UAV PARAMETER ESTIMATION THROUGH MACHINE LEARNING

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by

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Chapter 1: Introduction

1.1 - Motivation

Some of the biggest challenges in current applications of Unmanned Aerial Vehicles (UAVs) include safe operation, communication between manned and unmanned aircrafts, and robust control systems. Control system design typically needs an accurate model of the aircraft. To increase the model accuracy, model parameters need to be estimated. Dynamic aircraft systems have traditionally been estimated analytically from Newton's second law for rigid-body dynamics (Hoffer, 2014). These dynamic system models have been usually obtained through wind tunnel testing. Some important limitations of wind tunnel tests include the high costs involved, test equipment interface interactions (Bhavithavya, 2013), and limitation on flight regimes. System identification or system ID is an alternative to wind tunnel type model estimation(Bhavithavya, 2013). System identification involves parameter estimation to determine a mathematical model. These parameters are estimated indirectly from measured flight data. This parameter estimation process requires a careful consideration of the aircraft instrumentation for accurate measurements. It also requires careful design of the flight maneuver to ensure thorough excitation of the dynamics. Finally, one must select a suitable identification method.

The purpose of this thesis is to show the application of machine learning for parameter identification of a UAV model. The machine learning algorithm does not require developing parameterized models; hence it is an equation-less identification method of an aircraft. To avoid the expense of crashing a real UAV, a simulation model of the aircraft is generated. The parameters of the model can be modified in the simulation. The aircraft flight measurement data is obtained directly from the model as simulation outputs from a predetermined flight path. The data is submitted to a machine learning algorithm that is able to read and recognize the data. The machine

learning algorithm is trained with a set of flight data that incorporates variations in the parameters to be identified. Finally, the algorithm is tested by feeding unknown aircraft data and comparing the prediction of the machine learning algorithm to the known answers.

To obtain simulation data through autonomous UAV operation, a Software-In-the-Loop (SIL) simulation is constructed. In this case, the SIL is created by interconnecting the simulation software known as X-Plane, and the Ground Control Station (GCS) known as Mission Planner. X-Plane is a realistic flight simulator where the UAV model is generated and flown. Mission Planner is a GCS, which for this case, encompasses a software that allows the operator to have control of the UAV autonomously.

1.2 – Importance of System Identification

There are external forces and moments acting on a flight vehicle during operation that need to be considered in the creation of a dynamic system model. System identification allows for the creation of more complete and accurate aircraft models. It is important to have a complete and accurate model for two aspects. One being a complete breakdown of the components contributing to the response of the system. This results in a more complete understanding of the aircraft's dynamics. A more practical aspect of System Identification is that it enables the creation of accurate databases for flight simulators and off-line digital simulations (Jategaonkar, 2015). These databases have been useful for training applications when incorporated into simulators. Simulator training is a safer and cost-effective alternative to real testing.

Chapter 2: Literature Review

2.1 – System Identification

There are three main elements that can describe a dynamic system. Inputs, Outputs and the system's model functions. According to (Jategaonkar, 2015), there are three different types of problems in system theory:

1. Simulation problem, which is concerned with finding outputs from a given set of inputs where the functions are given.
2. Control problem, where in this case, the objective is to obtain the control inputs from the given outputs and functions.
3. Identification problem, where the goal is to find the system model functions from known system inputs and outputs.

The present work is concerned with problem number three above, namely, the identification problem. If we refer to the inputs as *u*, the outputs as *y*, and the system model functions as *f* and *g*. We can represent the model of a system mathematically as follows:

$$\xrightarrow{u\ inputs} \begin{pmatrix} \dot{x}(t) = f(x(t), u(t), \Theta) \\ y(t) = g(x(t), u(t), \Theta) \end{pmatrix} \xrightarrow{y\ outputs}$$

Figure 2.1: Dynamic System Model Mathematical Representation. (Jategaonkar, 2015)

In Figure 2.1, the functions *f* and *g* contain the unknown parameters Θ. Thus, system identification is concerned with determining the mathematical model's equations and unknown parameters Θ. These parameters are obtained from measured outputs that result from the systems known inputs.

Parameter estimation is the core activity within the system identification problem. Parameter estimation is concerned with finding the unknown parameters Θ that construct the system's models. In the following section. Some of the traditional estimation techniques are introduced.

2.2 – Traditional Parameter Estimation Techniques

The need to accurately characterize the aerodynamic characteristics of aircrafts such as lift, drag, or moment coefficients has been recognized since early stages of aircraft development. It is not possible to directly measure the aerodynamic forces and moments on a flight vehicle. However, parameter estimation provides means to estimate aerodynamic characteristics from measurements of acceleration, angular rates and flow angles (Jategaonkar, 2015). Some of the main traditional techniques for estimation are discussed next.

The first of them is the analytical method. The Engineering Science Data Unit and/or DATCOM have developed empirical relations from previous manned flight vehicle data (Bhavithavya, 2013). However, this method is based on assumptions that cannot be relied on due to the actual complexity of the phenomena involved in the more intricate designs of modern UAVs.

Another method is the use of numerical tools. Computational Fluid Dynamics (CFD) tools have been evolving to predict the forces and moments in UAVs. Similar to the analytical method, the complexity of the phenomena involved makes the simplifying assumptions on the models unreliable. The modeling of more realistic conditions come at the expense of high computational cost.

Another traditional method has been the use of experimental techniques. Among these, wind tunnel testing has been used to obtain flight vehicle data. However, this method is limited and can be influenced by the condition of the actual test tunnel.

Parameter estimation provides an alternative to overcome some of the drawbacks of traditional methods while yielding an accurate characterization of the system. The generation of mathematical models via parameter estimation allows to gain a deep understanding of the flight system (Bhavithavya, 2013).

2.3 – Equation-Error Estimation Method

The equation-error estimation method is based on regression analysis or Least-Squares (LS). The equation-error method estimates aerodynamic parameters by minimizing the sum of squared differences between the values of force and moment coefficients from actual flight output measurements and the mathematical model values (Morelli, 2006). The LS is an iterative process starting with an initial approximation vector θ of the parameters to yield a "better" estimation. These approximations are used as initial values for the next iteration to obtain an improved estimation. The process continues until the approximations converge to a stable value with minimal variation (Johnson, 1992). Here, the definition of "better" is a smaller difference between the fitted function and the experimental data as described earlier. For a given set of data consisting of x and $y(x)$, x is regarded as the independent variable and $y(x)$ is the dependent variable from a discrete amount of samples N. Figure 2.2 below provides a block schematic of the LS approach.

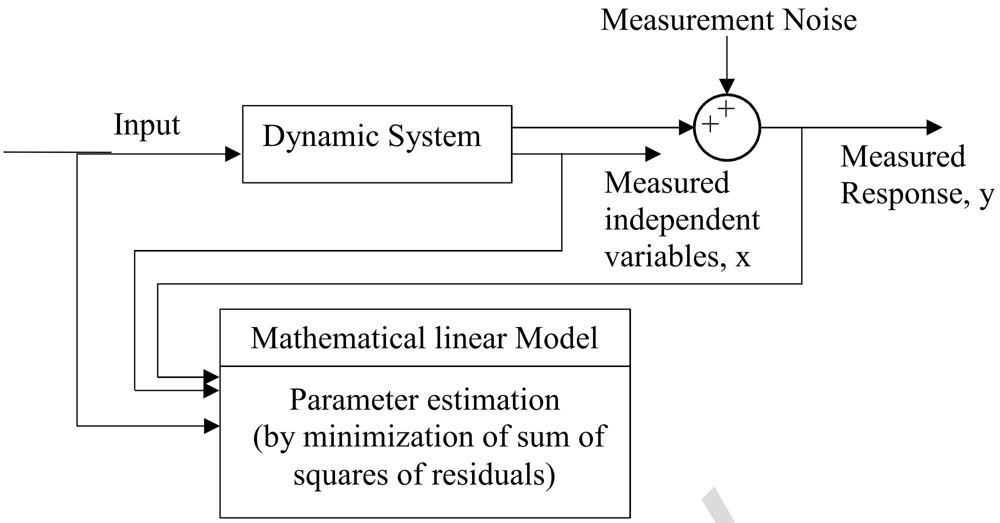

Figure 2.2: Block schematic of least-squares method. (Jategaonkar, 2015)

Assuming a linear relationship between the dependent and independent variables yields the following equation.

$$y(k) = x^T(k)\theta + \varepsilon(k); \quad k = 1,2,3 \ldots, N \qquad \text{Eq. 2.1}$$

where θ is the vector of unknown parameters and ε represents the equation error.

$$\varepsilon(k) = y(k) - x^T(k)\theta \qquad \text{Eq. 2.2}$$

The error can be written in matrix form,

$$\varepsilon = [\varepsilon(1)\ \varepsilon(2) \ldots\ \varepsilon(N)]^T \qquad \text{Eq. 2.3}$$

Using this error definition, the least-squares method estimates the unknown parameters θ by minimizing the sum of the squares or the weighted sum of the squares of the error values in the matrix in Eq. 2.3 (Jategaonkar, 2015).