Navigation and Control of Flexible Wing UAV Using Vision System

by

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Abstract

This thesis presents an advanced guidance and control system for unmanned aerial vehicles (UAV) with flexible wing. The control system is based on a stereo vision system and advanced fuzzy logic algorithms that can detect wing deflections and shapes. In general, this sensor has the capability, reliability, and performance of similar traditional control sensors, and provides reliable visual information that is useful for designing different control systems. The thesis proposes a novel Deflection-Detection-Vision-System (DDVS) to control a flexible wing of unmanned aerial vehicle (UAV). The technique measure the deflection of the flexible wing with a stereo camera and determines the three-dimensional (3D) coordinates to identify the wing shape. In addition, the fuzzy logic algorithm classifies the shapes and determines the flight parameters, such as the speed, angle of attack and roll angle. Three different algorithms (homography, Iterative Closest Point (ICP), and Horns Absolute Orientation) were used to determine the pose estimation based on the vision system. Those techniques were tested on the HD Life-web camera with a moving baseline before using a stereo camera to find a suitable baseline and distance. The relations between the optimal baseline and depth distance are discussed, and several experiments with different image noise levels are performed to determine noise levels influence on distance and pose estimate accuracy. Measurements and estimation errors are provided and compared using different methods. The Deflection-Detection-Vision-System (DDVS) consists

of a stereo camera positioned at the back end of the wing structure that reads the deflection of chosen landmark locations on the flexible wing for each image instantaneously. The DDVS characteristics and dynamic parameters were tested in wind tunnel at speeds ranging from 11 to 31 m/s, angles of attack (AOA) from -20° to 20° and roll angles from -10° to 10° .

Controlling an autonomous UAV with flexible wing can be difficult using classical methods. Fundamentally, the model is a highly nonlinear, and in such cases, intelligent control strategies offer more suitable and advanced approach to designing a controller for the nonlinear system. An autopilot controller based on an intelligent controller known as the Adaptive Neuro-Fuzzy Inference System (ANFIS) algorithm was developed, and it applies the neural networks and fuzzy logic features in hybrid control architecture. To achieve optimal performance, three ANFIS modules were designed to control the altitude, heading angle and speed of the flexible wing UAV. The longitudinal motion controller and the inner loop (pitch rate feedback) of the longitudinal system are designed first, then a pitch tracker with an ANFIS controller is developed. The design of the altitude and speed controllers is related to the guidance and control system (outer loop controller) using the ANFIS controller design. The ANFIS controller performance is compared and evaluated with the Proportional-Integral-Derivative (PID) controller. The lateral motion control is performed by an inner loop controller, that includes roll rate feedback, and the roll tracker is done with ANFIS controller. The heading direction controller based on ANFIS was added to supplement the guidance and control of the unmanned aerial vehicles. The proposed ANFIS controller was chosen because it has better performance than the classic controller. The controllers performance was verified using experimental data, as well as, extensive computer simulation. An inertial sensor was used and compared with DDVS for a flexible wing. In this work, the data fusion algorithm was applied to estimate

the attitude for pitch and roll angles. The fusion algorithm based on Adaptive Unscented Kalman Filter (AUKF) was integrating measurements from an accelerometer sensor and DDVS. This method is prevented from diverging by an adaptive procedure based on fuzzy logic that modifies the noise characteristics and tuning factors of the weighted covariance. The results obtained from experiments and simulation show that, the performance of AUKF is better than that of regular UKF. Also it show high performance in both disturbance rejection and robustness against sensors noise.

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Table of Contents

Abstract	ii
Acknowledgments	v
Table of Contents	vi
List of Tables	x
List of Figures	xi
Nomenclature	xvi
1 Introduction	1
1.1 Power Hang Glider	1
1.2 Motivation	6
1.3 Contributions and Publication	6
1.4 Thesis Outline	9
2 Literature Review	10
2.1 Computer Vision for UAV	10
2.2 Classification of The Wing Shape	11
2.3 Adaptive Unscented Kalman filter (AUKF)	12
2.4 Control (autopilot)	13

3	Machine Vision	15
3.1	Introduction	15
3.2	Stereo Vision Camera	15
3.3	Feature Detection and Tracking	19
3.4	RANdom SAMple Consensus (RANSAC)	20
3.5	Homography	21
3.6	Homography Estimation	24
3.7	Decomposition of Homography Matrix	25
3.7.1	Fast Homography Decomposition Method	25
3.7.2	Iterative Closest Point Algorithm (ICP)	27
3.7.3	Horn's Absolute Orientation Method	29
4	Equations of motion	31
4.1	Introduction	31
4.2	Mathematical Modeling	31
4.2.1	The Forces and Moments of The Gravity	33
4.2.2	The Aerodynamic Forces and Moments	34
4.2.3	Longitudinal Control	37
4.2.4	Lateral Control	38
4.2.5	Total Aerodynamics With Thrust Force	39
4.3	Equation of Motion Equilibrium	40
5	Control System Design	43
5.1	Introduction	43
5.2	Longitudinal Control	44
5.2.1	Inner Loop Pitch Attitude Tracker Design	44
5.2.2	Outer Loop Altitude Hold Controller	45

5.2.3	Airspeed Hold Controller	46
5.3	Lateral Control	46
5.3.1	Inner Loops Roll Angle Hold Controller	46
5.3.2	Heading Hold Controller	47
5.4	Controllability and Observability	48
5.5	PID Controller	49
5.6	ANFIS Controller	51
5.7	Hybrid Learning Algorithm	53
6	Sensor Fusion	54
6.1	Introduction	54
6.2	Attitude Determination	54
6.3	Accelerometer	56
6.4	Sensor Fusion	58
6.5	Adaptive Kalman Filter (AUKF)	59
6.5.1	Unscented Kalman Filter	60
6.5.2	Fuzzy Logic Adaptive System (FLAS)	63
7	Experimental Setup and Results	65
7.1	Introduction	65
7.2	Machine Vision	65
7.2.1	Camera Calibration	67
7.2.2	The Error Functions	69
7.2.3	The Pose Measurements	70
7.3	Results of the Flexible Wing	74
7.3.1	Wing Shape	75
7.3.2	Feature Extraction	81

7.3.3	Extract Deflection using the Stereo Camera	81
7.3.4	Classifying Wing Shapes with Fuzzy Logic	91
7.3.5	Test and Validation	95
7.4	Sensor Fusion	99
7.5	Autopilot	105
7.5.1	Longitudinal Autopilot Simulation	105
7.5.2	Lateral Autopilot Simulation	116
7.6	Future Works	120
8	Conclusion	121
	List of References	132
	Appendix A Equivalent Aerodynamic Stability Derivatives	133

List of Tables

6.1	Accelerometer noise density from manufacture	58
7.1	Specification of Microsoft LifeCam HD-3000	66
7.2	Estimation of mobile robot position for all algorithms	72
7.3	Estimation of mobile robot position for two baselines	73
7.4	Estimation of flying robot position for two baselines	73
7.5	Test Results for AOA	86
7.6	Test Results for Roll angle	87
7.7	Nodes deflection over the both sides.	92
7.8	Fuzzy rules for the flexible wing at a positive deflection	93
7.9	Fuzzy rules for the flexible wing at a negative deflection.	93
7.10	Experimental results for attitude angles	97
7.11	The Fuzzy Rule	100
7.12	Time domain analysis of pitch angle	110
7.13	Time domain analysis of speed	110
7.14	Time domain analysis of roll angle	117
7.15	Time domain analysis of heading angle	118
A.1	The longitudinal derivatives for the wing	134
A.2	The lateral derivatives for the wing	135

List of Figures

1.1	A typical ultralight trike with a Profi-TL wing [2]	2
1.2	A side view of the engine and its propeller [2]	2
1.3	High performance wing [2]	3
1.4	The wing structure beneath the canvas [2]	3
1.5	Reference frames for wing, tricycle, and the main center of gravity	4
1.6	An x-y plane view of Profi-TL wing [6]	5
1.7	Flexible wing UAV	5
3.1	StereoLabs ZED camera	16
3.2	Stereo camera modeling	16
3.3	Mathematical model of a stereo vision	19
3.4	The geometry of a homography mapping	22
4.1	Longitudinal geometry	32
4.2	Lateral geometry	32
4.3	Longitudinal geometry	38
4.4	Lateral geometry	39
5.1	1 Longitudinal Guidance and Control System for pitch hold	45
5.2	Longitudinal Guidance and Control System for altitude hold	45
5.3	Longitudinal Guidance and Control System for speed hold	46
5.4	Lateral Guidance and Control System for roll hold	47

5.5	Lateral Guidance and Control System for heading hold	47
5.6	Block Diagram of PID Controller [76]	50
5.7	TSK fuzzy model [83]	51
5.8	Adaptive neuro fuzzy interference system structure	53
6.1	ADXL 330 accelerometer sensor	57
6.2	Arduino Uno R3 board	58
6.3	Block diagram of AUKF	59
6.4	The feedback control system for the flexible wing UAV	59
6.5	The input and output of FLAS	64
7.1	Camera calibration toolbox for MATLAB with a model chessboard Plane	67
7.2	Camera extrinsic parameters	68
7.3	Plot of the log error against the noise levels	70
7.4	Relative translation error via noise level	70
7.5	Initial and desired targets from front view	71
7.6	Initial and desired targets from top view	71
7.7	The Detection-Deflection Vision System(DDVS) for the flexible wing model	75
7.8	Back view of the flexible wing in wind tunnel	76
7.9	Front view of the flexible wing in wind tunnel	76
7.10	Features position	77
7.11	Shape of wing at $V=31\text{m/s}$	77
7.12	Shape of wing at $V=11\text{m/s}$ and $\text{AOA}=+20^\circ$	78
7.13	Shape of wing at $V=21\text{m/s}$ and $\text{AOA}=+20^\circ$	78
7.14	Shape of wing at $V=31\text{m/s}$ and $\text{AOA}=+20^\circ$	79
7.15	Shape of wing at $V=31\text{m/s}$ and $\text{AOA}=-20^\circ$	79

7.16	Shape of wing at $V=31\text{m/s}$, Roll angle= 10^0 and $\text{AOA}=+20^0$	80
7.17	Shape of wing at $V=11\text{m/s}$, Roll angle= -10^0 and $\text{AOA}=-20^0$	80
7.18	The matching of the feature points	81
7.19	Shape of wing at $\text{AOA}=0^0$ and roll angle $=0^0$	82
7.20	Shape of wing at $\text{AOA}=-20^0$ and roll angle $=0^0$	83
7.21	Shape of wing at $\text{AOA}=0^0$ and roll angle $=-10^0$	83
7.22	Shape of wing at $\text{AOA}=-20^0$ and roll angle $=-10^0$	84
7.23	Shape of wing at $\text{AOA}=20^0$ and roll angle $=-10^0$	84
7.24	Shape of wing at $\text{AOA}=20^0$ and roll angle $=0^0$	85
7.25	Tracking points along the experimental tests	88
7.26	Maximum deflection vs. AOA	89
7.27	Maximum deflection vs. speed at $\text{AOA}=-20$ deg.	90
7.28	Maximum deflection vs. speed at $\text{AOA}=0$ deg.	90
7.29	Maximum deflection vs. speed at $\text{AOA}=20$ deg.	91
7.30	Block diagram of Fuzzy logic	92
7.31	Membership function of the input node 1	93
7.32	Membership function of the input node 2	94
7.33	Membership function of the output wind speed	94
7.34	Membership function of the output AOA	94
7.35	Membership function of the output roll angle	95
7.36	Two sensor are fixed in flexible wing	96
7.37	Accelerometer sensor with Arduino board	96
7.38	Pitch error for the proposed DDVS, accelerometer and AUKF	98
7.39	Roll error for the proposed DDVS, accelerometer and AUKF	98
7.40	Covariance membership function of input variable	101
7.41	Mean value membership function of input variable	101

7.42	Membership function of output variable	101
7.43	Pitch angle estimation obtained from the UKF and the AUKF	103
7.44	Roll angle estimation obtained from the UKF and the AUKF	103
7.45	The error estimation of pitch angle	104
7.46	The error estimation of roll angle	104
7.47	Input variable "error" for pitch angle	106
7.48	Input variable "error change" for pitch angle	106
7.49	Output surface of fuzzy modules for pitch angle	107
7.50	Input variable "error" for altitude control	107
7.51	Input variable "error change" for altitude control	107
7.52	Output surface of fuzzy modules for altitude control	108
7.53	Input variable "error" for speed control	108
7.54	Input variable "error change" for speed control	108
7.55	Output surface of fuzzy modules for speed control	109
7.56	Pitch-hold longitudinal autopilot response	110
7.57	Altitude-hold longitudinal autopilot response	111
7.58	Speed-hold longitudinal autopilot response	111
7.59	ANFIS pitch controller for tracking different signal input	112
7.60	ANFIS altitude controller for tracking different altitudese	113
7.61	ANFIS speed controller for tracking different speeds	113
7.62	The effect of disturbance on pitch tracker	114
7.63	The effect of disturbance on altitude	115
7.64	The effect of disturbance on speed	115
7.65	Roll controller for tracking different angles	117
7.66	Heading controller for tracking different angles	118
7.67	The effect of disturbance on roll angle	119

7.68 The effect of disturbance on heading	119
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Nomenclature

- For machine vision in Chapter 3

b the baseline

d the disparity

d the distance between the origin camera to the plane

(f_x, f_y) the focal length in x and y directions

H Homography matrix

I_{xx}, I_{yy}, I_{xy} the convolution of the second-order image derivatives computed

k an intrinsic camera matrix

(m, m^*) the normalized Euclidean coordinate vector

n the surface normal vector

(p, p^*) the pixel coordinate vector

P_A, P_B frames A and B

(p, x) two frames

R rotation matrix

s a scale vector

t translation vector

T translation vector

(u, v) pixel point

u_o, v_o the principal point in term of pixel dimension

(X, Y, Z) coordinate system

α_i the scalar depth ratio

β the skew coefficient

μ center of mass

$\sum$ the cross-covariance

Subscripts

cl the left camera

cr the right camera

l left

r right

w world

- For Kalman filter in Chapter 6

$A(k)$ the transition matrix

$B(k)$ the control matrix

$H(k)$ the measurement matrix

K_k Kalman filter gain

P_x a covariance

P_{vv} innovation covariance

P_{xy} cross covariance

Q system noise covariance matrix

R observation noise covariance matrix

$u(k)$ the input vector

$v(k)$ the measurement noise

v mean of residuals

$x(k)$ the state vector

X the sigma points
 $w(k)$ the process noise
W weighted points
 $z(k)$ the measurement vector

α the softening factor
 β the Gaussian factor
 λ the scaling parameter
 μ the first parameter for DOD
 ξ the second parameter for DOD

- For the dynamic model in Chapter 4

b wing span (m)
c local cord (m)
 $\bar{c} = \frac{2}{S} \int_0^{\frac{b}{2}} c^2 dy$ = mean aerodynamic cord (m)
 c_g center of gravity
 $C_D = \frac{D}{\frac{1}{2}\rho S V^2}$ = drag Coefficient
 $C_L = \frac{L}{\frac{1}{2}\rho S V^2}$ = lift Coefficient
 $C_{l\beta}, C_{n\beta}$ sideslip derivatives
 C_{lp}, C_{np} wing rolling derivatives
 C_{lr}, C_{nr} wing yawing derivatives
 $C_l = \frac{L}{\frac{1}{2}\rho b S V^2}$ = rolling-moment coefficient
 $\bar{C}_m = \frac{M}{\frac{1}{2}\rho S \bar{c} V^2}$ = pitching moment Coefficient
 C_{mq} wing pitching derivative
 $C_T = \frac{T}{\frac{1}{2}\rho S V^2}$ = thrust Coefficient

C_n	$\frac{N}{\frac{1}{2}\rho bSV^2}$ =yawing-moment coefficient
C_{wo}	$\frac{mg}{\frac{1}{2}\rho Su_o^2}$ =yawing-moment coefficient
C_x	$C_T + C_L\alpha_x - C_D$
C_z	$-(C_L + C_D\alpha_x)$
D	Drag (N)
I_x	$\int y^2 + z^2 dm$ =moment of inertia about x-axis ($kg.m^2$)
I_y	$\int x^2 + z^2 dm$ =moment of inertia about y-axis ($kg.m^2$)
I_z	$\int y^2 + x^2 dm$ =moment of inertia about z-axis ($kg.m^2$)
$I_{yz} = I_{zy}$	$\int yz dm$ =product of Inertia ($kg.m^2$)
$I_{xz} = I_{xy}$	$\int xz dm$ =product of Inertia ($kg.m^2$)
$I_{yx} = I_{xy}$	$\int yx dm$ =product of Inertia ($kg.m^2$)
L	lift (N)
L	rolling moment (N.m)
m	mass (kg)
M	pitching moment (N.m)
N	yawing moment (N.m)
p	roll rate (rad/s)
q	pitch rate (rad/s)
r	yaw rate (rad/s)
S	wing area (m^2)
u	axial velocity (m/s)
v	lateral velocity (m/s)
V_e	reference equilibrium airspeed (m/s)
w	normal velocity (m/s)
T	thrust (N)
(X,Y,Z)	component of resultant aerodynamic force (N)

α angle of attach(AOA) (radians)
 β sideslip angle (radians)
 δ longitudinal control angle (radians)
 δ_{th} thrust Control
 ρ air density (kg/m^3)
 (θ, ϕ, ψ) euler angles (radians)
 ξ lateral control angle (radians)

Subscripts

a aerodynamic
 c carriage or tricycle
 e equilibrium
 o the reference flight condition
 w wing

ABBREVIATION DEFINITIONS

<i>ANFIS</i>	<i>Adaptive Neuro – Fuzzy Inference System</i>
<i>AOA</i>	<i>Angle of attack</i>
<i>AUKF</i>	<i>Adaptive Unscented Kalman Filter</i>
<i>DDVS</i>	<i>Deflection – Detection Vision System</i>
<i>DLT</i>	<i>Direct Linear Transform</i>
<i>DOD</i>	<i>Degree of Divergence</i>
<i>EKF</i>	<i>Extended Kalman Filter</i>
<i>FLAS</i>	<i>Fuzzy Logic Adaptive System</i>
<i>ICP</i>	<i>Iterative Closest Point</i>
<i>PID</i>	<i>Proportional – Integral – Derivative</i>
<i>RANSAC</i>	<i>RANdom SAmples Consensus</i>
<i>SURF</i>	<i>Speeded Up Robust Features</i>
<i>UKF</i>	<i>Unscented Kalman Filter</i>
<i>UT</i>	<i>Unscented Transformation</i>

Chapter 1

Introduction

1.1 Power Hang Glider

Powered hang gliders, also known as ultralight trikes, flex-wing trikes, microlight trikes, or microlights, have attracted great attention in the air sports community since the 1980s. Recently, commercial companies and the military have shown interest in them as they are relatively affordable and have low maintenance and performance costs. These aerial vehicles can carry the pilot and one passengers, and are equipped with simple flight instruments for navigation. The ultralight trike structure and flight control principles are similar to non-motorized hang gliders, previously invented and patented by Francis Rogallo in 1948 [1]. However, ultralight trikes have a fuselage usually the shape of a trike that is suspended from the airframe and at the wing's center of gravity, as shown in Fig. 1.1.

A propeller is connected to an engine at the back of the vehicle to create thrust, as illustrated in Fig. 1.2. Thus, the pilot does not need to launch downhill as it is possible to take-off from level ground. Compared to a hang glider, the high-performance wing of an ultralight trike is to larger, with a stronger composite frame of cables, tubes, and canvas to maintain the wing configuration and handle the extra weight, as shown

in Fig. 1.3 and 1.4.

A regular fixed-wing aircraft is controlled [2] by the pilot, who can control the motion about the x , y and z axes during the flight. Longitudinal rotation (angular displacement about the x axis (roll) is the primary task of ailerons on the outer rear of each wing that can move up and down, while the rotation about the y axis (pitch) is governed by the lift wing (elevator) on the horizontal tail surface tilting up or down.

Figure 1.1: A typical ultralight trike with a Profi-TL wing [2]

Figure 1.2: A side view of the engine and its propeller [2]

Vertical rotation around the z axis (yaw) is controlled by tuning the vertical tail fin (rudder) side to side [3]. The control principles for an ultralight trike are quite different than those of fixed-wing aircraft, since an ultralight trike has no ailerons, elevators or rudders connected to the flight control mechanisms. It is controlled by simple weight shifts applied by the pilot (Fig. 1.5).

Figure 1.3: High performance wing [2]

Figure 1.4: The wing structure beneath the canvas [2]

Figure 1.5: Reference frames for wing, tricycle, and the main center of gravity

In the proposed model, the weight of the fuselage is the sum of weights of pilot, engine, seats, onboard instruments, fuel tank, propeller, and other devices or equipment attached to the fuselage. For example, moving the control bar to the left shifts the weight of the fuselage to the right and the center of gravity to the left, which changes the aerodynamic moment of the vehicle. Likewise, when the pilot moves the control bar to the right, the total suspending weight is shifted to the left. The side-to-side movement of the control bar allows the vehicle to perform roll task, that is, to rotate around the x axis. There are also responses when the control bar is shifted forward or backward, as this causes the vehicle to pitch (i.e. rotate about y axis) when taking-off, landing or changing altitude during flight [4].

There is no yaw control in the flight control mechanism, so to return to equilibrium the pilot must rely on the natural stability of the wing when simultaneously moving the control bar side-to-side and forward-to-backward [5]. Deriving the motion

Figure 1.6: An x-y plane view of Profi-TL wing [6]

Figure 1.7: Flexible wing UAV

equations is a key step in following a systematic approach to design a control motion algorithm for unmanned ultralight trike control in flight, which is the ultimate goal of this project. At this point, however, the main focus will be to develop the kinetics of this aerial vehicle, and derive the equilibrium governing equations of motion for an ultralight trike with a *Profi TL* wing and a hand-made trike, as illustrated in Fig. 1.6 and 1.7 [6].

1.2 Motivation

The primary aim of this thesis is to develop and implement a method or system that can visually guide and control a UAV. The extensive information that collected by a camera can be used for accurate high performance UAV control, navigation, guidance and tracking, and this data can be applied to the feedback of an aircraft's performance and behavior. The performance requirements to control a power hang glider vary as functions of the flight conditions (e.g. speed, altitude) and pilot commands. Intelligent control for a flexible wing UAV based on Deflection-Detection-Vision-System (DDVS) has been demonstrated, and it involves four different steps. First, a stereo camera identifies the shape of the wing; second, the wing shape is classify by fuzzy logic; third, the design, implementation and testing is conducted on the longitudinal and lateral autopilots for various stages of the flight; and finally, the sensor fusion is adapted to calculate attitude estimation by integrating the reference data collected from DDVS and the measurement data from the accelerometer, based on the Adaptive Unscented Kalman Filter (AUKF). This algorithm is designing to optimize the robust proposal method (DDVS) for pitch and roll angles.

1.3 Contributions and Publication

The main contributions of this thesis are summarized below:

1. Development of the Deflection-Detection-Vision-System (DDVS) that can be controlled from a platform using machine vision only. The algorithm provides a method to control the flexible wing, depending on identification the wing shape.
2. The three-dimensional (3D) pose estimation based on the stereo camera has been proposed and validated. The 3D point for an object (landmark) with

respect to the camera coordinate system (the relative position and attitude of the UAV with respect to landmarks) is obtained by using three methods (a fast Homography decomposition technique, Iterative Closest Point (ICP) and Horns Absolute Orientation).

3. A novel approach for determining wing shape and classification by employing machine vision and fuzzy logic to create a simple tool. This approach is a system that measures the wing deflection based on DDVS. Fuzzy logic is used to classify the wing shape and optimize particular flight performance criteria.
4. In this work, the longitudinal and lateral autopilots are implemented based on the Adaptive Neuro-Fuzzy Inference System (ANFIS) controller trained to learn and predict the responses of the UAV from the history of response and control signals.
5. A sensor fusion has been designed to verify the DDVS method, and to estimate the attitude angles using the Adaptive Unscented Kalman Filter (AUKF).

The publication related to this thesis work is listed below:

- Malik M. A. Al-Isawi, and J. Z. Sasiadek, Pose Estimation for Mobile Robot via Visual Navigation, Proceedings of the CARO3 3rd Conference on Aerospace Robotics, November 2015 and accepted for publication in Aerospace Robotics III, published by Springer Publishers.
- Malik M. A. Al-Isawi, and J. Z. Sasiadek, Navigation and Control of a Space Robot Capturing Moving Target, Proceedings of the RoMoCo17 The 11 International Workshop on Robot Motion and Control, 3-5 July 2017.
- Malik M. A. Al-Isawi, and J. Z. Sasiadek, Control of Flexible Wing UAV Using Stereo Camera, accepted for publication in Aerospace Robotics III, published by Springer Publishers.
- Malik M. A. Al-Isawi, and J. Z. Sasiadek, Guidance and Control of Autonomous, Flexible Wing UAV with Advanced Vision System, Proceeding of IEEE MMAR Conference in 2018.
- Malik M. A. Al-Isawi, and J. Z. Sasiadek, Guidance and Control of a Robot Capturing an Uncooperative Space Target, Journal of Intelligent and Robotic Systems (JIRS) 2018.

1.4 Thesis Outline

Chapter 2 presents a literature review of the computer vision, classification, adaptive Kalman filter and autopilot design.

Chapter 3 reviews the computer vision processing algorithms used for visual matching and tracking. It also explains how these algorithms are employed for the robust projective transformations estimation used to obtain the pose estimation.

Chapter 4 presents the modeling of hang glider based on the Newton-Euler formalism.

Chapter 5 discusses the longitudinal and lateral control system for a UAV, and explains the ANFIS controller.

Chapter 6 presents a sensor fusion to estimate and integrate different types of data using AUKF.

Chapter 7 highlights the experimental tests and results using a single camera and a stereo camera. It shows results for a novel system DDVS that classifies the wing shape to obtain the state vector of the UAV. An autopilot for both longitudinal and lateral motion control is designed and tested. Finally, sensor fusion integration for DDVS/ accelerometers data are shown and applied for the attitude control of UAV. Future work are suggested.

Chapter 8 includes the conclusions .

Chapter 2

Literature Review

2.1 Computer Vision for UAV

Computer vision has proven to be a powerful and low-cost sensor that is useful for many applications in robotics and control systems, and new approaches are continually being developed that reduce cost, size and weight, while increasing the capacity to acquire and process high-resolution images with adequate frequency for use in control systems on mobile and flying robotics. Several recent studies have focused on pose estimation or shape determination for many applications. The vision-based pose estimation technique evaluates and calculates relative translations and rotations of two images for the same target. The authors in [7] and [8] propose methods to reconstruct the camera's pose with respect to an object based on an accurate geometric model of the object. The pose estimation from homography and the investigation of measurement errors are shown in [9], and the general homography decomposition to evaluate robotic motion was used by [10]. Faugeras and Lustman [11] described a more specific decomposition of the homography when a robot is moving on a planar surface. Both approaches provide two possible solutions for the camera pose. A new algorithm for relative pose estimation between two images based on new decomposition was

proposed in [12]. The Iterative Closest Point (ICP) algorithm was used in [13] to estimate position and attitude based on 3D data, and the mathematical preliminaries of computing the closest point were shown in [14]. The performance was achieved with three different focal lengths. A closed-form solution for three or more points using unit quaternions was presented in [15]. The pose estimation for UAV pose estimation is shown in [16]. This algorithm allows accurate navigation when a GPS is absent, by using a stereo camera in UAV. The authors in [17] developed a new algorithm based on Extended Kalman Filter (EKF) for Pose estimation, and applied it to aerial UAV refueling in serious turbulence. A new algorithm for the Minimum number of points Linear pose estimation with known Zenith direction (MLZ) was presented by [18]. This algorithm estimated the pose of a camera with a known gravity vector.

2.2 Classification of The Wing Shape

The Fuzzy Logic control (FLC) has conducted some limited research regarding classifying deflections and control of a flexible wing using a vision system. Some of the work involved aerodynamic coefficients and the aeroelasticity of flying, and the authors in [19] focused on static aeroelasticity of flying wings. A theoretical study of dynamic response estimation of a highly flexible flying-wing are described in [20]. Aerodynamic coefficients and structural displacements from wind tunnel tests are presented in [21], and wing flexibility on a Micro Air Vehicles (MAV) is also investigated. The videogrammetry technique presented in [22] studied the deformation and attitude of static and dynamic wings in a wind-tunnel model, and non-contact videogrammetry techniques measured the dynamic behavior of flexible mini-UAV wings in wind tunnel tests [23]. The authors in [24] proposed a wing twist technique based on camera photogrammetrics, studies structure deformation and collected measurement data in

flight tests using digital image correlation [25]. Static aeroelasticity was also measured and discussed by [26]. In addition, the uncertainty of videogrammetric techniques was applied to wind tunnel models, and fuzzy logic implemented by [27] was used to find the surface deflections of a flexible wing to achieve the desired roll angle.

2.3 Adaptive Unscented Kalman filter (AUKF)

Many researchers focused their efforts on guidance and navigation aspects, and a navigation technique based on a visual servoing system combined with a six degree of freedom (DOF) robotic manipulator was used to capture a moving target [28]. A novel concept to identify a moving object and its trajectory design in space was presented in [29], [30], and [31], and focused on capturing an autonomous satellite using a visual servoing system. The pose of a large non-cooperative target was determined in [32] by using two cameras to facilitate recognition of a selected rectangular feature object.

The Unscented Kalman filter (UKF) based on a neural network (NN) algorithm was developed in [33], and these were integrated to estimate nonlinear states to enhance a nonlinear dynamic model. A novel adaptive UKF (AUKF) was developed by [34], and applied to nonlinear joint estimation for time-varying states and parameters. This algorithm was based on a cost function that determined the error between the covariance matrices of innovation and their corresponding estimates. The authors in [35] presented a new robust adaptive UKF that corrects the process noise covariance or measurement noise covariance, depending on the type of fault. The algorithm was applied to the attitude estimate of a pico satellite, and the orientation estimate of aircraft and UAV based on the AUKF presented in [36]. The proposed filter estimates the acceleration generated over regular cruising flights, and can predict the roll and pitch orientation angles with reasonable accuracy.

2.4 Control (autopilot)

Today, UAVs are becoming more useful due to their advantages for civil and military applications. Different control techniques have been successfully developed and verified for UAV flight control systems, including optimal control, predictive control, adaptive control and robust control [37], [38]. The most popular techniques has been a proportional-integral-derivative controller (PID), and analytical methods are used to tune the conventional structure of PID controller [39]. The author in [40] presents a new approach to control, stabilize and disturbance rejection of the attitude subsystem of a quadrotor. A self-tuned PID is used to design the controller of an autopilot based on the longitudinal for altitude and speed and lateral motion for heading angle of an Aerosonde UAV.

The fuzzy logic approach has the potential to compensate for the effects of non-linearity and uncertainty, and it provides strong robustness independent of the mathematical model of a system. In addition, designing a fuzzy logic controller is fast and simple and it is easily maintained because the rules can be understood and explained by human experts [41]. Autonomous UAV such as helicopters have been the most popular robotic platforms, as they are easy to control for vertical take-off and landing, as well as for stable flight [42], [43]. In [44], a stable gain-scheduling PID controller based on the grid point concept was developed for nonlinear systems. The autopilot controller provided more accurate tracking paths and robustness with respect to environmental disturbances, particularly wind. Small UAVs are highly sensitive to wind [45]. The fuzzy PID controller was developed to improve the longitudinal motion (pitch control) performance of the aircraft [46]. This paper focuses on how to combine the advantages of fuzzy control and PID control to improve the dynamic performance [47]. The longitudinal model of the Unmanned Aerial Vehicle (UAV) was

established and controlled using fuzzy PID [48], and the control strategies included velocity in inner loop and height in outer loop. The authors in [49] compared different controllers used with the dynamic model of a quadcopter platform. The controllers were an ITAE tuned PID, a classic Linear - Quadratic Regulator (LQR) and a PID tuned with an LQR loop. The conventional LQR method presented in [50] efficiently solved the problems of fixed-wing UAVs being disturbed by air current that reduce flight stability. Longitudinal control for a flying wing UAV based on LQR allowed it to achieve satisfactory longitudinal flying performance [51]. An Adaptive Neuro-Fuzzy Inference System (ANFIS) controller was developed to control the position of the UAV in 3D by adjusting the pitch and roll angles, and the throttle position. The ANFIS algorithm allows UAV to accomplish their mission autonomously [52]. Lateral controller developed by [53] used ANFIS to enhance performance, as ANFIS can approximate nonlinear functions, and doesn't need an accurate nonlinear model. ANFIS modules were designed and developed autonomous controllers to regulate the airspeed, heading angle and altitude of a fixed-wing UAV in longitudinal directional motion [54]. A direct heuristic dynamic programming (HDP) method using ANFIS was designed to control a hypersonic vehicle, and ANFIS was superior than neural networks with one-hidden-layer architectures, particularly when dealing with parametric uncertainties [55]. UAV performance was improved by using ANFIS techniques to a model of a low-cost vision UAV [56].

Chapter 3

Machine Vision

3.1 Introduction

This chapter introduces most of the image processing techniques for a variety of applications. First is a description of how pinhole and stereo cameras are modeled. Then feature detection and tracking methods are examined to determine the relevant interest feature points useful for identifying and tracking regions of interest in image sequences. Finally, different approaches to determine 3D pose are proposed.

3.2 Stereo Vision Camera

Stereo vision is a process to extract the depth of a 3-D scene from different points. A stereo camera is actually two cameras that are horizontally aligned, with a fixed distance known as the baseline. The ZED stereo camera as shown in Fig. [3.1](#) was selected to provide both vision and depth data, as can capture high-resolution side-by-side video on USB3. Furthermore, this camera is already calibrated has known intrinsic and extrinsic parameters, and its epipolar constraint can be used to reduce the time to search corresponding points in two images by searching only one line

Figure 3.1: StereoLabs ZED camera

Figure 3.2: Stereo camera modeling

in the image rather than the entire image [57]. This method can be computed by rectifying the homography between images so their epipolar lines are parallel and aligned, thereby making the search for corresponding points highly efficient. The mathematical model of stereo vision is as follows: Assume a feature point, F has the corresponding pixel points as the scene, F_l is the image formed on the left camera C_l and F_r is the image formed on the right camera C_r as shown in Fig. 3.2. The projection matrix can be given as:

- For the left camera

$$Z_l \begin{bmatrix} u_l \\ v_l \\ 1 \end{bmatrix} = \begin{bmatrix} f_x & \beta & u_0 \\ 0 & f_y & v_0 \\ 0 & 0 & 1 \end{bmatrix}_l \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} R & T \\ 0 & 1 \end{bmatrix}_l \begin{bmatrix} X \\ Y \\ Z \\ 1 \end{bmatrix}_w \quad (3.1)$$

or

$$Z_l \begin{bmatrix} u_l \\ v_l \\ 1 \end{bmatrix} = \begin{bmatrix} n_{11}^l & n_{12}^l & n_{13}^l & n_{14}^l \\ n_{21}^l & n_{22}^l & n_{23}^l & n_{24}^l \\ n_{31}^l & n_{32}^l & n_{33}^l & n_{34}^l \end{bmatrix} \begin{bmatrix} X \\ Y \\ Z \\ 1 \end{bmatrix}_w \quad (3.2)$$

Rearrange eq. 3.2

$$\begin{bmatrix} u_l n_{31}^l - n_{11}^l & u_l n_{32}^l - n_{12}^l & u_l n_{33}^l - n_{13}^l \\ v_l n_{31}^l - n_{21}^l & v_l n_{32}^l - n_{22}^l & v_l n_{33}^l - n_{23}^l \end{bmatrix} \begin{bmatrix} X \\ Y \\ Z \end{bmatrix} = \begin{bmatrix} -u_l n_{34}^l + n_{14}^l \\ -v_l n_{34}^l + n_{24}^l \end{bmatrix} \quad (3.3)$$

- For the right camera

$$Z_r \begin{bmatrix} u_r \\ v_r \\ 1 \end{bmatrix} = \begin{bmatrix} f_x & \beta & u_0 \\ 0 & f_y & v_0 \\ 0 & 0 & 1 \end{bmatrix}_r \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} R & T \\ 0 & 1 \end{bmatrix}_r \begin{bmatrix} X \\ Y \\ Z \\ 1 \end{bmatrix}_w \quad (3.4)$$

or

$$Z_r \begin{bmatrix} u_r \\ v_r \\ 1 \end{bmatrix} = \begin{bmatrix} n_{11}^r & n_{12}^r & n_{13}^r & n_{14}^r \\ n_{21}^r & n_{22}^r & n_{23}^r & n_{24}^r \\ n_{31}^r & n_{32}^r & n_{33}^r & n_{34}^r \end{bmatrix} \begin{bmatrix} X \\ Y \\ Z \\ 1 \end{bmatrix}_w \quad (3.5)$$

Rearrange eq. 3.5

$$\begin{bmatrix} u_r n_{31}^r - n_{11}^r & u_r n_{32}^r - n_{12}^r & u_r n_{33}^r - n_{13}^r \\ v_r n_{31}^r - n_{21}^r & v_r n_{32}^r - n_{22}^r & v_r n_{33}^r - n_{23}^r \end{bmatrix} \begin{bmatrix} X \\ Y \\ Z \end{bmatrix} = \begin{bmatrix} -u_r n_{34}^r + n_{14}^r \\ -v_r n_{34}^r + n_{24}^r \end{bmatrix} \quad (3.6)$$

where Z_l and Z_r are depth of left and right camera with respect to target.

The world coordinate system in Equation's 3.3 and 3.6 can be calculated with the least square method. The corresponding pixel points of F in the left and right images are at the same height, depending on the epipolar constraint as shown in Fig. 3.3. The depth equation can be derived based on the geometry of similar triangles,

Figure 3.3: Mathematical model of a stereo vision

$$Z = \frac{fb}{(x_l - x_r)} = \frac{fb}{d} \quad (3.7)$$

where b is the baseline, f is a focal length and d is the disparity. As the baseline and focal length of the stereo camera are known, the distance Z in the scene can be calculated based on the disparity between the two images. The corresponding points F_l and F_r are related by the homography matrix [58], [59].

3.3 Feature Detection and Tracking

Feature point detection is the first step in machine vision. It finds interest feature points in each frame, whereas the tracking of feature points refers to the corresponding of features from frame to frame [60]. Therefore, it is important to extract features from an image, such as corners, blobs and edges. The Speeded Up Robust Features (SURF) detection method developed by Bay et al. [61] is based on a Hessian matrix,

and since this matrix has robustness and computation speed method, it can be used to analyze local image structures. It is expressed in the form [62]:-

$$H = \begin{bmatrix} I_{xx} & I_{xy} \\ I_{xy} & I_{yy} \end{bmatrix} \quad (3.8)$$

where I_{xx} , I_{xy} , and I_{yy} are the convolution of the second-order image derivatives computed using the Gaussian function. To detect interest features, it searches for a subset of points where the derivative responses are high in two orthogonal directions, that is, the detector finds points where the determinant of the Hessian matrix has a local maximum.

3.4 RANdom SAmple Consensus (RANSAC)

RANSAC is an iterative method to estimate parameters of a mathematical model from a set of observed data which has outliers. It was introduced by Fischler and Bolles [63] using a set of data with a large number of outliers. According to [64] RANSAC is the most commonly used robust estimation method for homography. The idea behind the algorithm is simple. For several iterations, a random sample of four correspondences is selected, and the homography (H) is computed from them. All other correspondences are classified as inliers or outliers, depending on their concurrence with H. After the iterations are complete the iteration with the largest number of inliers is selected. H can then be recomputed from all the correspondence inliers in that iteration.

The RANSAC method can be summarized as:

1. Initialize the number of estimation, threshold and maximum inliers.

2. Calculate the number of iterations using the following equation [63], [65].

$$T = \frac{\log \epsilon}{\log(1 - q)} \quad (3.9)$$

where: ϵ is the probability of incorrect identification of the model, and q is calculated based on the following equation:

$$q = \left(\frac{N_i}{N}\right)^k \quad (3.10)$$

where N_i is the number of points that belong to the consensus set, N is the total number of points, and k is the minimal number of data necessary to clearly define the model.

3. Randomly select four feature pairs.
4. Check if these points are collinear, if so go to step 3.
5. Compute the homography H .
6. Compute the Euclidean distance between two points $d(H p_i, p_i^*)$
7. If $d \leq$ the threshold, then select the pairs that agree with the homography and record all the inliers.
8. Repeat steps 3 to 7 until the number of iteration has been reached.
9. Re-compute the H estimate using all the inliers.

3.5 Homography

Assume the camera is moving in the $x_i y_i$ plane and z axis is orthogonal to $x_i y_i$. The camera views four or more planar and non-collinear feature points lying in a plane in

Figure 3.4: The geometry of a homography mapping

front of the camera. The points expressed in frames (F and F^*) are denoted by $(x_i \ y_i \ z_i)$ and $(x_i^* \ y_i^* \ z_i^*) \in \mathbb{R}^3$ respectively [66], and the normalized Euclidean coordinate vector can be expressed by m and $m^* \in \mathbb{R}^3$.

$$m = \left[\frac{x_i}{z_i}, \frac{y_i}{z_i}, 1 \right]^T \quad \text{and} \quad m^* = \left[\frac{x_i^*}{z_i^*}, \frac{y_i^*}{z_i^*}, 1 \right]^T \quad (3.11)$$

As shown in Fig 3.4, the feature points m and m^* in frames (F and F^*) respectively are related by the homography matrix $H \in \mathbb{R}^{3 \times 3}$ [67] as:

$$m = \alpha_i H m^* \quad (3.12)$$

where $\alpha_i = \frac{z_i^*}{z_i}$, is the scalar depth ratio. From the projective geometry, the Euclidean coordinates for (m and m^*) can be expressed as image coordinates (pixel coordinates) as following:-

$$p = km \quad \text{and} \quad p^* = km^* \quad (3.13)$$

where $k \in R^{3 \times 3}$ is intrinsic camera matrix that can be determined by camera calibration [11]:-

$$k = \begin{bmatrix} f_x & \beta & u_0 \\ 0 & f_y & v_0 \\ 0 & 0 & 1 \end{bmatrix} \quad (3.14)$$

where (f_x, f_y) : are the focal lengths in the x and y directions, respectively. $(u_0$ and $v_0)$: are the coordinates of the principal point in terms of pixel dimensions. β is the skew coefficient between the cameras x and y axes, this is often zero. $(p_i$ and $p_i^*)$: are pixel coordinates of two images denoted by:

$$p = [u_i, v_i, 1]^T \quad \text{and} \quad p^* = [u_i^*, v_i^*, 1]^T \quad (3.15)$$

Using (3.13) in relation (3.12), we get

$$p_i = \alpha_i k H k^{-1} p_i^* = \alpha_i G p_i^* \quad (3.16)$$

$$H = k^{-1} G k \quad (3.17)$$

3.6 Homography Estimation

The pixel coordinates (p_i and p_i^*) for the two images denoted in Equation (3.15) and can be represented as [68], [69]:

$$\begin{bmatrix} u_i^* \\ v_i^* \\ 1 \end{bmatrix} = \begin{bmatrix} G_{11} & G_{12} & G_{13} \\ G_{21} & G_{22} & G_{23} \\ G_{31} & G_{32} & G_{33} \end{bmatrix} \begin{bmatrix} u_i \\ v_i \\ 1 \end{bmatrix} \quad (3.18)$$

$$u_i^* = \frac{G_{11}u_i + G_{12}v_i + G_{13}}{G_{31}u_i + G_{32}v_i + G_{33}} \quad (3.19)$$

$$v_i^* = \frac{G_{21}u_i + G_{22}v_i + G_{23}}{G_{31}u_i + G_{32}v_i + G_{33}} \quad (3.20)$$

Rearranging the equation above gives:-

$$A_i G = 0 \quad (3.21)$$

where $G = (G_{11}, G_{12}, G_{13}, G_{21}, G_{22}, G_{23}, G_{31}, G_{32}, G_{33})^T$ and,

$$A_i = \begin{bmatrix} u_i & v_i & 1 & 0 & 0 & 0 & -u_i u_i^* & -v_i u_i^* & -u_i^* \\ 0 & 0 & 0 & u_i & v_i & 1 & -u_i v_i^* & -v_i v_i^* & -v_i^* \end{bmatrix}$$

Since the homography matrix has eight degrees of freedom, at least four points on a plane are required to determine the homography up to a scale factor by solving (3.21) using the linear least square method.

3.7 Decomposition of Homography Matrix

The aim of this section is to extract information from the environment using the camera image, then determine the rotation and translation vectors from O to O^* with the homography matrix. There are several methods to decompose a homography matrix, and three different algorithms were used to explore the direct method for the vision system: fast Homography decomposition technique, Iterative Closest Point (ICP) and Horns Absolute Orientation. The Faugeras decomposition method is one of the most common methods [11].

3.7.1 Fast Homography Decomposition Method

The homography matrix H can be decomposed as:

$$H = R - \frac{t}{d}n^T \quad (3.22)$$

where $H \in R^{3 \times 3}$ is the homography matrix, and $R \in R^{3 \times 3}$ and $t \in R^3$ are the rotation matrix and the translation vector from O to O^* respectively. $d \in R$ is the distance between the origin camera and the plane π , and $n \in R^3$ is the surface normal vector to plane π as in [11], [67]: According to the planner motion of the camera, the rotation R and translation t can be written as follows:

$$R = \begin{bmatrix} \cos(\theta) & -\sin(\theta) & 0 \\ \sin(\theta) & \cos(\theta) & 0 \\ 0 & 0 & 1 \end{bmatrix} \quad (3.23)$$

$$T = \frac{t}{d} = \frac{1}{d} \begin{bmatrix} t_x & t_y & 0 \end{bmatrix}^T = \begin{bmatrix} T_1 & T_2 & 0 \end{bmatrix}^T \quad (3.24)$$

where $\theta \in R$ is the rotational angle around the z_i axis from O to O^* , t_x , and t_y are the translate along x_i and y_i respectively, and d is the distance from the origin of O to the reference plane π . The H matrix can be calculated by substituting (3.23 and 3.24) into (3.22) [58]:

$$H = \begin{bmatrix} \cos(\theta) + T_1 n_1 & -\sin(\theta) + T_1 n_2 & T_1 n_3 \\ \sin(\theta) + T_2 n_1 & \cos(\theta) + T_2 n_2 & T_2 n_3 \\ 0 & 0 & 1 \end{bmatrix} = \begin{bmatrix} h_{11} & h_{12} & h_{13} \\ h_{21} & h_{22} & h_{23} \\ 0 & 0 & 1 \end{bmatrix} \quad (3.25)$$

It is clear from (3.25) that the algorithm for homography decomposition will be divided into three cases, depending on h_{13} and h_{23} [58].

1. In case 1 $h_{13}^2 \neq 0, h_{23}^2 \neq 0$

$$T_1 = \epsilon_1 \sqrt{\frac{h_{13}^2[(h_{12} + h_{21})^2 + (h_{11} - h_{22})^2]}{h_{13}^2 + h_{23}^2}} + h_{13}^2 \quad (3.26)$$

$$T_2 = \epsilon_1 \text{sgn}(h_{23}, h_{13}) \sqrt{\frac{h_{23}^2[(h_{12} + h_{21})^2 + (h_{11} - h_{22})^2]}{h_{13}^2 + h_{23}^2}} + h_{23}^2 \quad (3.27)$$

where $\epsilon_1 = \mp 1$, two solutions of T can be selected according to [55], and we can compute the n vector in (3.22) as follows:

$$n_1 = \frac{t_1(h_{11} - h_{22}) + t_2(h_{12} + h_{21})}{t_1^2 + t_2^2} \quad (3.28)$$

$$n_2 = \frac{t_1(h_{12} + h_{21}) - t_2(h_{11} - h_{22})}{t_1^2 + t_2^2} \quad (3.29)$$

$$n_3 = \epsilon_1 \text{sgn}(h_{13}) \sqrt{\frac{h_{13}^2 + h_{23}^2}{t_1^2 + t_2^2}} \quad (3.30)$$

It is quite easy to calculate the rotation matrix from (3.22).

2. In case 2 $h_{13}^2 \neq 0, h_{23}^2 = 0$ or $h_{13}^2 = 0, h_{23}^2 \neq 0$

$$T_1 = \epsilon_1 \sqrt{\frac{h_{13}^2[(h_{12} + h_{21})^2 + (h_{11} - h_{22})^2]}{h_{13}^2 + h_{23}^2} + h_{13}^2} \quad (3.31)$$

$$T_2 = 0 \quad (3.32)$$

$$n_1 = \frac{(h_{11} - h_{22})}{t_1} \quad (3.33)$$

$$n_2 = \frac{(h_{12} + h_{21})}{t_1} \quad (3.34)$$

$$n_3 = \frac{h_{13}}{t_1} \quad (3.35)$$

we can also calculate the rotation matrix from (3.22).

3. In case 3 $h_{13}^2 = 0$, and $h_{23}^2 = 0$

we have: if $h_{11} = h_{22}$, and $h_{21} = -h_{12}$ then $T_1 = T_2 = 0$, and the homography degenerates to a rotation matrix. Otherwise, the decomposition degenerates to a simplified version of a 2 by 2 homography matrix. The Singular Value Decomposition (SVD) can be used to decompose the H matrix using the techniques similar to the Faugeras algorithm [11].

3.7.2 Iterative Closest Point Algorithm (ICP)

An ICP algorithm attempts to match two sets of points, one of which might be a reference image and another a set of data points describing the ranges to certain

points on an object. The ICP algorithm gives an estimate of camera translation and rotation between data taken from stereo images [13], [14]. The ICP algorithm is as follows:

A point set p of the source image point with N_p , and the destination points which become x with N_x are given

1. Compute the centers of mass for μ_p and μ_x :

$$\mu_p = \frac{1}{N_p} \sum_{i=1}^{N_p} p_i, \quad \mu_x = \frac{1}{N_x} \sum_{i=1}^{N_x} x_i \quad (3.36)$$

2. The cross-covariance is:

$$\sum px = \frac{1}{N_p} \sum_{i=1}^{N_p} [(p_i - \mu_p)](x_i - \mu_x)^T \quad (3.37)$$

3. The rotation matrix R is given by Singular Value Decomposition (SVD) of the matrix $\sum px$:

$$\sum px = USV^T, \text{ and } R = UV^T \quad (3.38)$$

4. The translation T associated with the transformation is:

$$T = \mu_x - R\mu_p \quad (3.39)$$

5. Terminate the iteration when the change in mean-square error falls below the threshold:

$$f(R, t) = \frac{1}{N_p} \sum_{i=1}^{N_p} ||x_i - Rp_i - T||^2 \quad (3.40)$$

6. Steps 1-5 are repeated until convergence is within the tolerance.

3.7.3 Horns Absolute Orientation Method

The transformation between two Cartesian coordinate systems can be considered the result of a rigid-body motion, and can thus be decomposed into rotation and translation. If the coordinates of the four points in each frame are $P_{A,i}$ and $P_{B,i}$, the mathematical relationship between these sets of points is [15]:

$$P_{A,i} = sR_{A/B}P_{B,i} + T_{A/B} \quad (3.41)$$

where s is a scale vector and $R_{A/B}$ and $T_{A/B}$ are rotation and translation matrices between frames A and frame B. The absolute orientation algorithm is as follow:

- Subtract the centroid of the point sets for both frames.

$$P_{A,i}^* = P_{A,i} - \sum_j P_{A,j}, \quad P_{B,i}^* = P_{B,i} - \sum_j P_{B,j} \quad (3.42)$$

- The intermediate matrices:

$$M = \begin{bmatrix} S_{xx} & S_{xy} & S_{xz} \\ S_{yx} & S_{yy} & S_{yz} \\ S_{zx} & S_{zy} & S_{zz} \end{bmatrix} = \sum_i P_{A,i}^* (P_{B,i}^*)^T \quad (3.43)$$

- and

$$N = \begin{bmatrix} S_{xx} + S_{yy} + S_{zz} & S_{yz} - S_{zy} & S_{zx} - S_{xz} & S_{xy} - S_{yx} \\ S_{yz} - S_{zy} & S_{xx} - S_{yy} - S_{zz} & S_{xy} + S_{yx} & S_{zx} + S_{xz} \\ S_{zx} - S_{xz} & S_{xy} + S_{yx} & -S_{xx} + S_{yy} - S_{zz} & S_{yz} + S_{zy} \\ S_{xy} - S_{yx} & S_{zx} + S_{xz} & S_{yz} + S_{zy} & -S_{xx} - S_{yy} + S_{zz} \end{bmatrix} \quad (3.44)$$

- The rotation between frames A and B is the quaternion matrix N which is the eigenvector corresponding to the maximum eigenvalue of N.
- The quaternion minimizes by the mean squared error function:

$$f = \sum_i \|P_{A,i} - sR_{A/B}P_{B,i} - T_{A/B}\|^2 \quad (3.45)$$

- The scale can be found as:

$$s = \frac{\sum_i \|P_{A,i}^*\|^2}{\sum_i \|P_{B,i}^*\|^2} \quad (3.46)$$

- The translation vector can be found by solving the last remaining variable in Equation (3.41).

Chapter 4

Equations of motion

4.1 Introduction

This chapter considers the mathematical models of a power hang glider (UAV). The model shown in Fig. 4.1 is a flexible multibody system that is subjected to gravity, aerodynamics, propulsion and control forces, and the bodies are broadly identified as the wing and the fuselage. There are two types of equations: kinematics and kinetics. Kinematics has to do with motion subjected to a general force, and kinetics examines the forces involved to produce motion. The equations of motion are linearized using perturbation theory, and the final results are state-space models of longitudinal and lateral motions.

4.2 Mathematical Modeling

The longitudinal geometry is shown in Fig. 4.1. an orthogonal fixed body axis system $oxyz$ is defined to the vehicle cg . It lies on the line that connects the wing's center of gravity (cg_w) that defined by the coordinates (X_w, Y_w, Z_w) and the center of gravity of the carriage (cg_c) is defined by coordinates (x_c, y_c, z_c) . In steady straight flight with

velocity V , the pitch attitude is θ , angle of attack is α and flight path angle γ . The longitudinal control angle δ_{long} is defined as the angle between the hang strap and a line parallel to the cg . The axial force X , normal force Z , thrust force T , and pitching moment M are shown in Fig. 4.1. The lateral geometry is shown in Fig. 4.2. However, the lateral control is δ_{lat} . Also the lateral side force Y , normal force Z and rolling moment L are shown in Fig. 4.2. The center of gravity changes when positioned on the line that connects the wing center of gravity and the fuselage center of gravity.

Figure 4.1: Longitudinal geometry

Figure 4.2: Lateral geometry

Calculation of the behavior of the system is based on all the forces exerted on different sections of the vehicle. The first step is to apply the inertia law for different frames of reference to determine a steady control phase. The equilibrium equations derived from [4] and modified for an ultralight trike are as follows: Linear and angular momentum rate changes are equal to the total external force and moment around the mass center of the ultralight trike, and can be defined as follows:

$$\begin{aligned}
 m(\dot{u} + qw) &= X_a + X_g \\
 m(\dot{v} - pw + ru) &= Y_a + Y_g \\
 m(\dot{w} + qu) &= Z_a + Z_g \\
 I_x \dot{p} - I_{xz} \dot{r} &= L_a + L_g \\
 I_y \dot{q} &= M_a + M_g \\
 I_z \dot{r} - I_{xz} \dot{p} &= N_a + N_g
 \end{aligned} \tag{4.1}$$

where m is the UAV mass, (I_x, I_y, I_z) are moments of inertia about the x, y, z axis, (L, M, N) are moments and (u, v, w) linear velocity and (p, q, r) are angular velocity.

The force and moment components can be further divided into two components gravitational and aerodynamic.

4.2.1 The Forces and Moments of The Gravity

$$\begin{aligned}
 X_g &= -mg(\sin\theta + \theta\cos\theta) \\
 Y_g &= mg(\psi\sin\theta + \phi\cos\theta) \\
 Z_g &= -mg(\theta\sin\theta - \cos\theta) \\
 L_g &= M_g = N_g = 0
 \end{aligned} \tag{4.2}$$

θ , ϕ , and ψ are aircraft pitch, roll, and yaw angles, respectively.

4.2.2 The Aerodynamic Forces and Moments

The components of aerodynamic force and moments of a hang glider at the center of gravity (cg) consist of steady trim and perturbation contributions as follows [72]

$$\begin{aligned}
X_a &= (X_w + X_c)_e + (X_w + X_c) \\
Y_a &= (Y_w + Y_c)_e + (Y_w + Y_c) \\
Z_a &= (Z_w + Z_c)_e + (Z_w + Z_c) \\
L_a &= (L_w + y_w Z_w - z_w Y_w)_e + (L_c + y_c Z_c - z_c Y_c)_e \\
&\quad + (L_w + y_w Z_w - z_w Y_w) + (L_c + y_c Z_c - z_c Y_c) \\
M_a &= (M_w - x_w Z_w + z_w X_w)_e + (M_c - x_c Z_c + z_c X_c)_e \\
&\quad + (M_w - x_w Z_w + z_w X_w) + (M_c - x_c Z_c + z_c X_c) \\
N_a &= (N_w + x_w Y_w - y_w X_w)_e + (N_c + x_c Y_c - y_c X_c)_e \\
&\quad + (N_w + x_w Y_w - y_w X_w) + (N_c + x_c Y_c - y_c X_c)
\end{aligned} \tag{4.3}$$

the subscripts w,c,and e refer to wing, trike, and steady equilibrium respectively.

The flight can be considered as a steady trimmed symmetric equilibrium, therefore:

$$\begin{aligned}
(Y_w = L_w = N_w)_e &= 0 \\
(Y_c = L_c = N_c)_e &= 0
\end{aligned} \tag{4.4}$$

Equation (4.3) is composed of two types of forces and moments that can be included: steady trim and perturbation contributions.

4.2.2.1 Steady equilibrium

By substituting Equation (4.4) in Equation (4.3), the equilibrium forces and moments can be determined as:

$$\begin{aligned}
(X_w + X_c)_e &= L_w \sin \alpha - (D_w + D_c) \cos \alpha \\
(Y_w + Y_c)_e &= 0 \\
(Z_w + Z_c)_e &= -L_w \cos \alpha - (D_w + D_c) \sin \alpha \\
(y_w Z_w + z_c Z_c)_e &= -y_w (L_w \cos \alpha + D_w \sin \alpha) - y_c D_c \sin \alpha \\
(M_w - x_w Z_w + z_w X_w)_e &+ (M_c - x_c Z_c + z_c X_c)_e = M_w \\
&+ (x_w D_w + z_w L_w + x_c D_c) \sin \alpha + (x_w L_w - z_w D_w + z_c D_c) \cos \alpha \\
(-y_w X_w + y_c X_c)_e &= -y_w (L_w \sin \alpha - D_w \cos \alpha) + y_c D_c \cos \alpha
\end{aligned} \tag{4.5}$$

4.2.2.2 Perturbation forces and moments

Small perturbations of the trim will generate unsteady aerodynamic forces and moments, which can be regarded as stability derivatives [4], [72]. Thus, perturbations of the wing are as follows:

$$\begin{aligned}
X_w &= \dot{X}_u u_w + \dot{X}_w w_w + \dot{X}_q q_w \\
Y_w &= \dot{Y}_v v_w + \dot{Y}_p p_w + \dot{Y}_r r_w \\
Z_w &= \dot{Z}_u u_w + \dot{Z}_w w_w + \dot{Z}_q q_w \\
L_w &= \dot{L}_v v_w + \dot{L}_p p_w + \dot{L}_r r_w \\
M_w &= \dot{M}_u u_w + \dot{M}_w w_w + \dot{M}_q q_w \\
N_w &= \dot{N}_v v_w + \dot{N}_p p_w + \dot{N}_r r_w
\end{aligned} \tag{4.6}$$

The perturbation velocities described in (4.6) with respect to the wing's reference

system are orthogonal at its center of gravity.

Accordingly, (4.6) can be expressed with respect to the trike (cg) as follows:

$$\begin{aligned}
 u_w &= u + qz_w \\
 v_w &= v - pz_w + rx_w \\
 w_w &= w - qx_w \\
 p_w &= p \\
 q_w &= q \\
 r_w &= r
 \end{aligned} \tag{4.7}$$

Substituting Equation(4.7) in Equation (4.6), will result in

$$\begin{aligned}
 X_w &= \dot{X}_u u + \dot{X}_w w + (z_w \dot{X}_u - x_w \dot{X}_w)q \\
 Y_w &= \dot{Y}_v v - z_w \dot{Y}_v p + x_w \dot{Y}_v r \\
 Z_w &= \dot{Z}_u u + \dot{Z}_w w + (\dot{Z}_q + z_w \dot{Z}_u - x_w \dot{Z}_w)q \\
 L_w &= \dot{L}_v v + (\dot{L}_p - z_w \dot{L}_v)p + (\dot{L}_r + x_w \dot{L}_v)r \\
 M_w &= \dot{M}_u u + \dot{M}_w w + (\dot{M}_q + z_w \dot{M}_u - x_w \dot{M}_w)q \\
 N_w &= \dot{N}_v v + (\dot{N}_p - z_w \dot{N}_v)p + (\dot{N}_r + x_w \dot{N}_v)r
 \end{aligned} \tag{4.8}$$

As with the derivatives for the wing in (4.8), the presence of the trike will affect the motion equation equilibrium. The derivatives are expressed as follows:

$$\dot{X}_q = \dot{Z}_q = \dot{Y}_p = \dot{Y}_r = 0$$

$$\dot{M}_u = \dot{M}_w = \dot{L}_v = \dot{L}_r = \dot{L}_p = \dot{N}_v = \dot{L}_p = 0$$

so,

$$\begin{aligned} X_c &= \dot{X}_u u + \dot{X}_w w + (z_c \dot{X}_u - x_c \dot{X}_w) q \\ Y_c &= \dot{Y}_v v - z_c \dot{Y}_v p + x_c \dot{Y}_v r \\ Z_c &= \dot{Z}_u u + \dot{Z}_w w + (z_c \dot{Z}_u - x_c \dot{Z}_w) q \\ L_c &= 0 \\ M_w &= \dot{M}_q q \\ N_w &= \dot{N}_r r \end{aligned} \tag{4.9}$$

Mathematically, it is more effective to express the equations in terms of longitudinal and lateral control angles (ζ, ξ) [4].

4.2.3 Longitudinal Control

The Longitudinal geometry of the wing is shown in Fig. 4.3.

$$\begin{aligned} x_w &= \frac{m_c}{m} (l_1 + l_2 \sin \delta_{long}) \\ x_c &= -\frac{m_w}{m} (l_1 + l_2 \sin \delta_{long}) \\ z_w &= -\frac{m_c}{m} l_2 \cos \delta_{long} \\ z_c &= \frac{m_w}{m} l_2 \cos \delta_{long} \end{aligned} \tag{4.10}$$

Figure 4.3: Longitudinal geometry

4.2.4 Lateral Control

The lateral geometry of wing is shown in Fig. 4.4.

$$\begin{aligned}
 y_w &= -\frac{m_c}{m} l_2 \cos \delta_{long} \sin \delta_{lat} \\
 y_c &= \frac{m_w}{m} l_2 \cos \delta_{long} \sin \delta_{lat} \\
 z_w &= -\frac{m_c}{m} l_2 \cos \delta_{long} \cos \delta_{lat} \\
 z_c &= \frac{m_w}{m} l_2 \cos \delta_{long} \cos \delta_{lat}
 \end{aligned} \tag{4.11}$$

If the control angles of the wing can be divided into a steady equilibrium term and perturbation, then it may be expressed as

$$\begin{aligned}
 \delta_{long} &= (\delta_{long})_e + \delta_{long} \\
 \delta_{lat} &= (\delta_{lat})_e + \delta_{lat}
 \end{aligned}$$

If the flight condition is a symmetric trim (i.e. $(\delta_{lat})_e = y_w = y_p = 0$), position of the wing and the tricycle can be expressed as

Figure 4.4: Lateral geometry

$$\begin{aligned}
 x_{we} + x_w &= \frac{m_c}{m}(l_1 + l_2 \sin(\delta_{long})_e + (l_2 \cos(\delta_{long})_e)\delta_{long}) \\
 x_{ce} + x_c &= -\frac{m_w}{m}(l_1 + l_2 \sin(\delta_{long})_e - (l_2 \cos(\delta_{long})_e)\delta_{long}) \\
 y_{we} + y_w &= -\frac{m_c}{m}(l_2 \cos(\delta_{long})_e)\delta_{lat} \\
 y_{ce} + y_c &= \frac{m_w}{m}(l_2 \cos(\delta_{long})_e)\delta_{lat} \\
 z_{we} + z_w &= \frac{m_c}{m}(-l_2 \cos(\delta_{long})_e + (l_2 \sin(\delta_{long})_e)\delta_{long}) \\
 z_{ce} + z_c &= -\frac{m_w}{m}(l_2 \cos(\delta_{long})_e - (l_2 \sin(\delta_{long})_e)\delta_{long})
 \end{aligned} \tag{4.12}$$

4.2.5 Total Aerodynamics With Thrust Force

The thrust force normally reacts to the trike center of gravity cg_c as illustrated in fig. 4.1. The total of the aerodynamic forces can be written as By substituting (4.10), (4.11), and (4.12) into (4.5), (4.8), and (4.9), and using Equation (4.3), we get:

$$\begin{aligned}
X_a &= L_w \sin\alpha - (D_w + D_c)\cos\alpha + \dot{X}_u u + \dot{X}_w w + \dot{X}_q q + \dot{X}_{\delta th} \delta_{th} \\
Y_a &= \dot{Y}_v v + \dot{Y}_p p + \dot{Y}_r r \\
Z_a &= -L_w \cos\alpha - (D_w + D_c)\sin\alpha + \dot{Z}_u u + \dot{Z}_w w + \dot{Z}_q q + \dot{Z}_{\delta th} \delta_{th} \\
L_a &= \dot{L}_v v + \dot{L}_p p + \dot{L}_r r + \dot{L}_\xi \xi + \dot{L}_{\delta th} \delta_{th} \\
M_a &= M_w + (x_w D_w + z_w L_w + x_c D_c)\sin\alpha + (x_w L_w - z_w D_w + z_c D_c)\cos\alpha \\
&\quad + \dot{M}_u u + \dot{M}_w w + \dot{M}_q q + \dot{M}_\delta \delta + \dot{M}_{\delta th} \delta_{th} \\
N_w &= \dot{N}_v v + \dot{N}_p p + \dot{N}_r r + \dot{N}_\xi \xi + \dot{N}_{\delta th} \delta_{th}
\end{aligned} \tag{4.13}$$

where,

$$\begin{aligned}
\dot{L}_\xi &= \frac{l_2}{m}(m_w Z_c - m_c Z_w)\cos\delta \\
\dot{M}_\delta &= \xi = \frac{l_2}{m}(m_w Z_c - m_c Z_w)\cos\delta + \xi + (m_w X_c - m_c X_w)\sin\delta \\
\dot{N}_\xi &= \frac{l_2}{m}(-m_w X_c + m_c X_w)\cos\delta \\
\dot{X}_{\delta th} &= X_{\delta th} \\
\dot{Z}_{\delta th} &= Z_{\delta th} \\
\dot{M}_{\delta th} &= -(z_p X_{\delta th} - x_p Z_{\delta th})
\end{aligned} \tag{4.14}$$

4.3 Equation of Motion Equilibrium

By substituting (4.2) and (4.13) into (4.1), the equation of motion for the wing and the trike can be written in the form of a matrix, as follows:

1. For the longitudinal motion

$$\begin{bmatrix} m & 0 & 0 & 0 \\ 0 & m & 0 & 0 \\ 0 & 0 & I_y & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} \dot{u} \\ \dot{w} \\ \dot{q} \\ \dot{\theta} \end{bmatrix} = A_{long} \begin{bmatrix} u \\ w \\ q \\ \theta \end{bmatrix} + B_{long} \begin{bmatrix} \delta_{long} \\ \delta_{th} \end{bmatrix} \quad (4.15)$$

where,

$$A_{long} = \begin{bmatrix} \dot{X}_u & \dot{X}_w & (\dot{X}_q - mw_e) & -mg \cos\theta_e \\ \dot{Z}_u & \dot{Z}_w & (\dot{Z}_q + mu_e) & -mg \sin\theta_e \\ \dot{M}_u & \dot{M}_w & \dot{M}_q & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix}$$

and

$$B_{long} = \begin{bmatrix} 0 & \dot{X}_{\delta th} \\ 0 & \dot{Z}_{\delta th} \\ \dot{M}_{\delta} & \dot{M}_{\delta th} \\ 0 & 0 \end{bmatrix}$$

2. For lateral motion are

$$\begin{bmatrix} m & 0 & 0 & 0 & 0 \\ 0 & I_x & -I_{xz} & 0 & 0 \\ 0 & -I_{xz} & I_z & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} \dot{v} \\ \dot{p} \\ \dot{r} \\ \dot{\phi} \\ \dot{\psi} \end{bmatrix} = A_{lat} \begin{bmatrix} v \\ p \\ r \\ \phi \\ \psi \end{bmatrix} + \begin{bmatrix} 0 \\ \dot{L}_\zeta \\ \dot{N}_\zeta \\ 0 \\ 0 \end{bmatrix} \delta_{lat} \quad (4.16)$$

where,

$$A_{lat} = \begin{bmatrix} \dot{Y}_v & (\dot{Y}_p + mw_e) & (\dot{Y}_r - mu_e) & mg \cos\theta_e & mg \sin\theta_e \\ \dot{L}_v & \dot{L}_p & \dot{L}_r & 0 & 0 \\ \dot{N}_v & \dot{N}_p & \dot{N}_r & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \end{bmatrix}$$

The coefficients for these equations and notions are shown in Appendix A.

Chapter 5

Control System Design

5.1 Introduction

One challenge when designing the UAV flight control system is development of a robust nonlinear control technique that can nullify the effect of uncertainties and external disturbances, particularly the wind. The autopilot is the most important function of the in the autonomous system, as it guides the UAV to complete missions. It controls all flight phases of the aircraft: take-off, climbing, level flight, descent, landing, and loitering. This chapter presents the design of the complete UAV autopilot system, both longitudinal and lateral. It includes the longitudinal dynamics (forward speed, pitching and altitude) and the lateral dynamics (rolling and heading) [70], [71] and [42]. The autopilot design applied to the hang glider model depends on state space linear models (longitudinal and lateral) in [4], and the ANFIS controller design and comparison with conventional PID controller. The first role of the longitudinal motion controller is the design of most inner loops (pitch rate feedback) of the longitudinal system, then the pitch tracker design with ANFIS controller. The guidance and control systems are related to the altitude hold controller of the ANFIS outer loop controller. The second task of the autopilot design is to develop the lateral motion

controller, which has two stages: the inner loop (roll tracker) and the heading control which is related to guidance and control (outer loop).

5.2 Longitudinal Control

The longitudinal controller is responsible for controlling the velocity, pitch angle and altitude. This is done with two loops: the pitch tracker and the outer loop altitude (h) and the speed (v_a) control. The controller produces a proper input value (δ_{long}) for a UAV based on an ANFIS controller, to track the reference values of altitude and airspeed. The control bar and the throttle are the inputs for the longitudinal motion controller. The control bar controls the inner loops of pitch and pitch rate and the outer loop height (h), while the throttle (δ_t) is the outer loop control speed [71]. The response of the altitude loop is tested by climbing to a desired altitude (h) and executing straight and level flight. The velocity response loop functions in the same way.

5.2.1 Inner Loop Pitch Attitude Tracker Design

The longitudinal inner loop is the pitch attitude controller and the pitch damper (stability augmentation system (SAS)) [42]. The primary job of a pitch tracker or a pitch attitude hold is to maintain the value of the pitch attitude (θ) that matches the reference commanded pitch. Fig. 5.1 shows a block diagram of a pitch attitude holds control system. The design can be performed using the short-period period approximation for aircraft dynamics, and adding an integrator to obtain approximate pitch from the pitch rate.

Figure 5.1: 1 Longitudinal Guidance and Control System for pitch hold

5.2.2 Outer Loop Altitude Hold Controller

The outer-loops were designed to meet the tracking command requirements for altitude and cruise speed, and the autopilot is used to track command requirements between the actual and the desired altitude. The flight altitude $h(t)$ is not part of the state in the mathematical model, so it should be modeled. In straight and level flight conditions, a change of altitude can be written as a function of the flight path angle and the velocity [72], so that

$$\dot{h} = v_a \gamma = v_a (\theta - \alpha) \quad (5.1)$$

The role of the longitudinal motion controller is to regulate straight, level flight, and climbing flight. Fig. 5.2 shows a block diagram of an altitude hold control system.

Figure 5.2: Longitudinal Guidance and Control System for altitude hold

5.2.3 Airspeed Hold Controller

The airspeed hold control loop maintains constant speed along a flight path. It is designed based on the cruise mode requirement shown in Fig. 5.3, using the sensor measurement as input, and controlling the throttle. For speed changes, the throttle deflection is based on current speed error. The command goes directly to the aircraft model without modification by the inner loop, and ranges from 0 and 1.

Figure 5.3: Longitudinal Guidance and Control System for speed hold

5.3 Lateral Control

This subsection focuses on the lateral control design of the direction controller, including both inner and outer loops. The outer loop uses heading signal (yaw angle) error to produce the reference command signal for the inner loop [73], and the inner loop uses command signal errors to create the deflection commands that are sent to the control components. The lateral controller produces a proper input value (δ_{lat}).

5.3.1 Inner Loops Roll Angle Hold Controller

The roll attitude autopilot is designed to maintain the aircraft at wing level for long flights. The roll-angle-hold (bank angle hold) controller is controlled by the autopilot system as shown by the block diagram Fig. 5.4 [73]. Roll rate is designed to provide the inner loop rate damping for a good performance roll angle and to track the roll

angle commands. The control bar controls the roll angle (δ_{lat}).

Figure 5.4: Lateral Guidance and Control System for roll hold

5.3.2 Heading Hold Controller

The heading-hold autopilot is largely designed to hold the aircraft on a specific heading, as shown in Fig. 5.5. The input command to the lateral autopilot is the desired heading, and the control bar command (δ_{lat}) is the output. The heading hold converts heading error to the roll attitude command, and the roll attitude hold transforms this error into a roll rate command. The roll rate hold turns roll rate errors into control bar commands (δ_{lat}) [73].

Figure 5.5: Lateral Guidance and Control System for heading hold

5.4 Controllability and Observability

The concepts of controllability and observability were introduced by R. Kalman in 1960. They are two of the important properties of control systems.

The concepts of controllability and observability for a linear time-invariant dynamical system of flexible wing UAV can be related to suitable linear systems of algebraic equations. It is well known that a solvable system of linear algebraic equations has a solution if and only if the rank of the system matrix is full. Observability and controllability tests will be connected to the rank tests of certain matrices: the controllability and observability matrices. For the purpose of studying its observability, we consider the linear system:

$$\begin{aligned}\dot{x}(t) &= Ax(t) + Bu(t) \\ y(t) &= Cx(t) + Du(t)\end{aligned}\tag{5.2}$$

Controllability determines whether it is possible to make system states evolve in time the way we want, using input system. To check whether particular system is controllable, matrix 5.3 could be used. If this matrix is full rank, then the system is said to be controllable [74].

$$C_{ntr} = \begin{bmatrix} B & AB & A^2B & \dots & A^{n-1}B \end{bmatrix}\tag{5.3}$$

Observability on the other hand, is to see if it is possible to determine all the states from output of the system and input signal. The linear continuous-time system and measurements in eq. 5.2 is observable if and only if the observability matrix has full rank.

$$O_{bse} = \begin{bmatrix} C \\ CA \\ CA^2 \\ \vdots \\ CA^{n-1} \end{bmatrix} \quad (5.4)$$

5.5 PID Controller

The proportional-integral-derivative (PID) control is one of the classic controller design techniques of UAV, based on a frequency domain analysis of system dynamics. A closed-loop controller uses feedback to control states or outputs of a dynamical system.

The feedback control is used to reduce the effect of uncertainty include disturbances and noise on the system [75]. There are many advantages of uses feedback controller then the open loop controllers:

1. Improve the response characteristics of the system.
2. Reject the effect of disturbance and noise.
3. Make the system stable.

Mathematically, a PID controller can be described as: [76]

$$g = K_p e(t) + K_i \int_0^t e(t) dt + k_d \frac{d}{dt} e(t) \quad (5.5)$$

where, K_p , K_i and K_d represent proportional, integral and derivative gains respectively. T , is the control signal, which will be sent to the process.

The PID controller commonly used in many industrial applications as easy to design and implement. The controller attempts to minimize the difference between desired and measurement signals as shown in Fig. 5.6. The controller is relatively easier to design and implement, compared to another type of controlle [77].

The Proportional gain reduces the rise time, steady-state error and noise at high frequencies. However, increasing the controller gain makes the system unstable.

The integral gain deals with a steady-state error by accelerating the movement of the process towards set-point. It can contribute to overshoot because it responds to accumulated error from the past that solved by adding the derivative term. The derivative gain slows down the rate change of the control signal and makes the overshoot smaller; it is no effect on the steady-state error. The combined controller-process stability is improved by the derivative term, but it makes the process unstable, and sensitive to noise in the error signal [78]. The procedure of the controller gains derived by using Ziegler-Nichols rule estimate interval change of PID parameters [79], [80]. The PID controller provides robust and reliable performance when the parameters are tuned well. The PID controller is a simply mathematical tuning system that lacks direct knowledge of the control process. It might cause a long settling time and constant overshoot until the error tends to zero

Figure 5.6: Block Diagram of PID Controller [76]

Figure 5.7: TSK fuzzy model [83]

5.6 ANFIS Controller

A neuro-fuzzy system was proposed by Jang [81]. An Adaptive Neuro-Fuzzy Inference Systems (ANFIS) [82] uses fuzzy logic and an artificial neural network. Fuzzy logic control deals with the uncertainty in complex problems, and it is an excellent tool for making decisions, based on their knowledge and database, but it can not learn. AN artificial neural network minimizes errors and optimizes the controller parameters but can not make decisions. Furthermore, the hybrid learning algorithm trains the membership functions, and fuzzy rules.

The ANFIS system and the Takagi-Sugeno fuzzy system are applied to automate fuzzy modeling by using measurement data. This consists of two input parameters, x and y , and one output with two rules, as shown in Fig. 5.7 [83]. The total output is a weighted average of each rule's output:

Rule 1: if x is A_1 and y is B_1 then $f_1 = p_1x + q_1y + r_1$

Rule 2: if x is A_2 and y is B_2 then $f_2 = p_2x + q_2y + r_2$

where x and y are two inputs, p , q and r are consequence parameters of the model resulting from the training procedure, and A and B are the fuzzy sets.

The ANFIS structure has five layers [81], as shown in Fig. 5.8.

Layer 1: The output for this layer (L_i^1) is a membership function (μ_{A_i}) of each input variable (x , and y).

$$L_{Ai}^1 = \mu_{Ai}(x) \quad L_{Bi}^1 = \mu_{Bi}(y) \quad i = 1, \dots, n \quad (5.6)$$

where n is the number of membership functions.

$$\mu_{Ai}(x) = \frac{1}{1 + [(\frac{x-c_i}{a_i})^2]^{b_i}}$$

where (a_i, b_i, c_i) is the parameter set that changes the shapes of the membership function. Parameters in this layer are referred to as the premise parameters.

Layer 2: This is the product of the two inputs.

$$L_i^2 = w_i = \mu_{Ai}(x) \cdot \mu_{Bi}(y) \quad i = 1, \dots, n \quad (5.7)$$

Layer 3: Each node in this layer determines the normalized firing strength as follows:

$$L_i^3 = \bar{w}_i = \frac{w_i}{w_1 + w_2} \quad i = 1, \dots, n \quad (5.8)$$

Layer 4: The output is a summation of the previous outputs, such as:

$$L_i^4 = \bar{w}_i(p_i x + q_i y + r_i) \quad i = 1, \dots, n \quad (5.9)$$

where p_i, q_i and r_i are the parameters from the training process.

Layer 5: This is the overall output and the final total of all the layers.

$$L_i^5 = \sum_i \bar{w}_i(p_i x + q_i y + r_i) \quad i = 1, \dots, n \quad (5.10)$$

Figure 5.8: Adaptive neuro fuzzy interference system structure

5.7 Hybrid Learning Algorithm

The hybrid learning algorithm consist of two passes: forward pass and backward pass. During the forward pass of the hybrid learning algorithm, the parameters of the input membership functions are kept constant and since the output side functions are linear in parameters, the output parameters go forward until layer four and the consequent parameters are adjusted by using a least squares method [84].

When the premise parameters are fixed, the totally output can be expressed as a linear combination of the consequent parameters as:

$$\begin{aligned}
 f &= \frac{w_1}{w_1 + w_2} f_1 + \frac{w_2}{w_1 + w_2} f_2 \\
 &= \bar{w}_1 f_1 + \bar{w}_2 f_2 \\
 &= (\bar{w}_1 x) p_1 + (\bar{w}_1 y) q_1 + (\bar{w}_1) r_1 + (\bar{w}_2 x) p_2 + (\bar{w}_2 y) q_2 + (\bar{w}_2) r_2
 \end{aligned} \tag{5.11}$$

During the backward pass, the output parameters are fixed, and the error propagate backward. The parameters of the input membership functions (premise parameters) are updated by gradient descent method.

Chapter 6

Sensor Fusion

6.1 Introduction

This chapter presents the knowledge of sensor fusion to improve the attitude estimation of a flexible wing UAV equipped with DDVS and an accelerometer sensor. We first describe the attitude determination to estimate the Euler angles and the sensors. Then a new filter known as the Adaptive Unscented Kalman Filter (AUKF) is applied to integrate two DDVS/Accelerometer measurement sensors for attitude estimation.

6.2 Attitude Determination

Computation of UAV attitude involves the determination of UAV pitch, roll, and heading angles. Pitch angle and roll angle can be determined through inertial measurements such as accelerometers and rate gyros. The accelerometers measure the acceleration of the UAV. The rate gyros measure the rotational velocity of the UAV. Both sensors include sensor biases and zero mean Gaussian random noise. The rotation between the UAV body frame and the local Cartesian frame is determined from the attitude angles.

$$\begin{bmatrix} \dot{\theta} \\ \dot{\phi} \\ \dot{\psi} \end{bmatrix} = \begin{bmatrix} 1 & \sin(\phi)\tan(\theta) & \cos(\phi)\tan(\theta) \\ 0 & \cos(\phi) & -\sin(\phi) \\ 0 & \sin(\phi)\sec(\theta) & \cos(\phi)\sec(\theta) \end{bmatrix} \begin{bmatrix} p \\ q \\ r \end{bmatrix} \quad (6.1)$$

where θ , ϕ , and ψ are pitch, roll and heading angles, the p , q , and r are angular velocities.

The pitch and roll angles can be determined either by computing the gravitational acceleration components on the body axes, or by using the Euler quaternion method [85]. The gravitational acceleration components give long-term accuracy and accompanied by high noise contents. While the quaternion method gives low noise contents and fast response, but tends to drift with time due to gyro bias errors. A common method for computing the attitude angle is the Euler quaternion method [86], which uses the Euler four symmetrical parameters (q_0, q_1, q_2, q_3) to define the UAV attitude. The relationship between the attitude angle and the four parameters are [87] [88]:

$$\begin{bmatrix} \phi \\ \theta \\ \psi \end{bmatrix} = \begin{bmatrix} \text{atan}\left(\frac{2(q_0q_2 - q_1q_3)}{q_0^2 + q_1^2 - q_2^2 - q_3^2}\right) \\ \text{asin}(2q_0q_3 + 2q_1q_2) \\ \text{atan}\left(\frac{2(q_0q_1 - q_2q_3)}{q_0^2 - q_1^2 + q_2^2 - q_3^2}\right) \end{bmatrix} \quad (6.2)$$

The kinematics equation (6.1) in quaternion components is:

$$\begin{bmatrix} \dot{q}_0 \\ \dot{q}_1 \\ \dot{q}_2 \\ \dot{q}_3 \end{bmatrix} = \frac{1}{2} \begin{bmatrix} 0 & -p & -q & -r \\ p & 0 & r & -q \\ q & -r & 0 & p \\ r & q & -p & 0 \end{bmatrix} \begin{bmatrix} q_0 \\ q_1 \\ q_2 \\ q_3 \end{bmatrix} \quad (6.3)$$

where the quaternion components driven from Euler angles are following:

$$q_0 = \cos\frac{\phi}{2}\cos\frac{\theta}{2}\cos\frac{\psi}{2} + \sin\frac{\phi}{2}\sin\frac{\theta}{2}\sin\frac{\psi}{2} \quad (6.4)$$

$$q_1 = \sin\frac{\phi}{2}\cos\frac{\theta}{2}\cos\frac{\psi}{2} - \cos\frac{\phi}{2}\sin\frac{\theta}{2}\sin\frac{\psi}{2} \quad (6.5)$$

$$q_2 = \cos\frac{\phi}{2}\sin\frac{\theta}{2}\cos\frac{\psi}{2} + \sin\frac{\phi}{2}\cos\frac{\theta}{2}\sin\frac{\psi}{2} \quad (6.6)$$

$$q_3 = \cos\frac{\phi}{2}\cos\frac{\theta}{2}\sin\frac{\psi}{2} + \sin\frac{\phi}{2}\sin\frac{\theta}{2}\cos\frac{\psi}{2} \quad (6.7)$$

And the quaternion is normal i.e($q_0^2 + q_1^2 + q_2^2 + q_3^2 = 1$)

6.3 Accelerometer

Accelerometer sensors are used in a variety of automation applications. They measure linear acceleration during static or quasi-static conditions and calculate the angles relative to the horizontal plane; this information determines the pitch and roll angles of the rigid body [89]. The orientation of the flexible wing is measured by a 3-axis ADXL 330 accelerometer with full-scale range of 3 g, as shown in Fig. 6.1, and based on

MEMS technology from Analog Devices. The onboard sensors can only communicate if there is a microcontroller reading the sensor values and processing the data signals.

Figure 6.1: ADXL 330 accelerometer sensor

The Arduino Uno R3 in Fig. 6.2 can produce the proper signals without extra configuration. Accelerometers provide roll and pitch angles using gravity, and their performance regarding noise (noise density expressed in g/ Hz) is supplied by the manufacturer, as presented in Table 6.1. The 3-axis ADXL 330 has good performance with respect to the noise density.

The roll and pitch angles are estimated by the following equations:

$$\theta = \text{atan} \frac{a_x}{\sqrt{a_y^2 + a_z^2}} \quad (6.8)$$

$$\phi = \text{atan} \frac{-a_y}{a_z} \quad (6.9)$$

where θ and ϕ are the pitch and the roll angles estimated from the accelerometer outputs, respectively, and a_x , a_y and a_z are the components of the acceleration measured by the accelerometer in the body coordinate frame.

Table 6.1: Accelerometer noise density from manufacture

	Noise Density [$\mu g/\sqrt{Hz}$]
x-axis	280
y-axis	280
z-axis	350

Figure 6.2: Arduino Uno R3 board

6.4 Sensor Fusion

This section examines the proposed sensor fusion. The methodology is used to calculate attitude estimation by integrating the reference data that is gathered from DDVS and measurement data from the accelerometer. The algorithm is designed to optimize and robust the DDVS for pitch and roll angles. The sensor fusion algorithm is based on the Adaptive Unscented Kalman Filter (AUKF), and is applied to estimate the state variables (attitude estimate). The input measurements to predict state variables are inertial accelerations according to the accelerometer and DDVS results. The block diagram of the sensor fusion algorithm using AUKF is shown in Fig. 6.3.

Errors associated with the accelerometer are affected by the results, and diverge with time [91]. The DDVS measurements are used in the AUKF to estimate the errors and obtain accurate and corrected attitudes.

Figure 6.3: Block diagram of AUKF

6.5 Adaptive Kalman Filter (AUKF)

It is difficult to design a UAV autopilot controller without considering the effect of signal noise and disturbance on the measurement state values; AUKF is designed to remove these impediments and estimate the actual state values. Fig. 6.4, illustrated a system based on a robust ANFIS controller and the propose DDVS, as well as a new AUKF to control the longitudinal and lateral autopilot of a flexible wing UAV.

Figure 6.4: The feedback control system for the flexible wing UAV

This system ensures system stability and improves the performance of a system under the noise conditions. The AUKF uses the Fuzzy Logic Adaptive System (FLAS) to prevent the estimate results from divergence [91]. It evaluate the UKF performance and tunes the factors in the weighted covariance to improve UKF accuracy [92]. The state estimate of DDVS and the sensor are x_n and x_a respectively, and the estimation output is x_e , as shown in Fig. 6.4. Thus the state form equation is:

$$x(k+1) = A(k)x(k) + B(k)u(k) + w(k) \quad (6.10)$$

$$z(k) = H(k)x(k) + v(k) \quad (6.11)$$

where $A(k)$ is the transition matrix, $x(k)$ the state vector, $B(k)$ the control matrix, $u(k)$ the input vector, $w(k)$ the process noise, $z(k)$ the measurement vector, $H(k)$ the measurement matrix and $v(k)$ the measurement noise. No correlation between $w(k)$ and $v(k)$ is assumed [91]:

$$E[w(k)w(i)^T] = \begin{cases} Q & \text{if } i = k \\ 0 & \text{if } i \neq k \end{cases}$$

$$E[v(k)v(i)^T] = \begin{cases} R & \text{if } i = k \\ 0 & \text{if } i \neq k \end{cases}$$

$$E[w(k)v(i)^T] = 0$$

6.5.1 Unscented Kalman Filter

The UKF algorithm produces several sampling points (sigma points) around the mean, based on the covariance. These points are propagated through nonlinear transformation (Unscented transformation (UT)) to improve the accuracy of the results [90], [92]. The UT is an alternative method to the analytical linearization approach. As random variable x of n -dimensions with mean $\hat{x}$ and covariance p_x can be increased using a nonlinear function.

The UKF algorithm is summarized as follows [90]:

1. The sigma points X and weighted points W can be determined as follows:

$$X = [\hat{x} \quad \hat{x} \pm (\sqrt{(n+\lambda)p_x})_i] ; i = 1, 2, \dots, 2n \quad (6.12)$$

$$W_0^{(m)} = \frac{\lambda}{n + \lambda} \quad (6.13)$$

$$W_0^{(c)} = W_0^{(m)} + (1 - \alpha^2 + \beta) \quad (6.14)$$

$$W_i^{(c)} = W_i^{(m)} = \frac{1}{2(n + \lambda)} \quad i = 1, 2, \dots, 2n \quad (6.15)$$

The scaling parameter is computed as $\lambda = \alpha^2(n + k) - n$, α computes the sigma points spread around $\hat{x}$ and it is a small positive value (e.g. $0.0001 \leq \alpha \leq 1$); k is scaling parameter (typically 0), and the optimal choice for Gaussians is $\beta = 2$. The weight of the mean and covariance are represented by Equations 6.12, 6.13, 6.14 and 6.15 [92].

2. Each sigma point is transformed through the nonlinear state prediction function, f .

$$(\hat{X}_{k,k-1})_i = f((X)_i) \quad i = 0, 1, \dots, 2n \quad (6.16)$$

3. Predicted mean value using weighted averages of the transformed sigma-points is calculated by:

$$(\hat{x}_{k,k-1})_i = \sum_{i=0}^{2n} W_i^{(m)} (\hat{X}_{k,k-1})_i \quad (6.17)$$

4. Predicted covariance is calculated by:

$$P_{k,k-1} = \sum_{i=0}^{2n} W_i^{(c)} [\hat{X}_{k,k-1} - \hat{x}_{k,k-1}] [\hat{X}_{k,k-1} - \hat{x}_{k,k-1}]^T + Q \quad (6.18)$$

5. Prediction points are calculated through observation model:

$$(\hat{Z}_{k,k-1})_i = h(\hat{X}_{k,k-1})_i \quad (6.19)$$

6. Predicted observation:

$$\hat{z}_{k,k-1} = \sum_{i=0}^{2n} W_i^{(m)} (\hat{Z}_{k,k-1})_i \quad (6.20)$$

7. Innovation covariance:

$$P_{vv} = \sum_{i=0}^{2n} W_i^{(c)} [\hat{Z}_{k,k-1} - \hat{z}_{k,k-1}] [\hat{Z}_{k,k-1} - \hat{z}_{k,k-1}]^T + R \quad (6.21)$$

8. Cross covariance:

$$P_{xz} = \sum_{i=0}^{2n} W_i^{(c)} [\hat{X}_{k,k-1} - \hat{x}_{k,k-1}] [\hat{Z}_{k,k-1} - \hat{z}_{k,k-1}]^T \quad (6.22)$$

9. Update:

$$K_k = P_{xz} P_{vv}^{-1} \quad (6.23)$$

$$\hat{x}_k = \hat{x}_{k,k-1} + K_k (z_k - \hat{z}_{k,k-1}) \quad (6.24)$$

$$P_k = P_{k,k-1} - K_k P_{vv} K_k^T \quad (6.25)$$

6.5.2 Fuzzy Logic Adaptive System (FLAS)

Fuzzy logic is used with the mathematical model to prevent UKF from divergence [91] [92]. In general, a fuzzy system consists of three components: fuzzification, fuzzy reasoning (fuzzy inference), and defuzzification. The fuzzification stage converts a crisp input value to a linguistic value, the fuzzy inference is responsible for fuzzy rules and fuzzy de-fuzzification converts the fuzzy output to a crisp value.

As the input of the fuzzy inference engine, the Degree of Divergence (DOD) has two parameters. The first is μ which is derived from the mean of residuals v [93], [94] as follows:

$$\mu = \frac{1}{n} \sum_{i=1}^n v_i \quad (6.26)$$

The second DOD parameter ξ is the covariance of residuals as follows:

$$\xi = \frac{v_k^T v_k}{n} \quad (6.27)$$

where n is the measurement number and, v_k is an innovation covariance.

$$v_k = z_k - \hat{z}_k \quad (6.28)$$

By monitoring the DOD parameters with fuzzy logic, the softening factor α (the output of FLAS) is tuned to the fuzzy rules and estimation accuracy, as shown in Fig. 6.5. As there are no specific criteria to find the softening factor, it must be determined empirically.

The models of weighted noise covariance matrices for EKF are presented as obtained by Sasiadek [93]. The set of covariance matrices are as follows:

Figure 6.5: The input and output of FLAS

$$R_k = R\alpha^{-2(k+1)} \quad (6.29)$$

$$Q_k = Q\alpha^{-2(k+1)} \quad (6.30)$$

where $\alpha \geq 1$ and matrices Q and R are constants. When k increases, the R and Q matrices decrease, and the most higher measurement gets the most weighting, Therefore, the weighted covariance is:

$$P_{k,k-1}^\alpha = P_{k,k-1}\alpha^{2k} \quad (6.31)$$

Substituting Equation(6.31) into Equations(6.21 ,6.22, and 6.25) we obtain,

$$P_{k,k-1} = \alpha^2 \sum_{i=0}^{2n} W_i^{(c)} [\hat{X}_{k,k-1} - \hat{x}_{k,k-1}] [\hat{X}_{k,k-1} - \hat{x}_{k,k-1}]^T + Q \quad (6.32)$$

$$P_{vv} = \alpha^{2k} \sum_{i=0}^{2n} W_i^{(c)} [\hat{Z}_{k,k-1} - \hat{z}_{k,k-1}] [\hat{Z}_{k,k-1} - \hat{z}_{k,k-1}]^T + \alpha^{-2} R \quad (6.33)$$

$$P_{xz} = \alpha^{2k} \sum_{i=0}^{2n} W_i^{(c)} [\hat{X}_{k,k-1} - \hat{x}_{k,k-1}] [\hat{Z}_{k,k-1} - \hat{z}_{k,k-1}]^T \quad (6.34)$$

Chapter 7

Experimental Setup and Results

7.1 Introduction

This chapter discusses the identification, classification and control of flexible wing UAV by machine vision that has been implemented and tested. Initially, the distinguishing features of the wing are extracted and 3D points are computing for each point using machine vision as described in Chapter three. Fuzzy logic classify the shape of the wing and ANFIS and PID controllers are used to design the autopilot. All simulation results were verified and validated.

7.2 Machine Vision

The most important methods of image processing, feature extraction, pose estimation, and tracking algorithms applied in this work were tested and discussed. To verify the performance of all algorithms for pose estimation and determine the translation and rotation between the two cameras, we should calibrated the camera and then calculated the intrinsic matrix K . The camera (Microsoft LifeCam HD-3000 are shown in Table [7.1](#).

Table 7.1: Specification of Microsoft LifeCam HD-3000

Specifications of Camera
Product Name	Microsoft LifeCam HD-3000	
Webcam Length	1.55 inches (39.3 millimeters)	
Webcam Width	1.75 inches (44.5 millimeters)	
Webcam Depth/Height	4.28 inches (109 millimeters)	
Webcam Weight	3.17 ounces (89.9 grams)	
Interface	High-speed USB compatible with the USB 2.0	
Imaging Rate	Up to 30 frames per second	
Field of View	68.5 diagonal field of view	
Fixed focus	from 0.3m to 1.5m	
True Color	Automatic image adjustment with manual override	
Imaging Features	16:9 widescreen 24-bit color depth	

7.2.1 Camera Calibration

The first step of camera calibration is to find a relationship between the object that appears on images and where it is in the world coordinate system. This involves calculating intrinsic parameters such as focal length, principal point and lens distortion, and extrinsic parameters such as the 3D position and orientation of the camera with respect to the world coordinate system. The inputs for this are several images of a model chessboard plane with calibration points, using corners of the plane as calibration points. Fig. 7.1 and 7.2 show calibration images.

Figure 7.1: Camera calibration toolbox for MATLAB with a model chessboard Plane

Figure 7.2: Camera extrinsic parameters

The k matrix for Microsoft LifeCam is:

$$k = \begin{bmatrix} 2380.8 & 0 & 1277 \\ 0 & 2371.6 & 935.4 \\ 0 & 0 & 1 \end{bmatrix} \quad (7.1)$$

While the k matrix for ZED stereo camera is:

$$k_{left} = \begin{bmatrix} 700.819 & 0 & 665.465 \\ 0 & 700.819 & 371.953 \\ 0 & 0 & 1 \end{bmatrix} \quad (7.2)$$

$$k_{right} = \begin{bmatrix} 698.76 & 0 & 640.082 \\ 0 & 698.76 & 375.129 \\ 0 & 0 & 1 \end{bmatrix} \quad (7.3)$$

7.2.2 The Error Functions

We use the error in the second image to evaluate the algorithms after transferring points from the first image using the computed homography matrix. All the methods were programmed and tested under the same image noise conditions. A Euclidean image is the distance in the second image between the measured point x_i^* and the point Hx_i . If d is the Euclidean distance between inhomogeneous points, the transfer error in the set of correspondences is

$$E = \sum_i d(x_i^* - Hx_i)^2 \quad (7.4)$$

The performance of three algorithms (DLT, RANSAC and Pseudo-inverse) in four-level Gaussian noise conditions was compared in Fig. 7.3. All performances degraded as the noise level increased, through the RANSAC algorithm had the better results than the others. To verify the decomposition homography algorithm performance, we added the same noise error to the second image and calculated the relative translation error as shown in Fig. 7.4. It is a clear that all errors increased proportionately with the level of noise added to the image feature points.

Figure 7.3: Plot of the log error against the noise levels

Figure 7.4: Relative translation error via noise level

7.2.3 The Pose Measurements

In this work, the accuracy and robustness of pose estimates is found using homography, the ICP algorithm and Horns absolute orientation method. All data are from two image views (front and top), as shown in Fig. 7.5 and 7.6, and compared with

respect to the relative motion parameters. These algorithms are studied in Table 7.2, 7.3 and 7.4, with varying distances and angles between the cameras. The data gathered by the mobile robot is shown in Tables 7.2, and 7.3, while that collected by the flying robot is presented in Table 7.4. The distortion increases as the distance and angle increase. When Tables 7.3 and 7.4 are at the real distance (10 0 0) t_1 is not affected, while t_2 increases as the object distance increases. When the real distance becomes (20 0 0) the t_1 is not affected, while t_2 decreases as object distance increases. When the baseline or distance increase, both t_1 and t_2 are affected.

Figure 7.5: Initial and desired targets from front view

Figure 7.6: Initial and desired targets from top view

Table 7.2: Estimation of mobile robot position for all algorithms

	Translational, Motion (t1, t2, t3) cm			
Object distance for z (cm)	2D Homography	ICP	Horns absolute orientation method	Real
70	(10.2 0.88 0)	(9.66 0.62 0)	(9.99 0.26 0)	(10 0 0)
80	(10.2 2.39 0)	(10.1 2.27 0)	(10.0 2.50 0)	(10 0 0)
90	(10.1 2.98 0)	(10.0 3.26 0)	(10.1 3.07 0)	(10 0 0)
150	(9.63 6.76 0)	(10.1 6.77 0)	(10.0 6.82 0)	(10 0 0)
70	(19.8 3.39 0)	(19.8 5.12 0)	(19.8 3.97 0)	(20 0 0)
80	(20.3 3.47 0)	(20.1 4.05 0)	(20.3 3.43 0)	(20 0 0)
90	(20.2 1.40 0)	(20.2 1.22 0)	(20.1 1.54 0)	(20 0 0)
150	(19.2 1.18 0)	(20.4 1.16 0)	(19.5 1.06 0)	(20 0 0)
150	(0.17 5.22 0)	(0.76 4.23 0)	(0.12 5.40 0)	(0 5 0)
150	(22.6 6.00 0)	(23.0 5.50 0)	(22.8 6.20 0)	(20 10 0)
150	(19.7 3.58 0)	(19.7 2.65 0)	(19.7 3.05 0)	(20 5 0)
300	(28.4 2.10 0)	(28.6 1.50 0)	(27.4 3.05 0)	(30 0 0)
500	(37.8 3.30 0)	(38.1 3.10 0)	(36.6 4.20 0)	(40 0 0)
1000	(45.5 4.30 0)	(46.3 4.01 0)	(44.7 4.50 0)	(50 0 0)

Table 7.3: Estimation of mobile robot position for two baselines

	Baseline = 10 cm		
Object distance for z (cm)	2D Homography	ICP	Horns absolute orientation method
70	(10.2 0.88 0)	(9.66 0.62 0)	(9.99 0.26 0)
80	(10.2 2.39 0)	(10.1 2.27 0)	(10.0 2.50 0)
90	(10.1 2.98 0)	(10.0 3.26 0)	(10.1 3.07 0)
150	(9.63 6.76 0)	(10.1 6.77 0)	(10.0 6.82 0)
	Baseline = 20 cm		
70	(19.8 3.39 0)	(19.8 5.12 0)	(19.8 3.97 0)
80	(20.3 3.47 0)	(20.1 4.05 0)	(20.3 3.43 0)
90	(20.2 1.40 0)	(20.2 1.22 0)	(20.1 1.54 0)
150	(19.2 1.18 0)	(20.4 1.16 0)	(19.5 1.06 0)

Table 7.4: Estimation of flying robot position for two baselines

	Baseline = 10 cm		
Object distance for z (cm)	2D Homography	ICP	Horns absolute orientation method
60	(10.2 0.33 0)	(9.80 0.32 0)	(10.1 0.56 0)
80	(10.2 3.13 0)	(10.1 2.15 0)	(10.1 3.10 0)
120	(10.3 3.19 0)	(10.2 3.70 0)	(10.1 3.26 0)
150	(9.32 7.16 0)	(10.2 5.87 0)	(10.1 7.14 0)
	Baseline = 20 cm		
60	(19.6 2.11 0)	(19.5 4.32 0)	(19.98 3.2 0)
80	(20.4 4.13 0)	(20.2 4.37 0)	(20.4 4.30 0)
120	(20.4 3.50 0)	(20.3 2.41 0)	(20.2 2.66 0)
150	(19.4 2.80 0)	(20.5 2.70 0)	(19.5 2.60 0)

7.3 Results of the Flexible Wing

The proposed DDVS for flexible wing model in this thesis is shown in Fig. 7.7. The process begins by capturing images using the ZED stereo camera, then extracting the features with the SURF method. After the 3D point is computed for each point with machine vision, the shape of the wing is identified as described in Chapter 3.

The shape is classified by fuzzy logic to determine the state of the system such as pitch angle, speed, and roll angle. Sensor fusion is used to estimate the state of the flexible wing by fusing the measurement states from DDVS with other sensor measurements. After the speed, pitch and roll angles are estimated, the errors from the desired and estimated state are input for the longitudinal and lateral autopilot controllers. These controllers are designed to control the flexible wing UAV based on ANFIS and PID controllers consider the disturbance in all states of the system.

In this thesis, experimental testing is performed to clarify the proposed approach to deflection measurement of a flexible wing using a stereo camera. The UAV platform used in wind tunnel testing has flexible 100 cm long wings with a 120 cm wingspan, and carries no internal components such as a fuselage or engine. The wing is composed of a plastic fiber and the body structure is made of wood. One advantages of flexible wings is they have greater resistance at high AOA, as well as increased roll stability. Six square markers attached to the end of the wing are used to gather the measurement data from the stereo camera as shown in Fig. 7.8, 7.9 and Fig. 7.10.

Figure 7.7: The Detection-Deflection Vision System(DDVS) for the flexible wing model

7.3.1 Wing Shape

The ZED stereo camera is attached behind the wing on the keel tube to ensure the wing is in the view and can provide vision data of the square markers. The testing

Figure 7.8: Back view of the flexible wing in wind tunnel

Figure 7.9: Front view of the flexible wing in wind tunnel

begins by measuring the deflection of the wing using the two left and right images. Pictures of the wing are taken at $\text{AOA}=0^\circ$, and roll angle= 0° , with specific wind velocities (11 to 31) m/s as shown in Fig. 7.11. The AOA value of the wing is then increased to $+20^\circ$, the roll angle is unchanged and pictures are taken at the same wind velocity values, as shows in Fig. 7.12, 7.13, and 7.14. The testing is repeated with the same conditions when the AOA reaches -20° , as shown in Fig. 7.15, then the roll angle is changed from zero to 10° and AOA to 20° with the same wind velocities, as shown in Fig. 7.16. Finally, the roll angle is set to -10° and AOA to -20° and

Figure 7.10: Features position

pictures are taken for different wind values, as shown in Fig. 7.17.

Figure 7.11: Shape of wing at $V=31\text{m/s}$

Figure 7.12: Shape of wing at $V=11\text{m/s}$ and $\text{AOA}=+20^\circ$

Figure 7.13: Shape of wing at $V=21\text{m/s}$ and $\text{AOA}=+20^\circ$

Figure 7.14: Shape of wing at $V=31\text{m/s}$ and $\text{AOA}=+20^\circ$

Figure 7.15: Shape of wing at $V=31\text{m/s}$ and $\text{AOA}=-20^\circ$

Figure 7.16: Shape of wing at $V=31\text{m/s}$, Roll angle= 10° and $\text{AOA}=+20^\circ$

Figure 7.17: Shape of wing at $V=11\text{m/s}$, Roll angle= -10° and $\text{AOA}=-20^\circ$

7.3.2 Feature Extraction

In this subsection, a stereo camera is used to generate multiple images and extract the most relevant features. The process starts by selecting a set of interest points and constructing their local feature descriptors using SURF. Then, representative points from the interest points are founded by using statistical analysis. The representative points of an object are interest points that distinguish information about an object, as shown in Fig. 7.18.

Figure 7.18: The matching of the feature points

7.3.3 Extract Deflection using the Stereo Camera

Several shapes of the flexible wing are observed in the wind tunnel. Once the wing is loaded, its deflected profile (shape) is computed using the six markers shown in Fig. 7.10. At $AOA=0$ and roll angle $=0$, five shapes of the wing across variety speed are shown in Fig. 7.19. The deflection is changed depending on the speed, the maximum deflection is -0.14 cm when the wind speed reached 31 m/s. The shape of the wing was symmetrical, and the peak deflection occurred at mid-distance of each side of the

wing as shown in Fig. 7.19.

Figure 7.19: Shape of wing at $\text{AOA}=0^\circ$ and roll angle $=0^\circ$

When the AOA is -20° , the maximum deflection increased to -0.5 cm, and the shape of the wing is also symmetrical on both sides as shown in Fig. 7.20. In Fig. 7.21 and 7.22, the roll angle become -10° for both the $\text{AOA}=0$ or the $\text{AOA}=-20^\circ$. The change in roll angle makes the wing shape not symmetrical on both sides. The same result form roll angle change when the $\text{AOA}=20^\circ$, as shown in Fig. 7.23 except the maximum deflection in the positive value. From observation, the greatest deflection occurred at the AOA is 20° , as shown in Fig. 7.24.

Figure 7.20: Shape of wing at $\text{AOA} = -20^\circ$ and roll angle $= 0^\circ$

Figure 7.21: Shape of wing at $\text{AOA} = 0^\circ$ and roll angle $= -10^\circ$

Figure 7.22: Shape of wing at $\text{AOA}=-20^\circ$ and roll angle $=-10^\circ$

Figure 7.23: Shape of wing at $\text{AOA}=20^\circ$ and roll angle $=-10^\circ$

Figure 7.24: Shape of wing at $\text{AOA}=20^\circ$ and roll angle $=0^\circ$

Table 7.5 and 7.6 show the maximum deflection of the flexible wing for each test cases. This table helps to clarify the accuracy of DDVS algorithm.

The dynamic effect on each point is shown in Fig. 7.25, and the deflection is negative values at the start experimental until to 50 sec, then tends to zero until 100 sec, finally, the deflection increases to positive values after 100 sec. The reason is at the start the AOA is -20° and after 50 sec close to zero, and after 100 sec the AOA is $+20^\circ$.

Table 7.5: Test Results for AOA

AOA (deg)	Speed (m/s)	Max. deflection (cm)
-20	11	-0.14
	15	-0.21
	21	-0.38
	25	-0.42
	31	-0.50
-10	11	-0.07
	15	-0.12
	21	-0.18
	25	-0.36
	31	-0.31
0	11	-0.03
	15	-0.04
	21	-0.06
	25	-0.09
	31	-0.14
10	11	1.42
	15	1.91
	21	3.16
	25	4.76
	31	6.33
20	11	2.28
	15	3.53
	21	5.51
	25	7.33
	31	10.3

Table 7.6: Test Results for Roll angle

Roll angle (deg)	Speed (m/s)	Max. deflection (cm)
-10	11	2.28
	15	3.53
	21	5.51
	25	7.33
	31	10.3
0	11	-0.03
	15	-0.04
	21	-0.06
	25	-0.09
	31	-0.14
10	11	2.28
	15	3.53
	21	5.51
	25	7.33
	31	10.3

Figure 7.25: Tracking points along the experimental tests

Fig. 7.26 shows the maximum wing deflection for five value of wind speed, when the AOA greater than zero, a slight increase in deflection is visible when the speed increased, and significant maximum deflection records at the 31 m/s.

The deflection decreased when the speed increased at $\text{AOA} = -20^\circ$, and 0° , as shown in Fig. 7.27, and 7.28, while the positive deflection value at $\text{AOA} = +20^\circ$ is increased when the speed increased as shown in Fig. 7.29.

Figure 7.26: Maximum deflection vs. AOA

Figure 7.27: Maximum deflection vs. speed at AOA=-20 deg.

Figure 7.28: Maximum deflection vs. speed at AOA=0 deg.

Figure 7.29: Maximum deflection vs. speed at AOA=20 deg.

7.3.4 Classifying Wing Shapes with Fuzzy Logic

The shapes of a flexible wing are determined by the values of the features (nodes). This work presents six nodes that can yield results, and the deflection values of these nodes for both sides are presented in Table 7.7. Thus, the input variables for fuzzy logic are six nodes, and the output variables are three outputs, as shown in Fig. 7.30. The fuzzy sets of the input variables are defined as negative large, negative middle, negative small, small, middle and large (NL NM NS S, M, L), and the output variables are defined as small, zero and large (S, Z, L) for simplicity. The rules of fuzzy logic are shown in Tables 7.8, and 7.9 and the membership function used is triangular. The values of nodes 1, 3, 4, and 6 are approximately the same, and according to Table 7.7 nodes 1 and node 5 have the same values. Nodes 1 and node 2 were chosen as input membership functions for the fuzzy logic, as shown in Fig. 7.31 and 7.32. Fig. 7.33, 7.34 and 7.35 illustrate the output variables speed, AOA and roll angle membership

functions.

Table 7.7: Nodes deflection over the both sides.

Classical Input		Deflection in cm					
	Node No.	NS	NM	NL	S	M	L
Left side of wing	1	-0.02	-0.1	-0.3	0.8	3.2	5.7
	2	-0.035	-0.14	-0.5	1.05	4.3	10.2
	3	-0.018	-0.1	-0.3	0.7	2.4	3.8
Right side of wing	4	-0.018	-0.1	-0.3	0.7	2.4	3.8
	5	-0.035	-0.14	-0.5	1.05	4.3	10.2
	6	-0.02	-0.1	-0.3	0.8	3.2	5.7

Figure 7.30: Block diagram of Fuzzy logic

Table 7.8: Fuzzy rules for the flexible wing at a positive deflection

V, AOA, R		Node 1,2,3		
		S	M	L
Node 4,5,6	S	S, M, Z	M, P, N	L, P, N
	M	M, P, P	M, M, Z	M, P, N
	L	L, P, P	M, P, P	L, L, Z

Table 7.9: Fuzzy rules for the flexible wing at a negative deflection.

V, AOA, R		Node 1,2,3		
		NL	NM	NS
Node 4,5,6	NL	L, Z, Z	M, N, N	L, N, N
	NM	M, N, P	M, M, Z	M, Z, N
	NS	L, N, P	M, Z, P	S, N, Z

Figure 7.31: Membership function of the input node 1

Figure 7.32: Membership function of the input node 2

Figure 7.33: Membership function of the output wind speed

Figure 7.34: Membership function of the output AOA

Figure 7.35: Membership function of the output roll angle

7.3.5 Test and Validation

The proposed DDVS method for experimental testing is evaluated by different sensors using AUKF, and the experiments are conducted using a flexible wing UAV in a wind tunnel, as shown in Fig. 7.36. An Arduino board with an accelerometer sensors was designed and built for the wing, as shown in Fig. 7.37. The goal of the experiments is to evaluate the accuracy of the attitude angles (pitch and roll) estimates and to test the proposed DDVS. Table 7.10 shows the experimental results for both the pitch and roll angles. It is noticed that the results coming from the proposed method is more accurate than the accelerometer results.

The pitch error and roll error that determined from the accelerometer, and DDVS, and the attitude error estimated by AUKF are shown in Fig. 7.38 and 7.39 respectively. It was found that the error associated with the proposed estimated 2-DOF attitude acceptable in comparison the attitude error reported by the accelerometer. While the error associated with AUKF algorithm is approached zero compared to the attitude error reported by both the accelerometer and DDVS. This strongly suggests that the AUKF estimates of roll and pitch are significantly more accurate than those

Figure 7.36: Two sensor are fixed in flexible wing

Figure 7.37: Accelerometer sensor with Arduino board

from the accelerometer and the DDVS.

Table 7.10: Experimental results for attitude angles

	Accelerometer	DDVS	True
Pitch angle (degree)	0	0	0
	8.21	9.71	10.0
	13.2	14.1	15.0
	17.8	20.3	20.0
	28.1	29.3	30.0
	-8.45	-9.72	-10.0
	-13.5	-14.3	-15.0
	-17.9	-19.7	-20.0
	-28.2	-29.4	-30.0
Roll angle (degree)	0	0	0
	8.82	9.51	10.0
	13.4	14.3	15.0
	-7.92	-9.45	-10.0
	-13.1	-14.2	-15.0

Figure 7.38: Pitch error for the proposed DDVS, accelerometer and AUKF

Figure 7.39: Roll error for the proposed DDVS, accelerometer and AUKF

7.4 Sensor Fusion

The sensor fusion algorithm is a technique to integrate different attitude measurements to provide a reliable representation of attitude measurement. The measurement data from sensors such as accelerometer, Gyro and DDVS proposal are combined using two filters: a regular UKF and a new AUKF. The data for both pitch and roll angles comes instantaneously from the two sensors at precisely the same time.

The dynamics equations for the UAV is driven based on the relationship between the UAV body rate (pitch, roll, and yaw rates) and the four parameters of the quaternion method described in Equation (6.3). Thus, the dynamic system can be expressed as [86]:

$$\dot{x} = Ax + w$$

$$z = h(x) + v$$

where $x = [q_0, q_1, q_2, q_3]$ the state vector, $z = [a_x, a_y, a_z]$ measurements vector where a_x, a_y and a_z are the compensated accelerations and w and v are processed noise and measurement noise, and are assumed to be uncorrelated Gaussian distributed white noise. The A and $h(x)$ are defined as [86] [94]:

$$A = \frac{1}{2} \begin{bmatrix} 0 & -p & -q & -r \\ p & 0 & r & -q \\ q & -r & 0 & p \\ r & q & -p & 0 \end{bmatrix}$$

$$h(x) \begin{bmatrix} 2(q_1q_3 - q_0q_2) \\ 2(q_2q_3 - q_0q_1) \\ q_0^2 - q_1^2 - q_2^2 + q_3^2 \end{bmatrix}$$

The measurements of pitch angle and roll angles are determined based on (6.7):

$$\begin{bmatrix} \theta \\ \phi \end{bmatrix} = \begin{bmatrix} \text{atan} \frac{a_y}{\sqrt{a_x^2 + a_z^2}} \\ \text{atan} \frac{-a_x}{a_z} \end{bmatrix}$$

For the simulation and experimental results, the noise covariance associated to the quaternion components are:

$Q = 1 \times 10^{-6} \cdot I_{4 \times 4}$ According to the standard deviation obtained from the measurement of the accelerometer, the measurement noise of the accelerometer R is

$$R = \text{diag}[0.0015, \quad 0.0015, \quad 0.0015]$$

The fuzzy rules for AUKF are shown in Table 7.11, and the membership function for the input and output variables are shown in Fig. 7.40, 7.41 and 7.42 respectively.

Table 7.11: The Fuzzy Rule

ξ/μ	Z	S	L
Z	S	Z	Z
S	S	M	S
L	L	L	M

Z: Zero; S: Small; M: Medium; L: Large

Figure 7.40: Covariance membership function of input variable

Figure 7.41: Mean value membership function of input variable

Figure 7.42: Membership function of output variable

Fig. 7.43 shows the estimation pitch angles with AUKF and UKF, and compares them with the real attitude angles when the pitch angle varies from -15 to 30 degrees for 40 sec. The pitch angle estimate by AUKF was found to be more accurate than the UKF estimate. Fig. 7.44 shows the roll angle result for both the AUKF and UKF filters when the angle changes from -15 to 15 degrees, and the AUKF It noticed that the noise in the roll angle was reduced with AUKF and the results is better compared to the result estimation by UKF.

The error in pitch and roll angles for the flexible wing UAV are shown in Fig. 7.45 and 7.46. As can be seen, the AUKF estimate errors are smaller than the UKF estimation error for both pitch and roll angles. However, the AUKF employs the fuzzy system to detect and prevent the UKF from divergence by monitoring the residual states. The efficiency of the proposed algorithm to estimate pitch and roll angles and their errors with the AUKF and UKF filters is shown in Fig. 7.45 and 7.46. In both cases, the same data gathered from the accelerometer and DDVS are used in the filter equations. As seen, the AUKF clearly a better performance than the UKF.

Figure 7.43: Pitch angle estimation obtained from the UKF and the AUKF

Figure 7.44: Roll angle estimation obtained from the UKF and the AUKF

Figure 7.45: The error estimation of pitch angle

Figure 7.46: The error estimation of roll angle

7.5 Autopilot

7.5.1 Longitudinal Autopilot Simulation

For the longitudinal control design, the ANFIS control method is applied and compared with the PID controller. The state-space model used to design these controllers is given as [4].

$$\begin{bmatrix} \dot{u} \\ \dot{w} \\ \dot{q} \\ \dot{\theta} \end{bmatrix} = \begin{bmatrix} -0.179 & 0.675 & 0.121 & -0.350 \\ -1.466 & -2.326 & 8.331 & 0.821 \\ 0.172 & -0.281 & -0.555 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} u \\ w \\ q \\ \theta \end{bmatrix} + \begin{bmatrix} 0 \\ 0 \\ 4.231 \\ 0 \end{bmatrix} \delta_{long} \quad (7.5)$$

The state-space matrices are determined using aerodynamic stability derivatives calculated in Chapter 4, and the explanation can be found in Appendix A. The controllability matrix is

$$C_{ntr} = \begin{bmatrix} B & AB & A^2B & \dots & A^{n-1}B \end{bmatrix} \quad (7.6)$$

The matrix C_{ntr} has full rank so, the system is controllable.

The inference system for longitudinal autopilot is comprised of three sub-systems: pitch angle, altitude and speed, all with six membership functions and 36 fuzzy rules. The input-output data of the PID controller are used as training data at different operating points. The first inputs for the inference system are the pitch, altitude, and speed errors, which are the differences between the desired and real values. The other inputs are the derivative errors for pitch, altitude and speed errors, which are also the differences between the desired and the real values. The input membership

functions and the output surfaces for pitch angle, altitude and speed are shown in Fig. 7.47, 7.48, 7.49, 7.50, 7.51, 7.52. 7.53, 7.54 and 7.55.

Figure 7.47: Input variable "error" for pitch angle

Figure 7.48: Input variable "error change" for pitch angle

Figure 7.49: Output surface of fuzzy modules for pitch angle

Figure 7.50: Input variable "error" for altitude control

Figure 7.51: Input variable "error change" for altitude control

Figure 7.52: Output surface of fuzzy modules for altitude control

Figure 7.53: Input variable "error" for speed control

Figure 7.54: Input variable "error change" for speed control

Figure 7.55: Output surface of fuzzy modules for speed control

7.5.1.1 Time Domain Analysis

The longitudinal autopilot performance for hang glider is simulated in three stages. First, the PID and ANFIS controllers are simulated in the inner pitch loop by moving a step input control bar (δ_{lon}) to the desired pitch angle when the PID gains are ($k_p = 1.2$; $k_i = 1$ and $k_d = 0.2$) as shown in Fig. 7.56. Second, the altitude response for two controllers is simulated by moving a step input control bar (δ_{lon}) to the desired altitude when the PID gains are ($k_p = 22$; $k_i = 11$ and $k_d = 10$), as shown in Fig. 7.57. Finally, the velocity response for two controllers is shown in Fig. 7.58 when the PID gains are ($k_p = 34$; $k_i = 24$ and $k_d = 8$). The longitudinal simulations in Tables 7.12, and 7.13 show the performance of the ANFIS and PID to control the altitude, velocity, and pitch angle of the UAV in response to the step inputs. These tables indicate that the rise time, settling time, overshoot and peak time of the designed controller (ANFIS) are better than those with PID.

Table 7.12: Time domain analysis of pitch angle

	Designed controller	Classic controller
Rise Time(s)	8.84	9.78
Settling Time (s)	43.8	47.3
Overshoot	7.36	12.7
Peak	10.8	11.3

Figure 7.56: Pitch-hold longitudinal autopilot response**Table 7.13:** Time domain analysis of speed

	Classic controller	Designed controller
Rise Time(s)	0.25	0.23
Settling Time (s)	6.04	3.42
Overshoot	65.1	60.2
Peak	1.65	1.60

Figure 7.57: Altitude-hold longitudinal autopilot response

Figure 7.58: Speed-hold longitudinal autopilot response

7.5.1.2 Tracking Different Signal Input

The ANFIS controller is tested to track different values of the pitch angle, and the response of pitch tracking with ± 2 values are shown in Fig. 7.59. When the reference altitude is doubled, the proposed ANFIS controller is tested with different altitude values. The response of the altitude control for tracking different altitudes are shown in Fig. 7.60, and the speed tracking response at different speed values based on ANFIS are shown in Fig. 7.61.

Figure 7.59: ANFIS pitch controller for tracking different signal input

Figure 7.60: ANFIS altitude controller for tracking different altitudes

Figure 7.61: ANFIS speed controller for tracking different speeds

7.5.1.3 Reject the Disturbance

The proposed controller can reject any temporary disturbances. Fig. 7.62 shows the controller response when a disturbance is applied to the system at ± 2 degrees for three and six seconds for the pitch angle. The ANFIS controller rejects -15 m disturbances at 15, and 22.5 seconds, as shown in Fig. 7.63. Fig. 7.64 shows that rejects +13 m/s disturbances at 10 and 20 seconds.

Figure 7.62: The effect of disturbance on pitch tracker

Figure 7.63: The effect of disturbance on altitude

Figure 7.64: The effect of disturbance on speed

7.5.2 Lateral Autopilot Simulation

The lateral autopilot design and testing is discussed in this section. ANFIS and PID controllers are applied to check system performance, and the state-space model is used to design the controllers. The state-space model is given as [4].

$$\begin{bmatrix} \dot{v} \\ \dot{p} \\ \dot{r} \\ \dot{\phi} \\ \dot{\psi} \end{bmatrix} = \begin{bmatrix} -0.226 & -0.0164 & -9.98 & 0.35 & 0.821 \\ -0.322 & -0.46918 & 0.1632 & 0 & 0 \\ 0.0275 & 0.0284 & -0.0289 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \end{bmatrix} \begin{bmatrix} v \\ p \\ r \\ \phi \\ \psi \end{bmatrix} + \begin{bmatrix} 0 \\ 1.263 \\ -0.263 \\ 0 \\ 0 \end{bmatrix} \delta_{lat} \quad (7.7)$$

The state-space matrices are determined using the aerodynamic stability derivatives calculated in Chapter 4, the explanation are provided in Appendix A. The controllability matrix is

$$C_{ntr} = \begin{bmatrix} B & AB & A^2B & \dots & A^{n-1}B \end{bmatrix} \quad (7.8)$$

The matrix C_{ntr} has full rank so, the system is controllable.

The inference system for the roll and heading angles are designed as shown in Section 5.3. The roll controller based on the ANFIS and PID controllers is tested to track roll angles from [3 to -3] degrees for 40 seconds, as shown in Fig. 7.65. Their performance is shown in Table 7.14. The ANFIS controller has a faster response than the PID with respect to the rising and settling times, and it also give a noticeably better overshoot than the PID controller. The heading control to track different reference angles for 200 seconds is shown in Fig. 7.66. Although, both controllers

follow the reference angle, the ANFIS has a faster response than the PID, as shown in Table 7.15.

Table 7.14: Time domain analysis of roll angle

	Classic controller	Designed controller
Rise Time(s)	0.66	0.15
Settling Time (s)	7.96	0.46
Overshoot	5.46	5.22
Peak	1.05	1.05

Figure 7.65: Roll controller for tracking different angles

Table 7.15: Time domain analysis of heading angle

	Classic controller	Designed controller
Rise Time(s)	4.85	4.20
Settling Time (s)	27.2	17.6
Overshoot	14.9	12.1
Peak	1.15	1.12

Figure 7.66: Heading controller for tracking different angles

The ANFIS controller can also reject any temporary disturbances, as shown in Figs. 7.67, and 7.68. It rejected disturbance when it was applied at 2 degrees for 10 and 20 seconds in roll angle, and for 40, and 60 seconds in heading.

Figure 7.67: The effect of disturbance on roll angle

Figure 7.68: The effect of disturbance on heading

7.6 Future Works

There are many potential opportunities to improve on this work, such as:

1. Investigation of different combinations of the wing skin and tracking point colors would enable their simultaneous use as a robust and a fast-visual algorithm for tracking shapes of planar structures.
2. Using another UAV model to validate the performance of the AUKF filter.
3. Use the DDVS system in actual flight tests, and understand that this is the only way to truly validate the control system developed in this thesis.
4. Used DDVS to calculate aerodynamic coefficient parameters and compare them with the experimental test results.
5. Verify the simulation results using flight tests.
6. Use multi-sensors to validate the results, and to estimate all states of a UAV using sensor fusion and AUKF.
7. Increasing autonomous capabilities by adding trajectory planning.

Chapter 8

Conclusion

A new Deflection-Detection Vision System (DDVS) was developed to control a UAV flexible wing, and it is a useful improvement for the UAV control the capabilities. The proposed DDVS includes identifying the flexible wing deflection and classifying its shape to determine the dynamics characteristics for the UAV. The system is comprised of three main elements: a vision system, the fuzzy logic algorithm and an Adaptive Neuro-Fuzzy Inference System ANFIS controller. A stereo camera is employed to improve state estimate and is a key sensor for tasks such as tracking, navigation and positioning. Three dimensional (3D) pose estimation method using planar homography between two images was developed and validated. The literature on homography estimation is quite extensive, and many advanced techniques are available. The Random Sample Consensus (RANSAC) stabilizes noise level results, while the other methods are strongly influenced by them. Furthermore, the smallest and relatively translation error occurred when the noise level is less than 0.5. Three algorithms (Decompose homography, Iterative Closest Point (ICP) and Horns Absolute Orientation method) were applied to determine the accuracy and robustness of each algorithm, and to find the optimal baseline distance between lenses. The distortion increases according to change in the z-distance or baseline, and are the result

of a distortion in images or inaccurate camera calibration. As seen in Table 7.2, a baseline of 10 cm when is more accurate when measuring an object distance equal to or less than 80 cm, while the most accurate baseline is 20 cm when measuring the distance of more than 80 cm. The vision system uses a ZED stereo camera to find the shape of a flexible wing, and fuzzy logic system was designed to classify the shape of the wing and reveal its dynamic behavior. Several experiments were performed to verify the accuracy of this technique over a broad range of conditions, including wind speed, angle of attack (AOA), and roll angle. The wind tunnel results show that the maximum wing deflection occurred at a wind speed is 31 m/s and an AOA equal 20° . Those parameters are used to achieve good system performance when following a desired reference, and the results demonstrate that the vision system is an integral part of an overall control system. The fuzzy logic system used using 18 rules to recognize a suitable wing shape and evaluate the system performance rapidly, and this resulted in a longitudinal and lateral autopilot design for the UAV. Two different techniques were developed for the autopilot design, Adaptive Neuro-Fuzzy Inference System (ANFIS) and a Proportional- Integral- Derivative (PID) controllers. Simulations compared the performance of both controllers with respect to the pitch, speed, roll and heading. The proposed methodology is based on a sensor fusion design to optimize the attitude accuracy and improve processing efficiency. The sensor fusion algorithm was tested and implemented to estimate the attitude of a flexible wing UAV. This method uses information from the Deflection-Detection Vision System (DDVS) and then integrated with data from the accelerometer sensor using a new filter called Adaptive Unscented Kalman Filter (AUKF). This filter employs fuzzy logic to improve the performance by tuning a suitable weighting factor to monitor the AUKF performance quickly. The experimental work was tested and the attitude estimated by the Unscented Kalman Filters (UKF) and AUKF then compared to

the real value. Experimental results show that the attitude errors are significantly reduced when using the proposed method rather than the UKF estimation method. This technique demonstrates a real-time solution to attitude estimation for a flexible wing UAV. Furthermore, a data fusion between DDVS and an accelerometer sensor that will improve the state of an UAV was successfully implemented. Environmental disturbances were also considered in the design architecture of the platform.

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Appendix A

Equivalent Aerodynamic Stability Derivatives

The equivalent aerodynamic stability derivatives for the wing and the tricycle [4].

$$\begin{aligned}\dot{X}_u & (\dot{X}_u)_w + (\dot{X}_u)_c \\ \dot{X}_w & (\dot{X}_w)_w + (\dot{X}_w)_c \\ \dot{X}_q & z_w(\dot{X}_u)_w + z_c(\dot{X}_u)_c - x_w(\dot{X}_w)_w - x_c(\dot{X}_w)_c \\ \dot{Z}_u & (\dot{Z}_u)_w + (\dot{Z}_u)_c \\ \dot{Z}_w & (\dot{Z}_w)_w + (\dot{Z}_w)_c \\ \dot{Z}_q & (\dot{Z}_q)_w + z_w(\dot{Z}_u)_w + z_c(\dot{Z}_u)_c - x_w(\dot{Z}_w)_w - x_c(\dot{Z}_w)_c \\ \dot{M}_u & (\dot{M}_u)_w - x_w(\dot{Z}_u)_w + z_w(\dot{X}_u)_w - x_c(\dot{Z}_u)_c + z_c(\dot{X}_u)_c \\ \dot{M}_w & (\dot{M}_w)_w - x_w(\dot{Z}_w)_w + z_w(\dot{X}_w)_w - x_c(\dot{Z}_w)_c + z_c(\dot{X}_w)_c \\ \dot{M}_q & (\dot{M}_q)_w + (\dot{M}_q)_c + z_w(\dot{M}_u)_w - x_w(\dot{M}_w)_w - x_w(\dot{Z}_q)_w - x_w z_w(\dot{Z}_u)_w + x_w^2(\dot{Z}_w)_w \\ & + z_w^2(\dot{X}_u)_w - x_w z_w(\dot{X}_w)_w - x_c z_c(\dot{Z}_u)_c + x_c^2(\dot{Z}_w)_c + z_c^2(\dot{X}_u)_c - x_c z_c(\dot{X}_w)_c\end{aligned}$$

$$\begin{aligned}
 \dot{Y}_v &= (\dot{Y}_v)_w + (\dot{Y}_v)_c \\
 \dot{Y}_p &= -z_w(\dot{Y}_v)_w + z_c(\dot{Y}_v)_c \\
 \dot{Y}_r &= x_w(\dot{Y}_v)_w + x_c(\dot{Y}_v)_c \\
 \dot{L}_v &= (\dot{L}_v)_w - z_w(\dot{Y}_v)_w - z_c(\dot{Y}_v)_c \\
 \dot{L}_p &= (\dot{L}_p)_w - z_w((\dot{L}_v)_w - z_w(\dot{Y}_v)_w) + z_c^2(\dot{Y}_v)_c \\
 \dot{L}_r &= (\dot{L}_r)_w + x_w(\dot{Y}_v)_w + x_c(\dot{Y}_v)_c \\
 \dot{N}_v &= (\dot{N}_v)_w + x_w(\dot{Y}_v)_w + x_c(\dot{Y}_v)_c \\
 \dot{N}_p &= (\dot{N}_p)_w - z_w((\dot{N}_v)_w - x_w(\dot{Y}_v)_w) - x_c z_c(\dot{Y}_v)_c \\
 \dot{N}_r &= (\dot{N}_r)_w + (\dot{N}_r)_c + x_w((\dot{N}_v)_w - x_w(\dot{Y}_v)_w) + x_c^2(\dot{Y}_v)_c
 \end{aligned}$$

Table A.1: The longitudinal derivatives for the wing

	Longitudinal Dimensional Derivatives		
	X	Z	M
u	$\rho u_0 SC_w \sin \theta + \frac{1}{2} \rho u_0 SC_{xu}$	$-\rho u_0 SC_w \cos \theta + \frac{1}{2} \rho u_0 SC_{zu}$	$\frac{1}{2} \rho u_0 \bar{c} SC_{mu}$
w	$\frac{1}{2} \rho u_0 SC_{x\alpha}$	$\frac{1}{2} \rho u_0 SC_{z\alpha}$	$\frac{1}{2} \rho u_0 \bar{c} SC_{m\alpha}$
q	$\frac{1}{4} \rho u_0 \bar{c} SC_{xq}$	$\frac{1}{4} \rho u_0 \bar{c} SC_{zq}$	$\frac{1}{4} \rho u_0 \bar{c}^2 SC_{mq}$

Table A.2: The lateral derivatives for the wing

	Lateral Dimensional Derivatives		
	Y	L	N
v	$\frac{1}{2}\rho u_0 SC_{y\beta}$	$\frac{1}{2}\rho u_0 b SC_{l\beta}$	$\frac{1}{2}\rho u_0 b SC_{n\beta}$
p	$\frac{1}{4}\rho u_0 b SC_{yp}$	$\frac{1}{4}\rho u_0 b^2 SC_{lp}$	$\frac{1}{4}\rho u_0 b^2 SC_{np}$
r	$\frac{1}{4}\rho u_0 b SC_{yr}$	$\frac{1}{4}\rho u_0 b^2 SC_{lr}$	$\frac{1}{4}\rho u_0 b^2 SC_{nr}$

- The Longitudinal Derivatives for tricycle are:

$$X_{uc} = \frac{1}{2}\rho S \frac{w_{eq}^2}{u_{eq}} C_{Tu} \cos \delta_{eq} + \frac{1}{2}\rho S u_{eq} [-2(C_{Dp})_{eq} \cos \alpha_{eq} + (2C_T + C_{Tu}) \cos \delta_{eq}]$$

$$Z_{uc} = \frac{1}{2}\rho S \frac{w_{eq}^2}{u_{eq}} C_{Tu} \sin \delta_{eq} + \frac{1}{2}\rho S u_{eq} [-2(C_{Dp})_{eq} \sin \alpha_{eq} + (2C_T + C_{Tu}) \sin \delta_{eq}]$$

$$M_{uc} = 0$$

$$X_{wc} = \frac{1}{2}\rho S w_{eq} [-2(C_{Dp})_{eq} \cos \alpha_{eq} + 2C_T \cos \delta_{eq}] + \frac{1}{2}\rho S (u_{eq} + \frac{w_{eq}^2}{u_{eq}}) C_{Dp} \sin \alpha_{eq}$$

$$Z_{wc} = \frac{1}{2}\rho S w_{eq} [-2(C_{Dp})_{eq} \sin \alpha_{eq} + 2C_T \sin \delta_{eq}] + \frac{1}{2}\rho S (u_{eq} + \frac{w_{eq}^2}{u_{eq}}) C_{Dp} \cos \alpha_{eq}$$

$$M_{wc} = 0$$

$$X_{qc} = 0$$

$$Z_{qc} = 0$$

$$M_{qc} = 0$$

(A.1)

- The Lateral Derivatives for tricycle are:

$$\begin{aligned}
 Y_{vc} &= \frac{1}{2}\rho S(u_{eq} + \frac{w_{eq}^2}{u_{eq}})[-2(C_{Dp})_{eq}\cos\alpha_{eq} - C_{Tu})\cos\delta_{eq}] \\
 L_{vc} &= 0 \\
 N_{vc} &= 0 \\
 Y_{pc} &= 0 \\
 Y_{rc} &= 0 \\
 L_{pc} &= 0 \\
 L_{rc} &= 0 \\
 N_{pc} &= 0 \\
 N_{rc} &= 0
 \end{aligned} \tag{A.2}$$

- The thrust Control Derivatives are:

$$\begin{aligned}
 X_{\delta th} &= \frac{1}{2}\rho SC_{T\delta th}\cos\delta_{eq} \\
 L_{\delta th} &= 0 \\
 Y_{\delta th} &= 0 \\
 M_{\delta th} &= 0 \\
 Z_{\delta th} &= \frac{1}{2}\rho SC_{T\delta th}\sin\delta_{eq} \\
 N_{\delta th} &= 0
 \end{aligned} \tag{A.3}$$

- The equivalent aerodynamic control derivatives are:

$$\begin{aligned}
 L_{\xi} &= \frac{m_cl_2}{m}L_w\cos(\delta)\cos(\alpha) \\
 M_{\delta} &= \frac{m_cl_2}{m}\cos(\delta)(L_w\cos(\delta - \alpha) + (D_w - \frac{m_w}{m_c}D_c)\sin(\delta - \alpha)) \\
 N_{\xi} &= 0
 \end{aligned} \tag{A.4}$$