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Modelling engineering systems using analytical and neural techniques: Hybridization

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ABSTRACT

From real input/output data, different control-oriented models of a quadrotor unmanned aerial vehicle (UAV) are obtained by applying different identification methods. Parametric techniques, neural networks, neuro-fuzzy inference systems, and the hybridization of some of them are applied. The identified models are analyzed and compared in the time and frequency domains. We conclude that the hybridization of analytical and intelligent techniques is a good choice to model of complex systems while keeping a good balance between accuracy and computational cost. In addition, off-line trained neural networks and adaptive networks with on-line learning are analyzed, and their advantages and disadvantages regarding modelling are presented. The influence of the partition of the training and validation dataset on the model error is also discussed.

1. Introduction

Modelling is one of the most important approaches to deal with complex systems. Any representation of a real system allows us to analyze its behaviour and to get a deeper knowledge of it. In the area of engineering control, the availability of simulation models is essential in order to design control laws and to test them without endangering the real system. Therefore, one of the most important steps to effectively control a physical system is to obtain reliable and useful models that describe its behaviour [1].

The importance of having a good model grows with the complexity of the system. On the one hand, the model must be as close as possible to reality but, on the other hand, the model should be kept as simple as possible in order to reduce the computational cost. Low computational cost is a key enabling factor to run the model in low-cost general-purpose hardware platforms [2]. The underlying idea of our proposal is to obtain models of complex systems by keeping an adequate balance between accuracy and the hardware resources needed to execute them.

Basically, there are two ways of approaching the modelling: the first one is to apply the well-known physical equations that govern the dynamic behaviour of the real system, and use this knowledge to generate the usually non-linear high-order differential equations that represent it. This methodology is straightforward when all variables are known, and the relations between them are relatively simple. However, these mathematical models are usually difficult to handle because of the nonlinear nature of the equations. Even more, there are real systems which are too complex to be modelled this way or it is even impossible to obtain an analytic expression of its dynamics. In this case, it is necessary to apply other approaches [3].

The second way identifies the model using experiments to obtain representative input and output data of the real system. Analyzing this information by the application of identification strategies, it is possible to estimate the internal relationship between inputs and outputs [4]. Then mapping mechanisms are applied to represent the hidden internal relations between inputs and outputs. These mapping procedures iteratively update their parameters to tune the model as well as to reduce its order [5]. The system is then considered as a black-box because there is not physical knowledge about the system represented in the model. Within this approach, called identification, parametric and intelligent methodologies are found. Among the latter, soft computing techniques, such as neural networks and neuro-fuzzy systems are included. These methods, closer to human learning, have been proved better when dealing with strongly non-linear and complex systems, such as marine and aerial autonomous vehicles [6–10].

Parametric techniques provide simple models but whose accuracy may not be highlighted. On the other hand, methods based

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on artificial intelligence generate models which better fit the real behaviour of the system but can be very demanding in terms of computational requirements.

These ideas suggest that a good choice would be to unite precision and simplicity in a single strategy. Following this line of thought, this paper aims to combine both types of techniques in order to get the best of both worlds, the straightforwardness of the parametric models and the accuracy of soft computing techniques. First, we have applied parametric techniques (ARX, ARMAX, and OE) independently, with different configuration. Then various types of neural networks (radial basis, feedforward), and neuro-fuzzy systems have been used to identify the UAV model. Finally, the hybridization of both approaches, the parametric and the intelligent ones, is proposed and the advantages of this combination are discussed.

Besides, we have also analyzed how the training dataset influences the obtained model when supervised neural networks are applied. In fact, off-line learning neural networks have the disadvantage of being very sensitive to the partition of the training dataset. On the contrary, adaptive neural networks with on-line learning are much more robust because they are continuously learning from the real data of the system. It is not necessary to select any dataset to train the network and therefore it is not biased. In addition, they can be used to identify models of systems whose dynamic changes over time, as for example, systems that work in outdoor environments subject to changing weather conditions [11].

In addition, this paper provides another original contribution to the system identification field: the definition of a new criterion to measure and analyze the performance of the models. This criterion is a hybrid Mean Square Error (MSE) computed by the combination of the estimated step response error in the time domain and the estimated frequency response error.

We are working with a real unmanned aerial vehicle (UAV), the Ardrone 2.0 (Parrot). This system is complex and strongly non-linear. Using real input/output data, different models of the quadrotor have been obtained by applying system identification based on neural, adaptive neural and neuro-fuzzy networks, traditional parametric methods, and the combination of these strategies. The resulting models have been compared in the time and frequency domains in terms of MSE. In today's world, UAVs' modelling is gaining importance because of their potential applications in different sectors such as defence, security, construction, agriculture, fire fighting, environment, entertainment, etc. These applications demand to get the most from these devices, and a necessary step to reach this target is to obtain models which help us to design smart controllers to stabilize the vehicle motion.

The paper is organized as follows: Section 2 presents a brief review of the literature related to the modelling of unmanned aerial vehicles, both the parametric approach and the intelligent approach. Section 3 describes the materials and methods, that is: the description of the UAV; the parametric and intelligent techniques applied; and the evaluation criteria used to rate the methods. The results of every identification technique and the influence of the on-line/off-line learning algorithm on the modelling are discussed in Section 4. The paper ends with the conclusions and future works.

2. Background

2.1. UAV identification by analytical techniques

In recent years, the research and development of unmanned aerial vehicles have gained much attention in academic communities around the world [12]. Focusing on modelling, different strategies can be found in the scientific literature, from analytical models based on physical equations representing the dynamic behaviour of the system up to intelligent models based on soft computing techniques [13].

One of the first analytical models of the dynamic behaviour of a helicopter was proposed by Gessow and Myers in 1952 [14]. Since them, many contribution can be found, first on helicopters as the work by Bramwell in 1976 [15] and then for any type of UAV. Analytic models of helicopters also appear in Cai et al. [16], Budiyono et al. [17] and El-Saadany et al. [18]. del Cerro et al. [19] present a hybrid model, analytical and empirical, where the parameters have been calculated by genetic algorithms. A very complete survey of mathematical models and control strategies for different types of aerial vehicles is presented in Castillo et al. [20].

Among these mathematical approaches, several authors obtain models of different UAVs by the application of parametric error techniques. Under some soft assumptions, a discrete-time multivariable non-linear stochastic system can be represented by the multi variable NARMAX model. For example, Wu et al. [21] applies ARX to identify the model of a micro air vehicle in loitering flight based on attitude performance evaluation. Morris et al. [22] and Cai et al. [16] use parametric error models based on state space to identify either a whole vehicle or a subsystem model, as for example the yaw motion. The model proposed by Mettler [23] is widely cited by other authors as a complex but effective model. Another parametric model of a helicopter is obtained applying a frequency domain method developed by the U.S. Army and NASA, known as Comprehensive Identification from Frequency Responses (CIFER) [24]. While CIFER was specifically developed for rotorcrafts, it has been successfully used in a wide range of fixed wing and rotary wing vehicles, and also in unconventional aircraft applications [25].

Other authors also use classical parametric structures to identify the model but then apply advanced strategies in order to tune the values of the model parameters. Some of them apply soft computing techniques for the tuning. For example, Ahmad uses the parametric model NARX (Nonlinear ARX) and he applies neural networks to adjust the parameters [26]. Another example is offered by del Cerro [19] where the tuning is done by genetic algorithms.

Hashimoto et al. [27] compares the performance of the identification models of an unmanned helicopter obtained by ARX, ARMAX, OE and BJ parametric structures. In our study we have also applied ARX, ARMAX and OE but, unluckily, Hashimoto does not provide quantitative results; therefore it has not been possible to compare our results with his models. Yuan and Katupitiya [28] apply the OE method to estimate the model of an unmanned helicopter. Manai [29] also uses OE structure for the identification of an UAV; in this case the purpose of the study is the design of controllers. Our paper is also aimed to design control oriented UAV models, but in our work we present a hybridization technique which is able to improve the accuracy while reducing the computational cost. Besides, we have also defined some figures to quantitatively evaluate the performance of the models.

2.2. UAV identification by neural networks and neuro-fuzzy inference systems

Some theoretical works have rigorously proved that, even with only one hidden layer, neural networks are universal function approximators [30]. Thus modelling non-linear systems by neural networks is a good alternative.

Among the application of neural networks to UAVs modelling, MLP and RBF networks are the most used to simulate the pitch, roll, yaw, and the position of the unmanned vehicles [31–38]. A RBF network is also used in [39]. Neural networks based on Nonlinear Auto-Regressive models with exogenous inputs (NARX models) have been also adopted due to its proven good performance especially for nonlinear complex systems [40]. Nevertheless, in this