REAL-TIME IDENTIFICATION OF AN UNMANNED QUADCOPTER FLIGHT DYNAMICS USING FULLY TUNED RADIAL BASIS FUNCTION NETWORK

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ABSTRACT

A quadcopter is a four-rotor unmanned aerial vehicle (UAV) with nonlinear and strongly coupled dynamics system. A precise dynamics model is important for developing a robust controller for a quadcopter. NN model capable to obtain the accurate dynamics model from actual data without having any governing mathematical model or priori assumptions. Recursive system identification based on neural network (NN) offers an alternative method for quadcopter dynamics modelling. Recursive learning algorithms, such as Constant Trace (CT) can be implemented to solve insufficient training data and over-fitting problems by developing a new model from real-time flight data in each time step. The modelling results from the NN model could be inaccurate due to inappropriate model structure selection, excessive number of hidden neurons and insufficient training data. Typically, the model structures and hidden neuron are determined by using trial and error approach to obtain the best network configuration. This study utilised a fully tuned radial basis function (RBF) neural network to obtain a minimal structure and avoid pre-determining the number of hidden neurons by introducing the adding and pruning neuron strategy. The prediction performance of the proposed fully tuned RBF was compared with Multilayer Perceptron (MLP), Hybrid Multilayer Perceptron (HMLP) and RBF networks trained with CT algorithm. The findings indicated that the fully tuned RBF with minimal resource allocating networks (MRAN) automatically selected seven neurons with 9.5177 % prediction accuracy and 5.89ms mean training time. The results also showed that the proposed extended minimal resource allocating networks (EMRAN) algorithm is capable to adapt with dynamics changes and infer quadcopter model with an even shorter training time (4.16ms) than MRAN and suitable for real-time system identification.

ABSTRAK

Quadcopter adalah pesawat udara tanpa pemandu (UAV) yang mempunyai empat kipas dengan sistem dinamik yang tidak linear. Model dinamik yang jitu adalah penting untuk membangunkan sistem kawalan quadcopter. Rangkaian neural tiruan (NN) berupaya menghasilkan sistem dinamik yang jitu dari sumber data sebenar tanpa membuat formula matematik atau maklumat awal. Pengenalpastian system dalam talian berasaskan NN menawarkan satu kaedah alternatif bagi memperolehi sistem dinamik untuk quadcopter. Pembelajaran algoritma secara dalam talian seperti Pengesan Malar (CT) dilaksanakan untuk menyelesaikan masalah data penerbangan tidak mencukupi dengan membangunkan dinamik model baru pada masa sebenar. Hasil pengenalpastian dari model NN tidak jitu disebabkan oleh pemilihan struktur model yang tidak sesuai, bilangan nod neural yang berlebihan serta data penerbangan yang tidak mencukupi. Lazimnya, model struktur dan nod-nod neural akan ditentukan menggunakan kaedah cuba dan ralat untuk mendapatkan konfigurasi rangkaian terbaik. Kajian ini menggunakan Rangkaian Neural Fungsi Asas Jejarian (RBF) penyelarasan secara menyeluruh dengan algoritma penambahan atau pengurangan nod-nod neural bagi mendapatkan struktur yang optimum dan mengelakkan ketidaktentuan bilangan nod neural. Prestasi RBF penyelarasan menyeluruh yang dicadangkan dibandingkan dengan Perseptron Berbilang Lapisan (MLP), Perseptron Berbilang Lapisan Hibrid (HMLP) dan RBF dengan algoritma CT. Dapatan kajian menunjukkan bahawa RBF penyelarasan menyeluruh dengan Pengagihan Sumber Rangkaian Minima (MRAN) automatik menggunakan tujuh node dengan 9.5177 % kejituan and 5.89ms purata masa latihan. Dapatan kajian juga menunjukkan Penambahan Pengagihan Sumber Rangkaian Minima (EMRAN) berupaya menghasilkan model dinamik dan menyesuaikan diri dengan perubahan dinamik dengan purata latihan rangkaian yang lebih singkat (4.16ms) dari MRAN dan sesuai untuk diimplimentasi dengan pengenalpastian system dalam talian.

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LIST OF SYMBOLS AND ABBREVIATIONS

ARX	-	Auto Regressive structure with eXtra inputs
BP	-	Back Propagation
CAD	-	Computer Aided Design
CIFER	-	Comprehensive Identification from Frequency Responses
CT	-	Constant Trace
DOF	-	Degree of Freedom
EKF	-	Extended Kalman Filter
EMRAN	-	Extended Minimal Resource Allocating Network
ESC	-	Electronic Speed Controller
FNN	-	Feed Forward Network
FPGA	-	Field Programmable Gate Array
GN	-	Gauss Newton
HMLP	-	Hybrid Multilayer Perceptron
IMU	-	Inertia Measurement Unit
LM	-	Levenberg-Marquardt
LMS	-	Least Mean Square
MIMO	-	Multiple Input Multiple Output
MLP	-	Multilayer Perceptron
MRAN	-	Minimal Resource Allocating Network

MSE	-	Mean Squared Error
NI	-	National Instrument
NN	-	Neural Network
NNARMAX	-	Neural network Auto Regressive Moving Average Model Structure with External Input
NNARX	-	Neural network Auto Regressive Structure with Extra Inputs
OSA	-	One Step Ahead Prediction
PPM		Pulse Position Modulation
PWM	-	Pulse Width Modulated
RANEKF	-	RAN based EKF
RAN	-	Resource Allocating Network
RBF	-	Radial Basis Function
rGN	-	Recursive Gauss Newton
RMSE	-	Root Mean Squared Error
RNN	-	Recurrent Forward Network
SI	-	System Identification
SIDPAC	-	System Identification Programs for Aircraft
SISO	-	Single Input Single Output
UART	-	Universal Asynchronous Receiver/Transmitter
UAV	-	Unmanned Aerial Vehicle
VSTOL	-	Vertical Take Off and Landing

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CHAPTER 1

INTRODUCTION

1.1 Background of study

A quadcopter is a type of rotorcraft-based unmanned aerial vehicle (UAV) flies by using four fixed pitch rotors by changing the speed of each rotor. It does not require any complex mechanical control mechanism for its propellers and it is easier to maintain. The quadcopter is preferred than a helicopter due better stability characteristic with similar hovering capability of conventional helicopter. Due to these advantages, multi-rotor aerial vehicles, such as the quadcopter, attract strong interest worldwide.

The quadcopter offers unique capabilities that enable it to take off and land vertically and hover and cruise at a lower speed. The quadcopter platform offers many potential applications in both military and civil compared to fixed-wing UAV. Quadcopters in military applications are mainly used for real-time reconnaissance surveillance and search and rescue missions. Meanwhile, in civil application, quadcopters are significantly used in aerial photography, delivery service (Wei, 2015), traffic monitoring and structural inspection (Altuğ, Ostrowski, & Taylor, 2005). The quadcopter is also widely used for university research, to be tested and developed in different fields of studies including flight control theory, real-time systems, navigation and robotics.

Most of the above-mentioned applications require the quadcopters to have a highly robust control system to hover steadily and in close proximity relative to the targets. Different types of flight controllers, such as PID (Kader, El-henawy, & Oda, 2014), Linear Quadratic Regulator (LQR) (Cowling et al., 2007), model predictive (Bangura & Mahony, 2014) and artificial neural networks (Boudjedir et al., 2012) have been developed for the quadcopters to fly autonomously and in close proximity to the targets. Hence, a comprehensive modelling work needs to be conducted to obtain an accurate flight dynamics model if one intends to design a robust flight control system. High accuracy and fidelity of mathematical models are essential in many flight applications especially in stability and control, system verification and simulation development (Klein & Morelli, 2006; Tischler & Remple, 2006).

The dynamics model of a quadcopter often involves certain assumptions to simplify the model complexity. High frequency and unmodelled dynamics are neglected to simplify the dynamics model analysis. Hence, flight controller design based on the simplified and unmodelled dynamics may not operate properly in a real application, leading to crash or unexpected control behaviours during flight (Cai, Chen, & Lee, 2006; Cai et al., 2016; Waslander, Hoffmann, & Tomlin, 2005). Thus, a comprehensive method to obtain a precise dynamics model is crucial to develop a robust controller for a quadcopter.

1.2 Problem statement

Quadcopter flight dynamics modelling is a numerical representation of flight dynamics response for a given input. System identification based on neural network (NN) can be used as an alternative method in quadcopter dynamics modelling. The NN model offers a flexible model structure that can be trained by using various numbers of efficient training algorithm. These advantages make NN can approximate complex nonlinear mapping and reduce the costs and efforts to model dynamics system (Collotta, Pau, & Caponetto, 2014; Lawryńczuk, 2014; Shamsudin & Chen, 2014; Zurada, 1996). However, the modelling result from the NN approach could be inaccurate due to improper model structure selection, an excessive number of neurons and insufficient training data for the system (Shamsudin & Chen, 2012). Furthermore, the NN modelling has disadvantages of longer training, slow convergence rate and susceptible to the over-fitting problem. In NN system identification, the performance of a NN model mostly depends on its generalisation capability which is related to the ability of the network to predict untrained data and over-fitting problem, leading to generalised poor performance (Urolagin, Prema, & Reddy, 2012).

The total number of hidden neurons in the hidden layer is the main parameter that determines the overall NN model structure. A typical selection of hidden neurons is based on the trial and error method or rule-of-thumb approach (Panchal & Panchal, 2014; Peyada & Ghosh, 2009). However, this approach is labourious and may not achieve an optimal NN architecture (Romero Ugalde et al., 2015). The selection of the number of neurons is a very crucial step during NN modelling and an incorrect number of neurons could lead to an inaccurate and poor prediction performance (Pairan & Shamsudin, 2017; Shamsudin & Chen, 2012). Hence, a good selection of NN structure and implementation of advanced NN architectures should improve the prediction performance and reduce the training time of the model (Panchal & Panchal, 2014; Shamsudin & Chen, 2012).

Standard offline/batch training neural network models, such as Levenberg-Marquardt (LM), Gauss-Newton (GN) and back-propagation are insufficient to represent the dynamics nonlinear systems over the entire flight envelope. These methods will fail to adapt to frequent dynamics changes as they are only suitable for time-invariant system (V. Puttige & Anavatti, 2007; Samal, 2009; Shamsudin, 2013). Since the quadcopter is a time-variant and nonlinear dynamics system, recursive training algorithms should be introduced to improve the prediction, adaptability of the dynamics model over the entire flight envelope and avoid the over-fitting problem (Hunter et al., 2012; Shamsudin, 2013).

This thesis attempts to overcome the drawbacks of system identification based on the NN by introducing recursive NN-based modelling by using fully tuned radial basis function (RBF) neural network. Fully tuned RBF with a recursive training algorithm was proposed to overcome the large numbers of hidden neurons and parameters selection dilemma, reduce training time and avoid the over-fitting data problem. The fully tuned neural network was applied to the quadcopter platform to model the nonlinear attitude dynamics by using raw flight data.

1.3 Objectives

This study intends to develop a real-time identification algorithm for modelling a quadcopter dynamics system using RBF NN with automatic tuning for all RBF network parameters. This study specifically aims:

1. Develop a comprehensive and adaptive system identification method for a quadcopter attitude dynamics system using fully tuned RBF NN.
2. Evaluate performance of a developed system identification algorithm in terms of prediction model error and execution speed in real-time hardware.
3. Generalize performance of NN model by establishing a relationship between the effect of regression size and the number of neurons.

1.4 Scope of Study

The scopes set for the research work are as follows:

1. Establishing comprehensive quadcopter flight dynamics model characteristics.
2. Developing a suitable real-time system identification algorithm for a quadcopter with execution speed of less than 30ms.
3. Developing a NN system identification algorithm using National Instrument MyRIO embedded device and LabVIEW development software.
4. Performing quadcopter flight test based on DJI flight controller with attitude hold mode.
5. Establishing network communication link between quadcopter and ground station by using WIFI on MyRIO that have an approximate communication range of 150m.

1.5 Significant of Study

This study will be significant in correct selection of neuron sizes or network parameter such as center and width that impact the prediction error of the NN network. The fully tuned RBF networks solved hidden neuron size dilemma using automatic tuning algorithm to obtain the optimum network structure with better training time and prediction quality. The method improves conventional hidden neuron selection process by integrating the growth of hidden neurons, center and width as part of training process. Thus, save time and effort compared to troublesome manual selection of network parameters.

The usage of recursive algorithms for NN model like Kalman Filter or recursive Gauss-Newton (rGN) can be applied to reduce computation complexity of the offline (batch) training method. The proposed MRAN and EMRAN recursive training algorithms introduce adding and pruning neuron strategy to offer a faster system identification method with adaptability to dynamics change compare with standard RBF network.

1.6 Thesis Organisation

The work presented in this thesis focuses on the development of a system identification method based on a fully tuned RBF to determine the attitude dynamics model of the quadcopter. The thesis is organized as follows: In Chapter 2, discusses on quadcopter flight dynamics modelling and system identification. In Chapter 3, research methodology in system identification method based on neural network and details about fully tuned neural network are addressed. Results and discussion are presented in chapter 4. Chapter 5 presents the concluding remarks.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

This chapter provides an overview of quadcopter dynamics and system identification based on neural network model. An unmanned aerial vehicle (UAV) is defined as an air vehicle that is able to perform flight missions without human pilot on board. Most UAVs are equipped with automatic flight control, communication systems, sensors and ground control station that can fly autonomously or remotely controlled (Office of the Secretary of Defence, 2003). The popularity of UAV has grown very fast and approximately over 1000 UAV models have been developed for military and civil applications (Guowei Cai, Dias, & Seneviratne, 2014).

UAV can be classified into fixed-wing, rotary wing and flapping wing UAVs. The fixed-wing UAV is developed for long range and high-altitude missions such as meteorological and environmental monitoring. Meanwhile, flapping wing UAV is replicating a bird's flying mechanism with a low power consumption and vertical take-off and landing (VTOL) capability. However, most flapping wing UAVs are still under development and have an extremely low payload capability (Norouzi Ghazbi, Aghli, Alimohammadi, & Akbari, 2016). Rotary wing UAVs such as helicopter and quadcopter are mainly used on missions that require hovering flight. The rotorcraft UAV also has VTOL capability and able to hover and cruise at a very low speed which make it the best UAV for searching and tracking ground targets.

The mechanical structure of a quadcopter is very simple and usually have two basic types of configuration which are the cross configuration and the plus configuration as shown in Figure 2.1. The cross configuration quadcopter is more stable and provides higher momentum than plus configuration, which will increase the manoeuvrability performance (Gupte, Mohandas, & Conrad, 2012). Reference frame for cross configuration quadcopter is shown in Figure 2.2. The position of the quadcopter can be addressed in a coordinate of body frame, b with reference to inertial frame, e. X_b, Y_b, and Z_b are the main axis of the body frame of quadcopter while X_e, Y_e, and Z_e are axis on inertial frame. Two diagonal rotors (M1 and M3) are rotating counter-clockwise whereas the other rotors (M2 and M4) rotate in the clockwise direction.

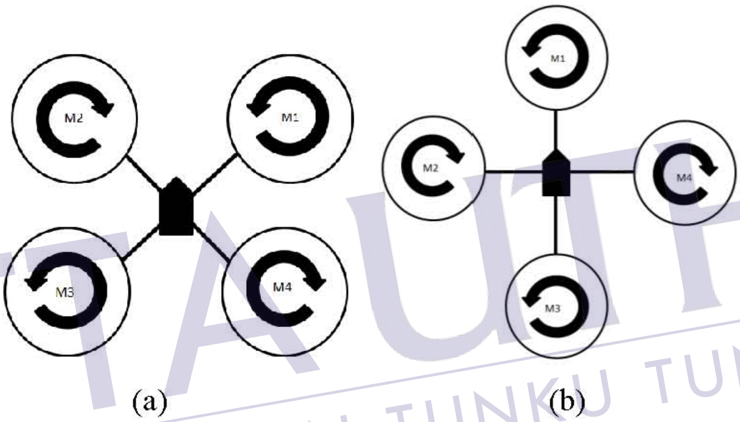

Figure 2.1: Quadcopter mechanical structure configuration (a) Cross configuration (b) Plus configuration

Red color rotation indicated that the speed of the motor is increasing and black rotation means the speed is decreasing. Thus, a quadcopter will have a forward pitch and create pitch angle (θ). Similarly, when flying in positive Y_b axis and create roll (ϕ) as in Figure 2.3(b), the quadcopter is required to decrease the propeller speed at M1 and M2 and increase the propeller speed at M3 and M4. To change the quadcopter heading in Z_b (ψ), the quadcopter must increase M1 and M3 rotor speed, and decrease rotor speed at M2 and M4 as shown in Figure 2.3 (c).

All rotor speeds need to be controlled to create any manoeuvre of the quadcopter since reducing the speed of one rotor will cause the quadcopter to change direction but there are also changes in the total yaw moment and thrust (Altuğ et al., 2005; McKerrow, 2004). Thus, the quadcopter is an unstable and highly coupled dynamics system, which made it difficult to control. Recent quadcopter design is expected to fly in uncertain environments and outside the traditional flight envelope region, thus, require the controller to have a higher level of robustness and adaptability (Collotta et al., 2014; L. Li, Sun, & Jin, 2015). Robust control techniques are necessary for the autonomous flight of the UAV to adapt themselves to the changes in dynamics of the vehicle. A comprehensive research done by Office of the Secretary of Defence (2003) concluded that flight control failure contributes about 26 percent of total UAV failures and second major problem contribution for UAV after power and propulsion failure. In order to minimize crash or failure during a mission, it is essential to have an automatic flight control system (AFCS) installed on-board and the design of AFCS is strongly related to the dynamic model of UAV. High fidelity model of a UAV is important to design an advanced automatic flight control system such as the nonlinear control, linear-quadratic regulator (LQR) and H_∞ control (Guowei Cai et al., 2014).

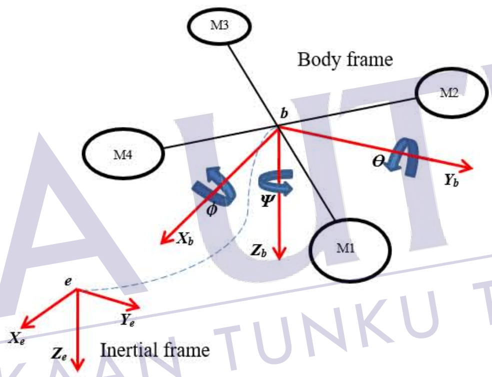

Figure 2.2: Cross quadcopter frame.

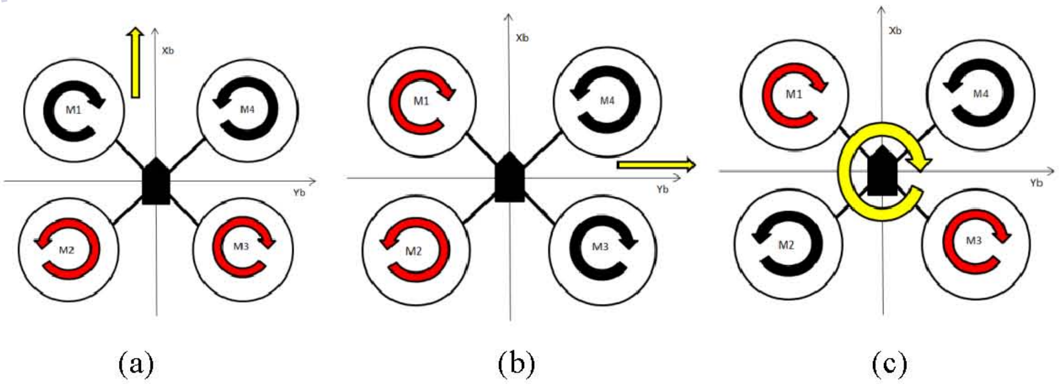

Figure 2.3: Speed of rotor for quadcopter flying movement (a) Pitch forward along X_b axis (b) Roll right along Y_b axis (c) Yaw clockwise along Z_b axis

2.2 Quadcopter Dynamic Modelling and System Identification

This section introduces dynamics modelling techniques used to determine the mathematical model of the quadcopter system. Two common methods were developed in modelling the quadcopter based on the first principle approach and system identification.

2.2.1 First principle approach method

The first principle method of quadcopter modelling used the Newton-Euler equations of motion to describe the system behaviour. The flight dynamics is then extended to include forces and moments balance of the vehicle platform with a certain number of assumptions and simplifications. Many unknown parameters in the mathematical model need to be measured or approximated, thus, make the modelling work complex (Norgaard, 2000). Several assumptions are used to simplify the mathematical model development as follows:

(i) The quadcopter frame is symmetrical in x and y-axis and rigid.
(ii) The center of gravity and center body principle axis are coinciding.
(iii) Aerodynamics effects such as flapping on rotors are ignored.
(iv) The propellers are rigid.

Figure 2.4 below shows the basic flight dynamics model for a quadcopter that represents four main components which are kinematics, 6 degree of freedom (DOF) rigid body dynamics, aerodynamic forces and moments and onboard stabilizer dynamics. The kinematics part shows the relative translational and rotational motion between the vehicle and local environment. The motion is defined by using Newton-Euler equations of motion which in the body frame (b) and the inertial (e). The kinematic equations are given by

$$\dot{\mathbf{P}}_n = \mathbf{R}_{e/b} \mathbf{V}_b \qquad (2.1)$$

$$\dot{\mathbf{\Phi}} = \mathbf{S}_{e/b} \boldsymbol{\omega}_b \qquad (2.2)$$

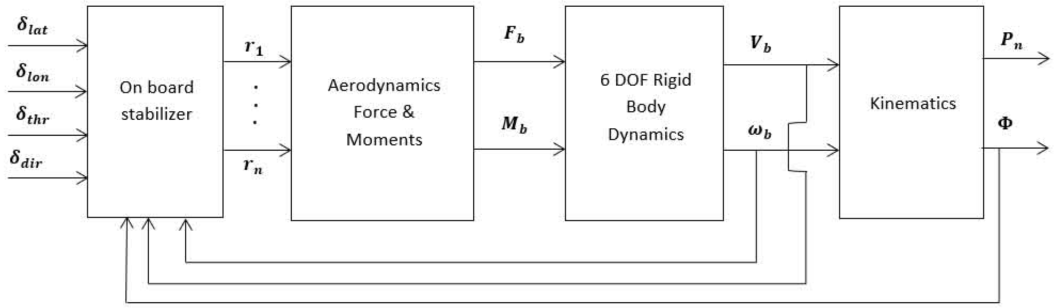

Figure 2.4: Flight dynamics model for quadcopter. (G. Cai et al., 2016)

where $\boldsymbol{P}_n = \begin{bmatrix} p_x & p_y & p_z \end{bmatrix}^T$ is the quadcopter position in inertial reference frame , $\boldsymbol{\Phi} = [\phi \;\; \theta \;\; \psi]^T$ is the Euler angle in Earth frame , $\boldsymbol{V}_b = [u \;\; v \;\; w]^T$ is linear velocity in body frame and $\boldsymbol{\omega}_b = [\; p \;\; q \;\; r \;]^T$ is the angular rate of quadcopter in the body reference frame. $\boldsymbol{R}_{e/b}$ and $\boldsymbol{S}_{e/b}$ are rotational matrices from the body reference to inertial reference frame (Guowei Cai et al., 2006).

The 6 DOF rigid-body dynamics component addresses the quadcopter translational and rotational dynamics in the body frame defined as follows:

$$\dot{\mathbf{V}}_b = -\boldsymbol{\omega}_b \times \mathrm{V}_b + \frac{\mathbf{F}_b}{m} + \frac{\mathbf{F}_g}{m} \tag{2.3}$$

$$\dot{\boldsymbol{\omega}}_b = \mathbf{J}^{-1}[\mathbf{M}_b - \boldsymbol{\omega}_b \times (\mathbf{J}\,\boldsymbol{\omega}_b)] \tag{2.4}$$

where m is the mass of quadcopter, $\boldsymbol{J}$ is the simplified inertia matrix, $\boldsymbol{F}_b$, $\boldsymbol{F}_g$ and $\boldsymbol{M}_b$ are the total force, gravity force and total moments, respectively.

The aerodynamic forces and moments component primarily contains forces and moments that act on the quadrotor due to four major sources which are the gravitational force, rotors movement, the gyroscopic effects and inertia counter torque (Phang, Cai, Chen, & Lee, 2012). The drag generated from the frame of the quadcopter can be neglected because the force is small compared to other force components. So, the equation for total force and moments is given by:

$$\begin{pmatrix} \boldsymbol{F}_b \\ \boldsymbol{M}_b \end{pmatrix} = \begin{pmatrix} \boldsymbol{F}_g \\ 0 \end{pmatrix} + \begin{pmatrix} \boldsymbol{F}_{rotor} \\ \boldsymbol{M}_{rotor} \end{pmatrix} + \begin{pmatrix} 0 \\ \boldsymbol{M}_{gryo} \end{pmatrix} + \begin{pmatrix} 0 \\ \boldsymbol{M}_{counter} \end{pmatrix} \tag{2.5}$$

where, $\boldsymbol{F}_g$ is the force due to gravity, $\boldsymbol{F}_{rotor}$ and $\boldsymbol{M}_{rotor}$ are the forces and moments due to the rotating rotor for each rotor, respectively, $\boldsymbol{M}_{gryo}$ is the total moments induced by the four rotors and the quadcopter rigid body and $\boldsymbol{M}_{counter}$ is the moment caused by changes in the rotational speed of the propeller.

The on board stabiliser component in the quadcopter flight dynamics is used as the control input mixer to stabilise the quadcopter. Several outputs of the

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