sensors.

Consideration of temperature is inherent in many daily applications. Temperature sensors

are everywhere from the thermostat at home, to heated seats in cars or chairs, to weather monitoring, etc. There is an abundant supply of temperature data, so with all this data available, can it be used for other purposes?

2.1.3 Layer 2 - Data Analytic Approaches

The second layer of our work then looks at three broad analytic approaches for sensors, and these are outlined in chapter 5:

1. **Sensory Validation**: Increasing Trust in Sensed Data
2. **Classification and Adaptation**: Urban Sensing and Security
3. **Multi-sensory Fusion**: Smart Environments, Infrastructure and Person Security

Scenario #1: Sensory Validation: Increasing Trust in Sensed Data

In this scenario, a method was designed to validate sensor inputs: using ambient physical sensors to validate AI camera analytics, and also an analysis of sensing security implications was performed.

At times, wrong information can be sensed as correct. As cyber-physical security issues take the centre stage in increasing resiliency of distributed sensor systems, validation of the data - ensuring the data is not compromised - is important. However, deploying a new redundant sensing system often is inhibited by modification constraints [3]. How do we overcome the constraints limiting new hardware deployment in a distributed sensing scenario, but still increase validation? Looking at a fog-computing deployment, this is addressed in the first part of chapter 5.

Scenario #2: Classification and Adaptation: Urban Sensing and Security

In this scenario, a method for urban sensing using imaging analytics with acoustic signals for uninhabited aerial vehicle (UAV) signature classification was proposed. Also, an environmental and physical sensor system for smart environments was created to perform human detection. This also includes and development of personalization in an IoT environment.

Scenario #3: Multi-sensory Fusion: Smart Environments, Infrastructure and Person Security

In this scenario, a multi-sensory adaptive sensor fusion approach is designed. LMS-based approaches to enable sensory substitution for posture detection and analytics in smart environments will be discussed.

2.1.4 Layer 3 - Response Mechanism and Resilience Feedback Loop

In chapter 6, the third layer of the research presents a framework of Response Mechanisms and Resilience Feedback, where a series of methods of using emerging sensing technologies is presented, such as human in the loop, sparse and distributed sensing, mobile sensing such as on UAVs, and over-the-top sensing, as well as additional sensory substitution algorithms to fill the gap where a full design and engineering implementation and installation of sensors is not possible.

An example scenario is a security environment where the decision-maker needs more information than is currently available. Resilience feedback calls for making do with what is available already, so resilience feedback becomes an answer in that ambient sensors in the facility that were not designed as part of a security system, can become part of the security system. Microphones, magnetometers, and other ambient sensors that were installed for other purposes can be used. Are there temperature sensors there? Can we get someone to walk by with a smart phone, watch, or leave a sensor node to deploy new sensing modalities? Whatever sensors are there, resilience feedback is about finding a way to use them.

This work seeks to combine the concept of sensory substitution - where already deployed sensors measuring one parameter can instead measure another, to overcome modification constraints [3], with various distributed computing and sensing techniques to improve resilience of critical infrastructure systems.

The resilience feedback loop is an approach being designed to improve situational awareness for critical infrastructure applications. An Industrial Internet of Things (IIoT) system is a connected network of sensors, controllers, and actuators used for industrial purposes. In many scenarios, an IIoT system may be able to make many decisions for humans. This is done in cars, airplanes, and many managed systems. However, in critical infrastructure systems, typically the final decision often must be made by a human or

human team in a very short period of time. Society expects that the key decision makers have been informed with the best possible information.

The concept of sensory substitution and Agile IoT [2, 3], enables the resilience feedback loop model, and distributed sensing systems play a key role in the entire feedback loop. Agile IoT refers to the idea that the Internet of Things is adaptable and flexible, and within the scope of this research, specifically it looks at sensory substitution as the key implementation method of Agile IoT. Sensory substitution is an approach that uses already existing sensors to measure quantities for which they were not originally deployed [3].

Response Mechanisms and Resilience Feedback are a series of methods of using emerging sensing technologies such as human-in-the-loop, sparse and distributed sensing, mobile sensing such as on UAVs, and over-the-top sensing, as well as additional sensory substitution algorithms to fill the gap where a full design and engineering implementation and installation of sensors is not possible. Resilience feedback, in conjunction with sensory substitution, can provide substantial situational awareness and increase public safety.

As can be seen in the high-level system diagram of resilience feedback in Figure 2.1, the goal of the entire system is to use what is available to provide key decision makers with sufficient information to take steps to resolve an issue at hand.

Although operating manuals are available in many system control rooms, easy-to-follow exhaustive checklists as to how to handle such a situation could help in terms of dealing with situations, but any action could be burdensome and gaps exist in terms of this. A “resilience feedback loop” is needed to close some of this gap.

We define, in the context of this work, “resilience feedback loop” to be rapid deployment agile sensing or agile data-gathering based on needed information.

We can use analytics to determine the level of realism of a particular event. For example, if we have a tree branch falling on a power line, specific characteristics could be seen, and with sensor analytics, the operator could be made aware of this information.

There is also much need for sensors and analytics in terms of physical security from intruders, both natural and human. For example, appropriate alarms must be sounded if there is sabotage suspected, and likewise, a tree falling onto a power line. Although both situations are different in nature, sensor analytics must be able to bring any breaches of security to the attention of the control technicians [17], [18].

Sensors have also been shown to have potential, specifically in environmental protection

situational awareness. For example, if we look at the July 2010 rupture of a crude pipeline in Michigan USA, we see a large problem in that it took the company more than 17 hours to realize that their pipeline was leaking into the Kalamazoo River. Combinations of sensing, including odour, can provide more awareness [19].

From sensors monitoring air quality, to motion sensors to help students track study times, to assistive devices for assisted daily living, to larger scale critical infrastructure monitoring networks such as traffic lights in urban centres and valves at water plants or energy facilities, there are endless applications for IoT systems.

People expect infrastructure such as the electricity system to be reliable. They trust it to be 24/7 with 99.9% uptime, and expect it should be there as they need it. As IoT expands into this area, much emphasis must be on securing these systems so the public can continue to trust their infrastructure. So too, they expect smart devices should be reliable within their homes.

The goal of any type of sensing is to provide relevant information to the relevant end user. That end-user may be an algorithm, a person, or some combination of the two. For many situational awareness and public safety requirements, the end user will likely be a human, who must make a tough decision. Providing all relevant information is of utmost importance. Many of the routes of sensory substitution and resilience feedback in our model lead to a human actor as the final decision-maker.

With Agile IoT sensing techniques and “resilience feedback loop” techniques of providing actionable intelligence by sharing relevant data to the right person at the right time in the right way, public safety and resilience can be increased.

2.2 Current and Future State of IoT Instrumentation System Design

Figure 2.2: Current and Future State - IoT Instrumentation Design. The Gray layer represents the current IoT design. The Yellow layer reflects contributions that work to solve the modification constraint. The Blue layer shows contributions that strive to solve the information feedback issue. The Green layer indicates contributions that solve parts of both modification constraints and information feedback issues.

In Figure 2.2, a typical instrumentation and measurement design is shown involving design, then deployment of the best hardware for the task, plus enhancements proposed in this thesis: the future state. In the thesis, the paradigm shifts where hardware may be constrained, but the requirement is still to collect a new type of data with the hardware available. These concepts will be explained through the subsequent sections.

Similarly for sensory validation, the requirement may still be to validate data with the already available hardware.

This can be further extended, as trusting in sensed data in a closed edge sensing system is often an accepted assumption in a new sensor system. In Figure 2.3, a typical instrumentation and measurement design is shown involving design, then deployment of specific hardware for the task, and in this workflow, the sensed data is trusted and actions are taken based on this data.

Figure 2.3: IoT Instrumentation Design: Actions Are Taken Based on Trusting Information Is Correct © IEEE

These concepts will be explained through the subsequent sections. The alternative approach based on sensory substitution and validation before trusting data, will be discussed in section 5.1.

Intelligence Requires Processing

According to the US Military, Joint Chiefs of Staff, the path from data to intelligence goes through much refining, as per Figure 2.4. Similarly too, an IoT system collects data from the environment, performs many levels of analytics, and finally produces situational awareness. Subsequently, responses to the information increase resilience, and we propose a “resilience feedback loop” to use agile sensing and responses. This may enable effective risk management for public safety.

Figure 2.4: Data to Intelligence © [20]

Situational Awareness to Action: Issues, Solutions, and Ideas - All Hazards

Analogy: Response in Aircraft

Sensor technology and analytics can be used for natural and human threats. This can help lead to an all-hazards risk management response for protection of critical infrastructure and threat differentiation. However, there may be a perception in some control rooms that IoT or SCADAs (Supervisory Control and Data Acquisition systems) always provide a warning alarm with actions to follow if a sensor is triggered, but frequently solutions

are not provided to the control room technicians as to how to deal with all the possible sensor inputs.

The use of sensors and analytics to determine different types of emergencies can be illustrated as in an aircraft. In the flight deck, a particular alarm may sound, for example, suppose a “MASTER CAUTION” warning is lit up on a Boeing 737, as shown below in Figure 2.5. In this situation, the course of action a pilot might take would be to look at an emergency checklist to safely deal with the issue. If “Engine Fire” alarm sounds, steps to extinguish the fire can be consulted. If the plane loses both engines, checklists can be followed for ditching the plane both over water and over land, and are provided in order to facilitate the safest situation. This feedback loop increases resilience of the aircraft, and serves as a model for increasing resilience of other infrastructure.

Figure 2.5: Master Caution Alarm on Boeing 737 Aircraft © 737ng.co.uk

2.3 End-To-End Usage Case, Triggers, and 3-Layered Approach

This thesis presents a solution with three distinct layers as shown in Figure 2.1.

It is very important to give decision makers in critical infrastructure the right information, at the right time, in the right place to enable quick actionable intelligence. However, sometimes the sensor needed may not always exist in the location needed at those right times. In circumstances like this, other sensors may exist in these locations. A goal then is to increase resilience of critical systems using these already present sensors in a new modality; thus, bringing zero sensing to a nonzero sensing level - where the sensor needed is currently not present.

A solution to the issues presented above can take the form of a three-layer approach. The

modification constraint approach is resolved using the first two layers: data capture and sensory substitution, and data analytics. The information feedback problem for long-term resilience is addressed and resolved using the response mechanism and resilience feedback loop.¹

The trigger for initiating the solutions presented in this thesis are external, typically by a human or other algorithmic operator that requires additional information. This information is either not available with currently deployed sensors, or the currently deployed sensors are unavailable or cannot be relied upon.

Examine a scenario where a security-resilience professional is responsible for security of a critical infrastructure site, but they have reason to believe that someone has been obtaining unauthorized access within that facility. The security-resilience professional has taken steps to address this by analyzing and reviewing camera footage of the relevant areas, access logs, and asking the guards about any suspicious behaviour. Traditional sensing does not immediately provide the answers needed: upon review of the video footage, nothing appears to be of a questionable nature. The guards do not risk report any suspicious issues, though one mentions they found a crashed drone on the outdoor lawn -- which they promptly put outside of the fence as they presumed it was a child's toy that got lost, like a drifting soccer ball.

Layer 1 As the security resilience professional, it becomes imperative to collect data to validate the potential security breach or confirm a lack thereof. They then trigger Layer 1 of the approach presented in this thesis: data capture and sensory substitution. The end-to-end description of the usage case begins with this situation of a room which a security-resilience professional is concerned that is being accessed when it should not be accessed. In the room, there already exist certain sensors. One of the sensors in the room is a camera, which is connected to the security centre. The room also has a switch that measures the events of opening and closing of the door. The information from the camera and switch are relayed to the security control room. Meanwhile, another sensor, connected to the Building Automation SCADA system (a system that controls the heating, ventilation, and air conditioning (HVAC)) is present in the room, and this sensor samples the temperature at regular intervals and relays this information to the maintenance control centre. The temperature sensor therefore is on an “air-gapped”

¹Note: IoT sensing typically involves multiple layers including the physical layer, the control system, the communication layer, and the applications. These components of the IoT systems are not to be confused with the solution layers presented in this thesis.

network, which can also be thought of as an “over-the-top” sensing network. Outside of this room is a small galley area with a sink and thermal sensors for fire protection. The thermal sensors are connected to the building fire monitoring system, and not the security system. Thus these sensors are also “over-the-top” and “air gapped” from the security system. The important distinction of these “other” sensors is that they are not connected to the security system. Since the camera system did not detect any activity, for all intents and purposes of analysis, it can be assumed that the regularly used sensor for detecting humans present (and the security system to which it is connected) cannot be trusted at this time. Therefore the sensor X is considered not present. Meanwhile, sensor Y, which is the HVAC temperature sensor, is present in the room. Also present is sensor Y2, the temperature sensor near the pipes of the kitchenette. In the event that someone is in the facility, temperature sensors can be used to indirectly measure the presence of a person. When air masses on opposite sides of the door are of different temperature, the opening of the door may have a direct impact on the temperature, and can be extracted or filtered from expected temperature variations [e.g. HVAC] to provide “door open event” timings. Similarly, if the person is onsite for a while, they may use the facilities pipes (e.g. water). Temperature variations on/near pipes that are not caused by a known or planned water use event (machines, etc) is likely attributed to human action. Layer 1 of this thesis will show ways of using pre-existing temperature sensors to determine activities, thereby replacing sensor X (door sensors, flow meters) with sensor Y (temperature sensor) to extract the desired measurand of human presence detection. This layer is discussed in detail in chapter 4. Layer 1 helps the security resilience professional to gain additional situational awareness with existing sensors.

Layer 2 Once it has been ascertained that there has been some unaccounted presence of a human, recall the scenario: the security resilience professional has checked the cameras and not locate the person of interest, but there are signs (using Layer 1) that there is human activity. It has become clear that at this time, the security resilience professional can not trust the security sensors to provide the true representation of the real-world information it observes. Validation of the trust of sensors will be covered in the second layer. The trigger for the second layer of data analytics is the need for further information. Information needs that may trigger layer two results from the need to extract additional information using the sensory substitution approach to validate sensors, fuse orthogonal sensor modalities to increase resilience, or to perform other data analytics techniques. This layer can enable validation of the camera using ambient magnetometers and photo

resistors to confirm the false negative from this scenario. Like temperature sensors, these physical sensors (magnetometers, photo-resistors, etc) are often commonly located in many rooms. This second layer also may help the security resilience professional to investigate further another aspect from the scenario: the report from one of the guards that they had discovered a UAV on the lawn. Although guards may have thought it was child's toy, that same drone could be on a targeted espionage mission. This second layer will use ambient microphones for UAV signature extraction and forensics to determine if this was a one-time visit, or if it is part of a regular campaign of flights. This second layer also uses multi-sensory fusion, adaptation, and classification with ambient temperature sensors to determine human presence and activity in a chair. If the person of interest is visiting the infrastructure site regularly, pertinent information includes where they sit, when, for how long, and in which posture. This information can then be used to infer and potentially estimate activities. The layer also discusses orthogonal sensor modalities and how this can improve confidence of sensing. For example in the chair algorithm, humans can be detected using temperature variations. This provides a non-zero level of confidence of human chair usage events where the sensor confidence had been zero (non-existent), but orthogonal sensing modalities can be additionally furthered: addition of microphones can improve confidence. Corroboration of orthogonal sensing modalities may then further increase confidence of sensing. This also may improve resiliency, as if this environment becomes too warm for the temperature sensors to be effective, instead microphones can be used for human posture change timing detection. Meanwhile if the environment is very noisy, temperature sensors will likely be unaffected and could be used for this detection. Thus orthogonal sensing modalities in Layer two have increased sensor confidence from zero to non-zero, then to an even higher level of confidence. Finally in this layer, the security implications of near field communication (NFC) is also explored. Further to the scenario, it is important for security professionals to look at all-hazards threats, for example, other potential methods of exfiltration of data. The concept of sensory substitution can be used to infer information using measurements collected on smart phones, and NFC tags can activate particular scripts to initiate this measurement and transmit the results. For example, a guard's phone could have had the inertial measurement unit (IMU) activated by an NFC tag, by scanning a particular QR code, or through opening a malicious URL. This could potentially enable scripts that extract the IMU data to a cloud location, thus enabling extraction of speed, motion, step count, etc. providing information to unauthorized actors. All of these considerations are important and covered by the second layer of the approach presented in this thesis in chapter 5.

Layer 3 One might ask if there is a need for continuing beyond the second layer since the acute problem of person detection is successful with just the first two layers. The first and second layer do provide the information to the right person at the right time, increasing sensing from zero confidence (where the sensor is not present) to using other sensing modalities which can then provide the information. Therefore, the key decision maker has enough information to fix the acute problem. However, Layer 3 is focused more on long-term monitoring and gathering additional information to enable resilience. Where Layer 1 and Layer 2 focus on *in situ* sensors, layer three focuses on response vectors that can include human-in-the-loop sensing and rapid deployment of other sensors. Increasing resilience requires deeper understanding of the motive of the person of interest, or increased monitoring for analytics of a natural event. This can be better captured with long-term monitoring rather than simply stopping the unauthorized access or dealing with the natural event. In the real world example, when a security resilience professional determines there is an acute problem or threat to critical infrastructure, certainly they should intervene right away. However, if possible, they may be better served by waiting and monitoring for the long-term to determine the larger strategy of the individual's trade-craft and thus who may really be behind the incursion. These longer term observations may provide a better level of resilience. Strategies for the third layer include over-the-top sensor measurements - that is, sensors that are connected using an alternative channel and not part of the existing building monitoring system. This is similar to the discussion above of using the HVAC network rather than the security network in the case of compromise. Another strategy includes deploying humans-as-a-sensor, human-in-the-loop sensing, or having humans rapidly deploy sensors to surgically target a particular measurement need by deploying a sensor where it is needed. Strategies of computer vision and resilience innovation (such as deep learning using machine vision) are also parts of Layer 3 that provide that monitoring for increased CI resilience. Another part of Layer 3 that could be used to address part of the scenario is using UAVs as a mobile sensing platform to rapidly gather information or deploy sensors. These approaches then can improve the long-term monitoring to increase long-term resilience and is presented in chapter 6.

Therefore, Layer 1 and Layer 2 focus primarily on the acute sensing needs based on particular threats and are triggered externally. Layer 3 is triggered by the outcomes of Layer 1 and Layer 2 that are based on the longer-term sensing needs to provide resilience in the long-term. Concluding this end-to-end example, it is clear that in the role of a security resilience professional, the approaches covered in this thesis enable rapid

data gathering when time and modification constraints prevent use of, or deployment of, sensors normally suited for the task. This approach enables a security professional to gather information where previously a sensor did not exist, therefore increasing the sensor confidence in this area from zero to a non-zero value. Orthogonal sensing modalities can enable resilient measurements using such alternative sensing techniques. Validation of sensors can then give rise to increasing trust in sensed data, and therefore ensuring the appropriate responses can be taken to acute problems. Finally, having dealt with the acute problems, the third layer allows for monitoring over the long term to verily increase resilience.

3 Related Work

The related work section is organized by topic to explain the work in the field, the gap being explored with this thesis, and the motivation and related work required to understand the technical contributions of this thesis.

In this section, the following technical topics are explored in the same order as the three major layers and the areas of work identified in Figure 2.1:

- In section 3.1, *Sensory Substitution* background of Layer 1 is discussed.
- In section 3.2: *Data Analytics: Algorithm Applications in Scenarios*, topics covered include *Sensory Validation*, *Classification and Adaptation: Robust Urban Sensing and Monitoring*, and *Multi-sensory Fusion: Smart Environments, Infrastructure, and Person Security* to present the background of Layer 2.
- In section 3.3 an overview of *Response Mechanisms and Resilience Feedback* related work for Layer 3 is presented
- Work in chapter 3 ends with section 3.4 where the *Summary - Overall Goal for Three-Layer Approach* is discussed as a summary of the chapter.

3.1 Sensory Substitution

The first major area of research focuses on an approach for sensor substitution / cross-modal sensing. This includes design of a framework and techniques for Agile IoT as part of a situational awareness approach which is proposed. Various authors have used IoT in multiple ways, and we explore this here. The discussion in this section are the related work that are furthered by work in chapter 4.

Internet of Things (IoT) can be used to improve lives by increasing the safety, security, and resilience of the critical infrastructure on which modern societies rely. Aging, under-monitored infrastructure can pose serious threats. Resiliency can improve with IoT-based

sensors for critical infrastructure. According to Stankovic, he believes that IoT could change the world [21].

The paradigm shift coming from this that is being proposed in this thesis is to measure Quantity X with a sensor designed to measure Quantity Y, and this related work leads to the material in chapter 4, chapter 5, and chapter 6.

Human Senses

One might ask where this paradigm can be found, and nature inspires this method. In winter, if someone has moved away from the front hall area of their home foyer, they will no longer see, nor hear, the opening of their front door. Yet, they do feel an abrupt presence of brisk air. Another sense has conveyed this same information. Biological processes have inspired much development. For instance, in the 1950s, Bremermann looked at the nervous system as a model of its environment [22], and biologically inspired algorithms have continued development with bacteria inspired algorithms [23], and up to today with such concepts as swarm intelligence [24]. Likewise, there has been research into compensatory devices to perform “sensory substitution” for humans with adapting senses [25]. In 2009, Auvray and Myin state that sensory substitution devices “provide through an unusual sensory modality, [...] access to features of the world that are normally accessed through another sensory modality.” [25] The scope of this is usually for human applications, but we extend this to sensors and algorithms in chapter 4.

Temperature Sensors in Modification Constrained Environments

Flow meters are commonly used for fluid measurements, and there have been many innovations on these sensors. In [26], authors improved a turbine flow meter with a novel flow sensor system based on magnetic suspension bearing, to monitor pipes. External sensors based on ultrasound also exist, and an innovation by [27] led to looking at the ultrasonic transducer positioning to improve accuracy of a clamp-on flow-meter. There has also been work on using in-line fluid characterization and visualization with pulsed Doppler ultrasound [28]. Acoustic methods include [29] using an acoustic flow sensor as a water flow sensor. Smart environments often call for internal flow meter sensors [30] for IoT applications, but our approach asks the question of what can be done without such new sensor deployments. As smart appliance uptake increases, fridges have much

intelligence today. Some fridges are able to predict the contents of the fridge automatically, and can suggest recipes based on those contents [31]. For retrofits; however, many fridges do not collect information. Some of the previous generation of fridge monitors logged data locally to be later extracted. To detect fridge door open events, some solutions could include recording motion of fridge doors using a variety of possible sensors. Fridge door activity systems have included mechanical switches, pressure sensors, and position sensors [32]. In terms of temperature monitoring for fridges, there has been work on placing temperature sensors inside refrigerated environments to monitor and track food [33] to look for spoilage, and temperature compliance of various fridges [34]. Many systems were fairly expensive solutions. When looking at the issue of modification constraints, it should be noted that most were not intended to be low-cost IoT sensors. Fridge monitoring temperature sensors are often placed inside the fridge, such as in the door or on one of the internal shelves. Smart environment monitoring and sensor systems has been explored by [35]. Expanding this area, we measure mechanical door events and flow events with already-deployed temperature sensors and explore this in chapter 4.

IoT in Infrastructure, Resilience, and All-Hazards Threats

IoT-based sensing is often used in smart environments, such as for activity classification [36]. Unique strategies for object identification is another area for IoT, such as work by Mirjalili [37] on a ubiquitous optical wireless tag for identifying objects in the physical space.

IoT is also being used in various applications leading towards or augmenting our work. For example in their 2014 paper, Lanzisera *et al* discussed the concept of communicating power supplies to save energy [38]. Networked power infrastructure could use information from the utility poles to anticipate problems from ice buildup, and with situational awareness, could perhaps enable prediction of an impending blackout and then activate a response. In work by Savazzi *et al*, they discuss issues surrounding the cloud connectivity and issues of 2.4GHz wireless signals [39].

Deploying sensors outdoors opens the possibility that signals could interfere with the sensor nodes, particularly while monitoring activities surrounding infrastructure, especially ice development and buildup. To increase resilience, an all-hazards approach is required. Threats to critical infrastructure increasingly are directed at cyber-security of SCADA (Supervisory Control And Data Acquisition) and ICS (Industrial Control Systems) [40], and by extension, Industrial IoT.

Sensors can indicate system compromise or unauthorized persons, and sensors can provide additional verification. Work has been done on multi-modal sensor fusion in telecom [41]. McEvoy and Wolthusen believes that security risks to sensors and monitoring highlight a requirement for the use of multiple sensors which make use of differing points of view for anomaly detection [42]. The numbers of IIoT devices will continue to increase [43].

By collecting large amounts of data from sensors, it is important to balance the problem of having too much data. If data is stored and slowly processed, important information might be missed, and add risk by not responding to an incident promptly [44].

With cloud and fog system deployments increasing in IoT, resources can be of concern [45].

The IEEE IoT Journal has previously looked at the issues of resiliency with work such as Industrial Internet of Things driven by SDN platform for smart grid resiliency [46].

A key philosophical change in thinking being proposed by the author of this thesis, building on this related work, in chapter 4 is that seemingly divergent areas of research and development such as IoT, IIoT, sensors, SCADA/ICS, critical infrastructure, cyber-security, data analytics, and situational awareness are not separate. Rather, through Agile IoT with sensor modality shifting and agile communication, these are all linked. Further increasing resilience can come from IoT systems as they can use existing sensors from prior installation and previously deployed purposes for new situational awareness. We build on this in chapter 4.

Impact of Ice and Weather on Critical Infrastructure

In the 2015 paper Impact of Climate Change on Civil Infrastructure – A State-of-the-Art Review, Ali and Mirza [47] discuss the impacts of weather-related incidents and how vulnerable civil infrastructure can be to weather-related disasters. They discuss 9 of Canada’s large natural disasters, including the 2014 and 2005 flooding in the prairies, Toronto floods of 2013 and 2005, Calgary flood of 2013, Peterborough flood of 2004, BC wildfires, ice storms, hurricane Juan, and the Saguenay flood of 1996. The estimated cost of these disasters was approximately \$11.5 billion (CAD), however, the cost of the Ice Storm of 1998 is upwards of \$5.4 billion (CAD) [47]. The ice storm, when looked at independently, cost a significant amount as compared to many of the other major disasters.

Figure 3.1: Transportation in cold climates such as on trains, must handle icing conditions on cables, wires, valves, stairways, and doors © IEEE

Ice on transportation infrastructure can be seen in Figure 3.1. Ice buildup on infrastructure such as cabling and sensors can cause disruption. Sensory substitution and resilience feedback is presented as an approach to use existing sensors to resolve these issues. This related work is built on in chapter 5.

Progression of Technology

Technological advancement might alleviate blackouts, or supply disruptions. Electrical outages can lead to significant losses to the economy [48]. Initially, most of these critical control systems were manually controlled. Industrial Internet of Things (IIoT) is the latest evolution of the technology in critical infrastructure [49]. Though new technology comes with new vulnerabilities, the anticipatory predictions made by algorithms regarding situational awareness seek to outweigh any new vulnerabilities, however security must become a prime focus during design and not as an afterthought. Progression from analog to digital to IoT and beyond have introduced many efficiencies, as well as vulnerabilities that can be exploited, such as human reliance on sensors that can be compromised with

cyber-physical attacks such as playback attacks [50]. This shows a need for increased situational awareness in literature, and we apply these concepts in chapter 4.

3.2 Data Analytics: Algorithm Applications in Scenarios

In this thesis, three analytics approaches are explored using the sensory substitution approach in chapter 5, and the relevant related work is presented here:

Sensory Validation

This background sets the stage for contributions in chapter 5.

Reliability of Sensing

Accurately sensing data is critical. In ideal circumstances, development of an engineering instrumentation and measurement system involves design and deployment of the ideal sensors to validate, but modification constraints could limit such an installation [3].

Many techniques of sensor validation exist that focus on the concept of “self validation” of the sensors. Those types of techniques are typically looking for inherent sensor calibration or physical fault issues, such as drift in temperature sensors or faults in pressure sensors [51]. How can we independently validate raw or processed data from distributed sensors?

Since edge sensor data is used by algorithms to make decisions, such as image processing for critical infrastructure, healthcare, and security applications, immense trust in the validity of the recorded data is paramount. The sensors may appear to be doing what they normally ought to do, but are they in actuality doing so?

This issue has been of interest in this field, as discussed in work about the trust of sensors [52]. Manipulation of sensors or data is a concern.

In fact, some work in this area discussed ways to detect signal injection attacks against alterations of sensor data [53]. The authors further the discussion of these important issues in this thesis.

Risk can be thought of as a function of particular activities and vulnerabilities, while resiliency is a function of fail-safe, redundancy, and situational awareness. Sensory signatures can substantially increase the situational awareness thus increase resiliency and

mitigate risk. To be resilient, a system needs to have redundancy, and to have redundancy, it is important to be able to analyze the environment using multiple sensing technologies, including algorithms that allow sensor uses for which they were not originally intended. Corroboration of the sensor data is important, and a technique for rapid sensor validation is Sensory Substitution as a part of Agile IoT [2].

We build on this related work by using a method of validating sensor inputs. This method was designed and relevant analytics were carried out towards ambient physical sensors for AI camera and sensing security implications. This work included both validation of sensing to prevent cyber-physical attacks and to correct false positives/negatives. The thesis also examines sensor activation issues including NFC. A framework and algorithm to validate sensor data using already existing sensors is presented in chapter 5.

Securing Sensing and Use of Near-Field Communication (NFC), HTML5 and IoT for Instrumentation in Smart Environments

As IoT instrumentation becomes more pervasive, and measurement of multiple parameters continues to expand, it is important not to overlook some security situations related to sensor systems. Sensory substitution can be a great measurement enabler, but can it open unintended measurement consequences?

People are interested in retrofitting and adopting personal health solutions, especially throughout their day. Everything is becoming connected - health, home automation, security, payments, to address the need for growing connectivity. NFC technology is being deployed for many smart medical scenarios [54]. Many sensor reliability issues explored, have been for other impacts of IoT proliferation, such as Satchel *et al*, who looked at the electromagnetic impacts on implanted medical devices [55]. Yi *et al* also looked at system architecture of an intelligent personal communication node [56]. There has also been work on power savings for NFC [57], exploring the current consumption of IoT devices [58], as well as power optimizations and battery lifetime issues [59]. Rahman *et al* looked at data integration between sensors in a BSN (body sensor network) and data from a social network [60]. Work has also included a nested sensor array focusing on near field targets [61]. Thinking about long-term sensing effects, Dapointe examined the effect of disturbances on magnetometer measurements [62], and Berbakov looked at the issue of indoor localization using non-Global Navigation Satellite System, rather using embedded smartphone sensors [63]. This thesis builds on the above research by addressing the impact of IoT proliferation from a sensor security perspective in chapter 5.

Classification and Adaptation: Robust Urban Sensing and Monitoring

This section discusses some key background before exploring these contributions in chapter 5: Sensory Adaptation for robust Urban Sensing and Security.

Urban UAV Acoustic Detection and Signature Classification

UAVs (uninhabited aerial vehicles) and RPAS (remotely piloted aerial systems) are becoming an issue in urban environments. We discuss sensory adaptation, and as discussed above, there is a need for uninhabited aerial systems (UAS) detection where specific UAS detection systems have not been deployed, but if there are sensors that are already deployed for other purposes in urban environments, they can be used. Though literature on UAS detection exists as well as acoustic detection for other sounds, we find an area to expand in literature by addressing this specific urban concern.

There has been much work on various aspects of RPAS detection and classification, usually involving deployment of specific hardware. The existing work primarily uses either 1) specific acoustic or non-acoustic deployments of sensors for non-UAS detection or 2) task-specific, purpose-built UAS detection systems (commercial or research). However, the field is open for additional work with using existing sensors re-purposed for UAS detection. In this work, we focus on what can be done in a typical urban scenario without new hardware.

For example, there has been work on the complex structure of RPAS detection and identification [64]. One approach has been detection and identification using radar in combining with infrared optoelectronic devices. Experimental analysis on the noise of propellers for small RPAS [65] was explored. A numerical analysis based on the compact formulation of the Ffowcs-Williams/Hawking equation and a simple model for the broadband noise was discussed [65]. In the article on the classification of small RPAS and birds by micro-Doppler signatures [66], this work examined a new approach for RPAS classification using continuous wave radar or high pulse repetition frequency (PRF) pulse radars and has been presented as an improvement. Additional work has been done on the wireless video noise classification for micro air vehicles [67] that decides if video is noise or useful frame-by-frame. Bio-inspired RPAS routing, source localization, and acoustic signature classification for persistent surveillance [68] is another interesting work that can

autonomously detect and locate the source of an acoustic event with very high accuracy and visually verify the event.

Work is ongoing on unmanned air vehicle safety event prediction, and classification [69], as well as a field trial of acoustic signature analysis for terrestrial vehicle classification [70]. There is also work on acoustic information fusion for ground vehicle classification [71], as well as regarding perimeter security on detecting acoustic signature of approaching vehicles using nonlinear neural computation [72]. Also, there is work on a computational approach for evaluating the acoustic detection of a military vehicle [73], showing the interest in parallel applications. The accuracy and best training approaches of the related systems is not within the scope of this thesis, as we focus on development of the system that overcomes the modification constraints rather than the most accurate system.

Most of the related work in this area requires deployment of hardware, so does not address the requirement of using what is already present only. Meanwhile, some work using low cost microphones has shown promise in accurate detection [9], so we will strive to use existing embedded or low-cost hardware. All of this research shows a field with much interest, and large areas for potential contributions. Using existing sensors (microphones) with algorithms for image analysis for UAV detection, has many opportunities and is a promising area for research, and our approach to this area is presented in this in subsection 5.2.1. Building on this related work, a method was proposed for an urban sensing environment using imaging analytics with acoustic signals for UAV signature classification. This sensory adaptation work also developed an environmental and physical sensor system for smart environments to perform human detection and develop personalization in an IoT environment, and this is presented in chapter 5.

Multi-sensory Fusion: Smart Environments, Infrastructure, and Person Security

This section reviews analytic approaches of multi-sensory fusion for smart environments, infrastructure and security using multiple sensors, and adaptive analytics.

One area of importance with multi-sensory fusion is security.

Using multi-sensory fusion for security applications, monitoring room occupancy and posture can monitor whether critical infrastructure operators are at their desk, and also

provide data that could additionally provide insight into emotional state of being including lack of awareness or aggressive agitation. This can be addressed with multi-sensory fusion. Performance and creativity can be linked to posture [74]. Posture shifts can be useful also, for workers in various CI occupations such as nuclear facilities and pilots where job alertness is critical. Multi-sensory fusion for posture monitoring also has applications in other fields, such as monitoring alertness of a driver in vehicles such as trains, cars, or trucks [75]. Some locations are specifically designed to be instrumented for monitoring; however, physical monitoring a person's actions is sometimes required when the selection and installation of the ideal sensors may not be possible in all residential and operational environments. Hence, there is a need for an approach to use already available sensors, or sensory substitution, which can be used in cases like this.

Posture Sensing with Embedded Temperature Sensors

This work spans security and health sectors. There has been work on smart chairs with pressure distribution and pattern recognition techniques [76]. Work on chair sensing has also looked at emotion recognition, such as boredom that can plague shut-ins [77], and can monitor other physiological signs [78]. Some posture work uses cameras for the position of specific parts of the body, such as the head [79]. Other research has examined using a variety of sensors and analytics approaches on programmable pervasive spaces where homes can sense themselves [80], and in-home physical activity tracking with a low-cost approach [81]. Pressure sensing has emerged as one leading posture recognition system, particularly for bed occupancy measurements [82], and when monitoring the relief of pressure points for pressure ulcer prevention [83]. Temperature drift in blood pressure measurements can lead to 9mmHg drift, so [84] shows that when temperature sensors are added, they can compensate for the drift. Can such a principle apply in other sensing technologies, such as posture? Other technologies have emerged, such as ultrasound for hip joint centre of pressure calculations [85].

Some of these systems are very expensive, so low-cost systems are of interest in order to lower the deployment barrier. Temperature sensors can be just a dollar per sensor, and temperature sensing, however, has not been utilized to its full capacity. These have a wide range of applications in many sectors, such as HVAC, meteorology, mechanical compliance, and physiological monitoring, such as in neonatal care [86]. Temperature effects on tissue from ultrasound has been examined [87], and new thermal applications are emerging such as Eulerian video magnification methods derived from thermal video to

determine physiological parameters [88]. In this thesis, we extend the uses of temperature sensors in physiological postural monitoring to show that temperature measurements can serve as either a supporting role, or the primary sensing technology for furniture-based occupancy and postural monitoring. In some cases, pressure sensors can yield inconclusive data. Temperature sensors can provide additional information to make the data conclusive.

Personalization and Human Detection with Ambient Sensors and Integration of Sensors into an IoT Smart Environment

In the concept of Internet of Things (IoT), personalization of the experience for the user is very important. In 2014, Tonneau *et al* discussed the “emergence of a new paradigm: the Internet of Things and of the physical world” [89]. IoT has begun to encompass and now connects more and more previously unconnected parts of people’s daily existence.

The smartphone has often been key to IoT applications, as shown by Agu [90] and others. Although in this work, we focus on the sensing and algorithms that lead toward unobtrusive human detection to enable personalization using Bluetooth connections to a host, however, the peer-to-peer (P2P) methodology discussed in [91] could be a promising methodology for communication. Research was undertaken on how to assess standing stability of a patient and thus look at the specific physiological characteristics of a person using unobtrusive floor mats [92]. This offers another method of integrating in a system that performs human identification using only unobtrusive sensors.

Smart Environments with NFC

Smart Environments can also use other existing technology such as NFC. Maintaining an independent quality of life is widely beneficial to patient health, for example could include an elderly person with declining cognitive and physical ability (mobility), or a post-surgical patient in convalescence at home.

In both cases, quality of life can be positively affected by smart home technology. Physical difficulties, situational distraction, and cognitive issues can be considered [93]. Smart homes also are very good, but sometimes aspects may be exploited more, so security and privacy issues must be considered. After medical procedures, a patient can be motivated if they see actual improvements as their body recuperates. A technically inclined patient may see their measurements, yet have little medical understanding. The gadgetry can

empower a savvy consumer to learn assorted health information regarding their medical condition.

In 2013, Swartzendruber *et al* looked at using RFID (Radio-Frequency Identification) as a tracking mechanism for volume management in lower limb amputees. They placed RFID tags at various locations in conjunction with a force-sensitive resistor and examined patient behaviour. Although they found promising results, they concluded that there was work to be done in terms of reliability [94]. Dünnebeil *et al* used NFC tags to provide secure and quick access to medical information, as well as an alternative ID form for various caregiver’s use [95]. In 2010, Crepaldi *et al* used the principle of creating a biosensor that receives its energy externally using an RF link, like a passive RFID tag, and features of RFID such as low power consumption [96]. Bravo *et al* have proposed applications of NFC for Alzheimer patients in a day centre and at home for visualization and monitoring [97].

Research on home environments, can use pressure sensors for physiological monitoring at home [98], and this could include NFC tags to extend the system discussed. NFC within home healthcare has been proposed by Iglesias *et al* by allowing NFC tags to enable users to identify themselves so that information can be collected and attributed to the correct user [99]. In 2008, there was a review of smart homes-present state and future challenges [100], and at that time, there was some foreshadowing of the incorporation of new technology such as NFC and smartphones into smart environments. Finally, there has been research into Touch and Run with NFC [101], which Dodson defines as an approach for contextual application innovation involving virtual tokens.

An interesting trend that could be an enabling technology to allow the use of NFC within smart environments are trends associated with Big Data. “In Big Data, data [is] rather a “fuel” that ‘powers’ the whole complex of technical facilities and infrastructure components built around a specific data origin and their target use” [102]. As such, tags can be a source of data or fuel in a big data ecosystem.

In 2013, Lin *et al* proposed a framework for NFC-based intelligent agents: a context-awareness enabler for social Internet of Things and how these applications need to be aware of user context and ambient intelligence in order to better enable the human-computer interactions. Examining the framework for development of NFC intelligence that combines NFC with traditional contextual data gathering techniques, they propose a framework based on developing a complete ontology knowledge-base. Lin shows the need for awareness of context in a smart home, and a possible framework for this [103].

Postural Monitoring

Personalized and preventative medicine is considered part of a “paradigm shift”, and a significant concern for deployment and proliferation of smart environments, and smart monitoring are the costs associated with specialized configuration and setup [104]. So, using existing sensors for a new purpose could help reduce the costs. Medical and health/wellness scenarios routinely involve temperature status and temperature readings. Thermometers and temperature sensors are prevalent in these sectors. Based on this related work, this thesis discusses using existing temperature sensors to detect other health parameters, such as postural monitoring, which is discussed in chapter 5.

Smart Environments Monitoring of physical parameters has also been explored; there is work on posture detection methods that focus on the development of textiles that act as the sensor, such as for sitting posture classification [105] and for posture analysis [106]. Many of these approaches use a variety of sensors and analytics for posture, and in later sections of this thesis, these concepts are built on by discussing the concept of sensory shifting where alternative techniques are used with available sensors. Pressure sensors are regularly used in reading postural state, and may be considered a gold standard, along with other medical techniques such as expert analysis and video analysis. In work by Al Khaburi, they discuss research about force and pressure sensors as part of a set of devices to correct pressure profiles or assist clinically [107]. Pressure sensors have been used extensively for patient monitoring, such as a pressure sensitive array under a mattress for detection of central apnea [108] as well as for measuring movement of a patient’s torso [109]. Pressure technology for posture and position continues to evolve, as shown by [108, 109].

Signal Processing and Classification The system presented in later in Sec 5.3.2 uses sound to identify a particular postural shift event. This can highlight the segment of temperature data that correlates to a movement event - including those under the acoustic noise floor, using a multi-sensory fusion approach to collect new data.

In 2014, Schopp *et al* discuss a method to observe relative motion indirectly, with three accelerometer triads, and no gyroscopes [110]. Adamo used sounds to measure moisture content in soil [111]. In the case of modeling different sensor modalities, Wu looked at the correlation of accelerometer and acoustic data for sensor fusion using the data from two

modalities [112]. These are some of the previous work that look at indirect measurement for a variety of applications.

Acoustic Sensors and Noise Reduction One of the other interesting approaches considered was using acoustic signals to unobtrusively identify postural changes with no extra hardware. This lead to LMS (least means squared) adaptive denoising for posture sensing, with an algorithm for sparsely distributed temperature and acoustic sensors.

Due to high levels of noise, noise reduction is important. Russo discussed performance of genetic optimization in a nonlinear system for active noise control based on Volterra filters, with higher accuracy than LMS [113]. In 2001, Ando discussed LMS and other techniques to compensate for temperature effects on other sensor types during continuous measurements. Though solving a different problem set, it does show the wide interest in adaptive techniques for error correction in realtime measurement and monitoring [114]. Concerned with the drawbacks of requiring a compromise between speed of convergence and final misadjustment, Arenas-Garcia created a filter combination that they call combination of LMS filters or CLMS with promising results [115].

A different question being answered will be what alternative sensing approaches can use existing sensors to look at measuring things for which they were not designed, such as temperature or sound to measure posture, and will be explored in subsection 5.3.2

3.3 Response Mechanisms and Resilience Feedback

This section discusses the related work pertaining to the proposed “resilience feedback loop”. This thesis proposes a Response Mechanism and Resilience Feedback approach to create a resilience feedback loop that feeds information extracted from human-in-the-loop sensing, rapid sensing, existing sensors, and new algorithms to increase resilience by informing key decision-makers. The background need for resilience feedback and technologies are presented in this section and the feedback loop and techniques are discussed in chapter 6.

Sensor Nodes to Improve Resilience: Problem Space

In Canada, the population density is roughly 4 people per square kilometre of area, yet most Canadians live within 100km of the northern border of the United States [116].

Despite this, Canada has thousands of kilometres of electrical lines that service geographically disperse communities from sea-to-sea - from the Arctic, the Atlantic, the Pacific, and mountainous territory. In 1998, a 4-day ice storm left ice as thick as 80mm coating the distribution towers, and 770 collapsed [117] in a very short time period. There is much interest in this field. Rattadilok and Petrovski have used “inferential measurement systems” where machine learning approaches are coming from the perspective of situational awareness [118].

For many years, there had been much work on machine vision for fixed and moving cameras and objects within the context of automatic traffic scene analysis in real time [119]. Similarly, much work in machine vision was detection of particular characteristics such as faces in images [120], but now machine vision can see far more. The technology includes ongoing commercial deployment in self-driving vehicle testing, and work is ongoing for object recognition in autonomous driving [121]. Inspired by work from parallel fields, we use machine vision for a different task of CI resilience.

There are nearly 10 million kilometers of electricity transmission lines in the United States and proportional numbers in most developed countries [122]. In terms of problem sets, an electrical industry concern has long been ensuring both trends of historical data and updated sensing and alerts be in a centralized location derived from various data sources to determine the health of critical assets [123], and integrating critical data systems with mapping information [124]. Preventative maintenance costs time and money, so determining where to focus resources to prevent a failure is of utmost benefit, and machine vision can help enhance preventative maintenance by directing teams to locations where problem trends have been observed.

Machine vision when combined with the concept of “Agile IoT”, where a sensor deployed to measure one quantity, provides another data element, could help in these cases. Cameras present for other reasons could determine relative angle of interest to provide situational awareness and quantitative data to improve resilience.

These areas show the field has much opportunity to use Agile IoT and sensory substitution approaches to increase situational awareness.

Much consideration is given to improving energy efficiency. Industrialized countries can consume up to 40% of all their energy expended in buildings [125], and HVAC systems can use up to 70% of this energy. In the Instrumentation and Measurement Journal, Cheng *et al* stated that “a proper space thermal model is needed”, and discuss their

measurement system developed for parameter identification and their algorithms [126], and this knowledge leaves a great foundation on which to build.

Many buildings are equipped with smart infrastructure that can sense occupancy of a room, follow schedules for setback temperature, and compensate for sun exposure. This data can improve situational awareness and some of this data may be released in accordance with the concept of Open Data. In the field, there is much work on using instrumentation and measurement for the improvement of HVAC systems. For example, Han *et al* in 2012 talked about a distributed sensor network for determining the occupancy and indoor environment quality of buildings [127]. In 2015, Wang *et al* looked at degradation and remaining useful life (RUL) prediction of dynamic systems, such as a heat exchanger in the HVAC systems [128]. In 2013, Preethichandra proposed a hardware system for monitoring indoor air quality for realtime information in assisted living [129]. In 2012, Abaalkhail *et al* proposed an intelligent energy controller algorithm that efficiently manages energy consumption for both heating and cooling spaces [130].

This thesis looks to address the gap as we discuss an independent, portable, smart, over-the-top system to provide additional measurements and situational awareness.

These seemingly distant sensing and data-gathering approaches, when brought together and analyzed and presented to a key decision-maker, enable enhanced situational awareness and therefore increased resilience. The feedback loop is presented in chapter 6.

3.4 Summary - Overall Goal for Three-Layer Approach

When considering the goal of increasing resilience in CI environments, it is of utmost importance to think of two distinct issues that must be resolved. First, the acute problems must be identified and corrected using whatever sensors are available. Second, the long-term should also be monitored to provide resilience, and this can include surgical deployment of sensors. Both problems must be solved to improve resilience.

Though solving acute problems does provide situational awareness, skipping the response mechanism could jettison the required long-term monitoring imperative for resilience. Likewise, long-term monitoring may provide some long-term resilience, but miss the situational awareness for acute sensing needs.

Layer 1 and Layer 2 provide a solution of situational awareness needs and Layer 3 provides a model towards long-term resilience. By developing a model that encompasses all three layers, the sensory substitution approach can provide situational awareness and resilience using available sensors.

4 Data Capture: Sensory Substitution

Figure 4.1: Layer 1 - Data Capture: Sensory Substitution

The first layer of our approach is dealing with the sensed state of the environment. Enabling technologies for this include utilizing existing and rapidly deployable sensing techniques that already exist in most or many IoT environments in urban scenarios and critical infrastructure applications. For example, it is expected that certain sensors may exist in such scenarios, however we may not know for sure which sensor is installed. Some of the most commonly installed sensors are likely to be temperature sensors, cameras, microphones, magnetometers, pressure sensors, or luminosity sensors. Many other types of sensors are deployed in such scenarios and could also be used, however the focus of this particular layer is on the most commonly used sensors. Various enabling technologies may allow the sensors to be used: this includes cloud computing, NFC, fog computing,

edge computing, open source hardware and software, and AI algorithms. Using these cloud fog and edge computing techniques with AI and deep learning trend analysis and adaptive processing and least-means square adaptive techniques (LMS), various scene analysis enablers may allow us to use available sensors.

Specifically, in order to enable this sensory substitution in agile IoT layer, we need to use sensor hardware, infrastructure, algorithms, or techniques designed to measure, output, or transmit X to instead do the same for Y.

This layer focuses on an approach that been proposed for sensory substitution and cross modal sensing with framework and techniques for Agile IoT. The goal of this is being part of a situational awareness approach with methods of using sensor modality shifting with temperature sensors to measure other, non-temperature data. Success with this has been presented in [2, 3]. These approaches are therefore used as the first layer of our approach.

This chapter proposes an approach for sensory substitution as a framework, and techniques for using existing rapid sensing systems. The scope of this chapter is shown in Figure 4.1, and this chapter serves as the basis and foundation of the data analytics approaches in chapter 5 and the response mechanism and resilience feedback loop in chapter 6. The design of the generalized sensory substitution method is described using sensor cross modality. It is also a framework to enable software algorithms (edge and cloud computing) to increase sensing throughout IoT and industrial IoT using sensory substitution. In this method, a temperature sensor designed to read temperature measurements, instead derives Measurement Y, providing new awareness with existing sensors. The design of a method of using sensor modality shifting with temperature sensors to measure other non-temperature data is presented: this generalized method is described in section 4.1: Cross Modal Sensing. The Discussion and Summary are then presented in section 4.2.

4.1 Cross Modal Sensing

Expanding the reach of sensors to provide information can enable new situational awareness with existing sensors.

Improve Critical Infrastructure Resilience in IoT

An existing temperature sensor can be reconfigured through IoT deployments to provide operational intelligence with immediate applications in many of the critical infrastructure sectors, such as water, energy, manufacturing, health, and transportation. Thus, Agile IoT reconfiguration can play a big role in reducing their downtime during an emergency.

An IoT middle-ware algorithm is presented that uses sensor data collected to measure Parameter X, to provide Parameter Y as well. The agility comes from sensor cross modality shifting and agility of the communication channel. This thesis links the concept of Agile IoT to the concept of agile communication to show that redundant communication through WSNs, as well as sensory substitution in critical infrastructure environments can lead to increased operational intelligence. Examples of critical infrastructure scenarios where this method is applied are pipes for flow in industrial/institutional settings, doors for health/food monitoring, and bridge/road for ice development monitoring [10, 9, 8, 3, 2].

Flexibility of sensor type provides an option for making an IoT system a rapid deployment and inexpensive method. In Internet of Things (IoT) sensor system design, if we wanted to build a low-cost monitoring system, we could choose the most inexpensive sensor system for that specific task. If we wanted to monitor pipe flow events, we might look for the most inexpensive flow-meter and installation for the task. Likewise if we were looking to monitor fridge open-close events, we could look for the least expensive and minimally obtrusive mechanical switches and wiring systems.

Rather than specifically tasking the desired sensor modality, we instead select a different type of inexpensive sensor, which may be a less likely sensor choice and which may already be deployed. Many measurement needs can be replaced with low-cost, real-time, easy-to-install temperature sensors. This concept is extended by performing sensory substitution for machine applications in an IoT sensing system.

Challenges of Resource Constrained Sensor Deployment in IoT When we extrapolate this situation to the deployment of sensors in smart environments, sometimes we can be inhibited as to what sensory inputs can be deployed. IoT system designers may not always consider modification regulations that operators may face regarding physical buildings. For example, if the thermostat needs to be replaced with a custom IoT node, the designers may assume it can be done, but what if the system has a centralized

building automation system, segments of which cannot be replaced? In a large building, if a sensory monitoring system calls for installing flow meters in pipes for utilization, IoT designers may often assume this can be done. In actual deployment, this may require new work orders, permits, or approvals. If the building is a government regulated facility such as a healthcare institution or certain commercial/industrial buildings, it may require significant new approvals to open a pipe to install sensors. Inspired by the biological phenomenon of sensory adaptation, we developed a system of sensor modality shifting: substituting one traditional or "ideal" sensor with another to enable IoT deployment in modification-constrained environments.

4.1.1 Method: Temperature Sensors in Modification Constrained Environments

We measure physical, non-temperature data by using temperature sensors. We present the results of our development of the methodology of sensor modality shifting by replacing task-specific IoT sensor types, with a different sensor type; by measuring Quantity X with a sensor designed to measure Quantity Y. It is shown through multiple examples the results of replacing flow meters in pipes with temperature sensors to measure pipe usage, and replacing mechanical switches in fridge doors with temperature sensors to measure door-open events. We thereby shift the modality of the temperature sensor from measuring the environment temperature to measuring other physical parameters.

Our modality shifting approach was applied to the following sensor types: flow meter, magnetic switch, and thermal imaging. Shifting sensor modality promotes simplification and affordability for such smart environments by providing flexibility to enable monitoring that may otherwise be limited or require substantial investments of time or money.

Modality Shifting Hardware

A temperature sensor works by detecting a transfer of thermal energy from the medium being sensed to the sensor. Through experimentation and pretesting, we observed that we need to see a change of 0.4°C in 15 seconds to detect a fridge door open/close event, and the event may be faster than this. Though some low cost temperature sensors may have an error rating of $\pm 0.5^{\circ}\text{C}$ or even $\pm 2^{\circ}\text{C}$, they still produce a sufficient measurement of the change in temperature, as the discrete measured value is not of interest, but rather

the relative change is of importance. The remainder of the sensor node - battery and microcontroller, could be pared down to the lowest cost and lowest power demand that still suit the application. There would be variable costs for data connectivity and server space, depending on the market (1KB of data cost varies significantly by locale). The system would use in-market costs for supplies of low-cost temperature sensors, wireless system-on-a-chip micro-controllers, and batteries. The final cost of a single node could be inexpensive enough to make mass deployment feasible.

Pre-testing

To examine carefully the temperature changes that are recorded, we first subjected the sensor, the BMP180 (a precision temperature sensor made by Bosch: -40°C to $+85^{\circ}\text{C}$ operational range), to a variety of temperature tests. These included raising the sensor's temperature to a known temperature, and recording the time it takes to return to ambient, and the same experiment was repeated with cold surfaces. An example test was one where the sensor was first cooled to 5°C , and then allowed to warm up in ambient air ($\sim 23^{\circ}\text{C}$). When the sensor converged to ambient, the sensor was raised to 38°C , and allowed to cool in ambient air ($\sim 23^{\circ}\text{C}$).

Using Temperature Sensors: Physical Fluid Motion in Pipes

Figure 4.2: Temperature sensors that acted in various modalities with quarter (25 cent) coin for size comparison © IEEE

Though many advances have been made with flow-meter technology, we follow a different - but inexpensive and unobtrusive - path to the same end. We do not use any flow meter technology to detect flow. We used a streamlined data gathering mechanism to extract just the data we needed by using temperature sensors, not in order to measure the discrete temperature of the pipes, but rather to detect usage and utilization of the pipe.

Temperature sensors are designed to measure temperature, and an example of one can be seen in Figure 4.2. We use the temperature sensor to measure types of outcome factors

for which it was not designed. We replace expensive or obtrusive sensors that perform usage measurement of pipes, such as flow sensors, with low-cost, wireless temperature sensors non-invasively applied to the exterior of the hot supply, cold supply, and drain pipes.

To detect fridge door motion events, we replace various other physical sensors with a temperature sensor located below the fridge.

Some work discusses temperature sensors in fridges, and other work suggests various sensors monitoring open events. An under-fridge temperature sensor to detect open-close activity has much potential, and is also a part of the work we have done. We approach this area from a different angle – we are not interested in the actual temperature of the fridge, nor any of its interior data at all. Part of the concept of the modality shifting sensors is the most unobtrusive sensor placement. Taking up space on a shelf may be part of the resource constraint. Rather, we use a temperature sensor below the fridge to monitor changes to the ambient air to detect fridge open events, and thus replace other sensors with an inexpensive, unobtrusive, external sensor that does not require installation inside the fridge.

4.1.2 Proposed Architecture

In many Internet of Things architectures that are deployed in critical infrastructure, a simplified model of a system can be seen in Figure 4.3. The flow is as follows: 1) Deployed sensor collects data. Pre-processing may occur at this state, 2) Communication channel opens and collected data is transmitted, 3) IoT middle-ware processes sensed data, and 4) Action occurs based on data (displayed to someone, actuator responds).

Figure 4.3: Common system architecture for IoT in Critical Infrastructure © IEEE

Figure 4.4: Proposed Agile IoT system architecture of IoT in Critical Infrastructure. Contributions are outlined in section 4.1.3, and are highlighted in this architecture in yellow, green, and orange. © IEEE

Security in IoT is often still an afterthought [131], and though the model shown in Figure 4.3 has sufficiently served many critical infrastructure applications though IIoT, SCADA, and ICS environments, acquiring additional data for infrastructure operators can increase resiliency. A key development is that many enhancements can be made using sensors that are often already deployed such as temperature sensors. For an Agile IoT re-deployment to increase resiliency in critical infrastructure environments, the following elements are essential, and were developed:

1. Enhance resiliency of the IoT communication method which discusses using existing sensors to provide alternative communication channels, and;
2. Increase critical infrastructure resiliency by using sensory substitution to facilitate sensor cross modality: to use in situ sensors to determine additional parameters

and increase situational awareness, without the need to install new task specific hardware, and

3. Apply this Agile IoT deployment to the critical infrastructure sectors to use exclusively temperature sensors to discover development of icing in transportation systems or energy infrastructure, determine fluid flow in a pipe, and determine mechanical door open events in food, health, or various smart environments.

The proposed Agile IoT system is shown in Figure 4.4. The ability of sensory systems in IIoT deployments to adapt using sensory substitution to collect information not originally intended to be collected with that hardware, is a major part of how the IIoT evolution can improve situational awareness and resiliency throughout the critical infrastructure sectors.

4.1.3 Method: Agile IoT for Resilience

Communication with Agile IoT Sensing The transmission of signals involves emitting a signal modulated at a particular frequency that contains data, and this is used in many fields [132]. In the event that the primary communications experience interference, tampering, or is disrupted, it is important to have an alternative available, using existing sensors.

WSN resiliency can include using another RF channel, and sensors and analytics already deployed for other purposes and how they can be used for communication is presented and discussed. Previously deployed sensors can permit a method incorporating sensory substitution for communications. These deployed sensors might include microphones, speakers, inertial measurement units (IMUs), or other sensors as they often are already deployed at critical infrastructure sites as part of security systems or within other monitoring devices. Using agile methods, communication can be enabled using non-RF methodologies as shown in Table 4.1.

WSNs Using ISM Bands - Spectrum Constraints and Resilience The coexistence of wireless sensor networks with Wi-Fi, microwave, and other public use of wireless signal without a backup strategy calls for a more resilient approach. The portion of the wireless spectrum that can be used by the public and is often shared with typical IoT communications, is known as the “ISM” or “Industry, Scientific, Medical” band on the wireless spectrum allocation tables. The coexistence of WSN and Wi-Fi networks

is a subject of interest to many researchers [133]. Within the context of IIoT, secure connectivity in a challenging environment is an issue [134].

Spectrum can be a finite resource. It would never be acceptable in a workplace for cranes and robotic arms to fail or be compromised, especially as a result of overloaded spectrum. In particularly resource constrained environments, such as manufacturing using IIoT, wireless spectrum including ISM may even be allocated by a central office within the organization: simply using a few channels for a Wi-Fi network may not be feasible. Additionally, in uncontrolled locations, the ISM band may be saturated with other devices that could limit the performance of this system. This saturation issue is a particular problem identified by [135].

Wireless sensor networks and their architecture are an essential component for deployment of the modality shifted sensors. When looking to support resilience, it is very important the network providing communication to the sensors is also resilient, so to ensure reliable transmission of sensed data, even when the network is not inherently reliable (e.g. subject to interference, saturation, etc).

Figure 4.5: WSN Architecture: Two parallel links to increase resiliency. One channel can use RF and the other uses an alternative non-RF communication methodology by applying Agile IoT to re-purpose existing sensors for communication © IEEE

Parallel Communication: Using Non-ISM, and Even Non-RF Methods to Communicate In applications where interference by other users is unlikely, ISM communication alone is sufficient for reliable communications, but to increase resilience, or in deployment situations where there is regular interference, an alternative communication approach is needed. Many alternatives require deployment of other RF solutions such as IEEE 802.15.4 Zigbee, ZWave, Flexnet, and Wireless Highway Addressable Remote Transducer Protocol (HART) [136].

Though many other RF options exist, this thesis proposes that for use in Industrial Internet of Things, wireless sensor networks have parallel channels which may not be RF. Therefore the primary channel is the common ISM band with low power components, and a second parallel channel uses sensors and actuators for communication using the Agile IoT approach in communication. Figure 4.5, shows a simulated design for increasing resiliency for deployment of WSNs in critical infrastructure. First is the primary low power ISM channel transmission, then second is a parallel alternative channel. In many locations where there is no constraint on the wireless deployment, ISM communications or other RF approaches exclusively could be sufficient. Multiple data paths using orthogonal modalities may be advantageous as a method resulting in improved resilience, because the data has two independent paths using independent modalities that it can travel. Thus, the WSN is more resilient itself, and use of the agile repurposing of existing sensors can enable this. Some examples of non-RF options include using distributed microphones for transmitting data, as well as using IMUs and vibration sensors to transmit data in a way similar to NFC (near field communication). See Table 4.1 for selected non-conventional communication strategies. We propose further that this concept is adopted as a secondary communication channel using the Agile IoT methodology described, where the existing sensors are used with signal processing middle-ware to agilely re-purpose the sensory data as communication streams.

Table 4.1: Selected Examples of Existing Sensors as an Alternative Communication Strategy © IEEE

Existing Sensor/Actuator	Measured Quantity	Agile Quantity	Reference
RF Antenna	RF Changes	SDR (Different RF)	[136]
Microphone and Speaker	Sound	Modulated data in sound wave	[137]
Inertial Measurement Unit	Vibration	Data in pulsed vibrations	[138][139]

Sensor Modality Shifting Middle-ware: Collect More Parameters With the Same Sensors and Paradigm Shift: Measure Quantity X with a Sensor Designed to Measure Quantity Y To be resilient, a system needs to have redundancy. To have redundancy, it is important to analyze the environment using multiple sensing technologies, including algorithms that allow a sensor to be used in ways it was not initially deployed.

Using a different sensors provides an option for making a new IoT application available, or can facilitate easier deployment. In typical design, when the goal is to build a low-cost monitoring system, the obvious solution is to choose the most inexpensive sensor system for that specific task. If the required measurement is to monitor pipe flow events, a solution might be to look for the most inexpensive flow-meter and installation for the task. Likewise when looking to monitor fridge open-close events, a step could be to look for the least expensive and minimally obtrusive mechanical switches and wiring systems.

Rather than the specifically tasked sensor, this method entails selecting a different type of inexpensive sensor - perhaps not even a desired choice - instead. Many measurement needs can be agilely replaced with already deployed sensors.

A discussion of sensory substitution methodology and analysis, and experiments of flow and mechanical event detection are presented in this chapter.

Almost Invisible Ice on Bridges, Sharp Curves, and Hills - Increased Monitoring, Reduction of Accidents Temperature sensors are also common in civil infrastructure such as transportation, energy, manufacturing, and other sectors, can be re-purposed agilely. Increased monitoring can enable data analytics that have yet to be realized. Enhancing resilience of infrastructure is paramount, as increasing resilience can come about with any technology or methodology that helps to restore systems as quickly as possible. A secondary goal of adding sensors and connecting infrastructure to the Internet of Things is to enable reduction of accidents. Almost-invisible ice (known as “black ice”) is quite dangerous. See Figure 4.6 for an example of this type of ice. Traffic signs could flash “hazardous ice” to drivers that danger is detected, such as when the conditions of the road are formidable to the development of ice on the bridge.

IoT Implementation A traditional model for IoT feedback could be Sensor → Microcontroller → Signs lighting up, however, by connecting this to the Internet of Things, the governmental agency responsible for highway traffic could send electronic mobile alerts to those on the affected highway, and also deploy a salt truck, heating coils, or emerging technology to mitigate the effects of the invisible ice. Thus the resilient feedback path could then be Sensor → Microcontroller → Signs lighting up, electronic mobile alerts to oncoming traffic, website updates, and deployment of crew to add salt to the bridge.

Figure 4.6: Invisible ice can have a high human cost © IEEE

Monitoring Environmental Conditions Regarding Electrical Infrastructure Freezing rain is a significant consideration for the advance warning about a potential for a utility pole power line to be damaged to the point of tipping over. A storm can affect each pole differently.

In 2004, Cortinas *et al* [140] developed research to analyze the events of freezing rain weather events in the USA and Canada between 1976 and 1990. They noted 7 key findings, and two that may help develop a predictive algorithm are: “6) freezing precipitation and ice pellets occur most frequently with a surface ([down to depths of] 2 m) temperature slightly less than 0°C; and 7) following most freezing rain events, the surface temperature remains at or below freezing for up to 10 h, and for up to 25 h for freezing drizzle [140].” Agilely reconfiguring existing sensors can look for those characteristics at each utility pole and distribute warnings accordingly.

In 2015, Wang *et al* looked specifically at this issue in a survey paper to discuss problems that can occur in the electricity transmission, and one of the big concerns mentioned by the authors was the issue of ice formation on the lines that could cause the lines to break

[141, 142]. They discuss the formula for thickness of ice on the lines and suggest looking at the ratio of ice thickness to design capability. To calculate the effect of icing, Wang *et al* discuss that by using ρ for the observed density of ice on the line, a for the major axis of the iced line, b for the minor axis of the line, and d is the diameter of the iced line exclusive of the ice [141, 142], the formula for thickness of the ice, B_0 can be used as in Equation 4.1:

$$B_0 = \frac{1}{2} \left(\sqrt{d^2 + \frac{\rho}{0.9} (a \times b \times d^2)} - d \right) \quad (4.1)$$

[141, 142]

The authors of [141, 142] suggest safe ratios of ice. If the calculated ice value versus the designed value ratio is below 0.4, there is little cause for concern, while 0.4 - 0.7 may be of concern, and 0.7 and above indicates a possible impending failure of the line due to ice [141, 142]. They also suggest measures should be taken to ensure that the lines are kept safe.

This thesis presents an IoT-Based monitoring system that can be part of the solution to this. Since the North American Ice Storm of 1998 hit eastern Ontario and Quebec and the US Northeast, the need for a smarter grid was identified. Assessment of damage took ample amounts of time, as did the repairs. A further complication, which continues today, is the unmonitored remoteness of some infrastructure. If an initial assessment of damage could have been made by a computer connected to the sensors, an algorithm could have estimated the extent of the damage, and immediately begin the necessary logistics of mobilizing crews and resources to the most important locations to restore the maximal amount of the grid most expeditiously.

Whether the event is a tree hitting a line, or ice bending the tower, or a tornado knocking over a site, when a disruption of power occurs, accurate and rapid localization impacts response time. The additional sensors could also significantly improve the resiliency by allowing the preventative maintenance of sites based on recordings of information before failure, resulting in decreased cost from downtime and from unnecessary maintenance. For example, if certain sites experience more angular changes (bending) than other changes, this could be logged, and such sites could take precedence for preventative maintenance, and sites experiencing less bending or deterioration could be left longer, as the stations where metal fatigue is less likely could have maintenance deferred.

Existing sensors in CI and ICS could be used to transmit the sensed data from the node to the an IoT cloud platform or equivalent. In a lab simulation, a NodeRed script was executed that enabled data to be viewed, processed, and stored. For the IoT application of detection of icing conditions, if the surface temperature was close to the freezing point ($\pm 2^{\circ}\text{C}$), an alert was generated and the relevant authority could receive a potential icing warning email.

The NodeRed script could call a PHP script to log all data on an SQL server. This included a unique device ID so that scripts could look at data from particular nodes only, or filter on other parameters, and the knowledge could be used to increase resilience.

Icing Software Phase I: Data Collection and Storage The IoT lab simulation used software for data collection and was a executed on a BeagleBone Black running Debian 7.9 (Wheezy) with an attached USB Hub WiFi and Bluetooth Adaptor. Though the system used WiFi and 4G modems to access the cloud, scripts could be used such that if WiFi is not available, data could be stored locally on the microSD card. The system used NodeJS version 0.10.x and related dependencies for the Linux instance. Using the IBM IoT framework, the BeagleBone Black transmitted the sensed data to the IoT Framework, and all the data is logged on a MySQL server. This data is then processed using a variety of PHP and NodeJS scripts. Automated data analytics can occur here, or offline as needed. The IoT Framework was connected to NodeRED cloud processing, and used PHP scripts to save the data into a cloud database.

Figure 4.7: NodeRED sample flowchart © IEEE

Icing Software Phase II: IoT Response and Data Gathering An example deployment used NodeRED Cloud Processing to initiate the IoT responses, such as email alerts or

SMS messages. Example IoT scripts included checking the temperature trends to determine if icing weather conditions occur, and sending an alert to the relevant authorities. For example, if the icing conditions were detected on a bridge, an email could go to the trucks responsible for distributing road salt. If icing conditions were detected on a utility pole, an alert could be sent to the relevant utility owner/operators. Finally, the data could also be stored in a MySQL server for future use and data analytics. See Figure 4.7 for the sample flowchart.

4.1.4 Results: Application of Methodology in Critical Infrastructure

Determine Icing in Transportation Systems or Energy Infrastructure This phase of the research uses already deployed temperature sensors to sense issues such as pole tilting and stretched power line sagging, or favourable icing conditions on poles or bridges to solve the response and information gathering needs using existing sensors to increase resilience.

Response Mechanism The experiment was performed both indoors in the lab, and outdoors during ice-developing conditions. There are two temperature sensors that were used for data collection. First was the infrared temperature sensor in the TI Sensortag (TI CC2541). This sensor uses infrared signatures to measure the temperatures of objects in close proximity (about 5-10cm). Additionally, a traditional digital thermometer was used for air temperature. The IR temperature sensor was much faster to determine temperature changes, however, had some negative bias which was trending downward relative to ground truth.

Comparison to Traditional Methodologies / Gold Standard The best gold standard for a sensor measurement is to observe the physical characteristic that the sensor is measuring and confirm that the sensed values are correct. The sensors were recorded using a standard HD camera and standalone digital thermometer for the purpose of comparing the collected data with the data collected by the IoT Sensor Node. For the testing in the lab, a 10Hz sampling rate was used. Error statistic was estimated to be less than 5% by comparing sensed data to the known ground truth and determining the number of incorrect samples using the following approach: Data from the sensor was compared to the visual recording, and assessed as to its validity by manually examining

the data from the graphs and reconciling the visual data along with the data from the standalone sensors recording to ensure the data logged by the IoT system is correct.

Ice Storm Monitoring During periods when Environment Canada issued Freezing Rain Warnings, the sensors were deployed. See Figure 4.8 for examples of ice buildup on transportation infrastructure surfaces, such as handrails and bridges, during the storms.

Figure 4.8: Beginning of ice buildup formation on Critical Transportation Infrastructure (bridge or ramp railings) © IEEE

The outdoor component of the prototype sensor node system contained two parts 1) the sensor and 2) the processing unit. The sensor component consisted of the TI SensorTag, and the node, which was affixed to a section of wooden utility pole (a simulation of the wooden electrical poles of interest). The experiment was repeated on different types of surfaces and materials. The sensor was oriented so the larger face of the sensor faced up to maximize the exposure to the rain. The air and surface temperatures recorded by the IoT system are shown in Figure 4.9 and Figure 4.10.

The data was recorded while ice was forming on the nearby surfaces, and it shows conditions that can be favourable to freezing of precipitation. See Figure 4.9 for a graph of conditions observed during freezing rain. Both the surface and air temperature sensors (red and blue lines) follow a similar trend during icing, and the yellow line of atmospheric pressure conditions were included for reference in the graph, but not used in the icing determination. The trends and characteristics are logged and used for future determination

Figure 4.9: Conditions experienced during IoT monitoring of freezing rain. Red and blue lines are for surface and ambient temperatures (different sensor types), and the orange line is for atmospheric pressure sensing © IEEE

of ice formation.

Later rainstorms, were also recorded for comparison. In this case, a freezing rain warning was issued, yet no freezing rain was observed. The data can be seen in Figure 4.10. Note the most significant difference between the scenario where the ice occurred and the scenario where no ice occurred is the ambient temperature difference that is about 1°C warmer.

IoT Response Mechanism - Emails and SMS Response mechanism can alert the owner-operator of even a small infrastructure asset, what and where damage has occurred, so that the most optimal algorithm can be developed to maximize crew efficiency and get the infrastructure restored as quickly as possible.

Agile IoT Agilely re-purposing temperature sensors in infrastructure is a relevant topic as it can help in many ways. 1) It can assist in rapid deployment of resources. Since many pieces of infrastructure are very remote, isolated, and difficult to access, smart monitoring with automated responses can provide new levels of situational awareness. 2) IoT distributed monitoring can provide new methods of intelligence gathering, as the system can survey damage (potential or occurred), can be corroborated with data from multiple sources, and can facilitate targeted responses. 3) The technique can enhance coordination, as the sensors and other data sources can coordinate with first responders,

Figure 4.10: Conditions experienced during monitoring where no freezing rain was experienced. Red and blue lines are for surface and ambient temperatures (different sensor types), and the orange line is for atmospheric pressure sensing © IEEE

websites, email systems, and even electronic messages before and after adverse events. These response vectors and information sharing techniques are enabled by Agile IoT using sensory substitution, and are further developed in chapter 6.

4.1.5 Temperature Sensors with Multiple Modalities

We began the quest of replacing traditional sensors with temperature sensors for measuring water usage and fridge usage.

Refrigerator Usage For smart detection of fridge utilization, typically, a magnetic switch sensor may need to be installed in the fridge. We first examined the easiest installation location: placing the sensor inside the fridge, in the shelf of the door. We used a video camera to validate the open events (as our gold standard), and our modality shift was to replace a switch with temperature sensors. Testing in Figure 4.11 was performed inside the refrigerator, and Figure 4.12 was performed under the refrigerator. As seen in Figure 4.11, the temperature readings tend to have a ΔT of between 2°C and 8°C . The room temperature was held constant at 23.5°C and the fridge was 6.5°C

Figure 4.11: Internal fridge temperature (blue). Selected door open events are highlighted with stars (red). Small oscillations of temperature are the fridge cooling cycle, while larger changes are door events. © IEEE

$\pm 1.5^{\circ}\text{C}$ for the heating/cooling cycle. Locations where the temperature doubled was a location where the door was held open for a few minutes to allow the warm air to fully enter the fridge. In extreme modification constrained environments, even installing a sensor on the shelf of the appliance may not be permitted. We also tested the sensor modality shift by placing a sensor under the fridge. A small coin sized device under the fridge may face fewer restrictions than a more invasive installation. With this setup, we show promising results.

Basic fluid dynamics reminds us that a volume of cooler fluid of the same medium will sink, so the cold air from the fridge opening will seep below the fridge. Our hypothesis was that there likely will be a consistently small, but measurable temperature change under the fridge during an opening event. A FLIR thermal camera was utilized to validate our hypothesis, and the result can be seen in Figure 4.13. We also repeated the experiment by placing the temperature sensor under the fridge and fixed to the leg opposite the hinge of the fridge.

In Figure 4.12, we can see the results of placing the sensor under the fridge. Figure 4.12 shows the under-fridge temperature cycle for open door events. There was more environmental variance, as the fridge was in an office environment. The heating, ventilation, and air conditioning (HVAC) setback points can be seen in the data. Despite this, the door open events were also very clear, as any variance over 0.4°C in less than 15 seconds indicated the beginning of the door opening event. In Figure 4.12 [top], the results appear to show an oscillation that occurs prior to settling to the measured temperature for a period of time. The duration of these pulsations decreased per unit time after the fridge door event had occurred as the air mass with the differential of temperature began to dissipate. Note that the time scale is on the order of days, so the actual time period

Figure 4.12: Under-fridge temperature testing: Any location where there was > 0.4 degree temperature change in less than 15 seconds was a door open event (indicated with a star). Top: 2 day time scale, Bottom: 1 hour time scale showing 2 door open events. These events were validated by confirming with the video footage. © IEEE

of settling appears distinctly. Since the purpose of the temperature sensor was to tell whether the refrigerator was open and the specific details of relevance, these oscillations bore no impact on this assessment.

In Figure 4.12 [bottom], we can see a zoomed in region showing the data that corresponds to a typical door open event. The distinct event shown in the raw data is a sudden temperature decrease, and has been observed as a decrease of greater than 0.4°C in less than 15 seconds. The modality shift from a magnetic switch to a temperature sensor was a success, as the unobtrusive temperature sensor was substituted for the magnetic switch, enabling IoT deployment in a modification-constrained environment.

Consideration of False Positives The limitations of false positives may be seen when a temperature trend could result from something other than the fridge or pipe events. In Figure 4.12 (top) visible in the data is the heating/cooling cycle of the room. If the fridge internal temperature varies by $1\text{--}3^{\circ}\text{C}$ within 15 seconds, or a change of 0.4°C is detected for the sensor under the fridge, an open event is detected. In normal operation, we did not observe an example of the HVAC system meeting this condition. In general, longer duration temperature swings reflect ambient conditions such as HVAC setback

Figure 4.13: Thermal image of cold air mass escaping from fridge [left]. The red circled portion shows the cold air flowing below the fridge. The fridge image [right] shows two tested sensor locations circled in red for both temperature sensor locations (inside on shelf, and below fridge). © IEEE

and cool-down phases. Further corroboration is that in the event of a fridge open event, following the rapid drop, the temperature will increase shortly to the previous temperature, whereas the daily HVAC cooling cycle is a relatively slower consistent increase or decrease to the room set point.

False positives may also be door and window open events, where air masses of a different temperature enter the room, mimicking the temperature trends expected. Possible mitigation strategies could include placing a secondary sensor elsewhere in the room. Should both the under-fridge sensor and the secondary sensor detect the same change, it is not an event of interest. Alternatively, another sensor node could be placed by each door and window, enabling the system to know at any given time what the status of all the doors and windows are. With appropriate analytics, it could be determined what the expected behaviour at the fridge should be, given the readings at the other sensors, making this system resilient to false positives.

Pipe Usage Considering an example of a location where installation of flow-meters was not possible, or too expensive, personally invasive options, such as visual and acoustic

Figure 4.14: Thermal image of sink, hot supply pipe, and drain during usage © IEEE

Figure 4.15: Temperature curve for water usage (5-min intervals of lukewarm-off, hot-off, cold-off, and hot-cold). © IEEE

options were ruled out, as they do not provide sufficient perceived privacy. Flow meters are also often chosen to determine water usage patterns, but were ruled out given the requirements of unobtrusive and inexpensive. Thermal imaging could be a good system to install to monitor pipe usage. Testing was also done with thermal imaging as shown in Figure 4.14, and further corroborates the validity of our sensor modality results: we show that temperature sensors can perform the modalities of a flow meter for water on/off status usage events. See Figure 4.15 for hot supply, cold supply, and drain temperature sensors during water usage. Water was run for 5 minute intervals, then switched off for 5 minute intervals, and the results can be seen in Figure 4.15, clearly delineating the location at which the taps are in use, versus when they are not. In the final test “Hot then Cold”, rather than switching the supply tap off between tests, the tap was rather

changed to the other temperature setting. When a sudden change of temperature occurs, this is the beginning of the water usage event. Whether hot, lukewarm, or cold water is used, it is still extremely clear when the water is in use, and how the resulting mix is composed.

In this environment, sensor modality shifting has been shown to be a valid method to enable a water usage timing monitor that does not require any installation. More intelligence and situational awareness can be derived from the same sensor.

4.2 Discussion and Summary

In this section, Agile IoT sensing in critical infrastructure is developed using the concept of sensor cross-modality shifting in IoT, where an existing sensor designed to measure Parameter X instead measures Parameter Y to provide additional situational awareness.

With the agile sensing in IoT approach, our algorithm shows that temperature sensors can take on the modality of other sensors. The agile sensing approach is also used to examine alternative communications where existing sensors can also be used for a secondary communication channel. Using alternatives to RF communication increases resiliency, and communication channels do not just need to be using wired or other RF channels, but rather using entirely different strategies. More data pathways with no new sensors increases resilience without increasing hardware, and therefore using in situ sensors to detect more than just the design parameter for which they were installed enables increased situational awareness.

The combination of a more resilient communication channel and better situational awareness increases the overall resilience of the IoT system, and when used in critical infrastructure applications such as bridge icing or fluid flow detection, resilience can be improved using the existing sensing hardware, thereby using agility of the IoT system to increase resiliency.

We have been able to demonstrate that a temperature sensor can take on the modality of other sensors. We developed a system of sensor modality shifting and showed examples of this thesis's methodology of substituting one traditional or "ideal" sensor with another to enable Agile IoT deployment. Such developments may introduce more flexibility for more rapid and widespread deployment of IoT where constraints up to now have limited proliferation.

The predictive capacity, can enable infrastructure personnel to ascertain future likelihood based on sensory inputs which can address problems before they begin. This helps ensure hospital equipment will continue to save lives, buildings will have lights and power, clean water will continue to be available, houses can be heated, manufacturing and industry will go forward, food and agriculture will continue along, transportation will keep moving, and electronic communication will continue to be reliable.

The testing demonstrated that a sensor can take on the modality of other sensors. We specifically showed the multiple modality of a temperature sensor by replacing two common IoT sensors in resource constrained environments. The output of this method as shown in Figure 4.1, can then enable Data Analytics: Approaches in Scenarios, Response Mechanism and Resilience Feedback, or be intelligence output on their own to enable situational awareness using available sensors.

This chapter proposed an approach for sensor substitution / cross-modal sensing. The resulting publications are [2] and [3]. The chapter also presented a design of framework and techniques for Agile IoT as part of a situational awareness approach.

5 Data Analytics: Approaches in Scenarios

Figure 5.1: Layer 2 - Data Analytics

The second layer of our framework are the data analytics approaches. These can be seen in Figure 5.1. The dark green line encircles the analytics approaches and the arrow indicates the outputs. The specific examples of the analytic approaches include sensory validation, classification and adaptation, and multi-sensory fusion.

The input can be existing and rapid sensing using available sensors (sensory substitution); that is the output from layer one of our approach. These algorithms can also operate independently of our three layered approach. The outputs from the analytic approaches can be directly used for situational awareness and intelligence or used as an input prerequisite for a resilience feedback loop.

Sensory validation and security involve the design of a method of validating sensor inputs. This includes using ambient physical sensors to validate cameras as well as performing

analysis of sensing security implications. This has been explored successfully by looking at the impact and awareness in [5]. Classification and adaptation is discussed, and involves a proposed algorithm for an urban sensing method using imaging analytics with acoustic signals for UAV signature classification. It also involves the design of an environmental and physical sensor system for smart environments for both human detection and personalization in IoT environments [7]. Multi-sensory fusion involves the design of smart environment infrastructure and related person detection approaches using sound and multi-sensory situational awareness algorithms, including determination of human posture. This has been explored using posture sensing and adaptive algorithms such as least-means squared (LMS) [8, 9]. It has also been explored with smart environments using near field communication and rapid HTML5 deployments [10].

The outputs from these analytical approaches can be an output in and of themselves or provided as inputs to the resilience feedback loop for further use. This is the second layer of our approach.

In chapter 4, the method of sensory substitution was presented, and this enables the Analytic Approaches discussed in chapter 5. In Figure 5.1, the scope of this chapter is shown. The resulting outputs from these approaches can be directly used as intelligence for situational awareness, or they can be the enabler for the resilience feedback loop what that be discussed in chapter 6.

The chapter discusses in detail the following three analytic approaches in application scenarios.

The first covered is in section 5.1, 1) Sensory Validation: Increasing Trust in Sensed Data, a method of validating sensor inputs by using ambient physical sensors for AI camera analytic validation. A sensory substitution algorithm can be used to validate sensor inputs in cyber-physical systems to increase security and resilience, and this is discussed in subsection 5.1.1: Cyber-Physical System Validation using Sensory Substitution. This analytic approach also performs an analysis of sensing security implications in a fog layer. The section then looks at the larger security implications of instrumentation sensing using mobile sensing techniques such as smartphones, and is discussed in subsection 5.1.2: Securing Sensing.

In section 5.2, 2) Classification and Adaptation: Urban Sensing and Security is presented. An urban sensing method is proposed using imaging analytics with acoustic signals for UAV signature classification. It also presents methods of detecting presence of UAVs using only the sounds they produce. Treating existing physical security systems

with the Agile IoT approach, this technique applies visual signal processing into the sound domain with machine vision and AI techniques. This enables using existing microphones and machine learning to detect UAVs using sound signatures and is presented in subsection 5.2.1: Urban Remotely Piloted Aircraft Systems (RPAS)/ Uninhabited Aerial Vehicles (UAV) Detection with In-Situ Sensors. An environmental and physical sensor system for smart environments is presented. Following that, is the performance of human detection and development of personalization in an IoT environment, and these are part of the sensory adaptation analytic example. An algorithm for IoT cloud sensory substitution using already deployed magnetometers and luminosity sensors for human identification is discussed in subsection 5.2.2: Personalization and Human Detection Using Sensory Adaptation with Ambient Sensors.

In section 5.3, 3) Multi-Sensory Fusion: Smart Environments, Infrastructure and Person Security is presented, where sound and multi-sensory situational awareness algorithms are developed, including LMS-based approaches to enable sensory substitution for posture detection and analytics in smart environments. Specifically, an algorithm based on sensory substitution was created to determine posture of a person using only strategically and sparsely deployed temperature sensors. The algorithm is discussed in subsection 5.3.1: Posture Sensing with Embedded Temperature Sensors. Example applications are in healthcare or critical infrastructure operator control rooms. This chapter then presents a generalized algorithm of sensory substitution with sensor fusion using already deployed temperature sensors and microphones, with a case study of postural change detection. This is discussed in subsection 5.3.2: Posture Detection using Sounds and Temperature: Sensor Fusion, LMS, and Sensory Substitution. Following that, this analytic approach presents a method to derive awareness in critical health applications using embedded smart phone sensors and communication, activated using NFC in subsection 5.3.3: Smart Environments with NFC.

The Discussion and Summary are then presented in section 5.4.

5.1 Sensory Validation: Increasing Trust in Sensed Data

A key question to be asked in the context of the rapid proliferation of IoT is, “Can We Trust Sensors? Should We Validate With Separate Systems?”. This is addressed with a method of validating sensor inputs by using ambient physical sensors for AI camera analytic validation in subsection 5.1.1: Cyber-Physical System Validation using

Sensory Substitution. Related to this question is, can sensory substitution enable any privacy/security issues, and by performing an analysis of sensing security implications of instrumentation using mobile sensing techniques is discussed in subsection 5.1.2: Securing Sensing.

5.1.1 Cyber-Physical System Validation using Sensory Substitution

5.1.1.1 A Case for Fog-Based Validation

With much data being collected at the edge (near the operating environment), data analytics solutions to validate sensory data is very important. Transmission of gigabytes or terabytes of data to cloud infrastructure for deep security analytics may defeat the purpose of edge computing and the bandwidth considerations that are often reasons for choosing edge computing to begin with.

Requiring a sensor node itself to perform necessary security validations perhaps may be too difficult at the edge, where computing capabilities are often fairly limited to basic filtering of the collected sensor inputs.

As additional data-driven applications require edge processing to reduce bandwidth, especially those involving high bandwidth requirements such as audio and visual sensing, security analytics must occur closer to the edge to provide sufficient bandwidth.

We propose in this part of the research, a fog-based layer for sensory validation for use where constraints may exist on deployment of new hardware at the edge (or as close to as possible to the physical operating environment). The solution focuses on fog-based analytic algorithms using (a) the initial sensed data using cameras - specifically the processed output from the edge, and (b) raw data from another ambient sensor. Using these inputs, we propose a fog-based sensory validation layer that is near the edge. This fog-based system does not require the initial raw camera data to be transmitted; however it does require the raw data of another sensor to be transmitted. This means validation layers may at times be better deployed near the edge rather than in the cloud. Since modification constraints are often of consideration, and edge processing capability may be limited, deployment of new hardware for processing additional sensing at the edge is often not feasible or reasonable. Though “fog” can have multiple meanings, for the purposes of this research, fog refers to as close as reasonably possible to the “edge” operating environment. This is why our system is deployed as a fog system. It could

be deployed at the edge if hardware is available, or on the cloud if sufficient bandwidth is available, however we look at this problem from the perspective that it is better to perform this analysis as close to the edge as possible to prevent false data from entering the system.

Such analytics should be part of the core infrastructure and inserted between the edge and the cloud, which is where the user reviews the information. We propose a framework where the additional sensed data validates the initially sensed data to reduce or prevent false negatives and positives.

We present the generalized framework of the system, discuss specific scenarios where sensory validation of edge-sensed data could have prevented an error, and then apply our fog-based validation framework in a specific usage case scenario of human detection in security systems.

Our initial results are shown for specific scenarios and are very positive.

5.1.1.2 Critical Cloud Cyber-Physical Systems: Can We Trust Sensors? Should We Validate With Separate Systems?

Distributed sensing systems can be compromised. Recent examples of cyber attacks on critical infrastructure systems have rendered multi-billion dollars worth of damage, showing how important sensor data integrity is. There is also interesting work looking at the possibility of cyber compromises leading to transportation system hijacking, particularly that of aircraft [143]. Increasing validation is increasingly important.

Energy and Health: Serious Examples of Adverse Consequences This section discusses how missing validation was thought to have enabled a major cyber-physical attack in Turkey on a pipeline owned by various entities including Azerbaijan. Though there were conflicting reports on the cause after the event was analysed, one perspective had been that it was a massive cyber attack [50]. Regardless, such incidents, and others scenarios that are like it, are possible cyber-physical attack methods [50]. With the possibility of such potential attacks, methods can include use of laptops, to not only access the SCADA (supervisory control and data acquisition: sensing and control) system, but also able to hack into the camera system [50]. They were able to replay an example scenario to the control room which indicated that there were no problems in the pipeline. They then executed an attack that caused significant damage to the pipeline. People in

the control room seemed to have no idea that the incident had occurred, because the attackers had been replaying valid camera footage as well as what appeared to be valid sensor data to the operators. Lack of validation resulted in them thinking that their pipeline was operating fine [50]. This same technique can be used in other heists such as store or warehouse robberies, or many other critical infrastructure scenarios. Another critical infrastructure - health - can also be impacted by sensor or data integrity issues or complete disruption [53].

Sensor Validation vs Playback Attack When looking at a solution, building a brand-new sensor data validation system from the ground up could be cost prohibitive in practice, and could be still hacked in similar ways. Using already deployed sensors as an IoT-based sensory substitution validation layer in the fog could actually provide a level of orthogonal redundancy as it can operate uniquely and independently. In previous work, we discussed an Internet of Things-based system that could collect data from under-monitored infrastructure [11] and throughout IoT applications [7]. In areas of limited monitoring, this may provide a level of information that is currently not readily available. In areas with existing sensors, this data could be fed into the control room and be used for sensory validation using sensory substitution [2].

The attack vector of the above cloud compromise cyber-physical case, was first and foremost to compromise the SCADA system so that an operator could see the data that they expect in a so-called playback-attack. This was done on both the sensors physically monitoring the product in the pipe, and also the security systems, such as the cameras that were part of the pipeline system. Many of the systems were thought to be compromised in the attack. Following this compromise of the system, the intruders were able to potentially open and close valves as they pleased, and because of the false data, no one in the control room was immediately aware of the situation. Had there been correct data transmitted to the control room, action could have been taken to lower the pressure in the pipe upstream to prevent a potential explosion at the site of the attack.

Sensory Substitution: Data Validation Lack of information, or in this case, *faulty information that appeared true*, left the operators in the control room believing there was no problem, when a multi-billion dollar problem had actually just occurred. To address the cyber-physical resiliency issue that was exposed by the cyber-incident: hacking the control system and thus blinding the operators, we must look at a key contributor: we trust that the data received is correct.

Had there been an alternate sensor data system, rather than only the information provided to operators via the control system, the operators may have had an opportunity for early intervention to prevent the disaster.

Situational Awareness: Requires Valid Data Situational awareness can be defined as “information gathered from a variety of sources that [...] can form the basis for incident management decision-making” [1], and an increase in situational awareness has a direct impact on resilience. To improve situational awareness, a multi-sensory approach is needed, though sometimes only one sensor type is pre-existing in a given scenario. A fog-based sensory validation method may be needed to provide validation without needing to introduce new hardware at the edge. Key issues include deriving increased validation with whatever equipment and sensors are already there, using already-deployed sensors to provide actionable intelligence, quickly augmenting data, examining what sensor data can reveal, and exploring security implications. Many practical benefits of sensing with rapidly deployable or already deployed sensors was explored [11]. By increasing sensor modalities, false positives and negatives can be addressed. Alternative sensing also can raise privacy considerations, such as discussed in [144]. The trade-offs must be considered when deploying new technologies. For increased resilience, not only is better situational awareness important, but also is the response.

In this section, the authors present a fog-layer sensor validation technique by corroborating an artificial intelligence visual algorithm with already deployed sensors to validate data and reduce or correct false predictions. This thesis proposes a validation framework for using existing sensors with analytics to increase situational awareness and improve resilience.

5.1.1.3 Methodology: New Over-The-Top Deployments and Already Deployed Sensors

Over-the-top networks are those that are either “air gapped” or are otherwise independent of existing networks (separate from the SCADA or IIoT infrastructure). This section outlines the method of sensory substitution to corroborate and validate an artificial intelligence visual prediction, and examples for detection of false positives and negatives or corroboration of true positives and negatives, using fog-based human detection validation is developed.

Figure 5.2: Sensory Validation with Sensory Substitution System Diagram (contributions in purple) © IEEE

Industry changes are often gradual, so sensing with what is there already is key for rapid deployment. Using the technique of Sensory Substitution, it is possible to detect events, leading to indirectly detecting security issues such as intruders or environmental issues using readily available sensors. For a thorough approach, we look at a system of sensor fusion to deliver the same – using the most accurate method available, looking specifically at the issue of human presence detection and validation.

Although operating manuals are available in many system control rooms, easy-to-follow exhaustive checklists as to how to handle situations could be useful. Sensory substitution for sensory validation is important to close some of this gap.

There is also much need for sensors and analytics in terms of physical security from intruders, both natural and human. For example, appropriate alarms must be sounded if there is sabotage suspected. Sensor analytics must be able to bring any breaches of security to the attention of the control technicians [17].

With agile IoT sensing techniques of providing actionable intelligence, public safety and resilience can be increased. The high-level approach to fog-based sensory validation can be seen in Figure 5.2.

Expected Accuracy Using the sensory substitution approach, more general data points can be derived using sensory substitution. A fog system includes multiple physical distributed sensors. Basic measurements could be derived, such as time of human detection by sensors for location estimation, but the ambient sensor may not replace the detailed motion captured by a video camera. However, this data can then corroborate the existing sensors such as cameras, motion sensors, or mechanical switches that are part of

the security system. For example, if the sensory substitution data validation algorithm detects a person, yet the video feed shows nothing of note, the integrity of the video feed can be called into question and someone can then inspect the sensors. This may enable detection of playback cyber-physical attacks.

Improving Agility of Sensing to Overcome Constraints and Create Response with Rapid Sensing

This validation approach addresses time and modification constraints to improve situational awareness – using available sensing. This contrasts with traditional sensor systems, where there are no modification constraints, and the “ideal” sensor can be deployed as needed. This method also addresses using Agile IoT sensing to provide information feedback and response vectors for situational awareness. This thesis focuses on the sensory substitution and Agile IoT, while the remaining aspects are part of the future work.

Specific Example: Smart Building Security Imagine a scenario for smart building security, where there are cameras deployed to detect people, but we want to track presence of people in a given area and want independent validation of the detection. Three methods to complete this task are shown in Figure 5.3, and details are presented below.

Figure 5.3: Three methods of detection of people. Contributions in Method 2 and 3 are discussed in subsubsection 5.1.1.3 © IEEE

Method of Detection #1 - Traditional Setup In this setup, deployed cameras are typically used for review after an incident and is primarily manual human work. This approach is the typical basic security monitoring system without analytics. This method is called for in the Sensory Substitution approach if Method #2 and Method #3 give conflicting results.

Method of Detection #2 - AI Analytics An artificial intelligence model is created to extract confidence of identification of the presence of person, based on an Open Source TensorFlow Pose Estimation Tool. This model is extended to provide the IoT front end and control room notifications of human presence, as well as the real-time comparisons with the ambient sensors in Method 3. The AI model is powerful for security applications, and once trained, can be deployed on various distributed computing systems.

Method of Detection #3 - Sensory Substitution This algorithm validates the presence of a person using available, distributed sensors and computing: in this case, magnetometers and luminescence sensors, which are typically installed in many locations. The algorithm is presented in detail in Figure 5.4. Data collected from these sensors is analyzed and compared with data collected in Method 2, the AI visual algorithm, to either corroborate or correct false predictions.

Methodologies Practical for Deployment A goal with this experimental setup was to be a real world environment. Similar visual algorithms such as facial recognition algorithms and artificial intelligence algorithms and similar techniques are used in office security such as large office complexes that have forgone traditional token-based access cards for AI facial recognition. Ensuring the validity of the human detection is critical, and the sensory substitution approach can be applied in many of those environments, since these environments likely already have luminescence sensors and magnetometers deployed at the edge for other purposes.

Figure 5.4: Algorithm for Reliability of Sensing: Validation and Data Integrity of Visual Sensing using Sensory Substitution © IEEE

5.1.1.4 Algorithm for IoT Sensor Reliability and Validation

Increasing Dependable Autonomy with Sensor Validation One of the goals of this work is to help make distributed sensing more versatile and reliable. Some assumptions must be made and are included in the Algorithm in Figure 5.4. If we suspect a potential cyber-attack, such as a playback attack or other means of falsifying the image, we should require physical sensor confirmation. Otherwise, the physical sensors can provide validation when confidence is weak. These analyses help validate results and improve confidence in the sensed data.

Data Integrity Issues When checking for playback-style attacks, the physical sensors should agree with camera. If light in room is “false” (below a set threshold such as 10 lux), but camera shows confidence of human presence, there are likely data integrity issues. Similarly, if the camera shows a high degree of confidence of human presence, and the magnetometer shows a steady-state, this may indicate a potential data integrity issue, or it might mean the person did not get close enough to the magnetometer to show a discernible changing field over the noise floor, so this scenario may require additional analysis.

In the ideal case, the visual artificial intelligence prediction of human presence and ambient sensors could corroborate each other, so the camera could show a high level of confidence of human presence, the magnetometer could show a changing field, and the luminescence sensor could show sufficient light.

Occlusion and Partial Images The sensory substitution approach can be used to make the system resilient to image occlusions or partial images in the camera. For example, if data integrity issues are not suspected, if the confidence of the AI camera algorithm is below a threshold such as 0.2, the true state output should only confirm human detection if the physical sensors agree, such as if the magnetometers show variation in temporal continuity with the low AI confidence of detection: a potential false negative can be corrected.

Low Light Conditions In the case that the ambient luminosity sensors show low light conditions, even if the AI camera human detection confidence is 0, the other ambient sensors can be used to fill this information gap. If the magnetic sensors show sharp

changes in field from steady-state, it shows the possibility of a false negative and a person may be present nonetheless. Meanwhile, if neither the AI visual method or ambient magnetic sensors indicate a person, the negative prediction for person presence can be corroborated and validated.

5.1.1.5 Human Presence and Pose Estimation

The core of the camera validation technique is to compare an AI visual human presence estimation, to ground truth. This is validated by comparing the human presence estimated from the camera with additional physical sensors (magnetometer, photoresistor, etc).

In order to arrive at the human confidence score, we used the deep learning Posenet [145] model which uses TensorFlow [146]. We adapted this model, and it was loaded with a client-side implementation (in the “fog”). The model in our experiment was stored on a server, and accessed via browser and loaded on an embedded device node that contained a camera, processing unit, magnetometer, and photoresistor. Once loaded on the embedded device, a live server connection was not required.

Sample data returned from the model in real time can be seen in Algorithm 5.1.

Algorithm 5.1 Selected Sample of Instantaneous Data Returned by AI Model of Human Detection (JavaScript Object Notation - JSON format)

```
{
  "score": **Overall confidence Number between 0 and 1**,
  "keypoints": [
    {
      "position": {
        "y": **Number between 0 and 360**,
        "x": **Number between 0 and 360**
      },
      "part": **One of the 17 waypoints, eg 'nose'**,
      "score": **Confidence Number between 0 and 1**
    },
    **Similar Data Structure for all detected points in sample,
    up to 17**
  ]
}
```

The Posenet framework calculates an instantaneous confidence prediction using 17 specific human way points including [145]:

1. nose
2. leftEye
3. rightEye
4. leftEar
5. rightEar
6. leftShoulder
7. rightShoulder
8. leftElbow
9. rightElbow
10. leftWrist
11. rightWrist
12. leftHip
13. rightHip
14. leftKnee
15. rightKnee
16. leftAnkle
17. rightAnkle

TensorFlow was used with the Posenet model to predict the human confidence using the AI visual algorithm. The combined instantaneous score is generated based on the confidence of presence of each of the way points. This score was then extracted and combined with the data from the orthogonal sensor modalities, luminescence sensors and magnetometers, to produce real-time graphs as per Figure 5.6. The values were then analyzed as per Figure 5.4 to determine the confidence of sensing and presence humans, and this enabled the identification of true positives, true negatives, false positives, and false negatives.

5.1.1.6 Scenario and Experimental Setup

Ambient Sensors Though most sensor data may not have as severe an outcome as the example presented in subsection 5.1.1, even sensors on a perimeter security fence reporting incorrect information could lead to undesired consequences. Typically, rooms often already have sensors that can be re-purposed - motion sensors, cameras, magnetic switches, but usually on a separate system for another purpose. Since they are not connected to the same system as the AI camera algorithm, using the sensors on the “air gapped” or separate system adds additional redundancy and validation using the existing sensors, further combating cyber-physical security gaps. The additional distributed sensors allow the framework of sensory substitution to validate distributed sensing data in a fog layer.

Room Floorplan Multiple rooms were tested. The work presented was performed in a typical security scenario, a room to be monitored that has a predictable human path – long and narrow (control for random human behaviour), a camera mounted in a typical location for security systems, and 2 locations for ambient sensor nodes. In this work, we used a luminosity sensor and magnetometer sensor that is typical in many already-installed security systems (S2), and another luminosity sensor and magnetometer node was located with the camera (S1). Figure 5.5 shows the experiment venue and floor plan used for the results presented.

Figure 5.5: Experimental Setup and Room Layout. S1 and S2 Represent 2 Selected Sensor Placements © IEEE

Motion Path, Data Collection, and Testing Movement, and lack thereof, was tested in the room location, as well as using static images to simulate an attempt to misinform the artificial intelligence system by giving erroneous information. Data was collected over several weeks and samples of human activity typically lasted 1-2 minutes. Of the 100 samples, they included various permutations of pacing about in a pattern, with and without ferromagnetic material, in the dark or with light, etc. A typical test included walking from S2 to S1 and back, and repeating multiple times. Selected tests include:

person pacing in normal lighting carrying typical phone and wallet, no person visible in scene, data integrity issue - cyber-only (algorithm provided incorrect image), data integrity issue - physical (static image of person physically placed), low lighting carrying typical phone and wallet, and partial occlusion of person pacing in normal lighting carrying typical phone and wallet.

Hardware and Software The code was executed using JavaScript rendered in HTML5. The entire machine learning camera model was executed at the edge, including image capture, processing and graphing. This step was taken to attempt to improve the data security as compared to transmission and storage of the raw data on the cloud. The confidence score final variable (human detected) was transmitted back to the fog validation layer. This greatly reduces exposure of confidential data, and the data is then validated by the other sensors. Samples were taken, processed, and plotted at 10Hz.

Luminosity Sensor: The AMS TCS 3400 sensor was used for the experiments. The sensor uses clear, red, green, blue, and infrared light source detection to determine the luminosity in Lux.

Magnetometer: Asahi Kasei Microdevices AK09911

Camera: 16MP Sony IMX 398 sensor with a 1.12 μm pixel size, down-sampled to capture a 1.2 megapixel video stream.

The sensory substitution approach does not require these specific sensors, or even these modalities, since software could be written to adapt whatever is available, be it microphone, temperature, or other sensors.

5.1.1.7 Results of Sensory Validation

Overview Corroboration of the sensors is a key usage of sensory substitution. Example results of corroboration can be seen in Figure 5.6. The peaks in magnetometer occur when the human enters close proximity to the nearby sensory node. The AI algorithm shows a false negative at this time because the camera sees an occluded part of a person, and is not able to confirm the presence of the person. With sensory substitution fog validation layer, the person detection can be performed by the magnetometer, preventing a false negative.

Figure 5.6: Results: Signal analysis in the time domain representing one of the tests performed. The upper graph is the average magnetic field (uT) in all directions, while the lower graph shows the camera based AI confidence (out of 1). Circled in red, the false negatives are detected using sensory substitution to correct human detection. © IEEE

Reliability Analysis Though an AI camera algorithm detects with high accuracy human presence, the confidence levels fall in scenarios where the entire person is not present in the camera frame. For example, typical values of the camera with a face only is 20-40% confidence, whereas the entire body gains confidence in excess of 70%. If the person moves too close to the camera, the confidence may drop to 0. There are other scenarios where the camera and AI are insufficient. In scenarios where confidence is low, additional sensors are needed to confirm the true presence. False negatives are detected by using Sensory Substitution, as the magnetometer detects the presence of the person when the camera does not.

Response Time Training or retraining a deep learning model can take time, so to ensure that the model can work quickly, structured programming can be used following decision-tree logic as per the algorithm in Figure 5.4, to ensure false positives are caught promptly. Informed responses enable re-training of the deep learning model and can further improve the system response.

There are scenarios where visual detection alone may be unable to provide the level of reliability, and can lead to false positives, such as a falsified image of a human in correct proportions. Also possible are false negatives such as in low light conditions, or if a person is not in frame. Poor confidence from the AI image model can also stem from obfuscations, low light conditions, or scenarios where a person is only partially in frame. Finally, like the

high-profile cyber-physical attacks, both false positives and false negatives are possible due to a cyber-attack such as a playback attack. The method algorithms are shown in Figure 5.4, and this algorithm leads to the results found in Table 5.1, and selected sensory substitution result data, where a false negative is corrected, can be seen in Figure 5.6.

In situations where someone is trying to conceal their identity, sensory substitution can help provide that information.

AI Algorithm Detects Person Using Cameras and Distributed Sensors Detects Person using Magnetometer The algorithm adapts the OpenSource Pose Estimation model to determine confidence of a human being present in a frame and plots this. The resulting data collected in Figure 5.6, show good corroboration between the AI algorithm and other distributed sensors.

Nearby magnetometers can validate the presence of a human, based on their smartphones magnetic signature, and this can be seen by the peaks in Figure 5.6. The change in magnetic field occurs when the person gets closer to the sensor and the camera algorithm can no longer see the entire person in the frame. This partial occlusion case is a great example of sensory substitution increasing the accuracy of the distributed system. This both enables correction of an instantaneous false negative in the AI prediction, but also provides a corroboration and validation of the longer-term (30 second) average prediction.

Using this model, unrealistic sensing conditions can be detected using only a few samples, and the model detects these false positives or negatives by implementing the logic of Figure 5.4 programmatically. The raw data can also be exported for a security professional to analyze so they can see why the model located a false positive/negative.

Table 5.1: Table of Results of IoT Sensor Validation in Specific Human Detection Scenarios © IEEE

<u>Scenario</u>	<u>Lumin- escence</u>	<u>Magneto- meter</u>	<u>Artificial Intelligence Confidence of Human Presence</u>	<u>Human Predicted</u>
Person pacing in normal lighting carrying typical phone and wallet	High	Changing	High	Correct measurement of true positive, corroborated using sensory substitution
No person visible in scene	High	Steady-State	Low	Correct measurement of true negative, corroborated using sensory substitution
Data integrity issue - cyber-only (algorithm provided incorrect image)	Low	Steady-State	High	False positive discovered by Sensory Substitution
Data integrity issue - physical (static image of person physically placed)	High	Steady-State	High	False positive discovered by Sensory Substitution
Low lighting carrying typical phone and wallet	Low	Changing	Low	False negative discovered by Sensory Substitution
Partial occlusion of person pacing in normal lighting carrying typical phone and wallet	High	Changing	Low	False negative discovered by Sensory Substitution

300 tests were run in various lighting conditions and pocket contents states, including keys, wallets, and phones, as indicated above. Typically, a single person is in the frame at a given time, but multiple participants were observed. The results show that the sensory substitution approach helps to detect false positives and false negatives from the visual algorithm, and also to corroborate true positives and true negatives. The Fog algorithm then can detect and present these situations via an alternative communication channel. Through testing, results were obtained using the algorithm, and can be seen in Table 5.1.

With validation discussed, the subsequent section presents a security analysis of sensory substitution and embedded sensors.

Alternative sensing also can raise privacy considerations, such as discussed in [144]. The trade-offs must be considered when deploying new technologies, and the subsequent section will address that.

5.1.2 Securing Sensing

Measurement Using HTML5 Scripts on a Smartphone In this section, measurement techniques are shown that can activate sensors and when used for instrumentation of an IoT environment, these techniques can at times be indispensable. However; if the same algorithms are activated by an unwanted source, the sensed information can be divulged to any site running the scripts. The methodology is presented in Figure 5.7.

Figure 5.7: Methodology of Sensor Compromise © IEEE

NFC for Launching HTML5 Scripting NFC, or near field communication, is a type of communication built into many smart phones and other connected electronics. Using standardized protocol, they can be programmed to contain small amounts of data enabling other transactions and/or commands to be issued. Payment cards, door access cards, museums and other tourist information, transit fare cards, and smart phones all use NFC for contact-less transfer of small amounts of information to begin or enable another process or mechanism. NFC tags can be programmed to automatically initiate a Wi-Fi connection, Bluetooth pairing, open a specific app, or contain a URL to execute. This section focuses primarily on the use of NFC that executes a URL. QR codes are a graphical form of a URL. When scanned with an appropriate smart phone, the URL is executed.

In Figure 5.8, a photo of a smart phone displaying the NFC Data Exchange Format (NDEF) [147] record (which is a message encapsulation format) pointing to a URL can be seen, as well as a keychain NFC tag placed under the device where the NFC scanner is located.

Figure 5.8: Smartphone Interface - scanning a tag (red, behind phone), and resulting NDEF can be seen on the screen. It contains a URL with protocol “http://” and value of “carleton.ca” © IEEE

5.1.2.1 Method of Sensing Using HTML5 vs Apps: Activation of Sensors With Only Stock Smartphone Software

HTML 5 is a standard of the hypertext markup language that contains methodologies for enabling code to access sensors located on the host device. This provides a vast array of options for developers to use in their Smart websites, applications, etc. HTML 5 scripts are executed by a web browser and do not require the user of the smart phone to install specific applications.

To activate the scripts, some smartphone-based IoT devices use purpose-built applications to activate sensors and perform measurements. Other straight off-the-shelf smartphone based IoT measurement systems use the built-in functionality of HTML5 for sensing. This does not require any 3rd party applications to be installed on the user endpoint device - only what is already on the device. This unobtrusive activation method typically

requires the user to initiate by 1) scan an NFC tag, where the NDEF record points to a URL of the sensing script, 2) a QR code, which when scanned also opens the URL of the sensing script, or 3) requires the user to type a URL, which is often an obfuscated or abbreviated URL (not human-readable).

5.1.2.2 Results: Sensor Activation Algorithm

Initiation of sensing using a smartphone typically involves 3 phases.

The first phase can be initiation, as described above.

The second phase can be data collection and transmission. The launched HTML5 script contains code to enable and transmit specific sensor data. Some may require human acceptance of a basic prompt, and others may not.

The third step typically is the data analytics to use the captured sensor data of someone going about their day; and unbeknownst to them, much information can be collected.

Users Do Not Need to Approve Sensor Access Seemingly harmless sensors, such as that of a gyroscope and accelerometer can also provide personally identifiable information. An HTML5 script can access these physical motion sensors with no user prompt at all, and the raw sensor data can then be used to calculate parameters such as speed or step count. For details on algorithms that extract these parameters, see [148, 149]. Combined with GPS data, this information could significantly provide unwanted information. Selected sensor access vectors are shown in Figure 5.9. In Figure 5.9 a) and c), the algorithms are to use the camera and GPS sensors respectively. Both require user prompt, but in the algorithm shown in Figure 5.9 b), it does not require any information from the user, and may automatically begin sampling data from the accelerometer and gyroscope.

Figure 5.9: Algorithms that can enable instrumentation and measurement using a smartphone: useful algorithms when part of a desired IoT application, but concerning if launched in an undesired manner. © IEEE

Nuisance Actuator Activation Additional security awareness from HTML5 in smartphone based IoT systems are some examples of the nuisance compromises that are possible by activating the device communication systems or actuators. For example, as shown in Figure 5.10, with no user confirmation, the communication network could be activated by initiating download of multiple large media files. This could undermine user trust in IoT applications, as using gigabytes of additional data could have a financial impact on a user of an IoT based system.

Figure 5.10: Selected algorithms that can use actuators in smartphone as a nuisance to user © IEEE

NFC Activated Sensors or Actuation Multiple sensors were tested, and a results summary can be found in Table 5.2, showing many types of instrumentation using smartphone sensors.

Table 5.2: Results Summary of Instrumentation Activation Tested Using HTML5 on Smartphones © IEEE

Instrumentation: Sensor or Actuator	Measurement, Information or Action Derived	User response needed?	Browser Support
Camera	Photo/Video	Yes	Most
IMU (Gyroscope, Accelerometer)	User Motion Data Stream	No	Most
Voltmeter (Battery)	Battery info, device usage	No	Some
Proximity Sensor	Proximity information	No	Some
GPS/GLONASS	Location data and trends	Yes	Most
Network Adaptor	Use and transmit data	No	Most
Motor	Use and deplete battery	Yes	Some
Microphone	Sound/Speech	Yes	Some

5.1.2.3 Discussion

There is a growing trend of distributed sensing in IoT devices in multiple sectors, and many are smartphones containing NFC and supporting HTML5.

IoT System Designer and User Awareness NFC, QR, and short-URL based measurement systems may continue to play a significant role in other IoT roll-outs. Since they require no specialized hardware other than the user's smartphone, the applications may continue to grow. It is important that both designers and users be aware of the potential for anyone to apply the same techniques as used by IoT products. Simple security awareness for IoT designers as well as end users can reduce the chance that unauthorized users access their sensor data. This work can then lead into an overall situational awareness approach.

Fusion for Multi-modal Approach to Situational Awareness This validation technique is useful for reliability of distributed sensing. As sensors become more pervasive, it is more and more important to be able to maximize what can be extracted from existing sensors before deploying more sensors – especially given the additional modification constraints. Extraction and derivation of additional data with existing sensors can raise privacy considerations, so impacts of deployment of such algorithms must be considered. More work can be done in adding features to the AI, allowing more biometric data to be collected and corroborated.

An effective approach may be to use analytics that use existing sensors and learning algorithms to provide the situational awareness that can assist with anticipating vulnerabilities, and thus further increase reliability.

5.1.3 Conclusion

The algorithm and results presented in subsection 5.1.1 can be used to increase the reliability of IoT systems, validating sensors to mitigate either common sensing errors or cyber-physical attacks like playback attacks.

AI-based security systems that include sensory substitution present enormous opportunity in security applications – if the data can be trusted. Using an AI person detection algorithm on a camera, and using sensory substitution to independently corroborate the findings of the AI makes the system become more resilient.

Not only is sensory substitution useful for validation of visual sensor data in the case of data integrity issues, but also in operational conditions that are sub-ideal such as low-light or partial image.

The method works and is effective. Incorrect person detection predictions from the camera artificial intelligence algorithm, such as false negatives and false positives, are corrected by sensory substitution. As the information collected by typical perimeter security sensors are used to validate other existing sensors, this shows the effectiveness of sensory substitution for data validation.

5.2 Classification and Adaptation: Urban Sensing and Security

With the analytic approach of classification and adaptation, we look at Urban Sensing and Security, where we propose an urban sensing method using imaging analytics with acoustic signals for UAV signature classification. It also presents methods of detecting presence of UAVs using only the sounds they produce and is presented in subsection 5.2.1: Urban Remotely Piloted Aircraft Systems (RPAS)/ Uninhabited Aerial Vehicles (UAV) Detection with In-Situ Sensors. Another urban issue to be addressed is environmental and physical sensor systems for smart environment performance of human detection. These issues are discussed in subsection 5.2.2: Personalization and Human Detection Using Sensory Adaptation with Ambient Sensors.

5.2.1 Urban Remotely Piloted Aircraft Systems (RPAS)/ Uninhabited Aerial Vehicles (UAV) Detection with In-Situ Sensors

Remotely piloted aircraft systems (RPAS) are poised to take a larger and larger market share and continue to be used in a variety of new applications in urban environments. The terms “Drones”, UAVs / UAS (uninhabited aerial vehicles / systems), and RPAS are often used interchangeably.

Responsible and Inappropriate Urban Use UAVs are frequently used responsibly in urban environments for applications including commercial uses, photography and film-making, security monitoring, real estate, construction, landscaping, property and infrastructure inspections, leisure, public safety (fires, emergency, natural disasters, investigations), weather, traffic, and much more. Usage is exponentially increasing, as the UAVs increase agility and lower cost. For example in 2017, in Daytona Beach, USA, police report increased use of drones because of cost differences. For example, calling in a piloted helicopter costs \$1.4 M as compared to \$1,200 for a drone [150]. After Hurricane Irma, UAV pre-and-post incident imaging enabled FEMA (the disaster relief agency in the USA) to much more quickly approve funding for rebuilding, substantially saving time and improving recovery [150]. Additionally, RPAS systems are set to soon potentially

replace ground vehicles as the last mile delivery system of choice, and serve many daily applications in urban life.

Figure 5.11: Two commercial RPAS, available at consumer electronic stores for only hundreds of dollars. Left: Parrot AR Drone, controlled by WiFi at an urban construction site; Right: DJI Phantom in frame of a suburban facility. This model is also famous for crashing into White House lawn and for running reconnaissance missions for paramilitary fighters. © IEEE – adapted under Creative Commons

UAVs also can be used irresponsibly, which can result in accidental nuisance. These social aspects of UAV use are of concern. They also have the potential to be misused for intentional abuse, such as activities that violate privacy, deliver unauthorized material, or potentially explosives or other hazardous items. UAVs often cross privacy lines.

As proliferation of these devices continues to increase, a larger number of these UAS may be involved in unwanted flights, perhaps such as flying over and interfering with communication satellites as shown in Figure 5.12. In typical urban scenarios, not only do these pose a threat to critical infrastructure, but they also are poised to cause smaller and more common threats of accidents and vandalism damages or interfere with daily urban activities. Was a drone involved?

When a property owner discovers an unmanned aircraft system flying above their site, how do they go about determining the next action to take? There are many opinions on the subject. Individual property owners such as residential and small businesses may have little recourse. Police and emergency services will not likely respond to an unmanned aircraft system that has not yet committed a crime of substance. However, even if the

unmanned aircraft system does commit an infraction e.g. photos of property, or landing and the damage, etc, in some cases, proof that involvement of drones was a factor in such an infraction can be important information to have, and acoustic analysis may be a key. Even providing proof that an RPAS was involved can be critical in emerging urban scenarios.

Consider someone on their own property, if a recreational UAV is flown above someone else's property, this is certainly a nuisance (irresponsible), but perhaps someone is taking photos of people on their own property truly invading privacy (misuse). UAVs can also inhibit other fliers with more urgent needs to fly. Flying near airports is quite intentional. Someone flying their commercial UAV near a fire may inhibit first responders from using their own UAVs or piloted helicopters. There are many possible problematic uses of UAVs that require monitoring, and some of them are intentional. There have been many reported incidents of late, highlighting the need for regulation updates. For example, in 2019, Canada updated its regulatory / licensing framework. As one part of the solution, sensory adaptation could be used to determine compliance with the regulations.

Emerging Problems: Agile Detection Needed One problem that can occur with the sheer increase in volume of UAS: accidents and mishaps. In more realistic or common scenarios, the likelihood of a crash or other accident between UAVs or between UAVs and another object is possible. A post-incident question may be whether there was UAV involvement in an incident. In all transportation systems, accidents are a common risk, and UAS are no exception to this. How do we monitor or detect UAS then?

Much research and product development has focused on specific RPAS detection systems. These are sensor systems using multi-modal sensing and sensor fusion to accurately detect and track, within certain realms, the presence of an RPAS. Purpose built UAV detection systems may commonly be used for detection and tracking in particular urban locations.

However as usage proliferates, many of the potential incidents may occur in an area that is not covered by a specific RPAS detection system. If we parallel this to specific scenarios of the day, traffic accidents between cars, bikes, motorcycles, pedestrians, and other road vehicles, these are typically not captured by a multi-modal sensing system. Often these accidents occur where there is minimal or no monitoring at all - and certainly not a specific drone-detection system. If there is monitoring, it may be a dash cam in one of the vehicles, a traffic camera, or ambient surveillance footage or sound recordings. This thesis looks at how to detect a drone in these limited-monitoring locations. In urban settings

where RPAS usage is proliferating in daily urban personal and commercial activities, it is becoming important to have a system to detect RPAS using available sensing. Knowing of the presence allows security teams to monitor or take evasive measures if deemed necessary, until the risk has been mitigated.

Our Approach Our approach is to use the concept of sensory substitution, which is using readily available sensors to detect something for which they were not initially deployed [3, 2]. In this case, we will use already existing microphone systems as part of ambient sensing for RPAS incursions. Whether the problem and concern is simply the presence of an RPAS in an area, or to determine whether or not an RPAS was involved in an accident or incident, the ambient sensors of microphones are available regularly in surveillance systems, dash cameras, or other regularly deployed systems. Even recorded cell phone conversations could be used potentially for identification of the presence of RPAS.

Rather than striving to create a new specifically purpose-built RPAS detection system, the goal of this thesis is to provide alternative detection strategies that work with sensors often already deployed for other purposes in urban environments.

5.2.1.1 RPAS Detection Approach in Urban Environments

In this section, we outline examples of sensory substitution used in multiple applications. We also look at a few methods of UAV detection, and reasons for choosing acoustic sensors for urban agile RPAS detection. To determine the best response mechanism to an unidentified RPAS, it is useful to know the type of RPAS and its characteristics.

RPAS Capabilities and Urban Risks RPAS, UAS, etc, have a large potential, and deployment of such systems may continue to increase in the next months and years to come [151]. RPAS can be any type of machine or robot capable of flight. Figure 5.11 shows two types of consumer-grade RPAS. There are clear security risks with these UAS within urban and suburban environments, and a prerequisite to any interdiction is detection. Small quad-copter RPAS that can be purchased from consumer electronics stores for a couple of hundred dollars (and up) can climb to 100m, and are agile enough, for example, to land on a transformer substation with a small load. Styrofoam-core and other fixed wing RPAS can be configured to fly set reconnaissance paths of 80km or

more on one battery charge. Hybrid RPAS (fixed wing and multi-rotor), such as those being developed by delivery service companies, have both the quad-copter features of agility and the ability to take off and land almost anywhere and ability to travel long distances and carry heavier payload. These capabilities may enable much use in urban environments.

Figure 5.12: RPAS flying over satellite dishes © IEEE

The purpose of the analysis and experiments is to determine which sensor modality appears best be able to use the sensory substitution approach to overcome the modification constraints for sensing UAVs in urban environments. In this section, we present our analysis, which leads to design of algorithms to use already-deployed acoustic sensors for agile UAS detection.

Since purpose-built RPAS detection systems may not have universal coverage, and yet, UAS deployment will far outpace deployment of dedicated RPAS detection systems, so it becomes clear that sensory substitution, or using the sensors present in the urban environment, is key.

This thesis's contribution is a method of drone detection for urban environments using sensory substitution: using already-deployed microphones to solve the problem of drone detection in urban environments.

RPAS Detection: RPAS as Risk to Urban Critical Infrastructure / Personal Property

Unauthorized RPAS may be a significant concern to property and facility owners, as they may target physical assets, people, and even target RPAS owned by the property owner.

Different sizes and types of RPAS, as well as in-market detection products and research were assessed.

We observe that existing products and research in this field can fall into the following categories:

1. visual detection
2. acoustic detection
3. RF detection
4. RADAR/Military
5. Other

A question considered when analyzing these approaches may be to determine which can be adapted for agile urban detection.

A Key Requirement for Detection and Choice of Sensor Detection of an RPAS requires knowing the physical characteristic to be measured, and then ensuring that cannot be disguised or disabled by its operator. When determining which available sensor to use for urban RPAS detection, it is important to consider the availability of the measurand as well as the availability of the sensor. Can the UAV become undetectable if a given sensor is chosen? With this in mind, we discuss whether each characteristic cannot easily be disabled or removed.

Each physical parameter that could be used for detection has limitations and considerations:

Radio Frequency (RF) Based Techniques Detection of RPAS is a complex undertaking, particularly when looking at the busy RF spectrum in urban settings as a basis of detection. The reason is that not only are unlicensed spectrum - the ISM (Industry, Scientific, and Medical) bands - commonly used by off-the-shelf RPAS very crowded with many other users such as WiFi, but also RPAS use a multitude of control and communication mechanisms, including:

- WiFi: (IEEE 802.11n)
- 3G Mobile (UTMS) / 4G Mobile (LTE) / 5G
- Infrared

- Radio Frequency Analog (RF)
- GPS Waypoints

Not only this, but RF communication links may be turned off, and some RPAS are autonomous (not using RF for portions of the trip).

Visual Detection Visual detection is an effective technique, as an RPAS may be in view during daylight operating conditions. However, adequate lighting and camera density/angles are needed for sufficient visibility. Though visual sensing is readily available, many relevant incidents may occur in low light conditions or with cameras facing the wrong angle to record it, or intentional obfuscation.

Acoustic Techniques A promising approach to detecting the presence of RPAS is through the study of the sound they generate (from rotors, motors, etc). This approach requires: investigating the various sounds generated by different RPAS, analyzing these sounds and finding common features, performing pattern recognition and classification algorithms, audio acquisition, and spectral analysis.

Audio is vastly universal because powered RPAS emit sounds. However, RPAS operating in a noisy environment could be difficult to detect. Removing noise and separating signals could help with performing detection, and a new approach to sound-based detection algorithms is needed. The proposed algorithm is presented later in this section.

Figure 5.13: Example sound data of recorded UAS. Left: Time domain signal from commercial drone, Right: Frequency domain signal from commercial drone © IEEE

Initial testing provided promise in using low-cost embedded microphones as the basis of our work. This validated the hypothesis that sensory substitution could be pursued for the problem of urban UAS detection. Figure 5.13 shows an example of an unfiltered audio signature of an RPAS that was collected from testing in a busy outdoor urban area, and the figure compares time domain signal and frequency domain signal. This test shows that existing hardware can provide sufficient audio signal for further processing. Testing was done in the laboratory, plus both indoor and outdoor. The time-domain signature shows the amplitude versus time, and the frequency domain signature shows the amplitude of the sounds at each frequency in a busy, urban area. Analysis and additional research of the signatures of one UAS may enable comparison with other RPAS.

Assessment of UAS Detection in Urban Environments and Choice of Sound for Agile Urban UAS Detection In the absence of bright lights, some video algorithms tend to fail. The resilient method that no longer requires light is sound or RF. RF, however, has not been able to easily differentiate between UAS systems when proprietary RF signals are used. This leaves sound. Sound is one of the only measures which cannot be easily eliminated, short of turning the propellers off. Use of sound for urban UAS detection can be of extreme benefit. The signature of an RPAS can be used to detect the device.

The sensor modality selected is microphones as a more universal substitution for dedicated RPAS detection systems. Microphones, whether fixed or in mobile sensors like phones, are becoming so prevalent that they can almost be considered ubiquitous in some urban environments. This thesis then focuses on using sensory substitution with acoustic sensors for UAS detection.

Framework and Analytical Approach Use of sensory substitution is an emerging technique of using already deployed sensors [3], of which there are many, in an urban environment.

Figure 5.14: Sensory Substitution for Urban RPAS detection, shown as a subset of the sensory substitution approach where the input is various ambient sensors, and the output is the situational awareness of urban UAS detection © IEEE

The methodology has been studied extensively, and is proposed as a method to solve the emerging urban problem: RPAS detection. See Figure 5.14 for the system diagram of Sensory Substitution, and how it leads to a solution in this case.

We present a proposed framework for signature detection of UAS using urban in-situ sensors, and present an algorithm for detection of RPAS using sound. In Method of Detection Using Sensory Adaptation, we discuss the various acoustic processing performed, and our algorithm that re-purposes image processing techniques with spectrograms of sound. Finally the work presents sample results for the algorithm proposed that shows the viability of this acoustic sound detection method using vision-based machine learning and AI algorithms with existing microphones.

The work focuses on the feasibility of development of an urban UAS detection system using existing sensors that overcomes the modification constraints that exist in urban environments. Since the goal of this work is not to develop the “best” detection strategy, but rather, development of a strategy that can use sensory substitution to overcome modification constraints, we do not compare accuracy with purpose-built UAS detection systems. Following the proof-of-concept and algorithm, detailed comparisons of accuracy

and optimizing of the algorithms will be future work.

This thesis provides example sound extraction methods, as well as an algorithm that uses image processing techniques with sound data to provide the classifier.

5.2.1.2 Method of Detection Using Sensory Adaptation

We discuss using sensory substitution with microphones to detect UAS systems. This specifically focuses on examples with “non-ideal” detection scenarios, in terms of hardware deployments. An ideal situation is an RPAS detection system deployed in the area of interest. At the moment, such deployments are confined to particular areas such as prisons, airports, or high-value infrastructure assets. The scope of this thesis focuses on urban areas where such systems do not exist, but other sensors already exist, such as common microphones.

System-Level Algorithm The system level methodology for using sensory substitution with already existing microphones for ambient urban RPAS detection is shown in Figure 5.15: the proposed system uses any available microphone to record sound segments, and the sound is transmitted and pre-processed. The sound segments are turned into spectrogram images and a classifier is trained on the sound spectrograms. Once trained, the system can then determine if a UAS is present from a live or recorded sound input. The experiment is a success if the system is accurate more then 90% of the time.

Figure 5.15: Block diagram of proposed urban UAS detection algorithm: UAVs emit sound, which is captured with any available microphone (in IP camera, standalone microphones, smartphones, etc), the sound is transmitted and analyzed using the trained neural network discussed below. © IEEE

RPAS Detection using CNN and Transfer Learning of Acoustic Signatures and Spectrogram Images

Work was done for detection of RPAS using convolutional neural networks (CNN) and transfer learning of acoustic signatures and spectrogram images.

Literature of RPAS noise use the Ffowcs-Williams/Hawking equation for aeroacoustics (Equation 5.1), and say that propeller design affects aeroacoustic response:

$$\begin{aligned} \frac{1}{a_0^2} \frac{\partial^2 p'}{\partial t^2} - \nabla^2 p' &= \frac{\partial^2}{\partial x_i \partial x_j} \{ T_{ij} H(f) \} \\ &- \frac{\partial}{\partial x_i} \{ [P_{ij} n_j + \rho u_i (u_n - v_n)] \delta(f) \} \\ &+ \frac{\partial}{\partial t} \{ [\rho_0 v_n + \rho (u_n - v_n)] \delta(f) \} \end{aligned} \quad [65]$$

$$\textit{Aeroacoustics Equation} \tag{5.1}$$

Though optimization of this equation is out of the scope of this work, it shows that many aspects of an RPAS propeller (and physical structure) affect its aeroacoustic response - differences that can be spotted in RPAS class differentiated sound spectrum images.

Acoustic Signature - Machine Learning Method to Detect RPAS Using Sound Represented as Spectrogram Images

Inspired by [7, 9, 3, 2, 152], we develop an approach for detection of RPAS using sound, represented by spectrogram images, and using existing microphones in urban environments for RPAS detection. The following section discusses the algorithm to classify RPAS using sounds. Sound is generated by vibrations of a material at a certain frequency. For example, voice is made by vocal chords that are tightened and loosened to vibrate at different frequencies to develop unique sounds. Likewise, operating UAS vibrate and create sounds. If looking at the holistic system sound characteristics, there is much variation within the class. Certain types of user-modifications can change particular types of sound characteristics. This being said, it is possible to use a sensor for X to measure Y, so we propose using microphones that are already commonly installed in urban environments as an RPAS detection tool.

An interesting part of this proposal is “algorithmic substitution”: using transfer learning with models designed for image processing to classify sound signals. This is done by expressing sound as images of spectrograms and training the deep learning model with these images. Combined with with sensory substitution, algorithmic substitution, and distributed microphones, it is possible to detect RPAS systems without use of a purpose-built UAV sensory system. This can enable agile UAS detection in a variety of urban environments.

Scenario and Data Collection Experiment An indoor and outdoor experimental setup was created. Various microphones were placed at distances from 1 to 20 metres and beyond from the UAS. Sound samples were taken with the drone taking off or hovering, with the goal of collecting various typical RPAS sounds. Also, during some tests, to record the takeoff and landing sounds and allow for significant audio collection without the drone flying away, the methodology employed was to cycle either the left or right controls of the aircraft controller, but not both at once as required for takeoff. A difference with only 2 motors at full thrust versus 4 is the power level of the sound produced; but this power level also differs depending on the aircraft distance from the controller during flight.

Note that for this thesis, the team made the assumption of sufficient SNR that the sounds of interest did not fall below the noise floor. How to handle the case of detection of the RPAS below the noise floor is future work.

Various UAS systems were included in the sound recordings, including home-made DIY drones, custom-made UAS designs, DJI Phantom, Parrot AR Drone, Parrot Mini, and many other commercially available off-the-shelf drones. The focus of this work is on detection in general, while later work will focus more on classification.

Various low-cost and device embedded microphones were used to collect the sounds in order to make the trained neural network more resilient. For the purposes of this thesis, though several microphones were used to record sounds, all preformed sufficiently for collecting UAS data.

RPAS Unique Sound Analysis - Field Results of Signature Extraction Extensive testing and sound recording has been performed of various RPAS sounds generated by different types and sizes of UAVs. Devices tested include DJI Phantom, Parrot AR Drone, Parrot Mini, a hexacopter, unnamed inexpensive toy UAVs, custom-built UAV, and DIY drones. Most were multi-rotor vs fixed wing. RPAS, when in operation, produce unique sounds. Samples using various RPAS were collected, including multiple different behaviours. The sound signature was filtered, extracted, and spectrograms were generated using Matlab. Human readable images are generated with axes, labels, and legends. Simultaneously, images for testing, training, and validation were generated with no labels so they can be processed using transfer learning.

Algorithm 5.2 Code to Split Up Sounds and Generate Spectrograms, Which Are Then Used For Training, Testing, and Validation

```
%% Declare Variables
currentDirectory = pwd; fileName = '__'; currentFile =
    strcat(currentDirectory, '/', fileName); testName = strcat
    (currentFile, '.png'); testNameNoAxis = strcat(currentFile
    , '-noAxis', '.png'); audioFile = strcat(currentFile, '.wav
    ');

%% Import Audio File
[signal, fs] = audioread(audioFile);
signal = signal(:,1); origSignal = signal;

%Break up sounds into equal parts
recordingLengthSec = length(signal)/fs;
NumberOfEqualSegments = floor(recordingLengthSec);
recordingLengthUnits = round(length(signal)/
    NumberOfEqualSegments);

currentStart = 1;
currentEnd = recordingLengthUnits;
% generate multiple graphs
for i =1:NumberOfEqualSegments-1
    % update signal
    signal=origSignal(currentStart:currentEnd);
    % put number of sample in the file
    testNameNoAxis = strcat(currentFile, '-noAxis', '-',
        int2str(i), '.png');

    %Larger Window Size value can increase frequency
        resolution
    %Smaller Window Size value can increase time resolution
    nwin = __ %Choose Kaiser Window length, eg fs/100;
    wind = __ %Choose Filter (and spape parameter), eg
        kaiser(nwin,17);
    nlap = __ % Choose samples of overlap, eg nwin-10;
    nfft = __ % Choose FFT length, eg 256;
    figure;
    spectrogram(signal,wind,nlap,nfft,fs,'yaxis')
    colorbar('off'); % surpress all but image for CNN
    axis off;
    saveas(gcf,testNameNoAxis);

    currentStart = currentEnd;
    currentEnd = currentStart+recordingLengthUnits;
end
```

Audio was pre-filtered using the approaches in subsection 5.3.2, but in some samples, no filtering was applied to add variety that reflects real-world operating conditions. A sample of code for generation of spectrograms based on the Kaiser filter is shown in Algorithm 5.2. The process entails import of each audio file, breaking up sounds into equal parts, generating multiple graphs, and repeating until all sound is in the form of spectrograms.

A key finding is that regardless of the RPAS behaviour, the core acoustic signature remains constant. Though multiple drones, including DIY drones, were recorded as part of this testing while performing different activities, Figure 5.16 - Figure 5.19 show acoustic signatures extracted from a single one of these types, the Phantom, which is a commercially available everyday recreational UAV.

Figure 5.16: Sound signature of stationary RPAS (10m from microphone) © IEEE

In Figure 5.16, the sound signature, as presented in a sonogram can be seen when measured at 10m (idling). In Figure 5.19, the sound of the rotors can be seen during various phases of flight including a landing. Note in Figure 5.16, the top graph is the frequency domain representation of the sound, and the bottom graph shows the unique sound signature spectrogram.

Holding constant environment (noise permitted, changing distance), spectrograms can be seen in Figure 5.17: left is at 1m, right is at 10m. Though the signature is of the same sound, the signal power per frequency is quite different due to attenuation.

Figure 5.17: Despite measuring RPAS sound at various distances, the signature is the same (left: 1m, right: 10m) © IEEE

Training CNN Using Transfer Learning With Sound Spectrogram Images The classification uses the TensorFlow deep learning system [146], taking an approach used in the video/image processing domain and customizing these algorithms for sound images. Since there is variability with RPAS sounds (small differences in the same model), variations may occur.

CNNs have many processing algorithms for data including images. The work done uses classifiers that are based on the concept of machine vision, looking for perceptible patterns in the generated spectrograms. Inception is the deep learning model– based on standard image processing using CNN – “Transfer learning”. Using the Inception model, the implementation of the convolutional neural networks look at feature extraction from the audio signature in pictorial form for characteristics in the spectrogram. The images used for training are similar to the spectrogram images as above, but with no embedded textual labels – and can be used in image processing algorithms for high-level classifications. An example from our data that is used as a training image for the CNN algorithm is seen in Figure 5.18.

Figure 5.18: Example of image fed into neural network for training © IEEE

Training the CNN on image files of spectrograms allows for accurate classification based on characteristics comparable to that of literature for results of type classification of images of other classes (e.g. a field vs road in an image).

Dozens of hours of UAV sounds were recorded. Clips were typically recorded in 30 second intervals at increasing distance (e.g. 1m, 2m, 3m, ..., 10m). Similar testing occurred both outdoors (grass and concrete environment) and indoors (small carpeted room and larger tiled space). Typical tests included applying about 50-75% of liftoff power while tethered to the ground. This is accomplished in many models of the UAV by holding controls up on one joystick but not both (as required for normal takeoff). Other tests included takeoff, hover or move for 20s, then land. Crashes were also recorded. Though some clips were filtered as per the techniques in subsection 5.3.2, some clips were left unfiltered with actual noises (e.g. train sounds, cars, wind, people, talking, etc.) included in some clips. Additionally, some clips had these sounds added to simulate these conditions by computer in post-processing (prior to generation of the spectrograms) to increase the robustness of the spectrogram database and thus the resilience of the final layer that is retrained to detect UAVs. Only clips that contained at least a few cycles of rotor noise were retained, which meant that clip length is $> 1s$. Sounds were clipped into equal segments of typically about 1 second each before the spectrograms were generated for each.

Thousands of sound segments were recorded with several UAS sound samples that were segmented and labeled. The spectrograms were generated, and the classifier was trained on a training set, while some were withheld for validation. Various simulated soundscapes and noise were added to train the classifier to be resilient to changes and variety. The training process of the CNN involved multiple combinations of noises and RPAS types.

Determining Behaviour Using Sound Not only can sound provide a signature of the type of RPAS that may be present, but it can also give empirical evidence of the kinds of behaviour of the RPAS. For example, in urban security applications, a security personnel may be interested if the UAS has landed on their property so they can go and retrieve it to mitigate the risk the RPAS poses.

Figure 5.19: Sound signature of moving RPAS, landing, and moving again © IEEE

Sound signatures can also provide an empirical indication of activity. For example, in the small segment shown in Figure 5.19, it is possible to see the soundscape of a UAS flying from 1-10 seconds, landing and idling from 11-24 seconds, taking off 24-26 seconds, and continuing the flight from 26-36 seconds.

5.2.1.3 Results and Discussion

The results of using sound with image classification show positive results in terms of correctly identifying presence of RPAS (preliminary >90% accuracy including multiple RPAS classes). This connects the concept of agile IoT and RPAS detection using a pre-existing sensor (microphone) deployed to measure X (urban monitoring other than UAVs)

to instead measure Y (UAV presence), providing situational awareness using a sensory substitution approach. This provides good performance, showing the algorithm applies the sensory substitution approach to overcome modification constraints in urban UAS detection, and future work will be to analyze the algorithm and improve the accuracy.

Results of the work show significant accuracy in the experiments for detection. Though empirical observations such as Figure 5.19 show initial promise, additional work remains on automated activity recognition (is the UAS crashing? hovering? etc). The results do not yet show that specific activities can be differentiated using this technique, however they do show promise this may be possible with more work.

The wide range of microphones used to collect the data, as well as the filtering of the sound spectrogram images enabled the neural network to accurately learn. With 90% accuracy with sound inputs from a variety of microphones, the experiments performed were a success. An urban UAS detection system using sensory substitution and existing microphones has been presented, and future work can build upon this technique.

The sensory substitution approach shows success in identifying the presence of RPAS. This shows that such an algorithm, as made more robust, could actually be used in many wide applications for information about RPAS usage. As last mile RPAS delivery may very quickly approach, rapid deployment of detection systems may be extremely critical, especially related to unintended situations involving UAVs. This method of sensory adaptation shows significant promise going forward.

After examining sensory adaptation in an urban example, in the subsequent section, we examine sensory adaptation in an urban monitoring application.

5.2.2 Personalization and Human Detection Using Sensory Adaptation with Ambient Sensors

A lot can be learned from mobility of persons through sensors both in urban and rural settings, which can provide situational awareness using sensory adaptation.

Human Detection To facilitate the personalization of a smart environment using sensors and IoT, it is important to ensure we can identify the person. Work toward the future vision of sensory substitution using available sensing must include identification of people without using “obtrusive” sensors such as cameras or requiring people carry a

RFID token. Building on the work of Russell [2], we can add additional sensing capability for identification of a person using commonly deployed sensors.

Experimental Setup A micro-controller and multiple sensor nodes were placed in and around door-frames, and contained various sensors including sensors for temperature, tilt, vibrations, light, motion, magnetism, and sounds, as well as an Arduino-derivative micro-controller and power source. In this application, the sensors are powered from the mains in the house, as they are integrated in the building, though it could be powered from a battery, or using existing sensors in the building.

Photo-resistor The photo-resistor senses changes in light, and will vary the resistance across the sensor based on the incoming light. In essence a photo-resistor acts as a shadow and light sensor [153]. Even in low ambient light or indoor lighting conditions, the photo-resistor may change with lighting changes. In the event of sufficient lighting, the person will walk past the photo-resistor and the shadow sensor may detect a shadow passing. We can see a particular characteristic shape in the response of the sensor that differs from that of a shadow when someone passes, and the distribution of the sensors can help us determine height of the person. Such sensors could detect changes in the intensity of light, even a brief momentary shadow. When that signal is spaced at intervals which correspond with human movements, this can indicate a human is present, and their characteristics.

Magnetic Heading Sensor The magnetic heading sensor determines the magnetic heading in degrees, but the sensor is sensitive to magnetic fields in general, and not just the earth's general field. If a magnetic device passes over the sensor, a particular characteristic shape may be induced. In a similar way, metallic objects can produce a range of responses, albeit with a smaller magnitude than a magnet. Mobile phones not only have a large amount of metal, but they also have magnets in them. Since a large number of individuals carry portable electronics, this detection strategy may be very useful in terms of identifying individuals. Not only smartphones could be detected, but many other common electronics.

Test Device The device consisted of the magnetometers, and a photo-resistor sensor boards. The sensors were connected to an OSEPP (Arduino-derivative) MEGA 2530 R3.

The “10DOF board” that contains the magnetometer, was connected to the PC using a connection type called I^2C that allows multiple addressable sensors to be connected using one bus or set of wires. The photo-resistor board provided the signal using an analog voltage signal. The sensors were mounted in the door area, and wires were used to connect the sensors to the micro-controller. The micro-controller was then connected to the computers for visualization and data analytics by Bluetooth. The 10DOF sensor board with the magnetometer can be seen in Figure 5.20.

Figure 5.20: 10 Degrees of Freedom (DOF) Sensor (Left) and Photo-resistor Light/Shadow Sensor (Right) © IEEE

The other important sensor is the photo-resistor, also shown in Figure 5.20. Note that these sensor boards are about 2cm wide. Sensors were mounted around the door areas.

Data Collection The sensors can collect data, and data analytics can process the magnetic heading on the micro-controller board, and the micro-controller board can be connected by a Bluetooth connection to a PC, though it could use another computer, such as a smartphone device or cloud application too. The data then is provided as a serial stream of numbers that could be processed. A big issue with any data collection from sensors is the vast amount of data that is somewhat daunting. For integration into a connected IoT environment, data analytics and processing is of utmost importance. The data can be processed and represented such that the data could be used to identify people, useful events, and traffic and passage of people.

5.2.2.1 Analytics - Interpretation of Sensor Input

Metal of changing velocity is not an innate component within an outdoor landscape, nor even within many parts of a building, so if then, moving metal is detected, it quite well could be a human, as they could be carrying magnetic components to be detected. If a

shadow is recorded, it could represent an intruder, an animal, or an authorized person. If a magnetic heading reading is recorded, it could mean the sensor has been moved, or there was a magnetic field close to the sensor that could be consistent with the personal items often found in a person's pocket. Sensor fusion is the process by which the outputs from two or more sensors are combined to produce an output that often validates the results. It may be useful to detect whether a shadow pattern consistent with someone passing by the sensor is actually a person, or is rather an animal or another object. The biggest distinguishing factor for a person over something else in nature is the presence of metal and magnets on our person. Keys can trigger metal detectors at the airport, and our mobile phone, which we all carry, has enough metal and magnetism to show a particular waveform. Changes and differences from the day-to-day ambient activity/non-activity in a particular environment could be of concern.

Data Processing The system made use of an algorithm to correct for placement issues so that rather than comparing actual values of magnetic heading, we could compare the change of magnetic heading whether up or down. We can do the same thing with the outputs from the photo-resistor. It is easier to compare changes in photo-resistance than it is to compare the actual magnitude of photo-resistance.

In the purposes of looking for shadows, seeing the actual magnitude of photo-resistance is not necessary, so we can determine what the average value of the signal is for a calibration period and then shift the signal by that factor to have the signal centred about zero. This enables us to see the same waveform, but based on a change of the norm rather than a magnitude value. This is of particular importance since the average value can change based on the time of day, and we would not want to mistakenly determine a person walked by when in reality the background (or average photo-resistance) had dropped because the sun had set. The photo-resistance, is adjusted to be “change” in photo-resistance. At rest, the change from minimum to maximum is 2 ohms, which is effectively negligible noise as compared to the response to stimulation.

Now, we want to see the response of the sensors, both magnetometer and photo-resistor based on people walking within close proximity of the sensors. Assumptions were made that a person passing the door-frame would pass within 10cm of the sensor. We believe this to be a realistic assumption in terms of useful monitoring, because sensitivity beyond that distance may facilitate a number of false positives. Different calibrations could adjust for other distances. Depending on the level of personalization desired and the nature of

the operational environment, the sensors could be deployed every 10cm, so that a more complete map of travel could be made of an individual, or there could be more space, and more assumptions may need to be made to determine the path of travel of individuals.

Photo-resistance and Magnetic Heading We can begin by looking at the change of photo-resistance when various smartphones are passed over the sensors at a distance of about 10cm (with and without rubber casing to simulate real operational environment). It is possible to see clearly the response of the photo-resistor sensor module and the detection of the shadow cast by the passing smartphone. It showcases a spike, representing a shadow, when the device passes the sensor, then returns to normal, then we see a spike as the device passes back past the sensor. In each cycle, the test was repeated for a total of 5 times back and forth each sample over and over again, and it is clearly identifiable by the visible peaks. Now a reasonable question to ask may be, how do we know it's a human induced shadow, and not some kind of shadow from the dog. To do that, it is also important to corroborate the information from the photo-resistor with the magnetometer information. The magnetometer can read the magnetic field in the proximity of the sensor, as the device not only has many metal components, it also has magnetic components that can be read by the magnetometer.

Figure 5.21: Smartphone detection using magnetic heading sensor - peaks indicate where sensor “sees” it pass the sensor in real-time © IEEE

It is possible in Figure 5.21 to clearly see when the smartphone device was passed over the sensor when the field quickly increases as the smartphone approaches, decreases as it leaves, then it is possible to observe the sensor output beginning to return to a steady state no field change), and then similarly the sensor then responds again to the device switching directions and leaving the field of view of the sensor.

There is a selection of data - several passes of the smartphone - shown in Figure 5.21. Although it is great to be able to see these signals, it is better if they are superimposed so it can be seen if they match from both types of sensors.

Figure 5.22: Superimposed sensor response to the smartphone - Magnetic sensor and light sensor © IEEE

Looking at the sensor response in Figure 5.22, it can be noted that at first glance, it appears that the sensors show the passing of the smartphone at the exact same time, but they actually differ slightly because of the characteristics of the sensing capability of the sensors. The photo-resistor measures the change in light reaching the sensor. This requires the object being measured be directly in front of the sensor and either occlude or contribute light reaching the sensor. Conversely, the magnetic heading sensor measures the “invisible” magnetic field being induced by the magnets in the smartphone. Look carefully at Figure 5.22 and it becomes possible to see how the magnetic heading sensor responds to the presence of the smartphone earlier than the photo-resistor responds to the shadow of the device.

We see similar response to the other smartphones tested and also the inanimate magnetic cell phone case. This shows promise in ubiquitous monitoring to integrate into the IoT environment.

5.2.2.2 Results: How do We Differentiate from Pets or Other Non-humans

We may, from time to time, want to be able to identify the family pet, so tests were performed to determine how our sensor system could detect an animal. Both a biological organism and inanimate objects that did not contain any metal were tested with the magnetic sensor and photo-resistor, and the results can be seen below.

Figure 5.23: Example of inanimate object passing the sensors - peaks indicate where sensor “sees” the object pass the sensor © IEEE

In Figure 5.22, it is very important to notice the response. If we see timed spikes at the exact same time in the sensor output from both the magnetometer and the photo-resistor, we may likely have a human or robot passing the sensor. If we only see the photo-resistor respond, a conclusion could be that the object could be either an inanimate object or a life form such as an animal. Additionally, the pressure sensitive floor mats could be integrated with this system, and if so, 4 paws that are relatively lighter than a human foot may be detected in conjunction with the peaks shown in Figure 5.23. The type of

locomotion is very different from human ambulation. Wearables such as smart collars could also be integrated.

Human Differentiation Using an array of sensors described above, it contributes in the direction of calculating the characteristics of the person such as their height and other traits. Combining this with several pressure sensitive floor apparatus, it may be possible to use a learning algorithm to determine what is likely passing the sensor.

Therefore, using already deployed sensors, increased situational awareness can be enabled.

Discussion

We show example scenarios of increasing robust urban sensing and monitoring in IoT environments using sensory adaptation. In the following section, we look at multi-sensory fusion.

5.3 Multi-sensory Fusion: Smart Environments, Infrastructure and Person Security

This sensory substitution method overview builds on chapter 4 and chapter 5, and presents the measurement technique of using sensors designed to measure Quantity X to instead look at measuring Quantity Y, and how this multi-sensory fusion can be used for biomedical and security applications.

When considering Multi-sensory Fusion: Smart Environments, Infrastructure and Person Security, work is done to determine posture of a person using only strategically deployed temperature sensors. The algorithm is discussed in subsection 5.3.1: Posture Sensing with Embedded Temperature Sensors. A generalized algorithm of sensory substitution with multi-sensor fusion using already deployed temperature sensors and microphones, is then presented in subsection 5.3.2: Posture Detection using Sounds and Temperature: Sensor Fusion, LMS, and Sensory Substitution. Following that, this analytic approach presents a method to enable smart environments using NFC and is presented in subsection 5.3.3: Smart Environments with NFC.

5.3.1 Posture Sensing with Embedded Temperature Sensors

In this section, we show results of a laboratory study of how we can determine posture of a subject using various arrays of low-cost temperature sensors per section or characteristic to be determined. We begin analysis with one sensor. This system can perform similar functionality to pressure sensor arrays to determine posture. It can also augment data from other sensors. Such temperature data can also provide another level of clinically useful information: situational awareness.

Posture recognition is a very important concept in terms of reducing occurrence of decubitus ulcers, or pressure sores for people who are bedridden, immobilized, with limited mobility, or in wheelchairs. Shifting or alternating position can also serve to reduce discomforts from many conditions and also from unrelated types of ailments.

When looking at which kinds of posture recognition methods are available, several centre around visual detection using a camera and pressure sensors.

Figure 5.24: Embedded temperature sensors in furniture - Left: chair with indicated temperature sensors, Right top: bed showing sensors insertion into temperature array pad, Right bottom: Selected variation of armrest temperature sensor configuration
© IEEE

In the work by Russell *et al*, a methodology of using low-cost micro-controllers for rapid prototyping of sensors, as well as a connectivity methodology was discussed [149] and

extended in this work. We use part of that Bluetooth methodology for our sensor integration design and build on it.

In work by Russell [149] it was shown that low-cost sensors can be used for rapid deployment and physiological monitoring. Pressure sensors can be purchased inexpensively, however their calibration can be a time expenditure. We selected to examine temperature sensor arrays.

Our hypothesis was that temperature sensors could be used a) instead of pressure sensors to determine posture state and changes in posture, and b) temperature sensor data can augment other sensed data to provide an even more accurate level of posture monitoring. How often does an increase of temperature prompt movement? Pressure sensitive mats alone cannot answer this, and nor can cameras. Such sensor fusion provides this data by including temperature sensing in configurations such as shown in Figure 5.24.

Much work has been done with the mindset of making deployment and rapid prototyping easier such as [148].

5.3.1.1 Method and Results

A chair was set up with multiple sensors as shown in Figure 5.24. First, a temperature sensor array using ds18b20 sensors was installed on the chair in a 4 x 3 array. The office chair was divided into four primary coordinates: seat, left arm rest, right arm rest, and back with temperature sensor arrays at each coordinate. One type of chair tested can be seen in Figure 5.24. In the image, it is possible to see that multiple sensors were installed, but the average temperature of the area of interest was included in the analysis. Second, a camera was set up in front of the chair to provide visual validation of the data collected by the pressure and temperature sensors. Finally, pressure sensor arrays were set up on the chair in a similar placement as to the temperature sensors, but not at armrest locations. Steady-state of the sensor system was recorded as a baseline. Tests were then performed on the chair by various users. The tests were as follows:

1. User sits upright, thus the seat temperature sensors can detect the changing temperature, and the user does not touch the armrest. This ensures the temperature sensors have adjusted to their body temperature and steady-state air temperature for extended periods.
2. User leans to the right and leans on the right armrest for extended periods.
3. User sits upright and does not touch the armrest for extended periods.

4. User leans to the left and leans on the left armrest for extended periods.
5. User stands

Further testing involved additional subjects with other characteristic traits, and individual mannerisms regarding their postural tendencies (and sometimes an unplanned brief sleep while in the chair). Additionally, a pressure sensitive mat, called the Sensimat was also tested. A cushion was placed on the mat. Permutations of these steps were also tested, such as the user simultaneously leaning on both armrests. Also other temperature sensor formations were examined, such as a sensor pad; the sensors were woven at intervals through a mat seen on a bed as shown in Figure 5.24. Additionally, other types of physical sensors were substituted for the ds18b20 throughout the tests. These results will be explored in future work. The data shown here is based on a duration of 3 minutes per activity.

System and Device Design, and Power Considerations The temperature sensors were sampled at 1Hz, and the data was collected with a micro-controller board and stored in a MySQL database for analysis. Offline analysis with Matlab and other tools were used for additional processing and to create images.

Regarding battery power for extended monitoring, temperature sensors can last for extended periods of time in embedded applications. Offline data logging and occasional transmission of data can enable use in the order of years. By reducing real-time synchronization, the battery life of our system can be prolonged by many months. The specification of the operational range of the ds18b20 sensors used is $-55^{\circ}C$ to $+125^{\circ}C$, with accuracy of $\pm 0.5^{\circ}C$ from $-10^{\circ}C$ - $+85^{\circ}C$. The array developed has been formed in multiple ways: as a pad/mat, embedded in furniture, and embedded in fabrics such as a slip cover on upholstered arm rests. The expected operating temperatures for indoor applications vary with ambient temperature, but typically range from $+20^{\circ}C$ - $+40^{\circ}C$. Because this system is intended to be widely deployed, the sensor type was selected primarily for its low cost and ease of integration. Though the required range for this application is only a small segment of the operating range of the sensor, the ds18b20 was still the best choice for our priorities than alternative sensors that had better resolution with a narrower sensing range.

Figure 5.25: Temperature recording during testing. Top: seat sensor data, Middle: right armrest sensor data, Bottom: left armrest sensor data © IEEE

Posture Sensor Data in Time Domain In Figure 5.25, we can see the temperature readings taken over an hour of testing, where the steps outlined were repeated in various permutations. In each region of the chair, we can explicitly see logarithmic temperature increases when the user is present. Mathematically, this is equivalent to the step response of the chair-sensor system, and the step is the application of the user’s body heat. When the user is no longer present at a given location on the chair, there begins an exponential temperature decay. Note that the minor discontinuities in the graph indicate locations of dropped data packets that did not impact the analysis, and may be corrected in future analysis with interpolation.

Figure 5.26: Temperature data fused in time domain. Note the end of leaning right and beginning of leaning left was detected immediately - only one sample later © IEEE

In Figure 5.26, we have superimposed the three regions analyzed - the seat, the left armrest, and the right armrest. It is possible to see 4 repetitions of the data collection in this selection of time. Note that the data in the first, second, and fourth data periods show the user leaning on the left and right armrests after a 2-3 minute gap, providing temporal separation, but in the third test, we see that the user quickly shifted from leaning on the right armrest to leaning on the left armrest in a very short period of time. This shift became visible immediately in just one sample.

These quick responses show that temperature sensors provide sufficient postural data.

Temperature Sensors - Step Response When the sensors are analyzed together, temperature changes can be seen in conjunction with any postural change, and can be corroborated with pressure data and imaging. Each posture change can be modeled as a scaled step input. The step response can be seen clearly in the time domain data, changing with each posture change.

Figure 5.27: Enlarged data results from one set of tests recorded from one subject showing temperature response for various postures © IEEE

In Figure 5.27, we provide a close-up of one test (approx 18 minutes of data), and in this, we can see each posture described earlier in this thesis. The step response for all of these temperature stimuli is logarithmic, though the time constant varies. The armrest time constants are similar, but the time constant of the seat differs due to the material properties on which the sensor is affixed.

Figure 5.28: Pressure readings during each posture sampled © IEEE

Occupancy and Observed Position The data in Figure 5.27 was analyzed and compared with the video analysis and pressure data from Figure 5.28. The observations described in Table 5.3 support our analysis that temperature sensors can indeed provide sufficient data to enable high-level postural identification independent from other sensors. Postural changes were observed accompanying a temperature change of $5^{\circ}C$ in the seat area of the chair and $6 - 7^{\circ}C$ on the armrests.

We compared the temperature data to the data provided by the commercially available Sensimat chair sensor at each postural change point, as seen in Figure 5.28. Temperature data combined with pressure data can enable additional insights. The resulting observations are outlined in Table 5.3, and pressure percentage (left, seat centre, and right) can be compared with the temperature sensor behaviour (left armrest, seat, and right armrest). The task numbers in the table also correspond to the labels in Figure 5.29 for further comparison.

Table 5.3: General Observations of Temperature Sensors Acting in Lieu of Pressure for Posture Detection

Task	Posture	Left		Right		Left		Right		Observations
		Pres- sure Be- haviour	Seat Pressure Behaviour	Pres- sure Be- haviour	Arm- rest Temp. Be- haviour	Pres- sure Be- haviour	Arm- rest Temp. Be- haviour	Seat Temp. Be- haviour	Arm- rest Temp. Be- haviour	
1	Sitting, not lean- ing	56%	Seat pressure appears 56.5%	57%	Steady- State	Logar- ithmic In- crease	Steady- State	Steady- State		The sitting posture was discernible clearly, as the temperature of the chair sensor arrays immediately shot up until converging in the low 30s (°C). The armrest sensor arrays maintained room temperature measurements confirming there was no leaning either directions. In later iterations, so long as the subject had been standing for a few seconds, a temperature differential could be seen if the user returned to sitting after standing.
2	Sitting, lean- ing right	49%	Seat pressure sustained, right higher pressure 53%	57%	Steady- State	Logar- ithmic In- crease	Logar- ithmic In- crease	Logar- ithmic In- crease		The temperature sensor arrays of the back/seat continued its logarithmic increase, indicating the subject continued to sit. Meanwhile, a step input was applied to the right armrest beginning a logarithmic trend, and the left armrest sensor arrays remained at room steady-state.
3	Sitting, not lean- ing	58%	Seat pressure balanced 57%	56%	Steady- State	Logar- ithmic In- crease	Expo- nential Decay			The temperature sensor arrays of the back/seat continued its logarithmic increase indicating continued sitting. The right armrest temperature began an exponential decay towards room temperature indicating the subject was no longer leaning toward the right. The left temperature sensor arrays remained at steady-state.
4	Sitting, lean- ing left	58%	Seat pressure sustained, left higher pressure 53%	47%	Logar- ithmic In- crease	Logar- ithmic In- crease	Expo- nential Decay to Steady- State			The temperature sensor arrays of the seat/back continued its logarithmic increase indicating continued sitting. The right armrest temperature continued an exponential decay towards room temperature approaching steady state, indicating there is no lean to the right. The left temperature sensor began a logarithmic increase.
5	Standing	0%	No pressure 0%	0%	Expo- nential Decay	Expo- nential Decay	Steady State			The seat and left armrest temperature began exponential decays, indicating that the user was no longer sitting or leaning on the left armrest. The right armrest remained at steady state.

5.3.2 Posture Detection using Sounds and Temperature: Sensor Fusion, LMS, and Sensory Substitution

Now, we build on the sensors above to make a multi-sensory posture detection system, still based on sensory substitution. In this section, the method of sensory substitution for human monitoring is presented by showing how to detect information about the physical actions of a person, namely postural states which are non-temperature and non-sound data, by using temperature sensors and acoustic sensors. In the case of measuring postural states and changes, an algorithm of trend-line analysis is required for temperature sensors to determine postural state, while an LMS denoising algorithm and thresholding algorithm is needed for acoustical sensors to determine postural changes.

Posture Change Detection Using LMS Denoised Acoustic Sensors Acoustic sensors were used with an algorithm that was created to determine postural changes using existing sounds in the environment. An LMS algorithm was used to de-noise simulated background sounds (e.g, a fan, or other typical office sounds). To detect an activity of interest in the message signal, detection is necessary to pause the denoising as appropriate.

The postural shift detection algorithm being developed uses the sounds associated with movement. Pre-shift sounds and temperature changes associated with a postural shift may not start precisely at the time of the shift. Rather, the pre-shift sounds associated with the shift begin a number of seconds prior to the shift. To identify the sounds associated with the shift and pre-shift, the sounds must be segmented from the stream of continuous data. The LMS algorithm was paused whenever the audio signal at any given point exceeded a predefined threshold. The sound peaks can also be used to provide data regarding postural change for use in deep learning / machine learning algorithms.

5.3.2.1 Posture Change Detection Using Both Acoustic and Temperature Sensors

More subtle movements may possibly be missed using an acoustic approach if the changes are small or appear to fall under the noise floor. Likewise, a temperature-based approach may not be as effective if the ambient temperature is close to body temperature (37°C). To provide a more resilient detection using the sensory substitution approach, the thesis presents a method of data fusion using both sensory substitution approaches in combination: the measurement approach using a microphone and the LMS filters, then

thresholding to identify postural shifts, and the temperature method, where logarithmic or exponential temperature trends in specific locations indicate specific postural state changes.

Baseline Comparison: Pressure Sensors A goal of the experiment is to use the method of sensory substitution without the need for a gold standard sensing technique such as pressure sensors or video. The first phase of the experiment involved looking at a gold standard technique (pressure) and recording pressure readings associated with predefined postural shifts of: lean left, lean right, sit, and stand. This thesis does not strive to emulate the accuracy of systems that use pressure for precise movement analysis such as [109], but rather to examine how alternative sensors perform in these cases.

Figure 5.29: Baseline sensor for comparing alternative sensory substitution approaches: pressure readings using a commercially available pressure sensitive mat (Sensimat) during two posture tests. 1: sitting, not leaning; 2: sitting, leaning right; 3: sitting, not leaning; 4 sitting, leaning left; 5: standing © IEEE

The recorded pressures are then compared to the temperature and sound data collected to show validity of the sensory substitution approach. Pressure data was collected using the commercially available Sensimat chair sensor at each postural change point, as seen in Figure 5.29.

5.3.2.2 Analytical Results, Observations, and Statistics - Temperature

In subsection 5.3.1, the role of temperature sensors in determining postural state is discussed. Results are shown in Table 5.4.

Regression was performed on the temperature trends observed. The instances where the subject lifted them self from a given area of the chair can be best modeled as a exponential decay in the general form of:

$$y = ab^x \quad (5.2)$$

The exponential decay was observed in each respective region as the subject stood up, leaned forward, or ceased to lean on an armrest.

Similarly, postural changes that involved the subject placing their body in a given area of the chair is best modeled as logarithmic temperature increases in the respective area of the chair in the general form:

$$y = C\log(x) \quad (5.3)$$

After removal of the particular appendage such as a limb, the sensor eventually converged towards a steady-state equal to the room temperature.

Statistics from our controlled experiment were calculated. Changes in temperature at a specific sensor zone from steady state or exponential decay to logarithmic growth as well changes in temperature from steady state or logarithmic growth to exponential decay were local critical points associated with a postural change event. Other than the case of temperature reaching a steady state (e.g., where the subject was not present, or was not moving for an extended period), the local maxima and minima typically indicated the timing of a postural change.

Table 5.4: Temperature Trends Observed and Statistics © IEEE

Location	Temperature Change (°C)	Standard Deviation (°C)
Left Armrest	3.0	0.37
Right Armrest	3.2	0.63
Seat	2.6	0.82
Back	1.3	0.44

The local maxima of the logarithmic increase portion of the temperature pattern indicated a postural change involving the removal of the subject from the location where this value was recorded. Similarly, the local minima at the end of the exponential decay indicated a postural change involving the person moving towards the zone location of the sensor. With testing duration of 10-15s per posture, temperatures generally were observed to rise about 3 degrees in this time-frame. Using this time-frame, and after adjustments were made to account for the ambient temperature trends, the average increase starting from contact in a zone to end of contact (e.g., the average temperature increase until associated peak at the end of the logarithmic growth for increases associated with postural shifts away from the zone containing the activated sensors) were observed as follows: left armrest: 3.0°C (standard deviation: 0.37), right armrest: 3.2°C (standard deviation 0.63), seat: 2.6°C (standard deviation 0.82), and back: 1.3°C (standard deviation 0.44). These statistics are based on our controlled observances. It should be considered that the relative temperature trends are dependent on many environmental factors such as material of the chair (hard plastic armrests vs foam seat), location of the subject, and ambient characteristics. These magnitudes may vary, but the correlation of the changing trends of exponential decay or logarithmic growth with postural states are consistent in most use scenarios.

5.3.2.3 Method - Acoustic Sensory Substitution

This section covers the sensory substitution approach for acoustic sensors, from the theory of adaptive algorithms to remove noise, to the experimental results of using sound to determine postural change events.

Adaptive Denoising of Audio When looking to cancel noise where other sounds may be present, adaptive algorithms can be used. A fixed filter is not a reasonable solution to a changing noise signal like the acoustic sensors near the chairs, because even if it were feasible in a particular circumstance, the filter characteristics may have to be adjusted with precision to attain the desired output. Even the slightest change in noise could result in undesired output. Adaptive FIR filters are filters where coefficients are continually adjusted on a step-by-step basis during filtering.

Figure 5.30: Active Noise Canceller - [9] © IEEE

To isolate sounds related to postural changes, it is a useful step to remove all other noises. An adaptive NLMS algorithm was selected to remove background noise from the signal. Widrow and Hoff in 1959 discovered the LMS algorithm [154]. The background theory of LMS and NLMS is based on work in the field including [154] and [9].

Least Means Square (LMS) [9] The LMS algorithm contains 2 general phases: filtering and adapting.

Steps of LMS

1. Perform filtering:

$$y(n) = \mathbf{w}^T(n)\mathbf{x}(n) \quad (5.4)$$

2. Perform error estimation:

$$e(n) = d(n) - y(n) \quad (5.5)$$

3. Perform adaptation of weights:

$$\mathbf{w}(n+1) = \mathbf{w}(n) + 2\mu e(n)\mathbf{x}(n) \quad (5.6)$$

See Figure 5.30 for the active noise canceller problem that was employed for the chair sound denoising problem solved.

Inputs μ is the step-size value that determines the speed of convergence, $\mathbf{w}(n)$ is the weight vector, $\mathbf{x}(n)$ is the input vector, and $\mathbf{d}(n)$ is the desired output.

Outputs from LMS $y(n)$ is the filter output and $\mathbf{w}(n+1)$ is the weight vector update.

Normalized Least Means Squared (NLMS) The NLMS algorithm makes the step size variable:

$$\mu = \frac{\bar{u}}{\delta + \|\mathbf{x}(n)\|^2} \quad (5.7)$$

Based on the NLMS formula, this equation enables calculation of the new weight vector:

$$\mathbf{w}(n+1) = \mathbf{w}(n) + 2 \frac{\bar{u}}{\delta + \|\mathbf{x}(n)\|^2} e(n) \mathbf{x}(n) \quad (5.8)$$

NLMS is the algorithm used to filter the acoustic signal prior to detecting the postural shift events.

The adaptive algorithms are used for adaptive noise cancellation. This technique estimates the noise that has corrupted the signal. The filter weights are adjusted such that an estimate of the noise signal can be provided and the noise can be subtracted from the corrupted signal, thus retrieving the original signal.

Use of Adaptive Processing in Acoustic Sensory Substitution Approach In order to perform adaptive noise cancellation, an algorithm must use two or more sensors. In the case of acoustic signals, the sensors are microphones. One microphone is placed on the chair, and the other nearby.

The first microphone will measure chair sounds plus noise, and the second measures noise alone. This type of adaptation will perform adjustments of a set of filter coefficients removing the noise from the noisy signal. This technique works when the noise component in the signal containing both noise and chair sounds and the noise recorded independently have a high degree of correlation.

A limiting factor of this technique is that the microphones should be separated sufficiently to prevent sounds from the chair from being included in the noise only input. The experiment assumes sufficient separation and was tested at various distances.

Acoustic Postural Change Detection Method A microphone was attached to the chair in an open-air portion of the lower-back area. As a fixed body, the chair transfers sound throughout the chassis. Leaning, touching the armrest, standing, sitting, and adjusting one's position provides a unique set of sounds.

The approach developed began with filtering this signal and use of a thresholding algorithm to record timings of postural shifts. This approach is robust for multiple testing scenarios in controlled environments, however to fully rely on this method requires an appreciation of the types of sounds that may be found in an office environment, home environment, bedroom, etc. Ambient sounds may bias the signal. For example if a thresholding algorithm is used, even with pre-filtering of frequencies known to contain human voice etc., other sounds may produce the expected amplitude to trigger the identification of a postural shift. This is relevant for deployment in a real-world scenario. For example, the user may switch on a loud fan, or wind or other background sounds may cause large amplitude signals to be recorded and mistaken for motion. The LMS algorithm is capable of adaptively removing the noise from the message signal.

The experiments involve multiple tests in laboratory environments where the temperature sensors and microphone data is corroborated. This data was collected in a lab environment where background sounds were limited. Testing also took place in various realistic scenarios, such as user utilizing a fan, keyboard typing, voice, and other such sounds that may take place near a chair in specific or particular environments. This testing shows that false positives for postural shifts using a microphone may be possible in such a scenario.

The audio signal was recorded and observed, as well as simulated typical office noises to corrupt the microphone signal. This noise was then removed using the LMS algorithm discussed above. This can reduce false positives of postural change events identified using the thresholding algorithm. In terms of wider deployment, the frequency response of each chair varies, so calibration may initially be necessary, and is not in the scope of this thesis. To simulate the office environment, various white noise was added of a large enough amplitude to ensure that it generated false positives. The corrupted signal that simulates office noise can be seen in Figure 5.31a). The postural change green

line is binary and is a demarcation of where the algorithm detected a postural change. The thresholding algorithm to determine postural shifts display many false positives of postural shifts with the noise present as seen in Figure 5.31a), whereas the actual number of shifts were 5 and can be seen detected correctly after the noise was removed in Figure 5.31d).

Hardware The microphones selected were low-cost microphones to show that the sensory substitution method can work with almost any kind of sensor, and especially microphones that may already be deployed, available, or for institutions with limited budget/economic considerations. The microphones from an Electra stereo earbud headphones with microphone product were used. The device specifications state a frequency range of 20Hz-20,000Hz and is extremely inexpensive. The audio was recorded at 8kHz and processing was done in Matlab and described in subsequent steps.

Adaptive Denoising Filter The input signal is the summation of the recordings from the chair, plus the ambient noise recording. For consistency, simulated noise was used, but typical noise was also tested. In a real world denoising application, it is expected that the noise that is present with the message signal and the noise recorded separately are correlated but different.

The resulting “noisy input” can be seen in Figure 5.31a), and when played, sounds like white noise static over the chair noises.

Using a looping structure or vector multiplication, the algorithm will run. The error signals are calculated by subtracting the desired signal from the output estimate. The new weights are calculated, as well as the mean squared error.

The adaptation is only performed when there are no chair sounds detected. To do this, an envelope detection algorithm is used. The envelope detection was used to determine when to stop and start adaptation, so as to ensure the algorithm does not remove a relevant sound of a potential postural change event, but rather remove background noises. To see the envelope detection and threshold result, view Figure 5.31b).

Figure 5.31: a) Top Left: Noisy sound, and timings of postural shifts as detected prior to removing noise. There are 5 true postural shifts, yet many more are detected (indicated by locations where green line is nonzero) because of the noise. Compare to d) for postural change detection after some noise is removed. b) Top Right: Plot of envelope for audio signal denoising: adaptation stops when envelope exceeds sound threshold to avoid removing sounds of interest c) Bottom Left: Result of denoising - background noise removed by algorithm d) Bottom Right Sound in time domain, and timings of postural shifts detected after removing noise. There are 5 true postural shifts, indicated by locations where green line is nonzero. © IEEE

Denoising and Removal of False Positive Events The result plots show the various signals superimposed to see the adaptation over the course of about 30 seconds, and can be seen in Figure 5.31c). In the first few cycles, the noisy signal is greatly reduced. For the first few seconds, remnants of the noise still are visible, but later on, the cleaned signal and original (no-noise) signal are superimposed, as all of the added noise is removed. This results in the clean signal without false positives that is thresholded and postural event change timings are detected. See Figure 5.31d) for the de-noised signal with no false positives.

5.3.2.4 Acoustic Results and Discussion

Figure 5.32: Sensory substitution: Combining both orthogonal sensor modalities for increased sensing confidence/validation; 1: sits leaning forward; 2: leans back; 3: leans right; 4: stops leaning right 5: simultaneously leans left; 6: stands up © IEEE

After multiple tests in various scenarios, it was observed that very large postural shifts such as sitting down on the chair could result in a very loud signal, in some cases resulting in saturation of the low-cost microphones. It was observed that large shifts such as leaning on the armrest typically resulted in a signal of 20% maximum amplitude. Small signals could be seen prior to shifts in many cases. In almost all controlled tests where a person makes a major postural shift, the microphone displays an amplitude of at least 15%. Initially, a threshold could be set at 15% amplitude as identification of a postural shift. It was observed that higher amplitude sounds sometimes were associated with stronger, faster movements and bodily shifts. In a noise free environment this is sufficient.

In real world deployment, switching on a background noise such as a fan presented signals that exceeded this 15% amplitude threshold - causing important signals to fall below the noise threshold; thus there is a clear need for an adaptive noise removal system for the postural shift identification and algorithm to function. This was tested and results can be seen in Figure 5.31d).

In controlled settings, over 100 tests were performed. Of these, over 90% of the postural changes were correctly detected, 2% were missed and about 8% were false positives. This shows promise in the method of acoustic sensory substitution and application of postural change detection. Future work may be in uncontrolled environments.

5.3.2.5 Results of Multi-Sensory Fusion of Temperature and Acoustic Methods

When both the temperature and acoustic method are used, sensory substitution provides an additional level of data validation. See Figure 5.32 for the results of the combined sensory fusion.

Sensory substitution also leads to data fusion approaches. For example, if both this in conjunction with awareness of context can lead to context aware reliability fusion [155, 41], where the robustness of multiple sensing modalities are greater than a single modality. Regarding this thesis's alternative sensor approach, if the location of interest is very noisy, the system can rely on the temperature method. Similarly, if there are particular temperature conditions, such as an ambient temperature that is close to 37°C (the body temperature), or is otherwise uncontrollable, the acoustic approach could be used. Such fusion can increase accuracy when both modalities are used, and can increase resilience should one modality not be available.

5.3.2.6 Discussion

Based on the results above, it has been shown that sensory substitution, detecting Quantity X with a sensor designed to measure Quantity Y is a feasible technique; specifically with the example that low-cost temperature sensors can be used to provide general posture data and with sensor fusion, sensory substitution has been developed with acoustic sensors, which can also provide postural change event timings. This increased the resilience of the method.

Since the temperature sensors can provide temperature change data with an accuracy of 0.5°C, and can sample at 1Hz, it can be possible to provide real-time temperature data within this tolerance. This information can perhaps soon help to provide insight into reasons that people shift positions and lean. Is there a certain temperature trend or acoustic pattern that can be seen prior to specific posture shifts? What is the underlying reason for their discomfort or pain? By how much does a posture shift alleviate a temperature buildup? Could there be earlier warning signs for initial affliction of pressure sores and for prevention of excoriation and complications of the pressure wounds, which lead to associated worsening stage pressure ulcers? These are questions that could possibly be answered in future research.

With labelled temperature data in all regions of interest on the chair, showing the true state of the motion based on acoustic sensors, the next step is to train a deep learning

algorithm to identify the small temperature patterns that exist, with smaller temperature patterns and corresponding acoustic patterns.

Future work can lead to using machine learning of temperature patterns for postural change identification. Use of adaptively corrected microphone thresholding algorithms to identify postural shifts could perhaps enable automatic correlation of a postural shift with a corresponding temperature trend.

Future work can also include extracting the temperature trends corresponding to a postural shift where the temperature trends may not always point to an obvious shift of the person. By identifying these shifts using sound, the corresponding temperature trends can then be extracted and used as training data in a deep learning algorithm. This classifier could then be trained to identify temperature events that are not perceivable by other algorithms.

In the following section, we look at multi-sensory fusion enabled with NFC.

5.3.3 Smart Environments with NFC

We present a system that collects data and disseminates sensor and activity data using a series of applications based on Near Field Communication (NFC) smart cards, HTML5, and an out-of-the-box smartphone in a smart environment. This thesis takes agile sensing and uses it for individualized medicine, tailoring the care based on situational awareness.

NFC Information and the Data Exchange Format NFC can be thought of as a continuation of the RFID technology using smart card technology and a standard frequency. “To understand NFC technology, we need to have a brief knowledge of the forerunners of NFC technology: the barcode as an earlier form of RFID technology, RFID, and the magnetic stripe card as an earlier form of smart cards and smart card technologies” [156]. Near-Field Communication (NFC) is a type of radio communication used to communicate short messages between an NFC tag and an NFC reader. Because NFC can transmit various types of data, a constant air interface format was needed, regardless of the end application. The NFC data exchange format encapsulates application-defined payloads, and is a message format [157, 158]. The structure of such a message is described below in Figure 5.33.

Figure 5.33: NFC data structure © IEEE

The record is composed of a header and a payload. The header contains important information such as the length of the payload, the type of the payload, and the payload identification [147]. The payload itself can be many different types of data, and we primarily use URLs as the payload type to trigger various HTML5 events. Security of NFC was covered in chapter 6, and here we talk of applications in smart environments.

NFC Tags NFC tags are passive electronic devices which communicate with an active NFC reader device. The NFC forum introduced a technology architecture/standard for NFC compliant devices in June 2006 [158]. A comparison of selected NFC Forum Tag Types are provided in Table 5.5.

Table 5.5: NFC Tag Types © IEEE

Property [157]	Tag 1	Tag 2	Tag 3	Tag 4
Standard	ISO14443A	ISO14443A	FeliCa	ISO14443A + B
State	read/write or read-only	read/write or read-only	read-only, data being entered at manufacture	read-only, data being entered at manufacture
Memory	96 bytes – 2kbytes	48 bytes-2kbytes	2 kbytes	Up to 32kbytes
Speed	106 kbit/s	106 kbit/s	212 kbit/s	106 kbit/s – 424kbits/s

5.3.3.1 Method

The smartphones selected for testing were various Android devices. The iPhone was excluded because the NFC chip is only enabled for use with Apple Pay, and is not usable for normal NFC functionality. We are specifically interested in what can be done out-of-the box, with no custom apps installed.

5.3.3.2 Results

An NFC and HTML5-based system was developed to provide several smart environment enhancements including emergency location, context-aware speech, and patient monitoring. Part of the unique nature of this approach was the methodology proposed – involving nothing but the included hardware and software of an off-the-shelf smartphone device – as well as the particular ways in which it was used. Many smart environment systems, both commercial and research, propose use of a host device app to interpret custom tags, and then respond with a particular behaviour, whereas this system used HTML5 to provide the particular action, making the system inherently universal. The system used standard NFC-writing software (NXP TagWriter) to write URLs to NFC-forum standardized tags. When the user could tap the back of the smartphone onto one of the tags, the stored URL on the tag was interpreted by operating system software on the smartphone device. The default browser can open (both Google Chrome and Mozilla Firefox were tested) when the URL was detected, and direct the browser to load a PHP script. This page generates the appropriate HTML5 code, which is loaded on the client device, and the functionality is performed.

NFC tags were placed in various locations to see the feasibility of utilization of NFC as proposed. An NFC tag serves as a link that starts a process. The NFC tags could serve a dual purpose 1) to provide information or a direct service to the user, and 2) to log the activities of the person for a loved one or healthcare professional to view.

General System and Assumptions The general methodology of the NFC-Smartphone system begins with the tag initiating the process. When a smartphone is tapped onto the tag, the tag can tell the smartphone to access a URL in the cloud. The cloud responds by sending an HTML5 script to the phone that runs and causes specific actions to occur, without the need for custom software taking advantage of all the features of HTML5 and modern smartphone browsers. It is assumed that NFC in smart environments has a

reliable data connection available (either WiFi or LTE/4G/5G data). Use of the system in areas where data is not available is future research.

NFC Tags Selected - Types: Sticker, Wristband, Key-chain, and Smart Card NFC tags come in all different shapes and sizes. It was decided to test NFC tags of different sizes, since the intended applications may vary, so it is important to get a sense of how each type performs in different situations. The NFC tags tested were the NFC Keychains - a 64 byte MiFare Ultralight, a 137 byte NFC Forum Type 2 tag, a 64 byte NFC Sticker MiFare Ultralight, and a 168 byte Red NFC Wristband – NFC Forum Type 2 tag, all from NXP Semiconductors (Germany).

Figure 5.34: Flowchart for help emergency bracelet

Emergency Bracelet A bracelet was designed to provide immediate emergency assistance. A script was designed that utilized HTML5 implementation to instantly generate a useful and detailed message that could be provided to first responders. The system

takes advantage of many features of HTML5. The process did require permission of the user one time to enable access to the GPS sensor. The email to a trusted person is sent server-side, and thus can be executed without requiring further user interaction; however, further interaction from the user is needed if the bracelet is configured for an SMS or voice call. The system diagram that was developed for enabling the emergency bracelet is provided in Figure 5.34.

In an emergency situation, this tag is designed to act as an emergency 9-1-1 Call. The script can act in 3 ways: 1 - send an email to a loved one with the person's GPS coordinates, 2 - call 9-1-1 to report that there is a need for assistance and provide dispatchers a summary of the person's medical conditions or, 3 – compose an SMS message to the person's loved ones with their GPS coordinates (see Figure 5.35) or compose an email that generates a link to Google Maps that the recipient promptly sees the vicinity of the person in need of attention and assistance.

Figure 5.35: Emergency SMS generated by tapping NFC tag © IEEE

Audio Messages Audio cues may serve to reinforce a task at hand, and to allow people to continue with their tasks. A web-based system was designed to facilitate text stored in an embedded link in the NFC tag to be vocalized by the smartphone with limited or no interaction on the part of the user. The system developed was updated to enable the reading of messages from within the script, setting up the stages for future implementation of the Internet of Things such as reading the messages stored on the cloud. The system flowchart is indicated in Figure 5.36.

Figure 5.36: Vocalization system methodology

Vocal Cues to Physical Environment In the home of a person who may experience memory issues, cognitive deficit, or other medical considerations, reminders are very important. Occasional prompting for every day activity using NFC tags for informational messages provides cues for the person. Tags were configured to provide useful messages regarding the physical layout of a building, such as “Ramp at length of 3.5m with angle 30 degrees” or “10cm up to next step, 15 steps remaining until level 2”, the number of steps, and other informational messages regarding areas where there are safety issues such as the kitchen, bathroom, and stairs.

Measurement of Sensor Data using Smartphones Triggered by NFC tags and HTML5 scripts The tags were used to load an HTML5 script that activated sensors in the phone including the accelerometer, gyroscope, and proximity sensor. The concept of Internet of Things was employed, as the data from the sensors can be logged server-side. This shows the preliminary benefit of using NFC tags to initiate logging of data which could have clinical utility. The concept of logging also enables a loved one to track the user to see when they began to move for the day, as well as monitor progress to see what they have done.

Figure 5.37: Data measured by sensors using HTML5 scripts triggered from the NFC tags, with no user intervention © IEEE

Upon tapping the NFC tag, an HTML5 script is loaded that begins collecting measurements from carefully selected sensors embedded in the phone. For the segment during testing of the smart environment, an HTML5 measurement script was being analysed, and the phone accelerometer and gyroscope were selected to be activated and the processed results of the script are displayed in Figure 5.37. The unique aspect of being able to use a stock Android phone and an NFC tag to initiate measurement algorithms is an example of the uniqueness of this methodology.

Future work includes processing of the sensor data with advanced algorithms to collect more information about detailed activities of an individual.

An application could be integrating a tag at the user's bedside where the phone could sit to charge. In this scenario, the tap updates a database so the people who are interested in seeing the behaviour of the person could see when they sleep.

Using the data measured from the sensor described above, the algorithm could also see how often they check their phone at night, and also when the patient wakes.

5.3.3.3 Discussion: Advantages and Considerations of using NFC in Smart Environments

1. **Price and Size:** NFC Tags are inexpensive enabling the system to be designed to use many of them.
2. **Internet of Things:** The tags each are programmed with a unique URL, and the script is executed when that URL is accessed.
3. **Size:** The tags are small. They are as thin as a millimetre, with the surface area of a coin. This enables stealth integration, as the tags can be incorporated into a picture or placed inconspicuously on the wall.
4. **Multiple Applications:** A family member can completely change the purpose of the tags by reprogramming the system. It can program it for someone coming in to assist the convalescence of a patient, such as a healthcare aide. It could provide detailed instructions for them: for the individual information about the client/patient and what their needs are as they recuperate.
5. **Quality Control for Healthcare Team:** Since they are tapping in to check for messages from the family or other authorized person, the arrival time and time of tasks could be recorded.

5.4 Discussion and Summary

It is very clear that low-cost temperature sensors can be used to provide general posture data without the necessity of other sensor types. This shows that already deployed temperature sensors can provide some insight into postural changes, providing increased situational awareness with existing sensors.

A system was developed to use only an NFC tag and HTML5 code on a smartphone to perform many applications of a smart environment. The methodology demonstrated in this thesis solves this issue while also demonstrating the feasibility and potential for NFC-based applications in a smart environment that can perform powerful features without the need for anything other than the out-of-box smartphone.

These multi-sensory fusion approaches and sensory activation mechanisms present three key analytics approach scenarios, and are a key algorithmic approach. The data emerging

from these approaches can be used to output intelligence for situational awareness or to enable the resilience feedback loop discussed in chapter 6.

Impact of Redundancy: Increasing Number of Sensors vs Increasing Sensor Modalities Increasing the number of sensors adds a level of redundancy, and can be a good choice in some circumstances. For example, should a single sensor fail, and another nearby sensor of the same modality be available, the sensor could address a gap in the sensing with minimal disruptions and a comparable level of sensing confidence. However, if the failure is endemic to the sensing modality, redundant sensors of the same modality may be affected similarly to the initial failed sensor. For example, a temperature sensor being used to measure human presence timings may fail if the ambient temperature in the room approaches 37°C (the temperature of the human body) and additional or redundant temperature sensors will also fail for the same reason. Meanwhile, adding additional sensors of orthogonal modalities can make the sensing resilient to these issues. For example, if an acoustic sensor is added to a system that uses thermal sensors, the orthogonal sensing modalities may be resilient to temperature-specific failures (such as the 37 degree example). In this case, the acoustic sensor could be used. Similarly, if filtering is affected by too much noise in the environment (SNR is very high), the use of temperature sensors rather than simple sensor redundancy improves resilience of sensing with increased orthogonal sensing.

This chapter presented data analytics approaches for three application scenarios. The resulting publications are: [4], [5], [6], [7], [8], [9], and [10]. This chapter covered:

- 1) **Sensory Validation: Increasing Trust in Sensed Data** - designed a method of validating sensor inputs: ambient physical sensors for AI camera analytic validation and also an analysis of sensing security implications was performed
- 2) **Classification and Adaptation: Urban Sensing and Security** - Proposed an urban sensing method using imaging analytics with acoustic signals for UAV signature classification. Designed an environmental and physical sensor system for smart environments to perform human detection and develop personalization in an IoT environment
- 3) **Multi-sensory Fusion: Smart Environments, Infrastructure and Person Security** - Designed sound and multi-sensory situational awareness algorithms: LMS-based approaches to enable sensory substitution for posture detection and analytics in smart environments

6 Response Mechanism and Resilience Feedback

Figure 6.1: Layer 3 - Response Mechanism and Resilience Feedback

The third layer is the response mechanism and resilience feedback loop. Circled in blue in Figure 6.1 is the response mechanism. The inputs include sensors and raw sensor data, data derived using sensory substitution in Agile IoT approaches, and data from the analytics approaches. The output from resilience feedback includes the output for key decision makers to make decisions, and also longer-term situational awareness and intelligence.

In chapter 4, sensory substitution was introduced and the output of this framework can enable a resilience feedback loop. Also, chapter 5 provided enhanced analytic approaches

to further refine the data and enable a resilience feedback loop. Figure 6.1 presents the response vectors and resilience feedback process.

This chapter presents a framework of response mechanisms and “resilience feedback loop”: providing enhanced situational awareness using various flexible techniques from mobile sensors, rapidly deployable sensor nodes, and human sensors. Various enablers and components of resilience feedback are presented in the subsequent sections. There is real-time information everywhere. Supplied with data from the sensory substitution approaches presented in chapter 4 and the data analytics approaches in chapter 5, this section describes a “Resilience feedback-loop”: which integrates sensory substitution approaches for improving resiliency using mobile and fixed sensor nodes, computer vision, and human-in-the loop measurements. It also proposes low-cost, rapid-deployment sensing instrumentation for critical IoT systems.

A vector of resilience feedback is for critical infrastructure awareness and monitoring using low-cost IoT sensing and data analytics with applications in smart grid for physical assets in section 6.2: Improving Resilience with Sensor Nodes. Another part of the feedback loop is using people and their phones as alternative sensing to increase situational awareness of infrastructure issues with machine vision and is covered in section 6.3: Computer Vision-Assisted Human-in-the-Loop Measurements. This section also presents a method of using already deployed vehicle-mounted cameras and Sensor Fusion to find problems with utility poles and cables in section 6.4: Resilience Innovation: Deep Learning using Machine Vision for Critical Infrastructure Resilience. UAVs can also act as a mobile sensor, and an analysis and field testing of UAV sensing for alternative offensive and defensive awareness and security of sites is discovered in section 6.5: UAVs as a Mobile Sensing Platform.

Another feedback loop is through rapidly deployable sensing equipment. This chapter also shows the proposed rapidly deployable and low-cost sensing hardware to enable rapid IoT deployment and sensory substitution deployment preparation with examples in critical building automation systems/HVAC applications in section 6.6: Sensing Physical Environments. The Discussion and Summary are then presented in section 6.7.

6.1 Resilience Feedback

In some critical infrastructure applications, a human must act as a decision-maker. Thus, resilience feedback is an approach that may ensure better informed decision-making.

Using fog and edge techniques to improve sensing, the concept of resilience feedback is applied to physical security: an algorithm for detection of transportation infrastructure using sounds for situational awareness. The utility of the application is shown in an example. Results show a flexible fog approach to increasing resilience by improving situational awareness of a human decision-maker. When an incident occurs, whether this be a power outage or an intrusion that has significant impact to critical infrastructure, the key decision maker must be notified as quickly as possible. A resilience feedback technique using fog and cloud computing, distributed sensing, and multiple algorithms in conjunction with sensory substitution is developed to provide the key decision makers with actionable information. Figure 6.1 shows the incident flow process: once a decision-maker has been informed, if they require additional information, a feedback path using human-in-the-loop sensing, RPAS/Mobile Edge sensing, NFC and Rapid Sensing, or existing sensors can be triggered or initiated.

The resilience feedback loop consists of two key phases. The first phase is Initial and Constant Re-evaluation of Sensing System Design which allows constant evaluation and reevaluation of data analytic techniques and hardware choices, and enables making changes as needed. The second is Response Mechanisms: Feedback System Design - and is focused on real-time response mechanisms when more information is needed. Also presented is an Example Scenario in Transportation Infrastructure.

6.1.1 Initial and Constant Re-evaluation of Sensing System Design

Sensing choice comes down to what types of constraints are being faced. Each of the three techniques below inform the key decision maker by providing relevant sensed information at the edge.

No Constraints If there is no constraint whatsoever, ideal sensors, and unlimited bandwidth / storage can be used in high capability cloud processing algorithms with low latency, etc. The output of this type of ideal system provides the decision maker information, though most real-world applications do have some constraints.

Time or Money Constraints When time is a constraint, resources can be leveraged at the edge [159]. When money constraints are a concern, a key technique is to look for low cost rapid deployment edge sensing systems [11]. Both constraints can be overcome, and

the output of this provides the initial information to the informed decision maker. This is presented in section 6.6: Sensing Physical Environments

Modification Constraints When modification constraints are present, sensory substitution techniques can be used, where available sensors are used to detect something for which they were not specifically designed [14]. Approaches include processing signals at the edge, and combined with data analytics for data recovery [160], or interpolation at the edge, this can provide the initial sensing. This was presented in chapter 4.

6.1.2 Response Mechanisms: Feedback System Design

Once the initial information has been provided, the decision-maker may need more information, and this requires the feedback sensing outlined in the 4 following subsections.

Human-in-the-Loop Sensing Humans can act as the edge sensor, particularly in conjunction with AI techniques such as visual detection systems. Making use of societal trends such as rapid photo gathering and posting on social media, this can be used with fog and cloud computing [14] and sampling cloud data sources [13] to aggregate and provide the informed decision maker with additional, targeted information. This is presented in section 6.3.

RPAS and Mobile Edge Sensors Small UAVs/RPAS (Uninhabited Aerial Vehicles/Remotely Piloted Aircraft Systems) can act as a mobile sensing unit, and can be deployed rapidly [161]. In natural disasters, for example ice storms and it's affect on infrastructure, post incident information gathering is very important to restore power quickly and can be informed by deep learning [12], and is discussed in section 6.4. Flying a UAV provides fog computing capability at the edge rapidly.

Rapid Sensing Tied into human in the loop sensing is NFC activation of sensors which may be used for data gathering exercises. Medical infrastructure and natural disasters both create the need for getting information rapidly [11], and these techniques can provide decision makers additional valuable data. This is presented in section 6.6.

Existing Sensors If existing sensors already are available, they can use sensory substitution techniques to determine new data, and this can enable the resilience feedback loop [14]. For example, already deployed microphones and fog computing capability could be used in a security scenario where nothing other than microphones exist, to determine activity. This fog computing system of using sensory substitution therefore provides a decision maker with relevant information. This builds off the techniques presented in chapter 4 and chapter 5.

6.1.3 Example Scenario in Transportation Infrastructure

Using microphones with fog computing, the method of resilience feedback can be applied. In the first part of the Resilience Feedback Loop in subsection 6.1.1: Initial and Constant Re-evaluation of Sensing System Design, initial edge computing can identify that there is an issue with transportation infrastructure. Typical in a security analysis is determining what is the full picture of the infrastructure status for rapid response. In this case, the decision-maker's situational awareness could be increased with knowledge of specific infrastructure events and timings. Using the techniques in subsection 6.1.2: Response Mechanisms: Feedback System Design, fog computing can be used with AI to determine useful events to inform the response. This can be visualized in the spectrogram below in Figure 6.2 , where this snapshot shows a car is driving on a snow-covered road while a slow-moving inter-city train approaches. The warning horn can be seen distinctly in the sound signature at about 10 seconds. Using AI and edge computing, this processed sensor data can flow back to the decision-maker who can then be informed to respond to the situation.

Figure 6.2: Sound Signature: Train Horn and Car Moving on Snow. Spectrogram of sound intensity at each frequency at each time, where blue is less intense and yellow is more intense.

6.2 Improving Resilience with Sensor Nodes

Fixed and rapidly deployable sensors are part of a resilience feedback loop and are introduced to improve rapid and efficient decision-making.

6.2.1 Method: Application of Distributed Sensors for Monitoring Electricity Towers

Experimental Setup and Remote Monitoring Micro-controllers and sensor nodes were placed on poles in the lab to simulate electricity poles. The nodes contain various sensors including sensors for temperature, tilt, vibrations, light, motion, magnetism, and sounds, as well as a micro-controller and battery. The pole's lower units were set for motion, light, magnetism, and sounds, while the upper units placements were looking for irregularities in temperature, light, vibrations, and tilt. For example, one series of structural failure tests included using select types of movement in conjunction with tilt. Another battery of testing involved material fatigue. Electricity towers in remote locations have limited monitoring. This is of significant concern for safety, functionality, and financial reasons. Although continuous constant monitoring of each kilometre of electrical transmission wire may be costly and difficult to analyze, deployment of low-cost sensors and micro-controllers are feasible for this duty.

Test Device Proof of concept experimentation for monitoring in and around grid assets used a device with scaled down electricity towers, 10 degree of freedom (DOF) sensor boards, magnetometers, and photoresistor sensor boards. The sensors were connected to an OSEPP (Arduino-derivative) MEGA 2530 R3. The data then is provided as a serial stream of numbers or analog voltages. The 10DOF sensor board was connected to the PC using a connection type called I^2C that allows multiple addressable sensors to be connected using one bus or set of wires [148]. The sensors were mounted on the pole, and wires were used to connect the sensors to the micro-controller.

Analytics: Identification of Natural Risks and Post-incident Analysis Wilderness flora and fauna live near and all around the energy infrastructure, therefore inherent natural risks exist. If a tree falls onto a section of power line, having sensors to detect the event and exact location may be beneficial. This data could be sent to inform the

operators. This warning allows for quicker response. A sensor system could also serve in post-event analysis to identify further issues, and pre-event to check if abnormal activity prior, led up to the incident.

The system that was created has inertial measurement units (IMU) which are composed of accelerometers and gyroscopes. It is also possible to corroborate camera or other recorded information and operational data with sensor data, for a more meaningful analysis post-event. Monitoring vast segments of wire can be useful pre and post event, as well as during the event.

6.2.2 Results and Algorithm

Real-time visualizations of collected tilting are shown for the operator. Wind and ice have historically affected electricity poles and wires, so our focus is on natural elements. A proof-of-concept inexpensive sensor and micro-controller based platform was created for detection. Physical construction of the device, the physical model and processing code, and a data visualization system were created. The device functioned using sensors to collect information, an algorithm to process sensor inputs into the conventional units, and analytics that determine certain risk parameters. The fusion of the information is used to inform the operator. Algorithms have been employed to determine a particular threshold of angle, and if that threshold is met, an operator is notified. A data visualization system that updates in real-time has been developed for the infrastructure operator's control room. The methodology can be seen in Figure 6.3 and Figure 6.4.

Figure 6.3: System Diagram, steps from data input to operator output © IEEE

Figure 6.4: Operator Interface - tipping warning © IEEE

6.3 Computer Vision-Assisted Human-in-the-Loop Measurements

Humans play a role in the resilience feedback loop, leveraging societal trends such as sharing photos, or acting as a deployed sensor.

In this section, we apply the concept of sensory substitution and Agile IoT by presenting a methodology of adding new sensing modalities and extracting additional data using existing sensors (cameras), without requiring new hardware. Infrastructure monitoring, supported by advanced machine vision algorithms, has two new avenues for substantive improvement in situational awareness and resiliency: intelligence from the general public [162], and intelligence using already deployed sensors [2].

Human Observations Found in the familiarity of daily routine, are observations about surroundings. Familiar faces of regular transit commuters boarding the same morning train at the same station stop day in and day out, is an example. Unfamiliar individuals or unusual activity is noticed. Any disruption to routine activity, or any sound, behaviour, length of time, or anything out of place, becomes noted without conscious effort.

Many instances of failed infrastructure are not immediately discovered by the operators or owners of the infrastructure, but rather, by the general public. People observe their surroundings and report what is wrong. Downed wires, potholes, flooding on the street, trees or other obstructions on the road or sidewalk, and other damaged infrastructure (such as the example in Figure 6.5) are also likely to be reported by the public.

Figure 6.5: Leaning utility pole and visualization of lines on the horizon © IEEE

People taking photos from heights such as rooftop garden terrace, high-rise balconies, and skyscraper office towers could provide additional camera angles and views of the top of poles and infrastructure. This could be applied as an edge computing application to provide infrastructure owner-operators new information to better respond to any problems.

6.3.1 Using Edge Computing and Computer Vision to Augment Qualitative by Increasing Quantitative Data

“Societal Sensing” - Data Infrastructure Monitoring This section capitalizes on the societal predisposition to instantly electronically “share” almost everything with their technological toys or gadgetry, and to use that information. Whether it is a smart watch

GPS data showing their workout statistics, dog walking patterns, posting accident reports on social media platforms, or snapping a sunset or an interesting scene and sharing with friends on various social platforms – this behaviour is commonplace, but it also provides qualitative measurements.

It is of interest to develop a framework to leverage this HCI (human-computer interaction) and technological adoption trend to improve resilience by leveraging edge computing to provide some quantitative data.

Human “Measurements”, Observations In reality, a large percentage of infrastructure problems are neither detected by direct measurements nor indirect measurements; but rather by the general public who report the problems [162]. Human “measurements” usually are very qualitative such as “the wire is sagging” or “the pole is leaning a lot”. Sometimes, they can be a bit descriptive, but without measurement tools readily available, even the best descriptions can be relative and qualitative. The most accurate quantitative measurements may be those where a network of IoT sensors are deployed to measure the specific quantity such as [10]. Smartphone cameras can play an important role as part of data acquisition in edge computing solutions.

When a user spots what could be a possible infrastructure problem, they could snap a quick photo, add a note if they wish, and hit go. This could even be incentivized by enabling sharing using other social platforms with their friends, but most importantly, the submitted information could be used to improve resiliency. In the example of a pole, they could even walk all the way around the pole, providing 360 degrees of images. This process of societal sensing can be seen in Figure 6.6.

Figure 6.6: Societal sensing data infrastructure monitoring: user, sensor (camera), processing – cloud (two paths, one from processing, one direct from sensor) – processing – repairs © IEEE

The process of generating intelligence begins in the background using machine vision. Operational analytic methods could include:

1. Cloud only. Images that are submitted are transferred from the device, and stored in the cloud, or

2. Edge only. Images are processed with embedded machine vision, and only results are transmitted, or
3. Hybrid. Images are processed at the edge, but if nothing can be identified, or the visualized environment is flagged as requiring follow-up, the device moves into cloud mode and the entire image is transferred to the cloud for further automated analysis or expert analysis.

This approach shows promise of adopting and repurposing a recent societal norm – societal information sharing – as a key sensing technique and a component of multi-modal sensing, and combining it with preventative monitoring, a more complete situational awareness of infrastructure could be achieved.

Visual Sensory Repurposing - Agile IoT for Cameras Cameras already deployed can be used to crowd-source infrastructure issues.

From detection of locations of potholes, broken equipment or hazards in playgrounds, washed-out sidings, to utility poles or wires that are leaning or sagging – already deployed cameras and people carrying them could help to provide useful data. An example of edge computing, using sensory substitution to enable cameras to determine tilt of utility poles as part of a preventative monitoring approach is shown in Figure 6.7.

Figure 6.7: Edge computing model, where data is processed on a microcontroller and results go to the cloud or to the infrastructure owner-operator directly © IEEE

Agile IoT is the concept discussed in chapter 4 and [2], which combines sensory substitution, where a sensor designed to measure X actually is used to determine Y, and IoT deployments to enable more measurements from the same set of equipment, or readily available equipment. Many cameras are deployed, so adapting them to also serve a role in preventative maintenance and resilience can be an appealing concept that may have a role in changing the methodology of infrastructure inspections. A potential issue of infrastructure monitoring is purchasing, installing, and maintaining new monitoring tools.

Though [11] provides an accurate solution to measure pole tilt using an edge-computing approach, that particular methodology requires installation and maintenance of sensor nodes on each and every pole.

6.3.2 Algorithm Design and Results

As a sample usage case for “societal sensing”, an algorithm for extracting quantitative information from utility pole images was created.

The design used for the image processing involves looking at the possible shapes, and for illustration, rectangular shapes were identified as possible utility poles. Points were selected and mathematical algorithms were used to calculate the angle in realtime. The algorithm can be seen in Algorithm 6.1. Please note that this algorithm is for demonstration and assumes the user positions the camera relative to the horizon. For real-world implementations, the algorithm may also need to correct for the angle of the horizon relative to the angle of the camera.

Algorithm 6.1 Sample apparatus tipping determination from Image Processing

Prerequisite: already installed camera, deployed for another purpose

- 1: Capture Video Stream (or presence of still image)
 - 2: Check for Errors
 - 3: While video stream present
 - 4: Gray-scale Image Mask
 - 5: Threshold Image with Dynamic Ranges
 - 6: Perform morphological operations
 - 7: Extract Contours (edge detection)
 - 8: If multiple shaped contours found then
 - 9: Filter to remove “noise” shapes
 - 10: End If
 - 11: For count smaller than # of contoured shapes then
 - 12: Fit bounding box around contoured shapes
 - 13: Calculate angle from corners and centre of rectangle
 - 14: If angle > danger threshold then
 - 15: Initiate alert
 - 16: Else If angle indicates minor lean then
 - 17: Log data of lean and relevant data
 - 18: Else
 - 19: Log data of lack of lean
 - 20: End If
 - 21: End For
 - 22: End while
-

Multiple cameras were tested, however the intention of this particular thesis is to use readily available sensors regardless of the quality. With resource constraints, existing infrastructure may not have the most high-end cameras, yet the task is to continue to work in this particular scenario. One camera used for some of the testing was only a 2 megapixel webcam, showing high quality equipment, though useful, may not always be necessary.

Figure 6.8: Utility pole simulation with poles segmented using machine vision and angles determined and indicated on the image © IEEE

The algorithm continues with error checking to ensure that the camera has captured good data. For field deployment, a sampling frequency should be set based on the speed of the moving camera. A lower sampling rate could be sufficient for slower operations, such as perhaps a body worn camera, a community member holding their smartphone camera, or a UAV in stationary positioning. Higher sampling rates have implications in terms of processing speed, and perhaps a queue of images may need to be temporally cached until processing is complete. A real-time and portable system was desired, and as such, using OpenCV library and building on publicly available source code, the results in a simulated environment using simplified shapes are effective. The results from a simulation using Algorithm 6.1 above is shown in Figure 6.8.

In real-world testing, the results were promising, though segmentation of the pole from the background was a challenge, initially. Note that for the purposes of the testing, the

camera angle was controlled to remove algorithmic corrections of the frame of reference. The image is sampled and thresholded to develop a mask. A series of morphological operations, erosions and dilations are applied to remove smaller elements before looking for the pole shape. The results were simulated with a variety of noise considerations. Additional processing was needed for scenes with complicated backgrounds or other factors. Testing occurred in both real-time and post-processing environments. Figure 6.8 and Figure 6.9 were extracted using real-time processing.

Figure 6.9: Real-world utility pole testing. Angle of pole successfully calculated, in two separate test cases © IEEE

An example image of two different pole samples after being run through the algorithm is shown in Figure 6.9. The superimposed green box indicates the approximate shape and angle of the pole based on the image mask. The angle is measured in degrees relative to the horizon, where the horizon can serve as the reference. Alerts can be synchronized using IoT systems and based on geographical locations supplied by the cameras, and aggregated for the utility operators.

Though angle may not provide sufficient information for operators, the algorithm, as applied in the real-world testing, shows the potential of the concept of societal edge computing for structures including infrastructure, which can be seen with this proof-of-concept. Pole tilt, location data, and scene analysis results can be sent to a control room

so appropriate actions can be taken, such as coordination with repair crews.

Limitations of approach: note that these results are meant to be a proof-of-concept of human-in-the-loop sensing for critical infrastructure and to showcase a part of the resilience feedback loop. Practical issues of optical angles and focal issues may need to be addressed to ensure the system can accurately determine pole tilt in robust situations regardless of the camera location. More work is required to ensure the system is ready for real-world deployment.

6.3.3 Discussion

Using the approach discussed, cameras from human users or already deployed cameras that provide qualitative data can now also provide quantitative data for state of infrastructure, and thus increase critical infrastructure situational awareness. The human-in-the loop algorithm derived from the concept of Agile IoT is able to provide additional information to CI operators than just the qualitative descriptions they are currently provided: using an “existing sensor” to provide new situational awareness.

Such quantitative measurements could then help with prioritizing repairs to reduce the likelihood of failure and to better allocate crew resources and time. This then increases resilience of the system.

6.4 Resilience Innovation: Deep Learning using Machine Vision for Critical Infrastructure Resilience

Ensuring the resiliency of critical infrastructure is essential in modern society, but much of the deployed infrastructure has yet to fully leverage modern technical developments. This intersects two unique fields: deep learning and critical infrastructure protection and illustrates how deep learning can improve resiliency within the electricity sector. Machine vision is the combination of machine intelligence, where computer systems automatically learn patterns from exemplar data, and image analysis, where objects of interest are automatically segmented and identified from video image data. This technology has the potential to automate threat assessment in the context of securing critical infrastructure. Rather than traditional reactionary approaches, we present here a method of leveraging deep learning for the detection of threats to critical infrastructure before failures occur.

This concept covers the state-of-the-art in deep learning for creating machine vision systems and the concepts are applied to increase resiliency of critical infrastructure. The intersection between machine vision and critical infrastructure is discussed, as are key benefits and challenges of invoking such an approach, and examples within several fields of critical infrastructure are presented. Automated inspection of power infrastructure using vehicle-mounted video acquisition equipment is explored, and a proof-of-concept implementation of a deep convolutional neural network is developed, achieving 95.5% accuracy in distinguishing power-related infrastructure within images largely typical of rural settings. These preliminary results show promise in the application of deep learning and machine vision to protecting critical infrastructure through preventative maintenance [12].

It is also important to determine ways to access data with resources already available through cloud resources, and work was done on a systematic Google Street Viewer, with aims to use the proprietary database to collect ample information to collect infrastructure assets and their state [13].

6.5 UAVs as a Mobile Sensing Platform

UAVs play a key role in the resilience feedback loop, in the role of offensive and emergency tasks: RPAS as a portable communication tool.

UAVs can be a significant value-added asset for infrastructure owner operators. RPAS can be used to gather intelligence, or to very quickly respond to situations where previously, responses may be slower.

Having eyes and ears is a significant feature for security teams, and having mobile eyes and ears is even better in terms of rapid response to all hazards threats, especially in remote regions.

Overcome Challenges UAVs can access any part of an owner/operator's property, and can in real-time, relay situational awareness to control rooms from any real physical location faster. For example, an intruder can be tracked remotely without risking employee health and safety.

Investigative Tasks UAVs can carry a camera to “watch” and also carry a microphone to “listen in”. Using a UAV for “listening in” presents a problem. For a security staff

to “listen in” effectively to gain actionable intelligence, other noise interference has to be attenuated. The noise of the rotors and motors provide such a low signal-to-noise ratio (SNR) that without more advanced research and development, little intelligible information can be collected with on-board microphones.

Using a UAV for security reconnaissance at a plant facility or intrusion is shown in Figure 6.10, but the noise of the UAV in operation can preclude effective 2-way communication.

Figure 6.10: Image showing UAV for two-way communication [Adapted from Creative Commons]

The most effective noise reduction may be for the UAV to remove the source of its own noise entirely by landing and switching off the motors. Landing is not always feasible as the UAV might need to stay in motion and go to several different locations.

For the UAV to communicate with the security team, rotor and motor noise must be largely removed. Based on the research conducted thus far, one of the biggest technical hurdles to overcome is noise removal. The issue of noise in multiple contexts was researched, and algorithms deployed and tested to reduce noise.

Much time was spent evaluating and lab testing of different static noise removal algorithms. Noise was removed using LMS, using similar techniques to that of subsection 5.3.2. Figure 6.11 shows the results of static noise removal from speech using adaptive algorithms. Similar algorithms could also be employed to remove noise with UAV applications.

Figure 6.11: Lab results: static noise removal: from time 0 to 28, signal contains noise.
© IEEE

Offensive and/or Emergency: UAV as a Portable Communication Tool The following laboratory results summarize work towards creating “ears” for control room operators by facilitating portable communication using a UAV. In summary, this shows:

- Adding a loudspeaker to a UAV worked and was feasible and during testing, and was audible from the ground (at a certain height above ground level).
- Adding a microphone to a UAV worked and was feasible, but the sounds were generally overpowered by rotor noise, which shows that appropriate filtering needs to be created.
- Landing the UAV is the most effective way for the UAV to act as an effective 2-way communication tool as this removed the rotor and motor noise, but even then, other noises also needed suppression.
- Suppressing noise is important. Research performed:
 - Adaptive filter algorithm tested with more static sources of noise
 - This algorithm can be further modified to attenuate rotor and other noise

This component forms one of the paths of the resilience feedback loop that provides decision-makers with relevant information.

6.6 Sensing Physical Environments

The system created is a rapid-deployment cloud connected sensor platform for building managers to increase situational awareness to assess building environmental conditions, collecting data, and performing analytics.

6.6.1 Method: Open Source Hardware and Software Design

For a low cost, rapidly deployable HVAC compliance system, we needed more ability than provided by the open-source hardware rapid prototyping system presented in [148]. “Open source hardware is hardware whose design is made publicly available so that anyone can study, modify, distribute, make, and sell the design or hardware based on that design.” [163]

Network Architecture and Design Requirements One key requirement of this system is to be over-the-top (OTT), and not part of existing SCADA systems or building monitoring and automation systems. In the event the installed system is compromised or malfunctioning, it is important that collected data is accurate.

Figure 6.12: System Block Diagram , Left to right: sensor, bus, microcontroller, connectivity, storage © IEEE, adapted from Creative Commons

To create the system, many choices must be made, and the system at a high level is presented in Figure 6.12.

Sensors, Sampling Rate, and Interface Sensors are the key component of this system, and it is important to select the most appropriate one for monitoring room efficiency, including temperature sensors, atmospheric pressure sensors, humidity sensors, light sensors, gas sensors (eg, CO₂), etc. We are most interested in the low-cost nature of the sensor system, so for HVAC, we require a system that can support low-cost temperature sensors. The BMP180 is a next-generation low cost, high accuracy temperature

sensor from Bosch. With the hardware configuration selected, the maximum sampling frequency was determined experimentally to be 3Hz in realtime or 10Hz offline logging. Sensors can be linked to a micro-controller using many methodologies. We chose I²C (Inter-Integrated Circuit), which is free to use, and has wide compatibility with many microcontroller boards. We selected the BMP180, for its I²C interface, wide user base, and microcontroller compatibility. Though not the cheapest sensor, it includes all needed features, plus an atmospheric pressure sensor with an inexpensive retail price. In future, more sensors could be used to increase accuracy.

Memory Which information should be stored at each sample? Minimum information stored could include date / time, sensor ID, pressure, and temperature. Although a single array element may only consume about 50-60 bytes, this data becomes very large very quickly. 11 days of readings sampled at 3Hz from two nodes resulted in 5 million samples and about 300 megabytes of disk space used. If the sampling rate was lowered to every minute or 10 minutes, the disk usage may be much lower, but the resolution likely may be less.

Communication / Connectivity When the system was operating in real-time upload mode using the Node JS and PHP scripts to transmit, the node used 8kByte/s up-link at any given time, which significantly impacts choice of wireless connectivity. A universal solution could be to use cellular connections, as the system may be more OTT, not relying on local connections at all. Though this is not a huge bandwidth requirement, it is beyond the average limit of 2G GPRS technology (35–171kbps), so requiring EDGE, 3G, 4G LTE, 5G, or WiFi speeds. This limits use of the technology to where modern networks exist. Another connectivity option is Bluetooth 4.0 Low Energy (BLE), also known as Bluetooth Smart. This is a personal area network with a typical throughput of 0.27 Mbps and range of less than 100m and low latency. Though BLE is much more energy efficient, the system requires a host to connect with, which may not always be ideal for distributed sensing applications.

Node Hardware Selection The designed system per node, is summarized in Table 6.1.

Table 6.1: Hardware Node Design Summary © IEEE

Sensor	Interface to Sensor	Microcontroller	Connectivity	Memory	Sampling Rate	Bandwidth	Data Analytics and Storage
BMP180: temperature and pressure	I2C	BeagleBone Black (1GHz ARM Cortex-A8)	Wi-Fi/ Cellular	Buffer max: 1 sample, transmit real-time	3Hz	8kBytes /sec	Cloud-based MySQL server

6.6.2 Results: Sensor Placement and Experimental Set-up and Building A and B: Set-point Compliance

Building A and B were monitored using the instrumentation system developed. The room presented from the study of Building A is southwest facing, and it gets strong afternoon sunlight. In Figure 6.13, some afternoons show very high temperature, and this coincides with warm outdoor temperatures and sunshine. Building B is northeast facing and gets sunlight in the morning.

Figure 6.13: HVAC Compliance - Building A and B compared to outdoor weather © IEEE

Internal Room Compliance Thermal Variation In Figure 6.14 below, the thermal variation can be seen between the radiator temperature, room temperature, and temperature measured at the windowsill. Data was recorded, and a plot is shown for a one-week period.

Figure 6.14: HVAC of various components in a room in Building B. Points noted are the minimum room temperature, the time the radiator reaches set point, and the time the room reaches the set point. Cold temperatures at window indicated in blue. © IEEE

It can be seen that the window temperature drops significantly during the night, as low as 13 degrees, and the room drops to 20 degrees. During the morning warm-up period, there is a delay of about 30 minutes on each day to reach the set point. The room reaches the set point (22.5) about 10-20 minutes after the radiator has reached it's maximum (about 25 degrees).

In Figure 6.13, there are 3 days each, respectively, where the indoor temperature exceeded the set point by 3 or more degrees. Normally, BAS systems can only provide this room-level information, but additional information was collected by both thermal imaging, and using distributed sensors as in Figure 6.14. Both can provide intelligence in terms of what happened to cause exceeding the set point. Looking at both the thermal profile from the window thermal image, and the data collected from the temperature sensors we deployed during these peaks, the temperature indicated is over 30 degrees.

Another point to be observed in Figure 6.14 is the window temperature. Though the room is at the set point (green line), an occupant's desk that is adjacent to the windowsill (and temperature sensor at that location) can still be cold (blue line). The temperature cycle closest to the window (as shown in Figure 6.14) verify that the heat distribution does

not sufficiently compensate for the incoming cold, despite the BAS sensor in the room indicating the room is at the set point. Therefore the system provides greater situational awareness.

6.7 Discussion and Summary

A rapid deployment prototype capable of monitoring an electricity transmission tower and providing its 3D visualization was created. The algorithms reading data from the device can interpret the inputs and warn the operator of significant movement trends. There are still many challenges in deploying such a platform for enabling implementation of distributed sensor systems to assess and inform. Further data analytics could predict material failure, reduce maintenance costs, and improve resiliency. This information provides the key decision-maker useful information.

Humans play a role as a sensor in the resilience feedback model. Cameras from human users or already deployed cameras that provide qualitative data can now also provide quantitative data for state of infrastructure, and thus increase critical infrastructure situational awareness. The human-in-the loop algorithm derived from the concept of Agile IoT is able to provide additional information to CI operators than just the qualitative descriptions they are currently provided: using an “existing sensor” to provide new situational awareness.

Supplied with data from the sensory substitution approaches in chapter 4 and the data analytics approaches in chapter 5, this section described a “Resilience feedback-loop”: which includes sensory substitution approaches for improving resiliency using mobile and fixed sensor nodes, computer vision, and human-in-the loop measurements. It also proposed low-cost, rapid-deployment sensing instrumentation for critical IoT systems. The information refined by the resilience feedback approach provides an output of intelligence for improving situational awareness.

Some of these techniques could be part of Building Information Modeling (BIM) solutions.

In this chapter, we developed the resilience feedback loop, which is a method of informing key decision-makers using various elements presented as part of a feedback system design. This can then improve resilience.

This chapter presented the resilience feedback-loop for additional sensing and long-term monitoring, including proposing sensory substitution approaches for improving resiliency using mobile and fixed sensor nodes, computer vision, and human-in-the loop measurements. The resulting publications are: [11], [12], [13], [14], and [15]. This chapter also proposed a low-cost, rapid-deployment sensing instrumentation for critical IoT systems, and performed an analysis of sensing security implications.

7 Impact of Research: Resulting Publications

This thesis presented algorithms, methodologies, and prototype cases to provide some answers to the hypothesis using a multi-sensor approach that uses the sensory substitution, Agile IoT methods, data analytics approaches, and a resilience feedback response. Peer reviewed publications authored as a result of research in this thesis are presented below to show the research impact of this thesis, for a total of 14 papers. Note that **Journal Papers** are presented in **bold typeface** and conferences in normal typeface.

1. **Data Capture- Sensory Substitution:** Proposed an approach for sensor substitution / cross-modal sensing and designed a framework and techniques for Agile IoT as part of a situational awareness approach and designed a method of using sensor modality shifting with temperature sensors to measure other non-temperature data

Resulting Publications:

- a) **L. Russell, R. Goubran, F. Kwamena, and F. Knoefel, “Agile IoT for Critical Infrastructure Resilience: Cross-modal Sensing as Part of a Situational Awareness Approach,” in *IEEE Internet of Things Journal*. Vol 5, No 6, pp. 4454-4465, 2018. [2]**
 - b) L. Russell, R. Goubran, F. Kwamena and F. Knoefel, "Sensor modality shifting in IoT deployment: Measuring non-temperature data using temperature sensors," *2017 IEEE Int. Sensors Appl. Symp.*, Glassboro, NJ, pp. 1-6 [3]
2. **Data Analytics:**
 - A) Sensory Validation: Designed a method of validating sensor inputs: ambient physical sensors for AI camera analytic validation and performed an analysis of sensing security implications
 - B) Classification and Adaptation: Proposed an urban sensing method using imag-

ing analytics with acoustic signals for UAV signature classification and designed an environmental and physical sensor system for smart environments to perform human detection, and also developed personalization in an IoT environment

C) Multi-sensory Fusion: Designed smart environments, infrastructure and person security using sound and multi-sensory situational awareness algorithms: LMS-based approaches to enable sensory substitution for posture detection and analytics in smart environments

Resulting Publications:

- a) L. Russell, F. Kwamena, and R. Goubran, "Towards Reliable IoT: Fog-Based AI Sensor Validation," in *2019 IEEE Cloud Summit*, Washington DC. [4]
 - b) L. Russell, F. Kwamena, and R. Goubran, "Sensing Instrumentation Using Smartphones: Securing Impact and Awareness," in *2018 IEEE Int. Instrum. Meas. Technol. Conf.*, Houston, TX, pp. 1-5. [5]
 - c) L. Russell, R. Goubran, and F. Kwamena, "Emerging Urban Challenge: RPAS / UAVs in Cities," in *2019 IEEE International Conference on Distributed Computing in Sensor Systems (DCOSS)*, Santorini, Greece, 2019. [6]
 - d) L. Russell, R. Goubran, and F. Kwamena, "Personalization Using Sensors for Preliminary Human Detection in an IoT Environment," in *2015 IEEE Int. Conf. Distrib. Comput. Sens. Syst.*, Fortaleza, Brazil, pp. 236–241. [7]
 - e) L. Russell, R. Goubran, and F. Kwamena, "Posture sensing using a low-cost temperature sensor array," in *2017 IEEE Int. Symp. Med. Meas. Appl.*, Rochester, MN (Mayo Clinic), pp. 443–447. [8]
 - f) **L. Russell, R. Goubran and F. Kwamena, "Posture Detection Using Sounds and Temperature: LMS-Based Approach to Enable Sensory Substitution," in *IEEE Trans. Instrum. and Meas.*, vol. 67, no. 7, pp. 1543-1554, 2018. [9]**
 - g) L. Russell, R. Goubran and F. Kwamena, "Smart environments using near-field communication and HTML5," in *2015 IEEE Int. Symp. Med. Meas. and Appl. (MeMeA)* Proceedings, Turin, Italy, 2015, pp. 549-554. [10]
3. **Response Mechanism:** Proposed rapid situational awareness using mobile and fixed sensor nodes, computer vision, human-in-the loop measurements, resilience innovation, and low-cost, rapid-deployment sensing instrumentation for critical IoT

systems; and proposed a “Resilience feedback-loop” that constantly improves sensory substitution approaches for increasing long-term resiliency.

Resulting Publications:

- a) L. Russell, R. Goubran and F. Kwamena, "Sensor Node to Improve Resiliency and Monitoring in Smart Grids: Taking the Lab to Field in Industry," in *2015 Int. Conf. Dist. Comput. in Sens. Syst., Fortaleza, Brazil*, pp. 208-209. [11]
- b) **K. Dick, L. Russell, Y. Souley Dosso, F. Kwamena, and J. R. Green, “Deep Learning for Critical Infrastructure Resilience: A Case Study,” *ASCE J. Infrastruct. Syst.*, vol. 25, no. 2, 2019. [12]**
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8 Conclusion and Future Work

In this thesis, sensory substitution and resilience feedback were presented as a framework to provide additional situational awareness using available sensors. The approach identifies gaps in modification constrained environments where traditional instrumentation and measurement engineering system design and deployment may not be viable. Each major section of this thesis work can be a contribution to knowledge, but the combined work produces a relevant and useful framework for stronger and more robust methods of increasing resilience using the methods presented in this thesis.

The thesis presented first the sensory substitution and Agile IoT approach that made use of existing and rapid sensing, and included various already existing sensors such as temperature, video/camera, magnetometer, photo resistor, microphone, temperature, and other sensors. Using enabling technologies such as cloud, fog, and edge computing, NFC, open source software and hardware, and other adaptive algorithms including AI and deep learning, the concepts of sensory substitution in Agile IoT were shown to collect ambient sensor values, and produce outputs that were suitable for:

1. Using with analytics approaches,
2. Using with a resilience feedback loop; or
3. Being directly output for intelligence and situational awareness, and for acute sensing needs.

The research also provided analytic approaches to take data and using the sensory substitution approach, solve emerging problems such as robust urban sensing and multi-sensory environments as well as security and validation challenges. Specifically sensory validation was presented to increase trust and security of sensed data. Sensory adaptation was presented to increase robust urban sensing and monitoring, and multi-sensory fusion was presented to improve smart environment infrastructure security using multiple sensors and adaptive analytics.

The third major portion of the thesis focused on a response mechanism centred around

an informed key decision maker. This resilience feedback loop consisted of an initial sensing system that provided the initial information after a scenario occurred. If there were no constraints, it may be possible to design, develop, and deploy an ideal distributed computing sensor system. If time or money are constraints, a low-cost rapid deployment distributed sensing system could be used. If modification constraints are found, sensory substitution as presented in the first portion of the thesis, could be used. These provided the initial situational awareness to provide relevant information to the key decision makers. The informed decision maker could then resolve the issue if enough information had been provided, or request more information. This used the feedback system proposed in this thesis. Various feedback included human-in-the-loop sensing where smart phones and human societal trends informed the decision maker, RPAS and mobile sensors were used to provide a mobile sensing platform, and NFC and rapid sensing was explained. If existing sensors were in an area, the resilience feedback loop could also use sensory substitution to derive additional measurements from existing sensors. These could inform the decision-maker who can then resolve the issue.

Each of the three major areas of this thesis could stand as independent contributions to knowledge, however to solve the initial hypothesis that situational awareness could be increased by using available sensors, all three major components of the thesis link together, at the end of the day, to produce an output of increased intelligence leading to better situational awareness, resilience of critical infrastructure, and with impacts across society.

Future of the First Layer

This layer introduced sensory substitution and Agile IoT. It involved testing of specific orthogonal sensor modalities to determine if they, as sensor Y, can act to replace sensor X. Specific successful pairings included X = temperature and Y = icing condition monitoring, mechanical switch state, fluid flow states, door open states, etc., and these were validated experimentally. The layer successfully showed the technique of sensory substitution and Agile IoT, including how it enables data capture, even when the sensor for the task does not exist.

Future work pertaining to Layer 1 can involve use of an iterative approach to test replacement of various sensors for X with many possible sensor modalities of Y, and determining which sensors are good substitutes for which. In the data analytics layer, other sensor

modalities are tested (e.g. $X = \text{video}$, $X = \text{sound}$, $X = \text{magnetometer}$), but the focus in layer two is the analytical approaches. Future work could thoroughly test a vast array of sensor pairs.

Future of the Second Layer

In the second layer, various approaches to increasing confidence of sensing using sensory substitution were presented. This included validation of sensing, using orthogonal sensing modalities, and sensor fusion to increase both confidence of sensing and also resilience of sensing. We also examined ways of applying analytical techniques designed for one sensing modality (e.g. visual) and applying it to an orthogonal sensing modality (e.g. sound). This shows that with analytics, sensing confidence can be increased using the sensing modalities that are available.

Future work could examine many combinations of orthogonal sensing modalities to see which can best increase either sensing confidence or increase resilience of sensing the desired measurement. Though some specific sensing combinations of orthogonal sensing modalities (e.g. photo resistors, magnetometers, microphones, and cameras) were shown to increase sensing confidence, there are many more combinations to be tested. Additional future work could focus on adopting algorithms from one sensor modality to others. Many techniques could be adapted for a variety of sensors to extract more information. There is much promise in work to identify and improve these algorithms.

Future of the Third Layer

The third layer focused on response mechanisms to increase situational awareness and resilience. While layer one and two focuses on detecting acute problems to inform responses, layer three adds new sensing modalities for longer-term monitoring to develop increased resilience. Examples include rapid deployment of new sensing capability (e.g. UAVs as mobile sensors), or using humans either to a) be the sensor themselves, or b) deploy sensors to strategically significant locations. It also focuses on ways to use sensory substitution for long-term monitoring. The third layer provides the long-term monitoring solutions to augment the acute monitoring for long-term situational awareness to improve resilience.

Layer three then provides many areas for potential future work. How better can we use

the human -in-the-loop as a sensor? What are the best techniques for rapid deployment of sensors? Tangential areas such as portability and power can also be addressed.

Additional Future Work and Directions

Future work that could have significant potential includes research in how to integrate this approach into control rooms and facilities: this could look at how existing software could interact with, extract, and process information in this way. Other future work could focus on the algorithms used and how to improve them, and also the human factors and technological human-computer interactions (HCI) that could be a potential prerequisite.

The work presented in this thesis provides significant ideas on which to build, with the goal that these techniques could have a positive impact on society.

Glossary

Definitions are by author, for the context of this work.

Actuator - An output device that responds to a control signal such as a vibration motor in a mobile communication device

ADC – Analog-to-Digital Converter – Converts analog wave-forms to digital representation

Agile IoT – Internet of Things analytical approaches that involve sensory substitution, algorithmic substitution, or communication channel substitution; especially for the purpose of acute sensing needs or increasing longer-term situational awareness using available sensors and algorithms

AI – Artificial Intelligence – Techniques for machines to learn or reason, such as recognizing patterns in images

Algorithm – Series of steps and/or processing tasks

Anomaly Detection – Discover unique or abnormal events

Audio/Acoustic Signature – Pattern of sound(s) associated with particular events

BAS – Building Automation System – Control system that manages a building, typically managing HVAC and other building systems based on sensors and actuators

BIM – Building Information Modeling – Generation of models of space and functions within spaces or buildings

CI – Critical Infrastructure – Infrastructure on which modern society relies, e.g. energy, health, transportation, information/communication, banking, water, food, etc

Classification – Determining to which group a set of data belongs

CNN – Convolutional Neural Network – A specialized/specific deep neural network type typically used for visual classification

Control Loop – Hardware and software components acting as a complete system to manage a process variable, e.g. maintaining a temperature set point in a Building Automation System (BAS)

CV – Computer Vision – Algorithms that allow computers to gather information using visual inputs

DC – Direct Current – Electrical flow in a single direction, such as that which is supplied by a typical battery

DL – Deep Learning – A subset of artificial intelligence that uses neural networks to learn from exemplar data

DOF – Degree of Freedom – Independent variables or parameters that can be measured in a sensor system (e.g. a 3 DOF accelerometer could measure x-acceleration, y-acceleration, and z-acceleration)

DSS – Distributed Sensor System – Multiple networked sensors monitoring different locations or parameters

Edge Computing – Computing as close to as possible to the physical operating environment or sensors

EMI – Electromagnetic Interference – A type of interference

Feedback Loop – a system design where the output of the system block feeds back into another block, thus adjusting the output

FFT – Fast Fourier Transform – An algorithm that converts data represented in time (or space) domain into frequency domain, enabling frequency analysis where data can be viewed in its frequency components

FIR – Finite Impulse Response – A filter type

Fog Computing – A technique of processing data as close as to the edge (operational environment/sensors) as reasonably possible to support the required application. For example, fog computing applications may require more power than an edge computing application, so may be somewhat distant, but not in remote cloud infrastructure

FOV – Field of View – Area visible to camera sensor (or human)

FTP – File Transfer Protocol – A technique to post files on a remote server, typically cloud web hosting solutions

HF – High-Frequency

HTML – Hypertext Markup Language – A language used in web programming

HCI – Human-Computer Interaction – Issues concerning how a user or operator interacts with a computing or information technology solution

Human-In-The-Loop – A type of algorithm that requires human interaction. This may include making observations or measurements (being the sensor), deploying a sensor, or making decisions

ICS – Industrial Control System – Control systems, sensors, and instrumentation that are used in industrial or process controls

IMU – Inertial Measurement Unit – A sensor type that typically measures acceleration and rotation

IoT – Internet of Things – A connected network of sensors, controllers, and actuators

IIoT – Industrial Internet of Things (IIoT) – A connected network of sensors, controllers, and actuators used for industrial purposes

LMS – Least Means Squared – A type of adaptive filter that can be resilient to changes in operational environments and often are used in noise removal

MAV – Micro Aerial Vehicle – Small aircraft

Measurement – A reading of a value, typically a physical quantity

Modification Constraint – A constraint that prevents modifications of the physical environment such as preventing installation of new hardware in an infrastructure facility

MSP – Mobile Sensing Platform

OTT – Over-The-Top – A sensor or sensor network that is “air gapped” or independent of the main sensor network

RAM – Random-Access Memory

Recognition – The act of a machine learning system to recognize an object

Resilience – How quickly business or normal operations resume after an incident

Resilience Feedback – using information gathered to improve sensing techniques and responses with the goals of either increasing sensing confidence, adding orthogonal sensor modalities, increasing situational awareness, or increasing resilience overall.

RF – Radio-Frequency

RPAS – Remotely Piloted Aircraft System, a formal term used by Transport Canada to refer to drones, UAVs/UAS, etc.

RPM – Revolutions Per Minute

SCADA – Supervisory Control and Data Acquisition System, see ICS

Sensor – A piece of hardware that measures a real-world parameter such as a device to measure temperature

Sensory Substitution – Replacement of a sensor designed to measure quantity X with a sensor designed to measure quantity Y, and relevant analytics to derive quantity X from a sensor for Y

Situational Awareness – Being knowledgeable on relevant information in a given scenario

SNR – Signal-to-Noise Ratio

Substitution – The act of replacing one for another alternative

Touch and Run with NFC – [101] defines as an approach for contextual application innovation involving virtual tokens

UAV – Uninhabited Aerial Vehicle, see RPAS

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