Neonatal Respiratory Rate
Monitoring using a Pressure-Sensitive Mat

by

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Abstract

Pressure measurement using a Pressure Sensitive Mat (PSM) enables a non-contact approach for monitoring patient vital signs such as respiration rate (RR) and heart rate (HR). Non-contact patient monitoring in Neonatal Intensive Care Units (NICU) can improve the quality of patient care and reduce patient discomfort. This thesis investigates the applicability of PSM for monitoring of neonatal patient respiration rate in the NICU.

A clinical trial was conducted with the Children's Hospital of Eastern Ontario (CHEO) collecting PSM data from 15 patients in three different bed types. Gold standard RR and annotations of patient movement and interventions were collected simultaneously. Algorithms for estimating RR were developed by optimizing spatial downsampling, reference signal selection, enhancement, and combining. The RR estimation results were evaluated against gold standard estimates from a commercial patient monitor. The best RR estimation method worked well when the patient is on ventilator support achieving a mean absolute error (MAE) of 3.9 ± 6.6 bpm on clean data without patient movements or interventions. For this patient, 89.7% of RR estimates were within the clinically acceptable range of ± 10 bpm, while 78.4% fell within the more stringent limits of ± 5 bpm.

When the RR estimation algorithm is evaluated on all patients, RR estimation performance is mixed. In particular, very low mass neonates and patients laying on multiple blankets presented challenges for RR estimation. Taken together, a 95% confidence interval (CI) for agreement between the estimated and gold standard RR was estimated to be $[-44.8, 51.9]$ bpm with a mean bias of 3.5 bpm, using a mixed effects limits of agreement (LoA)

analysis. The mixed effect analysis results indicated that while the bias on the RR estimation is low, the variance was unacceptably high. Therefore, further improvements to RR estimation method should focus on patient movement, signal to noise ratio (SNR), and the signal energy of the raw pressure signal. The results and findings from this thesis provide a benchmark for future improvements to RR estimation algorithms from neonatal PSM data.

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List of Abbreviations

ASCII - American Standard Code for Information Interchange

bpm - Breath per minute

CHEO - Children's Hospital of Eastern Ontario

CRF - Case Report Form

ECG - Electrocardiography

EGC - Equal Gain Combining

FFT - Fast Fourier Transform

HR - Heart Rate

IP - Impedance Pneumography

MAE - Mean Absolute Error

NAS - Network Attached Storage

NICU - Neonatal Intensive Care Unit

NIPPV - Nasal intermittent positive pressure ventilation

PAE - Percentage of Acceptable Estimates

PMDI - Patient Monitor Data Import

PSD - Power Spectral Density

PSM - Pressure Sensitive Mat

RGB-D - Red Green Blue - Depth

RR - Respiration Rate

SC - Selective Combining

SNR - Signal to Noise Ratio

Chapter 1: Introduction

This chapter presents the motivation for this thesis, discusses the problem statement, states major contributions, and describes the thesis structure.

1.1 Motivation

Patients admitted to Neonatal Intensive Care Units (NICU) require continuous monitoring of physiological parameters such as Respiration Rate (RR) and Heart Rate (HR). Widely used Respiration Rate (RR) monitoring techniques in NICU include Impedance Pneumography (IP) and flow measurement from mechanical ventilation [1], [2]. These invasive techniques are reliable and well-studied [3]–[5]. However, placement and removal of these devices causes discomfort, stress, and pain since they require direct contact with the patient. The undeveloped skin of a premature infant is easily irritated by repetitive application and removal of electrodes and adhesives [6]. This adversely affects the infant's well-being and development outcomes [7].

There is increasing research interest in the development of contact-less and unobtrusive RR monitoring. Technologies studied in the NICU include laser Doppler vibrometer (LDVi), optical and thermal imaging, load cells and, pressure sensors [8]–[14]. A Pressure Sensitive Mat (PSM) is a device for the measurement of 2D distribution of contact pressure. A PSM consists of a matrix of pressure sensors. Compared to LDVi and imaging based techniques, PSM has an advantage because it does not require the patient to be uncovered or to be in a room with bright lighting. PSM technology is also preferable over individual

pressure sensors and load cells due to a higher spatial resolution, which becomes advantageous during patient movements.

1.2 Problem Statement

RR measurement using PSM has been previously studied for the adult population [15]–[18]. A major difference that exists in using PSM with the neonatal population, as opposed to adults or older children, is the much smaller mass and pressure ranges [11]. Also, the expected range of normal RR for healthy neonates (20 – 60 bpm) is higher and wider compared to that of an adult at rest (12 – 20 bpm) [19][20]. In addition, factors such as patient movements, clinical interventions, and mattress types should be considered in order to evaluate the applicability of PSM for RR measurement in the NICU.

Artifacts from patient movements and clinical interventions are expected to negatively impact the accuracy of RR estimation using PSM. Previous work in [21] used an approach to identify and censor the recorded data during periods of movements. Other approaches include selection of the sensor that has the best breathing signal from an array of pressure sensors [22]–[24]. These works produced promising results when applied to data from adult population, but more work is needed to apply and evaluate them on neonatal PSM data.

The most commonly used bed types in NICU are overhead warmer, open crib, and incubator. The difference in firmness of each mattress type results in different levels of pressure distribution and patient support [25], [26]. This variance poses a challenge for reliable RR estimation using PSM in the NICU. However, PSM is suitable for neonatal

beds, since they have small size, and there are no articulations of the support structure like that can be found in an adult bed.

1.3 Publications Arising from this Research

The research described in this thesis is part of a larger collaborative project with the Children’s Hospital of Eastern Ontario (CHEO) and IBM Center for Advanced Studies (IBM CAS). My role in the larger project includes work that is beyond the scope of this thesis document. I have co-authored a number of publications arising from the iterative development of this research project. Each publication is briefly described below, including my role.

1. S. Nizami, **A. Bekele**, M. Hozayen, K. Greenwood, J. Harrold, and J. R. Green, “Comparing time and frequency domain estimation of neonatal respiratory rate using pressure-sensitive mats,” *2017 IEEE Int. Symp. Med. Meas. Appl. MeMeA 2017 - Proc.*, pp. 239–244, 2017 [13]

This work presented comparison of time and frequency domain approaches for neonatal RR estimation using data collected from a neonatal patient simulator. In this work, my contribution was in the development and evaluation of the RR estimation algorithms. These algorithms served as prototypes for the final algorithms reported here.

2. S. Nizami, **A. Bekele**, M. Hozayen, K. J. Greenwood, J. Harrold, and J. R. Green, “Measuring uncertainty during respiratory rate estimation using pressure-sensitive mats,” *IEEE Trans. Instrum. Meas.*, vol. 67, no. 7, pp. 1535–1542, 2018 [27].

This work was an extension of [13]. It presented characterization of uncertainty for RR estimation using a PSM. My contributions to this work

were implementation of the code for analysis of the data and interpretation of the results. The limits of agreement analysis in Chapter 7 of this thesis follows directly from my work in this manuscript.

3. S. Nizami, A. Basharat, A. Shaukat, U. Hameed, S. Raza, **A. Bekele**, R. Giffen, J.R. Green., “CEA: Clinical Event Annotator mHealth Application for Real-time Patient Monitoring,” Proc. 40th Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. (EMBC), Honolulu, HI, USA, no. May, 2018. [28].
4. A. Bekele, J. Samuel, S. Nizami S, A. Basharat, P.R. Giffen, J.R. Green, "Ontology Driven Temporal Event Annotator mHealth Application Framework," in *Proc. of CASCON, Markham, Canada*, 2018.

These two papers presented the clinical event annotation application design and implementation. The application was used to collect gold standard bedside annotations of patient movement and interventions. I contributed to this paper by designing the architecture of the application and serving as a mentor during the development process.

5. **A. Bekele et al.**, “Real-time Neonatal Respiratory Rate Estimation using a Pressure-Sensitive Mat,” in *Proc. of IEEE Int. Symp. Med. Meas. Appl. (MeMeA)*, Rome, Italy, 2018 [12]

This work presented a method for RR estimation evaluated on actual neonatal patient PSM data. My contributions to this work include, design, implementation and evaluation of the algorithm. I also participated in the

development of standard operating procedures (SOP) for data collection and collection of patient data at the bedside in the NICU.

6. Y. S. Dosso, **A. Bekele**, and J. R. Green, “Eulerian Magnification of Multi-Modal RGB-D Video for Heart Rate Estimation,” in *Proc. of IEEE Int. Symp. Med. Meas. Appl. (MeMeA), Rome, Italy*, 2018 [29]

My contributions to this paper centered on the development of a software method to record multi-hour RGB-D video from the Intel RealSense SR300 camera. This same software was used in the present study to record videos simultaneously with PSM data to retrospectively fine-tune the manual annotation of patient events.

Some of the above publications relate to preliminary algorithms that have been eclipsed by newer work. In the interest of efficiency, this thesis describes only the most recent and most effective approaches to neonatal PSM-based RR estimation. I would like to acknowledge that I am the primary author of portions of text from the above publications that are re-used in this thesis without quotation.

1.4 Summary of Contributions

The results in this thesis are presented in an additive sequence, such that design decisions are made sequentially, culminating with the final PSM-based neonatal RR estimation technique. The items listed in this section highlight the major contributions.

1. Developed a framework for collecting, reviewing, and processing PSM data from an XSensor PSM. This is described in Chapter 3 of this thesis.

2. Investigated a number of time- and frequency-based RR estimation algorithms based on the mean pressure signal from the PSM. Developed a novel time/frequency hybrid approach that surpasses approaches from previous work on neonatal data. This contribution is described in Chapter 4 of the thesis.
3. Compared several approaches to determining the best sensor from which to estimate RR. Also, examined several approaches to spatial pooling of sensors to provide improved RR estimates. This contribution is described in Chapter 5 of the thesis.
4. Conducted a limits of agreement analysis across 15 patients to determine the key determinants of RR estimation error. Explored several variables including patient mass, mattress type, and actual RR rate. This analysis is described in Chapter 7 of the thesis.

1.5 Thesis Structure

This thesis is composed of eight chapters. In chapter 2, background information and literature review of contactless RR measurement in the NICU is presented. In addition, PSM technology is discussed. Chapter 3 presents the details of the clinical study for data collection. Chapter 4 discusses approaches for RR estimation from spatially averaged PSM data and presents the evaluation and discussion of the results. Chapter 5 presents improvements of the results from Chapter 4 by taking advantage of spatial resolution of the PSM. Both methods for the selection of the optimal sensor from which to estimate RR and methods of weighted spatial pooling of sensors are examined. In Chapter 6, results for evaluation of the best RR estimation method across 15 patients are discussed. In Chapter

7, a mixed effects limits of agreement analysis is presented to identify factors that contribute to RR estimation errors. Conclusions and future work are discussed in Chapter 8.

Chapter 2: Background

In this section, background information and literature review of RR monitoring in the NICU, pressure based RR measurement, and the PSM technology is presented.

2.1 Respiration Rate Monitoring in NICU

RR is a significant vital sign monitored in the NICU. Abnormal respiratory rate is an early indicator of medical conditions such as hypoxia, hypercapnia, and respiratory or metabolic acidosis [20]. Hypoxia is a deficiency in the amount of oxygen reaching tissues [30]. Hypercapnia is a condition of abnormally elevated carbon dioxide levels in the blood [31].

RR measurement technologies can be divided into contact and contactless approaches. Techniques requiring direct contact with the patient include acoustic-based methods, airflow-based methods, chest and abdominal movement detection, transcutaneous CO₂ monitoring, oximetry probe-based methods, and ECG-derived respiration rate measurement. Contactless approaches include radar, optical imaging, thermal imaging, and contact pressure [32].

Contact-based and invasive RR measurements are common in the NICU. For example, RR can be tracked with high fidelity for a neonate using a ventilator [2]. Another more commonly used measurement technique is impedance pneumography (IP) which detects the breathing signal from chest movements using electrodes placed on the thorax of the patient, typically for recording ECG [4], [5].

A comprehensive investigation of contactless respiration monitoring in infants had been presented by Franks *et al.* in 1976 [33]. In the study, an air-filled mattress system, an under mattress pressure sensor, a magnetometer, capacitive change detector, and radar reflection system were explored. The study concluded that an under mattress pressure sensor is the simplest and satisfactory method compared to others by considering parental apprehension as a factor [33].

Since the work by Franks *et al.*, over the next decades several approaches were investigated for non-contact respiration monitoring, but mainly focused on the adult population, as summarized by Folke *et al.* [34]. They concluded that despite the large number of reported methods and devices for respiratory monitoring, convincing evidence of their clinical usefulness was still lacking. Another systematic review conducted more recently by Loon *et al.* noted that clinical research for evaluation of the non-invasive respiratory monitoring is still lacking [35]. They also concluded that improvements are needed on the methodological quality of studies evaluating electronic patient monitors.

Contactless RR and heart rate (HR) measurement based on laser Doppler vibrometry (LDVi) had been evaluated in the NICU [36]. The work by Scalise demonstrated non-contact monitoring of RR “at a distance” through analysis of data acquired from nine pre-term infants inside an incubator. The work highlighted potential limitation of LDVi during patient movements and dependence on surface characteristics which requires the patient to be fully uncovered.

2.2 Pressure-based Respiration Rate Measurement

Pressure- and force-based vital signs monitoring has been an active research area for several years, mainly due to the unobtrusive and non-contact nature of the sensors [1], [17], [18], [23], [24], [37][38][39].

Nishida *et al.* developed a pressure distribution sensing sheet consisting on 221 force sensing resistors and introduced methods for detecting patient respiration [39]. Their work was one of the earliest to demonstrate the feasibility of force sensing mats for patient monitoring in supine, prone, and lateral positions. However, their evaluation did not include comparison with a gold standard respiration monitoring device.

Watanabe *et al.* developed a noninvasive pneumatics-based system to measure heartbeat, respiration, snoring, and body movements of a subject in bed [37]. The system was composed of an air cushion, a pressure sensor, electric filters and a signal processor. They evaluated the system in a controlled bench test on 14 subjects aged 8 to 46 years and concluded that body movements are a major factor for error in the measurements.

An extensive investigation on respiration monitoring, apnea detection, and movement detection using pressure sensor array was conducted by Townsend *et al.* [38], [40] and Holtzman *et al.* [22]. Compared to the PSM being investigated in this thesis which has a total of 10,000 sensors, their study used only 48 pressure sensors. In [38] they developed algorithms for extracting the breathing signal from the pressure sensor array and compared their results with a state-of-the-art inductance plethysmography based respiratory

measurement device. Their evaluation, conducted on eight healthy adult participants, showed promising results for RR measurement using a PSM. They proposed techniques for reference breathing signal selection and combining of the signal from multiple sensors to improve the SNR of the breathing signal. For combining of signals from multiple sensors, they proposed two simple approaches, Selection Combining (SC) and Equal Gain Combining (EGC). For SC, the best reference signal that matches the criteria is selected as the breathing signal. For EGC, the reference signal is combined with signals from additional sensors to enhance the breathing signal. Phase-shift and polarity adjustments are applied to the signals before they are combined with equal weights assigned to each sensor. The breathing signal selection criteria and combining approaches developed as part of their work are summarized and adopted in Chapter 5 of this thesis, where they are evaluated on neonatal data.

Building upon the work by Townsend *et al.* [38], comprehensive investigation has been done in the area of improving the SNR for breathing signal extracted from PSM by combining signal from multiple sensors. The work by Hotlzman *et al.* [41] introduced an approach that computes optimal weights for combining using maximal ratio based on variance and PSD. This was done to maximize the SNR of the breathing signal. Recently, Azimi *et al.* [42] have proposed more complex combining approaches based on Pearson's correlation coefficient (PCC) and a Minimum-Variance Distortionless Response (MVDR) beamformer. Their evaluation on data collected from a single healthy adult person showed promising results for the proposed combining approaches. They indicated newer approaches performed better in comparison to the SC and EGC methods discussed in [38]

based on the available data. However, they concluded that more experiments are required to evaluate them on close-to-reality data.

It has been shown that artifacts from movement negatively impact RR estimation. A number of approaches have been proposed to mitigate this problem. In [21], the authors propose identifying duration of the movement and censoring RR estimation to improve the accuracy of estimation over a longer period. This works well when the duration of movement is small, but for neonatal RR estimation, typically the duration of movements and interventions is longer, making the option to suspend RR estimation unacceptable. The work in [22] presents methods for selection of the best sensor from the PSM as an approach for mitigation of movement artifacts for RR estimation. Others have explored ways to detect and separate movement and respiration signal [23], [24], [43]. All of these approaches have their advantages and should be explored further to test them on neonatal data. However, movement detection is out of the scope of this thesis. Instead, gold standard bedside movement annotation is used for evaluating RR estimation in both the presence and absence of patient movement.

Liu *et al.* developed a high-density pressure sensing system made of e-Textile that profiles the underbody pressure distribution [16]. Their work demonstrated breathing signal and movement detection on healthy adult subjects weighing 46–83 kg. Their system achieved a maximum breathing detection of 45 bpm, which is insufficient for neonatal respiration monitoring. They highlighted monitoring of a subject with movements was challenging and that high density pressure sensors were required for accurate localization.

Pressure-based respiration monitors for babies are commercially available (e.g. [44]). Most of these products are focused on apnea detection and generation of alarms. There is a lack of literature on their applicability in the NICU where continuous RR estimation is required. Independent, quantitative analysis of their false and missed alarm rates are not available. They also do not provide application program interfaces for secondary analyses of their datasets.

2.3 Pressure Sensitive Mats

A recent review of current state of the art smart fabric sensors and e-textile technologies mentions that fabric units can be constructed to include sensing properties that can be optical, resistive or capacitive [45]. The sensing elements translate applied physical load on the mat to measurement of contact pressure in the immediate region of the sensor.

Other than the clinical environment, PSM technology has applications in other domains such as ergonomics, automotive technology, and civil engineering [46]–[48]. In the medical sector, PSM have been used for gait analysis, concussion assessment, and patient monitoring [49]–[51].

Metrological properties of PSM, including rise time, percentage change in creep, drift, and repeatability, vary based on intrinsic properties of the sensor technology. Nizami *et al.* conducted experiments to evaluate dynamical metrological properties in three different PSM technologies: (i) S4 (S4 Sensors Inc.) embedded with Kinotex fiber-optic sensors (Nitta Corp., Osaka, Japan), (ii) Tekscan BRE5400-1 resistive ink PSM (Tekscan, Boston,

USA, tekscan.com), and (iii) XSensor LX100:36.36.02 capacitive PSM (XSensor Technology Corp. Calgary, Canada, XSensor.com) [52]. Results showed that XSensor has greater reliability when compared with the other two PSM. The PSM used in the present study is similar to the XSensor evaluated in [52].

2.4 Summary

The development of contact-less and none-invasive RR monitoring has been an active research area for a number of years. PSM technology had been studied for monitoring patient vitals including RR for the adult population. There is currently a research gap in evaluating the applicability of PSM for monitoring RR of neonates in the NICU, as they present unique challenges due to their size, mass, and physiology.

Chapter 3: Experiment Setup and Data collection

The study was conducted at the Children's Hospital in Eastern Ontario (CHEO), Ottawa, Canada and was approved by the research ethics boards of both the hospital and Carleton University. Furthermore, the use of the PSM in a clinical setting was approved by Health Canada as a Class II Medical Device under Investigational Testing Authorization #265088. The experiment setup for the clinical study along with the data collection protocol is detailed in this chapter.

3.1 Equipment and Experiment Setup

Figure 3.1 shows the overview of the setup. The following subsections present detailed description of equipment used.

(1) - Pressure Sensitive Mat, (2) - Patient Monitor, (3) – Camera, (4) – Data acquisition laptop,
(5) – Bedside Annotation App, (6) – Neonatal bed (Overhead warmer), (7) - Ventilator

Figure 3.1 Overview of equipment setup

3.1.1 Pressure Sensitive Mat

The PSM used is LX100:100.100.05 (XSensor Technology Corp. Calgary, Canada, XSensor.com). It has a spatial resolution of 5.08 mm with an overall sensing area of 50.8 x 50.8 mm² and a total of 10,000 sensors. It can measure pressure in the range of 0.07 – 2.7N/cm² with rated 5% error margin. It has a thickness of 0.09 cm at the sensing area. A picture of the PSM is show in Figure 3.2.

The PSM was placed under the patient, above the bed mattress, and was covered with the bed sheet. Some patients were also wrapped in additional blankets. The data from the PSM comprise pressure values from each sensor in N/m². The PSM connects to an X3 Pro Sensor Pack that feeds into an X3 Pro Electronic Platform that is connected via USB to a laptop running the XSensor X3 Pro V8 software. The X3 Pro software was used to record PSM data. Then, the data were exported as ASCII data then converted to MATLAB ® format for analysis using a custom script.

Figure 3.2: XSensor LX100:100.100.05 PSM

3.1.2 Patient Monitor

The patient monitor used was Draeger Infinity Delta (Draeger Medical Systems, Inc. Telford, PA, USA). It uses Impedance Pneumography (IP) for RR measurement. Its range for RR is 0 – 155 bpm, with an error of 1 bpm or 2%. It provides a serial port (RS232) interface in which patient data can be exported. Custom Patient Monitor Data Import (PMDI) software was used for data export to ASCII [53].

3.1.3 Camera

RealSense SR300 RGB-D camera (© Intel Corporation, Santa Clara, CA, USA) was used to record color, near-infrared, and depth video feeds of each experiment. These data were primarily intended to be used for another research to develop patient monitoring using imaging modality. However, the color video data were also used to verify and refine the data quality of bedside annotations. Bedside annotations were post-processed by correcting annotation start and end times and also adding new annotations that were missed during the experiment.

3.1.4 Data Acquisition Laptop

A data acquisition laptop was setup with the PMDI software, customized Intel RealSense Viewer software and the XSensor X3 Pro V8 software to record all data. PSM data from a single experiment has size of approximately 6 GB for 6 hours. All de-identified data were backed up to a dedicated network attached storage (NAS) device following each patient recording.

3.1.5 Bedside Annotation App

During the study, bed side annotations of events comprising clinical routine care, physiological events, and interventions were recorded using a custom developed mobile app [28]. These data were used to segment the PSM data into three different conditions of clean, during patient movement and during routine care/interventions.

3.1.6 Neonatal Beds

Three different neonatal beds used in the CHEO NICU shown in Figure 3.3, were included in the study. These are Giraffe overhead warmer neonatal bed (GE Healthcare, USA), open crib and incubator. The mattress in the overhead warmer and the incubator has a size of 65x48x4 cm (25.5L x 19W x 1.5D in). The crib mattress is approximately double the size and depth of the overhead warmer, and is significantly firmer.

Figure 3.3 Neonatal beds in the NICU: (a) Overhead warmer, (b) Open crib, (c) Incubator

3.2 Data Collection

Patient data were collected in an NICU from four sources simultaneously: a PSM placed under the patient, a Draeger patient monitor, a custom bedside event annotation application

running on a tablet, and a RGB-D video camera placed directly above the patient. The PSM data were used to develop an algorithm for estimating the patient's RR. The patient monitor data were used as gold standard for evaluating RR estimates. The bedside event annotation data were used to capture the times of patient movements, routine care events, and clinical interventions. After data collection in the NICU, the bedside annotation data were manually validated and corrected using the video as a reference.

The PSM data were acquired at a sample rate of 18 Hz. Each sample consists of pressure measurement from a grid of 100 x 100 sensors. Figure 3.4 shows a sample pressure distribution image and associated color map legend.

Figure 3.4: Sample pressure distribution image from PSM

Processed RR estimates in Breath Per Minute (bpm) were acquired from the Draeger patient monitor, through the RS232 interface at 1 Hz using Patient Monitor Data Import (PMDI) software developed in our lab [53]. The patient monitor uses impedance pneumography (IP) to derive the breathing signal and compute the RR estimate. The data

exported from the patient monitor comprise RR estimates in bpm derived with a proprietary algorithm that examines a sliding 10 sec window. It was not possible to export the raw IP signal from the patient monitor.

The overarching study aims to record data from 35 patients, stratified by mass and bed type. Data collection for this study is ongoing; however, data from 15 patients are currently available and are included in the present analysis. Table 3.1 lists the patients along with the relevant study parameters.

Table 3.1 List of participants with study parameters

<i>Patient ID*</i>	<i>Sex</i>	<i>Weight (grams)</i>	<i>Bed type</i>	<i>Vent. Mode</i>	<i>Duration of data by condition (sec)</i>			<i>Total duration (sec)</i>
					Clean	Movement	Intervention	
<i>1</i>	M	2465	OW	CV	14723	914	2822	18459
<i>2</i>	M	3620	C	RA	12806	2477	1298	16581
<i>5</i>	M	3480	C	RA	11318	2335	1607	15260
<i>6</i>	M	3504	OW	RA	7438	2991	582	11011
<i>8</i>	F	2340	C	RA	20188	905	298	21391
<i>9</i>	F	2520	C	RA	14633	1522	49	16204
<i>10</i>	M	353	C	NIPPV	9819	1927	3176	14922
<i>11</i>	F	2415	C	RA	10609	1436	214	12259
<i>13</i>	M	4435	C	RA	13258	501	2731	16490
<i>14</i>	F	2800	OW	RA	16102	938	2249	19289
<i>15</i>	F	3250	OW	RA	15083	1604	196	16883
<i>16</i>	F	3460	OW	NIPPV	11913	839	3679	16431
<i>17</i>	M	2765	OW	RA	11244	179	3372	14795
<i>18</i>	F	1290	INC	RA	8383	273	349	9005
<i>19</i>	M	1604	INC	RA	7985	4384	497	12766
<i>Avg.</i>	--	2687	--	--	12366	1548	1541	15450

* Patient ID is not contiguous, since for some consented patients, the experiment was not conducted

because the patient was discharged from the NICU prior to data collection.

3.2.1 Data Collection Parameters

Contextual information for each patient was captured at the beginning of the experiment on a case report form (CRF). A sample CRF is presented in Appendix D . The CRF includes the following information.

- i. Patient ID: - This is anonymized unique identifier for each patient. This ID is not linkable to actual patient information such as name, after data collection has been completed for that patient.
- ii. Sex: - The gender of the patient. There was no systematic effort to balance the experiment for both genders’.
- iii. Weight: - The experiment was stratified by weight to collect data from small, medium and large weight groups.
- iv. Bed type: - The overarching experiment was designed to collect equal amount of from each bed type: overhead warmer (OW), crib (C) and incubator (INC),
- v. Ventilation mode: - This represents the type of ventilation used for the patient. Room air (RA) ventilation means, the patient was breathing normally and no active support was used. Conventional Ventilator (CV) mean the patient was put on a ventilator that assisted with the breathing. Nasa Intermittent Positive Pressure Ventilation (NIPPV) is a special minimally invasive breathing support that uses short tubes reaching only to the back of the nose.
- vi. Duration of data by condition: - After excluding segments of the data where the patient was removed from the mat, the data from each patient was grouped into segments based on the condition of movement annotated by the bedside event

annotator. The three conditions were: clean data without patient movements or externally applied pressure, data that includes patient movements but not externally applied pressure and, data that contains externally applied pressure due to clinical interventions or routine care.

3.2.2 Data Quality

During data collection, a number of factors may contribute to decrease in data quality. For example, the timings for gold standard bed side annotations of patient movements, routine care and clinical interventions may not be accurate to within less than a few seconds, due to human error.

Another factor for decrease in data quality is reliability of the gold standard RR estimates from patient monitor. Studies have shown that IP-based RR measurements are susceptible to poor performance in the presence of movements [3], [54], [55]. Empirically, clinical staff have also indicated that they often observe poor RR estimation quality from such a signal. This makes it difficult to understand the true source of error when comparing RR estimates from PSM to the gold standard, during movements.

In order to improve data quality, only the gold standard estimates that fall in the expected normal neonatal respiration rates of 22 – 108 bpm are included in the analysis. In addition, samples within 10 secs of start and end of the data collection and, when the patient is removed from the PSM are discarded.

Chapter 4: Respiratory Rate Estimation

4.1 Introduction

In this chapter an algorithm for estimating RR from PSM data is presented. For a patient placed on top of the PSM, the PSM data represents pressure distribution measured over time. The pressure distribution of the PSM may change due to two main factors:

1. Internally Induced

These are movements arising from the patient's own body. They can be further classified into three different components:

- a. Diaphragm movement due to breathing
- b. Head, limb and torso movements
- c. Myocardial contractility

2. Externally Applied

These comprise external pressure that is applied to the PSM during routine care or clinical interventions such as a diaper change, feeding, intubation, *etc.*

The RR of the patient can be measured from the breathing signal arising from movement of the diaphragm. Breathing is a rhythmic physical process consisting of two steps: inspiration and expiration [56]. In neonatal patients, this process can be spontaneous breathing or artificial ventilation.

For normal spontaneous breathing, inspiration is an active process driven by both the intercostal muscles between the ribs and the diaphragm. The intercostal muscles move the chest upwards while the diaphragm moves towards the legs expanding the chest cavity. This fills the lungs with air. On the PSM, the combined effect of redistribution of mass and change in contact area increases the total applied pressure.

On the other hand, during expiration the intercostal muscles and diaphragm return to their resting positions, pushing air out of the lungs. On the PSM, the total mass is redistributed resulting in reduced total applied pressure. The mechanics of breathing including inspiration and expiration is illustrated in Figure 4.1.

Figure 4.1: Illustration of diaphragm movement during breathing

For artificial ventilation the driving pressure for inspiration is generated by the ventilator. But the resultant effect on the PSM is similar to normal spontaneous breathing.

The breathing signal can be extracted from the rhythmic change of the pressure measured by the PSM. However, body movements (other than the diaphragm) and externally applied pressure introduce unwanted artifacts that reduce the signal quality. Therefore, further processing of the signal is required before the RR can be estimated.

4.2 RR Estimation Algorithm

The algorithm for estimation of RR from PSM data consists of five steps as shown in Figure 4.2.

Figure 4.2: RR estimation algorithm steps

The first two steps are spatial processing and temporal windowing. Spatial processing examines downsampling and the different ways of leveraging spatial pooling as a weighted combination of neighboring sensors. Temporal windowing refers to the number of samples that are included in the analysis for estimating RR at any given time. The combined output of the two steps is a list of candidate signals representing the pressure measurement over time.

The third step is breathing signal selection. In this step, each of the candidate signals resulting from the first two steps are evaluated using a criterion to assess their potential for robust estimation of RR. The best signal that matches a criterion for breathing pattern is selected as a reference from the list of candidate signals. In the fourth step, the selected reference breathing signal is enhanced by carefully combining it with other candidate signals with the aim of improving its SNR. In the last step, the RR can be estimated from

the breathing signal through time domain analysis, frequency domain analysis or a combined approach.

The focus of the remaining sections in this chapter will be to present and evaluate the methods for the last step in the RR estimation algorithm. In Chapter 5, the remaining steps of the algorithm are presented and evaluated. To be clear, all results in the current chapter are based on applying RR estimation algorithms to the time-varying pressure signal representing the spatial average of total applied pressure across the entire PSM.

4.3 Signal Preprocessing

4.3.1 Breathing Signal Extraction

We can model PSM data as a time series sequence of pressure measurements, $P(i, x, y)$, defined as the pressure measurement at frame number i , from the sensor located at column x and row y . Let the sensors of the PSM be arranged in a square grid of $N \times N$. Then we have $1 \leq x \leq N$ and $1 \leq y \leq N$. The orientation of the PSM relative to the position the patient is not relevant for the methods of analysis discussed here.

The breathing signal, S can simply be extracted by taking the spatial average of the raw pressure values. It should be noted that the work by Townsend *et al.* [38] has shown that an improved breathing signal can be extracted by optimizing the spatial resolution of the PSM; this will be explored in Chapter 5.

$$S[i] = \frac{\sum_{1 \leq x, y \leq N} P(i, x, y)}{N^2}$$

For estimation of RR, the signal is analyzed over a time window W . This means, an estimate of RR for a time t is computed using the signal values spanning $[t - W, t]$.

The window size W was selected to be 10 seconds (180 samples). This allows comparison of the RR estimate with the patient monitor, which also computes RR estimates from the same window.

Figure 4.3: Sample average pressure signal: (a) breathing signal is seen clearly, (b) breathing signal has artifacts

4.3.2 Filtering

The breathing signal extracted from the PSM is expected to contain both low frequency and high frequency artifacts. The low frequency artifacts come from patient movements and externally applied pressure. The high frequency artifacts contain measurement noise or signal from myocardial contractility. The latter is useful by itself to estimate patient heart rate (HR), but since the interest here is RR it should be filtered out.

Before a filter is applied the mean loading of the breathing signal is removed. This is done by subtracting the mean of the values in the window W from each sample. This allows one to emphasize the signals from the active sensors.

To remove low and high frequency artifacts, a band pass filter is applied. The low and high cutoff frequencies are chosen to be 0.35 Hz (22 bpm) and 1.8 Hz (108 bpm) respectively to represent the expected normal neonatal respiration rates with added margins to account for abnormalities [19]. This was implemented using a second-order Butterworth filter, due to the smooth roll off around the cutoff frequencies. This filter is not linear phase, and could result distortion on the output waveform. However, this is not expected to have an impact for RR estimation as long as the waveform is not modified such that the peak finding algorithm fails to identify the peaks.

Figure 4.4: Magnitude and phase response of band pass filter

Townsend *et al.* used a low pass filter for the study on adult patients [38]. In order to evaluate that approach, a low pass filter was also applied by itself.

Figure 4.5: Magnitude and phase response of low pass filter

4.4 Methods

For estimation of the RR from the extracted breathing signal, three methods are discussed: Time domain method, Frequency domain method, and a Combined method.

4.4.1 Time Domain Method

This method extracts peaks from the time domain signal and computes the period of the breathing signal as the average inter-peak interval. This is conceptually similar to previously published RR estimation methods used in adults [16]. The RR is computed as per the following equation:

$$RR = \frac{(n-1) \times Fs}{last-first} \times 60 \text{ bpm}$$

Here:

n = number of identified peaks

$last$ = sample number of last identified peak

$first$ = sample number of first identified peak

Fs = sample rate

A peak is identified as a local maxima of the signal. A minimum distance of 4 samples between peaks was used, allowing for a maximum RR of 135 bpm at $Fs = 18$ Hz. This maximum limit is chosen to cover the full range of expected RR for neonates [19]. Figure 4.6 shows waveforms of the raw average pressure signal, the normalized and pre-processing signal and the detected peaks for time domain RR estimation.

Figure 4.6: RR estimation with time domain method. (a) Raw average pressure signal, (b) Pre-processed signal, (c) Detected peaks

4.4.2 Frequency Domain Method

In order to estimate the RR using the frequency domain method, first the power spectral density (PSD) of the breathing signal is computed using Fast Fourier Transform (FFT). Then, the frequency with the highest power contribution, is selected and multiplied by 60 to estimate the RR in bpm. For the FFT, the transform length was selected to be 1024 samples. With the sample frequency of 18 Hz, this results in a time window of 56.9 sec and a spectral interpolation resolution of 0.02 Hz (~ 1 bpm).

$$RR = f_p \times 60 \text{ bpm}, \text{ where } f_p = \operatorname{argmax}_f P_{xx}$$

Here:

P_{xx} = power spectrum of the signal computed with FFT

f_p = frequency at the higher peak of the power spectrum

Figure 4.7 shows the spectrum of the breathing signal with gold standard RR of 72 bpm and the corresponding detected peak at 1.16 Hz (69.9 bpm).

Figure 4.7: Single-sided amplitude spectrum of breathing signal with gold standard RR estimate of 72 bpm and computed RR estimate of 69.9 bpm

4.4.3 Combined Method

The combined method uses both time and frequency domain approaches to estimate RR. This method improves underestimation of the RR due to undetected peaks by the time domain RR method described in section 4.4.1. In the combined method, the time domain RR estimate is first used to compute a lower cutoff frequency. This frequency is used to establish a lower limit for the spectral peak search of the subsequently applied frequency domain method (described in section 4.4.2).

The cutoff frequency, f_c , is computed by subtracting an error margin from the time domain RR estimate and converting it to Hz. The combined method is defined in the following equations:

$$RR = f_p \times 60 \text{ bpm}, \text{ where } f_p = \operatorname{argmax}_{f: f > f_c} P_{xx}$$

$$f_c = \frac{(RR_T - r)}{60}$$

Here:

P_{xx} = power spectrum of the signal computed with FFT

RR_T = RR estimate from time domain method

r = the error margin for time domain method in bpm

f_c = cutoff frequency from which peak search on the spectrum will start

f_p = the peak on the spectrum after the cutoff frequency

The error margin (r) was selected to be 12 bpm. The purpose of the error margin is to account for underestimation of RR using the time domain method. For a window of 10 seconds, this tolerates missing 2 peaks using the time domain method. Figure 4.8 shows the spectrum of the breathing signal with gold standard RR estimate of 64 bpm and the detected peak with the combined method at 1.06 Hz (63.4 bpm).

Figure 4.8: Single-sided amplitude spectrum of breathing signal with gold standard estimate of 64 bpm and computed RR estimate of 63.4 bpm

4.5 Evaluation

In this section the methodology used for evaluating the RR estimation methods is detailed.

4.5.1 Evaluation Data

Here, the RR estimation methods were evaluated on the data from Patient 1, Patient 2 and Patient 5. Patient 1 was using a conventional ventilator which supported the breathing. Therefore, the breathing signal was stronger than other patients. Evaluation of methods using the RR data from all patients is given in Chapter 5.

The evaluation was done separately for each of the three data conditions described in Chapter 3.

4.5.2 Evaluation Metrics

For evaluation, the mean absolute error (MAE) and percentage of clinically acceptable estimates (PAE) were computed in comparison to gold standard patient monitor estimates.

The mean absolute error was computed as follows:

$$MAE = \frac{\sum |RR_{est} - RR_{pm}|}{N}$$

Here:

MAE = mean absolute error

RR_{est} = estimates from algorithm

RR_{pm} = gold standard estimates from patient monitor

N = total number of estimates

The percentage of clinically acceptable estimates was computed as:

$$PAE = \frac{C}{N_E}$$

Here:

C = count of estimates where $MAE < 5 \text{ bpm}$

N_E = number of total estimates

4.5.3 Evaluation of Breathing Signal Quality

The breathing signal quality was evaluated by computing its SNR. To compute the SNR, two assumptions were made. First, the true breathing signal was assumed to be a pure sinusoidal signal and its frequency was derived from the patient monitor RR estimate in bpm.

Second, any signal components other than the purely sinusoidal breathing signal are assumed to be noise.

It should be noted that the first assumption is not valid for all cases. This is because, as shown in [38], the breathing signal frequency and amplitude changes during normal, deep, and shallow breaths. But, the assumption will still hold if breathing signal is short term stationary over the selected 10 second window.

The SNR was computed in a manner similar to the approach presented in [38]. First, the PSD of the signal was obtained using FFT. Then, the power for the breathing signal and its harmonics were estimated from the PSD. The noise power was estimated by subtracting

the breathing signal power from the total power. For the FFT, the transform length was selected to be 1024 samples. The equation for the SNR is as follows:

$$SNR = 10 \log \left(\frac{Signal\ Power}{Noise\ Power} \right) = 10 \log \left(\frac{Signal\ Power}{Total\ Power - Signal\ Power} \right)$$

4.5.4 Evaluation Parameters

The evaluation was run on each method by varying the pre-filtering approach. In total, nine methods were evaluated. The name and description of the methods are as follows:

- TIME: Time domain method on un-filtered signal
- TIME_LP: Time domain method on low pass filtered signal
- TIME_BP: Time domain method on band pass filtered signal
- FREQ: Frequency domain method on un-filtered signal
- FREQ_LP: Frequency domain method on low pass filtered signal
- FREQ_BP: Frequency domain method on band pass filtered signal
- COMB: Combined method on un-filtered signal
- COMB_LP: Combined method on low pass filtered signal
- COMB_BP: Combined method on band pass filtered signal

In addition, the SNR was computed each condition of data. The results from the evaluation are presented in the next section.

4.6 Results

Here, results from Patient 1 are presented. The results for Patient 2 and Patient 5 are given in Appendix A . The total number of estimates evaluated for each group is presented in

Table 4.1. Each estimate represents one seconds of data. The analysis is evaluated on a 10 second window prior to the time corresponding to the estimate.

Table 4.1: Number of estimates for each group of data

Patient ID	Number of estimates			Total
	Clean	Movement	Interventions	
1	14723	914	2822	18459

The mean and standard deviation of the SNR for each group are given in Table 4.2 and plotted in Figure 4.9. It can be seen that, the mean SNR is generally higher for the Clean condition than for the movement and intervention conditions. Furthermore, the low pass filtering method does not appear to improve the SNR for any condition.

Table 4.2: Mean SNR and standard deviation for different filtering methods (Patient 1)

Filtering Method	Mean SNR (dB) +/- Standard Deviation		
	Clean	Movement	Interventions
NONE	-18.7 +/- 10.2	-20.5 +/- 9.7	-21.0 +/- 10.8
Low Pass (LP)	-22.0 +/- 14.0	-24.5 +/- 13.0	- 24.3 +/- 13.9
Band Pass (BP)	-19.8 +/- 15.0	-21.4 +/- 14.0	-21.2 +/- 14.7

Figure 4.9: Mean SNR and standard deviation for different filtering methods

The MAE and the associated standard deviations for all methods and conditions are given in Table 4.3 and plotted in Figure 4.10. It can be seen that the methods with band pass filter achieved the smallest MAE.

Table 4.3: MAE and standard deviation for methods and conditions (patient 1)

Method	MAE (bpm) +/- Standard Deviation		
	clean	movement	Interventions
TIME	67.4 +/- 15.6	61.6 +/- 14.3	63.0 +/- 16.2
TIME_LP	5.4 +/- 6.6	7.1 +/- 7.8	7.2 +/- 8.4
TIME_BP	4.7 +/- 5.9	6.3 +/- 7.1	6.6 +/- 7.6
FREQ	32.0 +/- 32.3	45.4 +/- 32.0	43.1 +/- 31.6
FREQ_LP	33.4 +/- 32.2	46.1 +/- 31.8	44.0 +/- 31.2
FREQ_BP	13.5 +/- 20.2	26.0 +/- 25.3	20.8 +/- 23.6
COMB	125.3 +/- 97.7	88.8 +/- 53.4	99.0 +/- 77.5
COMB_LP	4.7 +/- 7.8	7.3 +/- 11.9	7.1 +/- 10.0
COMB_BP	4.4 +/- 6.9	6.5 +/- 10.2	6.5 +/- 9.0

Figure 4.10: MAE for all data conditions and RR estimation methods (patient 1)

The PAE for all methods and conditions are given in Table 4.4 and plotted in Figure 4.11.

The highest PAE was achieved by the combined method with a band pass filter on clean data.

Table 4.4: PAE for methods and conditions (patient 1)

Method	PAE (%)		
	clean	movement	interventions
TIME	0	0	0.14
TIME_LP	63.31	52.63	55.84
TIME_BP	68.86	57.55	59.74
FREQ	48.52	32.50	32.46
FREQ_LP	46.31	31.51	30.97
FREQ_BP	65.52	45.23	49.43
COMB	0.14	0	0.28
COMB_LP	75.76	65.10	62.51
COMB_BP	76.6	66.20	65.20

Figure 4.11: PAE for all data conditions and RR estimation methods (patient 1)

4.7 Discussion

As can be seen in Table 4.1, the RR estimation methods were evaluated on a total of 18,459 estimates representing 5.13 hours. From the total, 14,723 (79.8 %) of RR estimates were from clean data without patient movements or interventions, 914 (4.9 %) were from data with patient movement, and 2822 (15.3 %) were from data with interventions.

From all three groups, the highest mean SNR for the breathing signal was -18.7 ± 10.2 dB obtained for clean data as expected. Contrary to what would be expected, low pass filtering has actually decreased the mean SNR compared to no filtering as can be seen in Table 4.2. This could be because some of the breathing information is below the selected low pass filter cut off frequency or certain movements artifacts have frequency components overlapping with lower cutoff for breathing signal.

It can be observed from Table 4.3 that filtering significantly improves the MAE for all data groups and all methods. Band pass filtering results in lower MAE compared to low pass filtering. This shows lower frequency artifacts are indeed a source of noise for the breathing signal, and eventually contribute to the RR estimation error. Mean loading removal may not be strictly required when band pass filtering is also used; however, removal of this pre-processing step was not explored in this thesis. In addition, instead of the band pass filter with wide pass band as evaluated here, adaptive filtering could be explored to increase the amount of noise removed by filtering.

For clean data, the lowest MAE (4.4 ± 6.9 bpm) was obtained from the combined method. But, when compared to the time domain method (4.7 ± 5.9 bpm), the difference is only 0.32 bpm. However, the combined method achieves a PAE of 76.6 % compared to 68.86 % from the time domain method as shown in Table 4.4. The combined method also outperforms the other methods for data with movement and interventions.

For data with movement and interventions, the MAE is higher and the PAE is lower than that of clean data. This indicates none of the RR estimation methods are robust for data segments with artifacts.

The frequency domain method has a large standard deviation for MAE across all data groups. This could be because spectral peak searching is susceptible to noise. On the other hand, the time domain method has a smaller standard deviation and lower MAE. But, it has a smaller PAE compared to the combined method. This shows the combined method brings in the strength of both time and frequency domain methods to improve the RR estimation.

4.8 Conclusion

In conclusion, it was shown that RR can be estimated by extracting the breathing signal as the average pressure of each frame of PSM data over time. The raw average pressure data was pre-processed by removing the mean loading and filtering. A mean absolute error of 4.4 ± 6.9 bpm was achieved on clean data segments with a method that combines both time and frequency domain approach. For this approach, 76.6% of estimates were within clinically acceptable error bounds (± 5 bpm). On segments of the data with patient

movements and clinical interventions, the error was higher indicating a weakness with the method.

In Chapter 5, techniques that take advantage of the spatial resolution of the PSM to improve the combined RR estimation method are presented.

Chapter 5: Breathing Signal Selection and Enhancement

5.1 Introduction

Figure 4.2 is reproduced here for clarity, with the topics pertaining to Chapter 5 highlighted.

Figure 5.1: RR estimation algorithm steps

This chapter builds up on the results from Chapter 4. The objective is to improve the RR estimation by leveraging the spatial resolution of the PSM. Spatial processing examines downsampling and the different ways of leveraging spatial pooling as a weighted combination of neighboring sensors.

Previous work from Townsend *et al.* and Holtzman *et al.* has shown that selecting the best sensor that carries the respiration information from the grid of sensors improves the SNR [22], [38]. The signal from this sensor can be used as a reference signal to estimate the RR. In addition, signals from additional sensors containing respiration information can be combined with the reference signal resulting in a higher amplitude signal. However, combining signals that have opposite polarity or phase shift can result in loss of

information. This can be addressed through polarity and delay analysis to ensure that signals are aligned before adding them together [38].

In terms of temporal windowing, a fixed window of 10 s of data were used for each RR estimate, as mentioned in the previous chapter. This preprocessing step was not fully explored; this is left for future work.

Several criteria for selection of the best reference sensor for RR estimation have been proposed in the literature including amplitude-based, spectral-ratio-based, and band-power-based [22], [38], [57]. Here, these approaches are evaluated on neonatal data after some modifications to work on neonatal respiration rate frequencies.

For enhancement of the reference signal using supplementary sensors, two approaches are proposed. The first approach uses the top ranked signals based on the selection criteria. The other approach further filters the signals based on spatial distance from the reference sensor before combining.

In the subsequent sections, the methods for selection and enhancement of the reference signal are detailed. Then, the evaluation results are presented along with discussion and conclusion.

5.2 Spatial Resolution of PSM

As opposed to using a single pressure sensor under a patient, PSM use a grid of sensors to create a 2D map of contact pressure. In this way, changes in pressure can be measured for

specific locations on the patient's body. The spatial resolution of a PSM describes the physical distance between adjacent sensors. Previous studies have used PSM of varying spatial resolutions. The present study uses an XSensor LX100:100:100.05 which has a spatial resolution of only 5.08 mm, among the highest sensor densities currently available in commercial PSM. However, it is unclear how much spatial resolution is sufficient for the purpose of RR estimation.

Measurement from a grid of sensors can be analyzed at different spatial scales. This is analogous to resizing of an image by downsampling. There are two main advantages of spatial downsampling.

- i. It reduces the number of candidate signals for sensor selection which, in turn, reduces processing time for extraction of breathing signal.
- ii. Since the signal value is computed by weighted average of multiple sensor values, it results in a less noisy candidate signal in the presence of movement artifacts. This can be seen in Figure 5.3.

An interpolation kernel function is typically applied to the original signal prior to subsampling. A common interpolation kernel is bilinear kernel, which computes the output value as a weighted average of values from the nearest 2-by-2 neighborhood. For a grid of $N \times N$ sensors, when combined with an antialiasing filter, downsampling using a bilinear kernel with a scale of $\frac{1}{N}$ can be made equivalent to averaging of the pressure measurements from a single frame as done in 4.2. Of the many possible filter choices, bilinear kernel with antialiasing filter was selected due to the satisfying result that it converges to a global

average as the downsampling reaches a single pseudo-sensor. The algorithm used for downsampling and antialiasing is discussed in [58]. For the implementation, ‘*imresize*’ function in MATLAB was used with bilinear kernel option and antialiasing.

Figure 5.2: Pressure values from all 10,000 sensors of the PSM over time

Figure 5.2 shows the plot of pressure measurement from all 10,000 sensors of the PSM. It should be noted that breathing signal is not clear from this plot. But, after spatially

Figure 5.3: Pressure values from 400 spatially downsampled pseudo-sensors of the PSM over time

downsampling the pressure measurement by a scale of 0.2, the breathing signal becomes clearly visible for some pseudo-sensors, as shown in Figure 5.3.

It is also interesting to note that the signal extracted by computing the average from all sensors (as done in Chapter 4) has very little breathing information, as shown in Figure 5.4 (a). On the other hand, breathing can be seen on the signal extracted from a suitably selected reference sensor in Figure 5.4 (b). Figure 5.4 (c) shows the pre-processed breathing signal from which RR can be estimated. The pre-processing was done by removing the mean loading and applying band pass filter as described in Section 4.3.2.

Figure 5.4: Extracted breathing signal. (a) Average from all sensors, (b) Selected signal after spatial downsampling, (c) Selected signal after pre-processing

The methods for selection of the reference signal are presented in the subsequent sections. This is followed by evaluation of the methods in conjunction with varied parameters of spatial downsampling. Discussion and conclusions from results are also presented.

5.3 Selection of Reference signal

In this section, previously developed methods for selecting the reference signal from a list of candidate signals are briefly presented.

5.3.1 Band Power Method

The band power method was discussed in Niizeki *et al.* [57]. For each candidate signal the power within the expected breathing frequency band is estimated from the PSD. The signal with the highest power within that band is selected to be a reference. This approach is shown to work well when the breathing signal is strong, but has limitations when the noise from movement artifacts overlaps with the respiration band.

5.3.2 Amplitude Method

This method was proposed in Townsend *et al.* [38]. For each candidate signal, the signal amplitude was approximated by dividing the average peak-to-valley distance by two. The signal with the highest amplitude is selected as a reference signal. However, sensors affected by movement artifacts typically contain large amplitudes; this risks selecting an artifact-dominated sensor. This limitation was noted by Holtzman *et al.* [22] who proposed an alternative spectral ratio criteria.

5.3.3 Spectral Ratio Method

The spectral ratio method proposed by Holtzman *et al.* is effective in selecting signals that contain respiration, while discriminating against those with movement artifacts [22]. A spectral ratio fitness value is calculated as follows:

$$r = \frac{P_{breath}}{P_{noise}} \times P_{total}$$

Here:

P_{total} = the total spectral power in the breathing frequency band

P_{breath} = the power of breathing signal

P_{noise} = the total noise power

The total power (P_{total}) is estimated from the PSD of the breathing signal computed with FFT. The transform length for the FFT was 1024 samples. The power of the breathing signal (P_{breath}) was estimated from the highest peak in the breathing frequency band after subtracting noise power at that peak. By considering all other in-band frequencies to be noise, the total noise power (P_{noise}) is estimated by multiplying the median of the power at frequencies other than the breathing signal by the band width.

5.4 Enhancement of the Reference Signal

The reference signal can be combined with signals from other sensors to take advantage of PSM spatial resolution. This involves two steps: 1) selection of supplementary sensors for enhancement and 2) combining.

5.4.1 Selection of Sensors for Enhancement

The sensor selection criteria can be extended to rank sensors believed to contain breathing information, with the reference signal being top ranked. Then, the top K sensors after the reference signal, can be considered as potential enhancement signals. The most appropriate value for K was experimentally evaluated in combination with the scale factor used for PSM and is presented in Section 5.5 below.

The enhancement signals can also be filtered based on their spatial location relative to the reference sensor. It is expected that breathing signal is most strong in the abdomen and torso body parts of the patient. Therefore, by restricting the enhancement signals to be spatially near the reference sensor it is possible to avoid combining the reference signal with a sensor that scores high on the selection criteria but contains movement artifacts. This assumes that the strongest signal is located in the region of interest (thorax) and does not require pose estimation or explicit region of interest selection.

5.4.2 Combining Signals from Multiple Sensors

For combining of signals the equal gain combining approach from Townsend *et al.* [38] was used because of its simplicity. During respiration, the diaphragm movement has a component in the lateral direction, resulting in delayed signals on PSM sensors. This can be seen in Figure 5.5.

Simply combining the sensors, without first adjusting for delay, results in a loss of information due to destructive addition. Therefore, a method proposed in [38] is adopted here to preprocess the enhancement signals by adjusting the delay and polarity using cross-correlation, as detailed in the following.

Figure 5.5: Pre-processed candidate breathing signals showing delay

First, the cross-correlation between each enhancement signal and the reference signal are calculated. Then, the cross-correlation between the inverted version of each enhancement signal and reference signal is computed. The two cross-correlation values are compared at a delay of zero and the signal with the higher value is combined with the reference signal.

In addition, based on the cross-correlation values, the signals are aligned using the delay value that maximizes the cross-correlation. This maximum value is restricted to be between ± 1 sec as proposed in [38].

5.5 Evaluation

The spatial downsampling, reference signal selection, and signal enhancement methods were evaluated on the data from Patient 1, Patient 2 and Patient 5, using combinations of the possible design parameters as detailed in the following.

For the scale parameter of spatial downsampling, values of 1, 0.5, and 0.2 were examined. Downsampling by these factors resulted in grids with dimensions of 100 x 100, 50 x 50 and 20 x 20 grid of sensors, respectively. The varied parameters and the methods are listed below with their description:

- SCL100_SR: scale of 1 and sensor selection with spectral ratio method
- SCL50_SR: scale of 0.5 and sensor selection with spectral ratio method
- SCL20_SR: scale of 0.2 and sensor selection with spectral ratio method
- SCL100_AMP: scale of 1 and sensor selection with amplitude method
- SCL50_AMP: scale of 0.5 and sensor selection with amplitude method
- SCL20_AMP: scale of 0.2 and sensor selection with amplitude method
- SCL100_BP: scale of 1 and sensor selection with band power method
- SCL50_BP: scale of 0.5 and sensor selection with band power method
- SCL20_BP: scale of 0.2 and sensor selection with band power method

Once the optimal downsampling factor and reference signal selection criterion were established, the number of supplementary sensors (to be combined with the reference signal) was examined. The K parameter for selecting the number of supplementary sensors

to be combined with the reference signal was varied with values of 5, 10 and 20 to evaluate its effect on improving the RR estimation.

As with the previous chapter, the SNR, MAE and PAE metrics were used for the evaluation.

5.6 Results

Here, the results from Patient 1 are presented. The results from Patient 2 and Patient 5 are presented in Appendix B .

5.6.1 Results from Spatial Downsampling and Signal Selection

Table 5.1 details the data used for evaluating the downsampling and signal selection steps.

Table 5.1: Data used for evaluating spatial downsampling and signal selection

Patient ID	Number of estimates			Total
	Clean	Movement	Interventions	
1	1200	914	1200	3314

The mean SNR for spatial downsampling and signal selection methods across the three data conditions is presented in Table 5.2 and Figure 5.6. Bolding indicates the top three SNR values in each column. It is hard to conclude which method is superior due to the high standard deviation of the results. However, the mean values for the band-power method were smaller in comparison to the other methods.

Table 5.2: Mean SNR for spatial downsampling and signal selection

Method	Mean SNR (dB) +/- Standard Deviation		
	Clean	Movement	Interventions
SCL100_SR	-20.9 +/- 11.0	-22.6 +/- 11.9	-22.3 +/- 11.8
SCL50_SR	-20.3 +/- 15.2	-22.7 +/- 15.2	-22.0 +/- 15.0
SCL20_SR	-20.2 +/- 16.0	-22.4 +/- 15.9	-21.7 +/- 16.0
SCL100_BP	-19.4 +/- 13.7	-20.3 +/- 14.1	-20.8 +/- 13.6
SCL50_BP	-19.7 +/- 15.5	-21.2 +/- 16.0	-21.0 +/- 15.4
SCL20_BP	-19.7 +/- 16.2	-21.0 +/- 16.2	-20.8 +/- 16.1
SCL100_AMP	-20.2 +/- 11.0	-21.0 +/- 10.8	-20.8 +/- 10.8
SCL50_AMP	-20.4 +/- 14.2	-21.7 +/- 13.7	-21.4 +/- 13.6
SCL20_AMP	-20.2 +/- 15.3	-21.7 +/- 15.1	-21.4 +/- 14.9

Figure 5.6: Plot of mean SNR results for spatial downsampling and signal selection

The MAE for spatial downsampling and signal selection for the three data conditions are presented in Table 5.3 and Figure 5.7. A spatial scaling factor of 0.2 combined with band-power method results in the smallest MAE for all data conditions. In Table 5.3, bolding indicates the top two MAE values.

Table 5.3: MAE for spatial downsampling and signal selection

Method	MAE (bpm)		
	clean	movement	interventions
SCL100_SR	18.2 +/- 16.9	23.1 +/- 18.9	23.0 +/- 19.0
SCL50_SR	8.8 +/- 13.4	13.0 +/- 16.6	14.6 +/- 17.3
SCL20_SR	6.6 +/- 10.9	9.8 +/- 13.3	10.7 +/- 14.5
SCL100_BP	9.7 +/- 13.0	11.6 +/- 14.5	14.0 +/- 15.4
SCL50_BP	6.1 +/- 9.8	7.7 +/- 11.6	9.8 +/- 13.3
SCL20_BP	4.3 +/- 7.3	5.7 +/- 9.6	6.9 +/- 10.4
SCL100_AMP	18.7 +/- 17.2	23.3 +/- 19.1	22.0 +/- 17.9
SCL50_AMP	9.6 +/- 12.5	12.8 +/- 14.7	14.6 +/- 16.0
SCL20_AMP	6.8 +/- 10.4	9.0 +/- 12.4	10.1 +/- 13.0

Figure 5.7: Plot of MAE for spatial downsampling and signal selection

The PAE for spatial downsampling and signal selection for the three data conditions are presented in Table 5.4 and Figure 5.8. A spatial scaling factor of 0.2 combined with band-power method results in the highest PAE for all data conditions.

Table 5.4: PAE for spatial downsampling and signal selection

Method	PAE (%)		
	Clean	Movement	Interventions
SCL100_SR	30.25	26.26	26.17
SCL50_SR	65.42	54.92	49.58
SCL20_SR	71.42	60.07	59.33
SCL100_BP	59.5	55.47	46.42
SCL50_BP	72.92	65.54	59.57
SCL20_BP	77.75	72.43	67.08
SCL100_AMP	33.58	30.31	25.33
SCL50_AMP	58.83	50.33	44.33
SCL20_AMP	68.92	61.27	56.5

Figure 5.8: Plot of PAE for spatial downsampling and signal selection

5.6.2 Results from Signal Enhancement with top-K Method

The top-K method combines the reference sensor signal with the top-ranking K supplemental sensors, as ranked by the selection criterion. Table 5.5 summarizes the data used to evaluate this method.

Table 5.5: Data used for evaluating signal enhancement with top-K method

Patient ID	Number of estimates			Total
	Clean	Movement	Interventions	
1	14723	914	2822	18459

The mean SNR for signal enhancement with the top-K method across the three data conditions are presented in Table 5.6 and Figure 5.9. Here, E5, E10, and E20 denote K values of 5, 10, and 20, respectively. No significant improvements were observed for mean SNR as compared to the results of spatial downsampling and signal selection given in Table 5.2.

Table 5.6: Mean SNR for signal enhancement with top-K method

Method	Mean SNR (dB)		
	Clean	Movement	Interventions
SCL20_SR_E5	-20.1 +/- 16.4	-21.8 +/- 16.2	-21.2 +/- 16.1
SCL20_BP_E5	-19.9 +/- 16.4	-21.1 +/- 16.2	-20.9 +/- 16.1
SCL20_AMP_E5	-20.0 +/- 15.1	-21.6 +/- 15.7	-21.3 +/- 15.4
SCL20_SR_E20	-20.2 +/- 16.5	-22.1 +/- 16.4	-21.3 +/- 16.1
SCL20_BP_E20	-20.2 +/- 16.7	-21.9 +/- 16.5	-21.2 +/- 16.2
SCL20_AMP_E20	-20.3 +/- 16.2	-22.2 +/- 16.0	-21.6 +/- 15.7
SCL20_AMP_E10	-20.2 +/- 16.6	-21.9 +/- 16.4	-21.2 +/- 16.0
SCL20_AMP_E10	-20.0 +/- 16.6	-21.6 +/- 16.5	-21.1 +/- 16.2
SCL20_AMP_E10	-20.1 +/- 16.0	-22.0 +/- 15.8	-21.5 +/- 15.5

Figure 5.9: Plot of mean SNR for signal enhancement with top-K method

The MAE for signal enhancement with top-K method across the three data conditions are presented in Table 5.7 and Figure 5.10. It is interesting to note that, as the cut-off threshold is increased, the MAE also increases.

Table 5.7: MAE for signal enhancement with top-K method

Method	MAE (bpm)		
	Clean	Movement	Interventions
SCL20_SR_E5	5.4 +/- 9.4	7.1 +/- 11.5	8.0 +/- 11.8
SCL20_BP_E5	4.0 +/- 6.7	5.1 +/- 8.3	6.4 +/- 9.4
SCL20_AMP_E5	5.0 +/- 8.6	6.8 +/- 10.4	7.3 +/- 10.4
SCL20_SR_E20	5.1 +/- 8.8	7.1 +/- 11.2	7.1 +/- 10.4
SCL20_BP_E20	4.2 +/- 7.1	5.7 +/- 8.7	6.1 +/- 8.7
SCL20_AMP_E20	5.0 +/- 8.4	6.5 +/- 9.8	7.3 +/- 10.5
SCL20_AMP_E10	5.1 +/- 8.9	7.1 +/- 11.1	7.3 +/- 11.0
SCL20_AMP_E10	4.1 +/- 6.9	5.4 +/- 8.8	6.3 +/- 8.9
SCL20_AMP_E10	4.9 +/- 8.3	6.6 +/- 10.0	7.4 +/- 10.4

Figure 5.10: Plot of MAE for signal enhancement with cut off method

The PAE for signal enhancement with top-K method across the three data conditions are presented in Table 5.8 and Figure 5.11. No significant improvement in PAE is observed as the cut-off threshold is increased.

Table 5.8: PAE for signal enhancement with cut off method

Method	PAE (%)		
	Clean	Movement	Interventions
SCL20_SR_E5	75.7	68.05	64.92
SCL20_BP_E5	78.68	72.65	68.04
SCL20_AMP_E5	75.29	66.96	64.35
SCL20_SR_E20	75.67	68.38	66.05
SCL20_BP_E20	77.99	70.24	67.29
SCL20_AMP_E20	75.55	68.6	63.96
SCL20_AMP_E10	76.00	68.82	66.48
SCL20_AMP_E10	78.5	72.32	67.11
SCL20_AMP_E10	75.33	68.49	63.71

Figure 5.11: Plot of PAE for signal enhancement with cut off method

5.7 Discussion

In this section, the results from spatial downsampling, signal selection, and signal enhancement are discussed.

5.7.1 Discussion of Spatial Downsampling and Signal Selection

The results presented in Table 5.2 and Figure 5.6 show that band power method of the signal selection criterion resulted in the smallest mean SNR (although not statistically significantly better). However, there was no improvement of the mean SNR across the three spatial downsampling parameters used. As expected, the mean SNR was lower for data with movement and interventions.

The spatial downsampling scale of 0.2 resulted in a smaller MAE and PAE as shown in Table 5.3 and Table 5.4, respectively. It can also be seen that a scale of 0.5 performed better than a scale 1. When comparing these results to Chapter 4, there is a small improvement

of both MAE and PAE metrics for clean data, but the improvement is greatest for data with movement and interventions.

5.7.2 Discussion of Signal Enhancement

It is interesting to note from Table 5.6, Table 5.7 and Table 5.8 that signal enhancement had only a minor improvement on the mean SNR, MAE, and PAE metrics. When looking at the parameters of the top-K method, the smallest parameter, which was 5, resulted in the better performance overall.

The results for the distance-based enhancement method given in Appendix C indicate there was no significant improvement for all metrics as compared to the top-K method.

5.8 Conclusion

It was shown that spatial downsampling improves the performance of RR estimation in terms of mean SNR, MAE, and PAE. However, the scale parameter of the downsampling is an important factor. Scale factors of 0.2 and 0.5 resulted in better performance than a scale factor of 1 representing no downsampling. Also, a scale of 0.2 outperformed 0.5, indicating that the optimum scaling factor may be smaller than 0.2; thus further work is required to determine the true optimal value.

From the three signal selection criteria presented, the band power method resulted better performance overall. From this, we may conclude that the best breathing signal for RR estimation may have power contributions across bands of frequencies rather than concentrated at a single peak and its harmonics.

From the signal enhancement results, we may conclude that combining the best reference signal, with more signals either through cut off method or distance method only has a minor impact on the RR estimation performance. This indicates, that despite careful combination of signals to avoid loss of information due to delay difference, the combined signal wasn't good enough to significantly improve the RR estimation.

In conclusion, the parameters that improved performance of RR estimation are used to establish the best RR estimation method. These are, spatial downsampling scale of 0.2, band-power criteria for reference signals selection, the top 5 signals for signal enhancement and the combined method from Chapter 4 for RR estimation. These parameters will be used when computing all results in the remainder of this thesis.

In Chapter 6, extensive evaluation of the best RR estimation method on data from all patients is presented.

Chapter 6: Evaluation of Best RR Estimation Method

6.1 Introduction

In this chapter, the best RR estimation method from Chapter 5 is evaluated on the data from all patients.

6.2 Evaluation

As with the previous chapter, the SNR, MAE and PAE metrics were used for the evaluation. A more relaxed metric for percentage of acceptable estimates, PAE_10 was also used. In addition, signal energy of the extracted breathing signal was computed.

PAE_10 is computed similar to PAE as defined in Chapter 4, but the range for acceptable error is expanded to +/- 10 bpm. This standard has been used in previous studies by our lab and others [60] [27].

The RR estimation error is computed as the difference between the estimate arising from the best method (RR_{est}) and gold standard estimates from commercial patient monitor (RR_{pm}).

$$RR_{error} = RR_{est} - RR_{pm}$$

The signal energy (ENE) for the extracted breathing signal was computed from the time domain signal as the squared sum of the values for each sample.

6.3 Results

The best RR method was evaluated on the data from all patients. The MAE and PAE for all data conditions are presented in Table 6.1. The bolding in the table indicates the top three values for each column.

The results show, the performance of the method on Patient 1 and Patient 5 were higher compared to the other patients. It can also be noted that, the standard deviation of the MAE for most patients is larger compared to the mean.

The RR estimation errors for all patients and each data condition are presented in Figure 6.1, Figure 6.2, Figure 6.3, and Figure 6.4.

For the box plots, the central mark indicates the median, and the bottom and top edges of the box indicate the 25th and 75th percentiles, respectively. The whiskers extend to the most extreme data points that are not considered outliers. Data points are considered outliers if they are greater than $q_3 + 1.5 \times (q_3 - q_1)$ or less than $q_1 - 1.5 \times (q_3 - q_1)$ where q_1 and q_3 are the 25th and 75th percentiles of the sample data, respectively. With this definition, the whiskers cover approximately 99.3% of the data, assuming the data are normally distributed.

Table 6.1: Results for best RR estimation method for all patients and data conditions

Patient ID	Data Collection and Evaluation Metrics											
	Clean			Movement			Intervention			All		
	MAE +/- SD (bpm)	PAE (%)	PAE_10 (%)	MAE +/- SD (bpm)	PAE (%)	PAE_10 (%)	MAE +/- SD (bpm)	PAE (%)	PAE_10 (%)	MAE +/- SD (bpm)	PAE (%)	PAE_10 (%)
1	3.9 +/- 6.6	79.38	89.70	4.7 +/- 7.7	74.75	87.49	6.1 +/- 9.4	69.58	81.27	4.3 +/- 7.2	77.67	88.32
2	20.3 +/- 19.1	27.38	41.98	19.2 +/- 16.3	20.44	37.02	20.6 +/- 16.0	19.49	31.92	20.1 +/- 18.6	25.84	40.58
5	7.3 +/- 9.6	60.96	77.27	10.5 +/- 11.7	48.37	62.78	12.4 +/- 12.9	39.59	57.54	8.1 +/- 10.4	57.44	73.68
6	19.9 +/- 19.2	30.03	41.69	15.5 +/- 12.7	25.29	41.29	18.3 +/- 12.6	14.99	31.69	18.6 +/- 17.4	27.97	41.07
8	21.0 +/- 17.7	21.76	35.16	27.7 +/- 19.0	14.08	22.71	26.6 +/- 18.0	13.42	22.94	21.3 +/- 17.8	21.36	34.53
9	14.5 +/- 14.8	33.84	52.13	17.2 +/- 15.3	24.93	43.34	33.5 +/- 15.8	2.22	11.11	14.7 +/- 14.9	33.04	51.32
10	12.1 +/- 14.2	44.85	62.23	23.6 +/- 17.9	16.94	29.19	17.4 +/- 17.3	32.31	48.11	14.6 +/- 15.9	38.80	55.21
11	11.2 +/- 12.3	42.64	61.13	12.8 +/- 13.1	37.53	54.99	17.2 +/- 19.6	40.86	51.61	11.4 +/- 12.5	42.17	60.50
13	21.0 +/- 19.7	27.84	41.25	22.0 +/- 19.7	26.58	36.39	30.4 +/- 19.5	7.57	15.54	22.4 +/- 19.9	24.81	37.30
14	15.8 +/- 16.3	34.61	49.83	19.5 +/- 15.7	21.28	34.53	20.3 +/- 16.3	19.06	33.93	16.4 +/- 16.3	32.67	47.78
15	12.5 +/- 14.0	41.98	58.74	17.0 +/- 12.9	18.20	36.40	22.5 +/- 15.7	7.78	21.11	13.0 +/- 14.0	39.65	56.52
16	48.5 +/- 27.4	6.23	10.55	25.8 +/- 23.6	17.18	30.59	42.9 +/- 28.0	9.84	17.33	46.3 +/- 27.8	7.50	12.91
17	17.3 +/- 14.4	20.90	38.78	18.9 +/- 16.6	21.89	43.79	18.5 +/- 13.2	18.00	34.15	17.6 +/- 14.2	20.30	37.89
18	21.8 +/- 18.3	22.07	36.05	23.6 +/- 15.3	11.11	21.48	22.6 +/- 14.0	6.43	22.86	21.8 +/- 18.1	21.24	35.18
19	35.9 +/- 20.7	5.83	11.63	29.3 +/- 19.8	8.69	18.32	21.3 +/- 17.7	17.19	31.77	33.1 +/- 20.7	7.23	14.67

From Figure 6.1, it can be noted that there were outliers for the RR estimation errors for all patients. Also, the median error is close to zero for all patients except for Patient 13, Patient 16, Patient 17, Patient 18 and Patient 19. For these four patients, the method has essentially failed to estimate RR.

Figure 6.1: RR estimate errors of best method for all patients on clean data

From Figure 6.2, it can be seen that, for data with movement, the median of the error is below zero for most of the patients. This indicates a tendency for under estimation of RR during periods of patient movement.

Figure 6.2: RR estimate errors of best method for all patients on data with movement

For data with interventions, the box for the errors is wide for most patients as seen in Figure 6.3. The median error is also far from zero for most patients. This indicates the RR estimation method has relatively poor performance during interventions.

Figure 6.3: RR estimate errors of best method for all patients on data with interventions

The plot of RR estimation errors for all conditions in Figure 6.4, is similar to that of Figure 6.1, since most samples are from clean data and therefore these results dominate the aggregate statistics.

Figure 6.4: RR estimate errors of best method for all patients on all data

6.3.1 Exploring Signal Energy as a Factor in RR Estimation Error

To explore why the RR estimation method performed very poorly for some patients, while somewhat robustly for others, Figure 6.5 and Figure 6.6 show scatter plots of signal energy vs. RR estimation error for all data points, where a point is an individual RR estimation from 10 s of data. Each data point is colored by the Patient ID. It can be observed that the signal energy for Patient 19, Patient 18, and Patient 16 are much lower when compared to the other patients. It is also key to note that these same patients have the highest variance of RR errors. On the other hand, from Figure 6.6, it can be seen that Patient 1 and Patient 5 have higher signal energy and smaller RR errors.

Figure 6.5: Signal energy vs RR error for all patients

Figure 6.6: Signal energy vs RR error for all patients (zoomed view)

6.4 Discussion

It can be seen from Table 6.1, that the best RR estimation method performed well on Patient 1, Patient 5 and Patient 11, achieving MAE metrics of 3.9 ± 6.6 bpm, 7.3 ± 9.6 bpm and 11.2 ± 12.3 bpm respectively, on clean data. PAE₁₀ was 89.70% for Patient 1, 77.27% for Patient 5 and 61.13% for Patient 11. Since Patient 1 was using artificial ventilator, it was expected that the RR signal from the PSM would be stronger leading to good RR estimation. Both Patient 5 and Patient 11, were breathing without any artificial support.

For patients who were breathing without ventilator support, better performance was observed for clean data, with higher MAE for data with patient movements and interventions. For data with patient movements, the median of the RR estimation error was below zero for most patients. This indicates, the method has a tendency to under estimate RR during movements. This insight can be used for future work to investigate improved approaches for signal extraction, signal enhancement and RR estimation.

For Patient 16, Patient 18 and Patient 19, the RR estimation method resulted in a large error. It was observed that the breathing signal energy was much lower for these patients as compared to the others. Patient 16 had a weight of 3460 g and was on overhead warmer bed. Both Patient 18 and Patient 19 were on incubator bed and weigh only 1290 and 1604 g. Both patients weigh much less than the average weight of all patients, which was 2687 g. Since all three patients had a weak breathing signal, one plausible explanation for the source of error is the amount of extra layers of blanket that may have been present between the patient body and the PSM. This does indeed appear to be the case, and was confirmed

by inspecting the video data for all three patients. The exact height or firmness of the bedding between the patient and the PSM is not known since it was not controlled in the experiment design. In practical situations, nurses often find it necessary to add bedding to adjust the comfort of the patient. However, for future experiments, the thickness of the bedding under the patient could be quantified and included in the analysis. These results show that, when RR measurement system using PSM is deployed in the NICU, it is important for the system to provide feedback about the signal strength based on real-time conditions.

The observed PAE values are far below what would be required for clinical deployment of this solution. One would require the method to estimate RR within ± 5 bpm most of the time. These results reflect the difficulty of the problem. For example, in studies that estimate RR using PSM in adults, it is common to see SNR values greater than zero. In the present study, the typical SNR is far below zero, indicating that the strength of the respiration signal is extremely weak.

6.5 Conclusion

The overall performance of the best RR estimation method in terms of MAE and PAE was promising based on results observed from three patients. Large standard deviations for RR errors were observed for all three data conditions and all patients. This indicates, there is room for improvement in optimizing the parameters of the method to account for practical conditions.

In Chapter 7, a mixed effects limits of agreement analysis is presented to derive a 95% confidence interval for RR estimation and to identify factors that significantly contribute to estimation error.

Chapter 7: Mixed Effects Limits of Agreement Analysis

7.1 Introduction

The main objective of this chapter is to present a statistical approach for estimating 95% limits of agreement (LoA) between best RR estimation method from Chapter 5 and the patient monitor gold standard results across the data from all patients. In addition, a linear mixed effects model analysis is presented to identify significant factors that contribute to RR estimation error.

The Bland-Altman method of limits of agreement is a well-established method to assess how well measurements produced by two raters or devices agree with each other. This defines the extent to which they could be used interchangeably without causing any practical problems [59]. To compute the LoA, the differences between measurements by the two methods for each individual are obtained and the mean (m) and standard deviation (σ) of the differences are calculated. The 95% limits of agreement is then estimated as $[m - 1.96\sigma, m + 1.96\sigma]$. These limits are expected to contain the difference between measurements by the two methods for 95% of pairs of future measurements on similar individuals

A mixed effect limits of agreement analysis extends the traditional Bland-Altman method and makes it useful for deriving the LoA in the presence of multiple sources of variability [60]. This approach improves the generalizability of the confidence interval produced by the Bland-Altman method.

The observed difference (error) between measurements from two methods can be described using a linear regression model. The dependent variable for the model is the error and the independent (predictor) variables are factors that vary between each measurement. There are two types of predictor variables. The first type are systematic factors that can be controlled in the experiment, called fixed effects. An example fixed effect would be the bed mattress type used to measure data, where the bed mattress type would be varied systematically in the experiment design. The other type are non-systematic elements of the model that have no structure, called random effects. An example random effect would be the patient ID assigned to a particular time series, where the patient ID is not meaningful in the experiment design. A linear model that has both fixed and random effects is called a linear mixed effects model.

7.2 Method

The mixed effect LoA analysis presented here is based on the work by Parker *et al.* [60]. A 95% confidence interval (CI) is derived for agreement between RR estimation method developed in Chapter 5 with the gold standard RR estimates from commercial patient monitor.

7.2.1 Linear Mixed Effects Model Formula

The linear mixed effect model formula is as follows:

$$Y = X\beta + Zb + \varepsilon$$

Here for a total of N RR estimates, p fixed effects and, q random effects:

Y is $N \times 1$ vector of difference between estimate from RR method and gold standard RR

X is $N \times p$ matrix of fixed effect values

β is $p \times 1$ vector of fixed effects

Z is $N \times q$ matrix of random effect values

b is $q \times 1$ vector of random effects

ε is $N \times 1$ residuals vector

The model was fitted with seven fixed effects and one random effect. The list of fixed effects is as follows:

- i. *sex*: The gender of the patient. It has two possible values: male or female.
- ii. *bed*: The type of bed where the measurement is taken. It has three possible values: overhead warmer, crib and incubator.
- iii. *ventilation*: The ventilation mode for the patient. it has three possible values: room air, NIPPV, and conventional ventilator
- iv. *weight*: The weight of the patient in grams. This is a continuous value
- v. *movement*: The type of movement when the RR is estimated. This has three values similar to the groups of data from Chapter 4. They are, clean data, patient movement, and external intervention.
- vi. *snr*: This is the breathing signal SNR computed as per the description in Chapter 4.
- vii. *energy*: This is the raw extracted signal energy computed as per the description in Chapter 6.

The *patient* id was treated as a random effect. This was done to maximize generalizability of the results to the wider neonatal population as per the recommendations in [60].

Using Wilkinson notation [61], the mixed effects formula is described as follows:

$$rr_{error} \sim movement + sex + bed + weight + ventilation + snr + energy + (1|patient)$$

7.2.2 Linear Mixed Effects Model Assumptions

The assumptions for the linear mixed-effects model, along with the respective descriptions, are stated below [62]:

1. Linearity: The dependent variable, which is the RR error, is a linear combination of the independent variables (the effects).
2. Absence of Collinearity: The fixed effects should not be highly correlated with each other.
3. Homoscedasticity: The variance of the data should be approximately equal across the range of predicted values.
4. Normality of residuals: The residuals of the fitted model should have normal distribution.
5. Absence of influential data points: Data points that are outliers should be looked at carefully
6. Independence: The data points should be independent and, if there are multiple data points from the same Patient ID, then Patient ID should be included as a random effect to the model.

All of the assumptions of the linear mixed effect model are key for robust interpretation of the results. Linearity, absence of collinearity and independence assumptions can be addressed by design of the experiment. For the analysis discussed in this chapter, the five fixed effects have been selected so that they are not meaningfully correlated with each other. To satisfy the independence assumption, Patient ID has been included as a random effect in the model.

The homoscedasticity, normality of residuals, and absence of influential data points assumptions are discussed based on the results in the subsequent sections.

7.2.3 Limits of Agreement Calculation

The 95% LoA confidence interval lower and upper estimates are computed as follows:

$$CI_{lower} = m - 1.96\sigma$$

$$CI_{upper} = m + 1.96\sigma$$

The standard deviation (σ) is estimated from the fixed mixed effects model by combining the between patient variance (σ_1^2) and the within patient variance (σ_2^2) using the following formula:

$$\sigma^2 = \sigma_1^2 + \sigma_2^2$$

The mean bias (m) is estimated by fitting a separate mixed effects model that only includes the random effects.

7.3 Results

In this section, the RR estimation errors for all patients and the results from the fitted mixed effect model are presented, including the test for the model assumptions and statistical significance of effects.

7.3.1 Tests for Model Assumptions

The normality assumption can be tested from the histogram and normal probability plot of residuals as shown in Figure 7.1 and Figure 7.2. The results show a heavy tailed distribution. However, normality is the least important assumption for linear mixed effect model. Linear mixed effect models are known to be relatively robust against violation of normality assumption [62]. Therefore, the model can be useful, even if this assumption is not met.

Figure 7.1: Histogram of residuals for linear mixed effects model

Figure 7.2: Normal probability plot of residuals for linear mixed effects model

Homoscedasticity was tested by plotting the fitted values of the model against the residuals as shown in Figure 7.3. The plot has some stripes, indicating that the data used to fit the model has mostly categorical values. However, the values above and below zero for the residuals are roughly equal across the fitted values. For this reason, it can be concluded that there is no obvious violation of homoscedasticity assumption.

Figure 7.3: Residuals vs fitted values for linear mixed effects model

7.3.2 Results for Significance

The fitted linear mixed effects model archives R^2 value of 0.3831. The model was significant ($F(10, 193449) = 2341.0, p < 0.0001$).

The analysis of variance (ANOVA) for the mixed effects terms is presented in Table 7.1. For each fixed-effects term, an F-test is performed with the null hypothesis that all coefficients representing the fixed effect terms are 0. In the table, $FStat$ is the F-statistic and $DF1$ and $DF2$ are the degrees of freedom.

Table 7.1: Results of ANOVA for linear mixed effects model

<i>Fixed effect</i>	<i>FStat</i>	<i>DF1</i>	<i>DF2</i>	<i>p-value</i>
<i>movement</i>	1394.5	2	193450	0.0000
<i>sex</i>	0.3986	1	193450	0.5278
<i>bed</i>	1.1014	2	193450	0.3324
<i>weight</i>	0.0896	1	193450	0.7647
<i>ventilation</i>	1.6158	2	193450	0.1987
<i>snr</i>	12331	1	193450	0.0000
<i>energy</i>	5025.9	1	193450	0.0000

7.3.3 Limits of Agreement Results

The estimate for the between patient variance (σ_1^2) of the RR estimation error was derived from the mixed effects model to be 196.39. The within patient variance (σ_2^2) was estimated to be 445.21. The standard deviation to be used in the limits of agreement formula was then computed to be 25.32. The mean bias was estimated from the random effects model to be 3.5 bpm. The 95% CI was then computed to be [-46.1, 53.1] bpm.

7.4 Discussion

It can be noted from Table 7.1, *movement*, *snr* and *energy* effects can be considered to have significant contribution to explain RR estimation error ($p < 0.01$). The finding that energy is a significant factor in RR estimation error is consistent with the findings in Section 6.3.1.

The results indicate movement remains a significant factor for RR estimation error. As discussed in Chapter 2, there are a number of proposed methods for mitigation of movement artifacts on adult PSM data in the literature. Future improvement to the RR estimation method could adopt those methods and evaluate them on neonatal data.

It is interesting to note that SNR was found to be a significant factor to explain RR estimation error. This shows that the SNR improvement techniques presented in Chapter 5, for spatial downsampling, breathing signal selection, combining, and enhancement indeed have effect in reducing RR estimation error. However, the large standard deviation observed from the overall result, indicates there is still room for improvement in that regard.

The mean bias for RR estimation was 3.5 bpm, estimated from the random effects model. The derived 95% CI for RR estimation was, [-46.1, 53.1] bpm. This CI is very wide due mainly to the large standard deviation. This was not surprising, since similar variance was observed in Chapter 6 in the plots of RR estimation errors for all patients and data conditions.

The wide range obtained for the CI can be primarily explained by the variance of RR errors from the estimation method. The method estimates values close to gold standard when it works well, but sometimes produces high error levels due to the factors discussed above. One way to address this would be to produce a measure of confidence for RR estimation and suppress estimation during times when the confidence is too low. However, this may not be acceptable in clinical practice due to the requirement of continuous RR monitoring, especially if an alternative RR measurement device is not available.

7.5 Conclusion

A mixed effect limits of agreement analysis was conducted to derive a 95% CI for RR estimation method from PSM across data collected from 15 patients. The mixed effects model was designed with seven fixed effects and one random effect. The fixed effects were *movement*, *sex*, *bed*, *ventilation*, *weight*, *snr* and *energy*. The patient ID was represented using a random effect. The various assumptions required to apply the limits of agreement method using a mixed effects model were checked and verified to hold with the exception of normality. Violation of the normality assumption is not a significant issue, according to the literature.

Patient movement, SNR, and signal energy were found to be significant factors for explaining RR estimation error. The results were inconclusive for significance of the other fixed effects. The mean bias for RR estimation was estimated to be 3.5 bpm. The 95% CI for RR estimation was found to be [-46.1, 53.1] bpm. The CI was wide mainly due to the large standard deviation. Analysis presented in this chapter can be used as a framework for evaluation of future improvements to the RR estimation method focusing on the significant factors that were identified.

Chapter 8: Conclusions and Future Work

8.1 Conclusions

The objective of this thesis was to develop and evaluate methods for neonatal RR monitoring using data from a PSM. RR measurement using PSM has been previously studied for adult population. However, due to the difference in expected range of RR between neonates and adults, investigation was required to evaluate existing approaches on neonatal PSM data and develop new methods to identify and tackle factors that impose challenges for neonatal RR estimation such as patient movements and signal quality.

A clinical study was conducted collecting data from patients in the NICU. The data comprised pressure measurements using a PSM and bed side annotations of patient movements and clinical events. In addition, gold standard RR estimates exported from a commercial patient monitor were recorded and used for evaluation of RR estimation.

First, the breathing signal was extracted as the average pressure in each frame of PSM data over time. Then, the RR (in bpm) was estimated through time domain, frequency domain, and combined approaches. The results were evaluated separately on three conditions of data: clean data, data with patient movement and, data with interventions. The combined method showed better performance on all three data conditions in comparison to time domain and frequency domain methods. However, the errors were higher during times of patient movements and interventions indicating limitations with the method.

To improve the results, the PSM data were preprocessed using spatial downsampling, time windowing, reference signal selection, and signal enhancement. This allowed to fully leverage the spatial resolution of the PSM. After evaluating different scale parameters including full scale that includes all sensors, it was shown that spatial downsampling improves the SNR of the extracted breathing signal contributing to improved RR estimation. The best results were obtained for a scale of 0.2, resulting in 20 x 20 pseudo sensors after downsampling.

For reference signal selection, three methods proposed in literature were evaluated. These were band power method, amplitude method, and spectral ratio method. Among these, the band power method performed slightly better on all data conditions. Statistical significance of the observed differences could not be established due to the large observed variance.

For signal enhancement, a method that combines the top 5 sensors ranked by the signal selection criteria performed slightly better than the method that simply selects the best reference signal. Further restricting the supplementary sensors to be spatial neighbours of the reference signal did not produce further improvements.

In the end, the best method was presented that used spatial downsampling with scale of 0.2, band-power criteria for reference signal selection, the top 5 signals for signal enhancement, and the combined method for RR estimation. This method achieved a mean absolute error (MAE) of 3.92 $\pm$ 6.61 bpm on clean data without patient movements or interventions when the patient is on ventilator support. For this patient, 89.7% of RR estimates were within the clinically acceptable range of $\pm$ 10 bpm, while 78.4% fell within the more stringent limits of $\pm$ 5 bpm. Results over all 15 patients were less strong, with the median MAE among all 15 patients being 17.57 bpm. Although there was no bias in the RR estimation error, the variance

of the observed errors was very high. Retrospective analysis of the video for the patients presenting the largest RR estimation error seems to indicate that very low mass neonates and patients with extra bedding above the PSM are particularly challenging.

Finally, a mixed effects limits of agreement analysis was conducted comparing results from the best RR estimation method to the gold standard estimates, using data from all 15 patients. From the analysis, patient movement, SNR and signal energy were found to be a significant factor for explaining error in RR estimation. The mean bias was estimated to be 3.5 bpm, and the 95% CI was [-46.1, 53.1] bpm. A wide CI was obtained mainly due to the high standard deviation from RR estimation errors. This indicates room for improvement in the RR estimation method. However, the LoA analysis presented in this thesis can be used as framework for evaluation of future improvements to the RR estimation method.

8.2 Future Work

The work in this thesis has developed and evaluated methods for neonatal RR monitoring using PSM data. However, more work is needed to improve the variance in RR estimation error and agreement with the gold standard patient monitor. Recommendation for future work are presented in the following subsections.

8.2.1 Develop a Measure of Confidence

It was shown that SNR and signal energy are significant factors that explain the large variance in RR estimation error. A measure of confidence can be developed to take account of these factors and improve the reliability of RR estimation.

8.2.2 Investigate Minimum Sensor Density

It was shown that spatial downsampling helped to improve RR estimation. In this work, the downsampling was done, by weighted combination of all sensors. An alternative approach could apply strict subsampling. These approaches can be further investigated to determine the minimum sensor density required for RR estimation. This has cost saving advantages since a high density PSM comes with higher cost.

8.2.3 Combined Spatial and Temporal Breathing Signal Enhancement

It was shown that there is a delay between the breathing signal obtained from the reference sensor and nearby sensors on the PSM. Future work may look at beamforming approach for combining directional signals for signal enhancement since the pattern of delays may correspond with the physiology of breathing.

8.2.4 Creating Tailored Algorithms for Specific Conditions

The LOA results indicated that movement, snr, and energy were significant factors in determining RR estimation error. Once the data collection is complete and all 35 patients have been recorded, the LOA should be repeated. It is expected that, given more data, factors such as bed type or patient gestational age may emerge as significant factors. If so, then it may be worth developing custom algorithms for each bed type, etc.

Lastly, it was hypothesized that patients who are laying on multiple blankets present a challenge for RR estimation. This hypothesis can be further investigated by examining data from patients had changes in bedding depth during a single recording.

Appendices

Appendix A - Additional Chapter 4 Results

Here, results of evaluation of methods discussed in Chapter 4 on data from Patient 2 and Patient 5 are presented. While results are systematically inferior to those observed on Patient 1, the relative performance of each method is consistent with the results presented in Chapter 4.

A.1 Results from Patient 2

It should be noted that RR estimation results from patient 2 without the improvements discussed in Chapter 5 were unsatisfactory. From video data, it was confirmed that the patient was rolled up with extra sheets of blanket for most of the duration of the study resulting in a very weak pressure measurement.

Patient ID	Number of estimates			Total
	clean	movement	interventions	
2	12806	2477	1298	16581

Filtering Method	Mean SNR (dB) +/- Standard Deviation		
	clean	movement	interventions
NONE	-20.1 +/- 8.3	-25.6 +/- 8.5	-26.0 +/- 8.0
Low Pass (LP)	-20.5 +/- 10.9	-27.2 +/- 10.5	-28.8 +/- 10.8
Band Pass (BP)	-17.2 +/- 10.6	-21.3 +/- 11.2	-23.7 +/- 11.9

Method	MAE (bpm) +/- Standard Deviation		
	clean	movement	interventions
TIME	96.3 +/- 24.1	85.5 +/- 25.2	72.9 +/- 26.0
TIME_LP	38.0 +/- 23.5	23.4 +/- 17.6	23.8 +/- 18.6
TIME_BP	31.9 +/- 21.4	21.3 +/- 16.9	22.0 +/- 15.9
FREQ	32.1 +/- 26.6	44.8 +/- 23.1	57.8 +/- 30.8
FREQ_LP	32.1 +/- 25.0	45.0 +/- 23.0	56.1 +/- 24.1
FREQ_BP	15.9 +/- 18.7	25.3 +/- 21.9	35.5 +/- 24.5
COMB	220.8 +/- 130.7	176.1 +/- 126.2	140.7 +/- 112.1
COMB_LP	39.1 +/- 27.5	23.9 +/- 19.3	25.3 +/- 20.3
COMB_BP	31.8 +/- 24.0	21.4 +/- 18.0	23.5 +/- 17.3

Method	PAE (%)		
	clean	movement	interventions
TIME	0.15	0.24	0.38
TIME_LP	7.25	13.28	15.25
TIME_BP	10.1	16.59	16.18
FREQ	17.84	2.22	0.85
FREQ_LP	17.39	2.05	0.85
FREQ_BP	37.39	15.74	9.40
COMB	0.07	0.12	0.46
COMB_LP	10.69	14.73	15.02
COMB_BP	14.86	18.85	12.79

A.2 Results from Patient 5

Patient ID	Number of estimates			Total
	clean	movement	interventions	
5	11319	2335	1607	15261

Filtering Method	Mean SNR (dB) +/- Standard Deviation		
	clean	movement	interventions
NONE	-19.6 +/- 9.5	-22.9 +/- 10.5	-23.5 +/- 10.3
Low Pass (LP)	-20.4 +/- 12.0	-24.7 +/- 12.6	-25.9 +/- 13.1
Band Pass (BP)	-17.7 +/- 12.0	-20.4 +/- 12.6	-22.2 +/- 13.3

Method	MAE (bpm) +/- Standard Deviation		
	clean	movement	interventions
TIME	85.1 +/- 22.2	77.3 +/- 20.9	75.7 +/- 22.5
TIME_LP	23.2 +/- 21.1	11.7 +/- 12.6	13.0 +/- 12.9
TIME_BP	18.6 +/- 18.6	10.7 +/- 11.2	11.6 +/- 12.1
FREQ	30.7 +/- 28.9	36.7 +/- 26.1	43.6 +/- 27.0
FREQ_LP	29.9 +/- 26.7	36.9 +/- 26.0	43.8 +/- 26.84
FREQ_BP	14.2 +/- 190.1	20.9 +/- 19.5	24.4 +/- 21.4
COMB	185.0 +/- 131.5	148.0 +/- 120.4	132.5 +/- 115.4
COMB_LP	24.5 +/- 24.6	13.5 +/- 14.8	14.8 +/- 14.7
COMB_BP	19.4 +/- 21.1	12.1 +/- 12.6	13.8 +/- 13.7

Method	PAE (%)		
	clean	movement	interventions
TIME	0.28	0.17	0.18
TIME_LP	26.25	39.18	35.28
TIME_BP	32.56	42.65	40.07
FREQ	32.06	22.61	20.04
FREQ_LP	31.79	22.44	19.73
FREQ_BP	47.69	29.72	27.00
COMB	0.31	0.09	0.12
COMB_LP	30.60	38.15	34.22
COMB_BP	36.57	39.53	34.54

Appendix B Additional Chapter 5 Results

As with Appendix A, we here present the results from the analysis described in Chapter 5 on two additional patients: Patient 2 and Patient 5. Neither of these patients were on a ventilator. Although RR estimation error is higher for these patients than for Patient 1, the relative performance of each method is consistent with the results presented in Chapter 5.

B.1 Results from Patient 2

Patient ID	Number of estimates			Total
	clean	movement	interventions	
2	1200	1200	1200	3600

B.2 Results from Patient 5

Patient ID	Number of estimates			Total
	clean	movement	interventions	
5	1200	1200	1200	3600

Appendix C Results for Signal Enhancement with Distance Method

This Appendix presents the results of enhancing the reference sensor with the top-ranking supplementary sensors, as done in Chapter 5; however, the supplementary sensors are restricted to falling within a fixed Euclidean distance from the location of the reference sensor. This approach did not lead to significant improvement over the spatially unrestricted enhancement method reported in Chapter 5.

Appendix D Sample Case Report Form (CRF)

Study ID #: _____

Case Report Form

Pressure sensitive mats for patient monitoring in the NICU

Demographic information for the newborn:

Gender: ☐ Female ☐ Male

Gestational Age: ____ weeks ____ days

Weight at birth: ____ grams

Pressure mat testing: (data on day of pressure mat evaluation)

Age on day of evaluation: ____ days Weight on day of evaluation: ____ grams

Bed Type: ☐ Incubator ☐ Overhead warmer ☐ Crib

Sat probe position: ☐ Right Arm ☐ Right Leg ☐ Left Arm ☐ Left Leg

Monitor Alarm Limits:

Lower → Heart Rate: ____ Respiratory Rate: ____ Saturation: ____

Upper → Heart Rate: ____ Respiratory Rate: ____ Saturation: ____

Ventilation support:

Ventilation mode		Ventilation settings		
☐ Room Air		N/A		
☐ Nasal Prongs		lpm		
☐ CPAP		cm H2O		
☐ NIPPV		rate x PIP/PEEP		
☐ Ventilator →	☐ Conventional	Rate:	PIP:	PEEP:
	☐ HFO	MAP:	VG/Amp:	Freq:
	☐ HFJV	Rate:	PIP:	PEEP:

Include any medication which might affect patient movement/activity

Medication	Infusion vs bolus		Dose
☐ Fentanyl	☐ Infusion	☐ Bolus	
☐ Methadone	☐ Infusion	☐ Bolus	
☐ Midazolam	☐ Infusion	☐ Bolus	
☐ Morphine	☐ Infusion	☐ Bolus	
☐ Phenobarbital	☐ Infusion	☐ Bolus	
☐ Other: _____	☐ Infusion	☐ Bolus	
☐ Other: _____	☐ Infusion	☐ Bolus	

Major clinical diagnoses:

Appendix E Example Cases When RR Estimation Failed

E.1 Low Signal Energy

The plot below shows a sample signal from Patient 18, where the RR estimation error was - 23.1 bpm. The gold standard estimate for this case was 51.0 bpm. It can be noted that the amplitude of the reference breathing signal was less than 0.05 psi for most samples.

E.2 Movement Artifact

The plot below shows a sample signal from Patient 11, where the RR estimation error was -17.0 bpm. The gold standard estimate for this case was 69.0 bpm. It can be seen that a movement artifact between sample 115 and 140 dominates the breathing signal suppressing the peaks for RR estimation. One suggestion to avoid this would be to localize the movement artifact using techniques such as wavelet analysis and exclude it.

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