Identification of Orientation Dynamics of Miniature Helicopter in Hover Mode

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Abstract: Reliable operation of helicopters in hover mode is essential for carrying out missions of surveillance, reconnaissance, and deployment of communication networks in disaster hit areas, among many others. Achieving autonomous operation in hover mode requires the development of robust model-based controllers. In this paper, the use of linear and nonlinear models to identify the orientation dynamics of a small scale helicopter is addressed. A linear architecture that combines the input-output dynamics and perturbation-output dynamics is introduced in this paper. In contrast to the linear models that have been reported in the literature, no assumptions about decoupled roll-pitch-yaw axes are made in the proposed approach. The nonlinear model of orientation dynamics is identified using artificial recurrent neural networks. Verification of these models is performed using actual data collected during the flight of the helicopter. The results show that incorporating the perturbation dynamics in the model can result in a description that can accurately predict the dynamics during actual flight conditions.

1 INTRODUCTION

Surveillance and reconnaissance missions typically require operation in hard to reach and possibly hostile areas. Additionally, most of these missions require extended hours of continuous operation since the zones of interest are typically remote. Therefore, a good way to reduce the exposure of human operators to such dangers and to relieve them from the exhaustive long operating hours is through the use of autonomous unmanned aerial vehicles (UAV). Small scale helicopters stand out among the existing UAV platforms because of their unique capability to hover, to vertically take-off/land, and to follow complex flight trajectories.

Despite the interest that autonomous helicopters have received in recent years, further technological challenges have to be addressed before these systems can find large scale acceptance. Instrumentation has to be improved to meet the requirements of: (i) high computational power, (ii) low energy consumption, (iii) low weight, and (iv) low cost. In addition, robust controllers have to be developed to safely guide helicopters throughout their missions. Therefore, a complete knowledge of the underlying forces and moments is crucial for proper design of these controllers.

The capability of helicopters to operate in hover mode is essential for applications like surveillance, deployment of communication networks in disaster hit areas, and aerial photography, among others. Controlling the orientation dynamics of the helicopter is crucial for maintaining the aircraft operating in hover mode. Changing operational conditions due to wind gusts, rotor speed variations and different payloads affect the orientation dynamics of the helicopter (Bejar et al., 2007). Therefore, accurate models are needed to develop robust controllers and increase the system performance in variable operation conditions (Shin et al., 2005); (Beainy et al., 2009). Theoretical models have been proposed and the dynamical equations representing these models have been derived using helicopter parameters such as moments of inertia and blade flapping angle (Gessow and Myers, 1985); (Padfield, 2007); (Budiyono, 2007). However, differences in fuselage dimensions, weight etc., limit the applicability of these models to the different micro-helicopters that are commercially available.

In this paper, an alternative approach to

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obtaining mathematical models of small scale helicopter through practical identification methods is followed (Morris et al., 1994); (Remple, 2007); (Putro et al., 2009); (Taha et al., 2010); (Deboucha and Taha, 2010); (Wang et al., 2011a). In this method, a candidate model is proposed and the unknown parameters are estimated by fitting the response of the candidate model to dynamic data collected from the system.

Collecting helicopter flight data is a challenging task because of the inherent instability of the system. A trend in previous research (Lidstone, 2003); (Song, 2010) has been to affix the rotorcraft to a safety structure in an attempt to lower the risks of experimentation. The main disadvantage of this approach is that the safety structures unavoidably affect the dynamics of the system deteriorating the model fidelity under real operation conditions.

The experimental approach presented in this paper follows a different path where the system data is collected in free flight operation (Mettler et al., 1999); (Abbeel et al., 2010). In our study, an experienced pilot generates control signals that excite the helicopter orientation dynamics and keep the system in hover mode.

Strong assumptions about the system behaviour were used in the development of linear models used in previous research. In (Wang et al., 2011b) the orientation dynamics in different axes (i.e. roll, pitch, yaw) were assumed to be decoupled and individual Single-Input Single-Output (SISO) models were identified for each axis. In (Morris et al., 1994) a state space structure that assumed coupling between the rate of change of the angular dynamics was proposed. As a result, these models do not accurately describe cross coupled dynamics observed in the data.

Unlike previous works, we propose a linear model without assumptions about de-coupled orientation axes. Using black-box identification techniques, a 6^{th} order state space model is identified in this paper. The proposed model is used to estimate the orientation dynamics including the relationships between the axes. The results obtained show that the model is able to predict cross-axes dynamics that previous models could not predict.

Previous works have also focused on identification of large Radio Controlled (RC) helicopters (i.e rotor diameters > 1200 mm). Large RC helicopters are not as agile as the miniature (i.e. rotor diameter < 1200 mm) version due to their large inertia. However, miniature helicopters have less payload capabilities compared to large RC helicopters. This represents a further challenge during their instrumentation. In this research, a low-weight, low-cost acquisition system specifically targeted for identification and control of miniature RC helicopters is developed.

Previous works have identified models assuming that no perturbations were present during the data acquisition experiments. This assumption is valid when the effects of the forces applied by the actuators are more significant than the effects of the external forces. Unfortunately, this is not the case with miniature RC helicopters that have smaller inertia and less actuator power compared to large RC helicopters. Therefore, ignoring the effects of perturbations during the identification of miniature RC helicopters would significantly deteriorate the performance of the models. In the proposed approach the perturbations are considered during the identification process. Separate input-output and perturbation-output dynamic models are identified. The proposed structure prevents the model from over-fitting the data that improves model fidelity in variable operation scenarios.

Nonlinear models have also been employed to describe helicopter orientation dynamics. In particular, artificial neural networks (ANNs) have been extensively used because of their ability to describe complex relationships (Suresh et al., 2002, Putro et al., 2009, Taha et al., 2010). In this research, an artificial neural network with autoregressive components is investigated. Unlike the state space model, also identified in this paper, the neural network model does not decouple the input-output dynamics from the perturbation-output dynamics.

The accuracy of the identified models is studied by comparing the output of the model with actual system outputs. The models are evaluated with the data set used for training (i.e. identification) and also with an independent data set. The difference in the observed performance with the identification and the validation data sets is used as an indicator of the effectiveness of the model. The results obtained show that including perturbation dynamics prevents the model from erroneously interpreting the effects of perturbations as if they were caused by the inputs of the system.

The rest of this paper is organized as follows: Section 2 presents a description of the system. Section 3 introduces the structure of the proposed models. The collection of flight data is explained in Section 4 and the identification of the parameters in the model is discussed in Section 5. Finally in Section 6, the performance of the models is analysed and the conclusions of the study are presented in Section 7.

2 SYSTEM DESCRIPTION

Data collection is conducted using a fully instrumented Blade 450-3D miniature RC helicopter (Figure 1). This UAV belongs to the family of Cyclic/Collective Pitch Mixing (CCPM) helicopters. CCPM is an electronic control scheme of the swashplate designed to reduce the mechanical complexity of the systems used in full scale helicopters without compromising the agility of the rotorcraft.

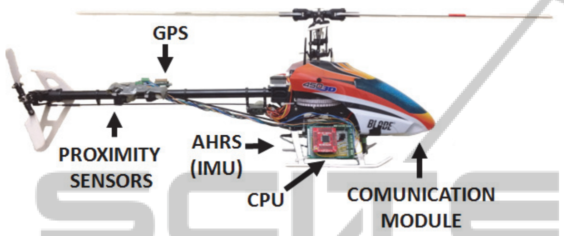

Figure 1: Fully instrumented miniature helicopter used in this research. The location of the sensors, CPU and communication module is shown.

The diameter of the sweep of the rotor blades is commonly used to categorize the size of the helicopters. Helicopter rotor diameters commonly reported in the literature are presented in Table 1. Note that the Blade 450 3D used in this paper has a rotor diameter of 721 mm which makes it smaller than the helicopters used in related works.

Table 1: Helicopter sizes comparison.

Research	*Rotor Diameter (mm)*
(Mettler et al., 1999)	3070
(Harbick et al., 2004)	1800
(Shin et al., 2005)	1790
(Harbick et al., 2004)	1524
(Abbeel et al., 2010)	1440
(Taha et al., 2010)	1340
(Raptis and Valavanis, 2009)	914
(He et al., 2011)	780
This Research	**721**

In the Blade 450-3D the elevation and orientation are controlled through three servo motors. These motors govern the collective and cyclic pitch of the main rotor. The heading is guided through the tail rotor pitch angle which is controlled with an additional servo motor. The system counts with ten minutes of fly autonomy provided by a 2200 mAh lithium-ion battery.

Lightweight instrumentation is developed to measure the states of the helicopter. The orientation of the helicopter is measured every 20 ms using an Attitude Heading Reference System (AHRS) with embedded Kalman filter. The position of the aircraft is estimated every second using a GPS unit. Ultrasonic and infrared proximity sensors are used to obtain the estimated height when the aircraft is close to the ground. The data acquisition by the onboard sensors is coordinated by a 32-bit 15 MHz CPU.

The helicopter attitude (θ, ϕ) and heading ψ measured from the AHRS form the output of the orientation dynamics model studied in this paper. Additional information such as the rate of change of the roll-pitch-yaw angles $(\dot{\theta}, \dot{\phi}, \dot{\psi})$ and the airframe acceleration $(a_x,\ a_y,\ a_z)$ are also estimated from the 3-axes accelerometer, 3-axes gyroscope, and 3 axes magnetometer IMU measurements.

The data acquired from the onboard sensors is transmitted wirelessly to the ground station (Figure 2). A RF receiver identical to the one used on the helicopter is used to capture the control signals transmitted to the helicopter by the ground station. The throttle δ_{thr}, collective pitch δ_{col}, lateral pitch δ_{lat}, longitudinal pitch δ_{lon} and tail pitch δ_{tail} signals are reconstructed on the ground from the duplicate receiver measurements. Particularly, (δ_{lat}, δ_{lon}, δ_{tail}) are the control signals used in the orientation dynamics models studied in this paper.

Since the input and output signals are measured with different acquisition systems and rates, a synchronization scheme is developed to construct the data sets used to identify the dynamics of the helicopter. This is accomplished by using time stamps on all the measurements and then interpolating the data to generate input/output data sets that are synchronized in time.

Figure 2: Ground station (1) Computer (2) RF receiver (3) Joystick for assisted teleoperation (4) Duplicate onboard RF-receiver acquisition system (5) Radio control for manual operation.

3 PROPOSED MODELS

The first step in the system identification process is the determination of the inputs and outputs of the desired model. The model of orientation dynamics is shown in Figure 3.

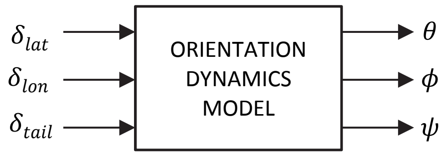

Figure 3: Inputs and outputs of the system.

Inputs and outputs are expressed in vector form before introducing the proposed model structures.

$$u(t) = \begin{bmatrix} \delta_{lat}(t) \\ \delta_{lon}(t) \\ \delta_{ped}(t) \end{bmatrix} \quad y(t) = \begin{bmatrix} \phi(t) \\ \theta(t) \\ \psi(t) \end{bmatrix} \tag{1}$$

3.1 Linear Model

A time invariant, State Space (SS) model is used as linear description of the system. The effects of stochastic perturbations $Kw(t)$ are included in the model as shown bellow

$$\begin{aligned} x(t+T) &= Ax(t) + Bu(t) + Kw(t) \\ y(t) &= C\,x(t) + D\,u(t) + v(t) \end{aligned} \tag{2}$$

where $A \in \mathbb{R}^6$, $B \in \mathbb{R}^{3\times6}$, $C \in \mathbb{R}^{6\times3}$, $D \in \mathbb{R}^{3\times3}$, $K \in \mathbb{R}^{3\times3}$. Here, $x(t) \in \mathbb{R}^6$ is the vector of state variables. The perturbation $w(t) \in \mathbb{R}^3$ and measurement noise $v(t) \in \mathbb{R}^6$ are vectors with independent white Gaussian elements. The model structure is presented graphically in Figure 4.

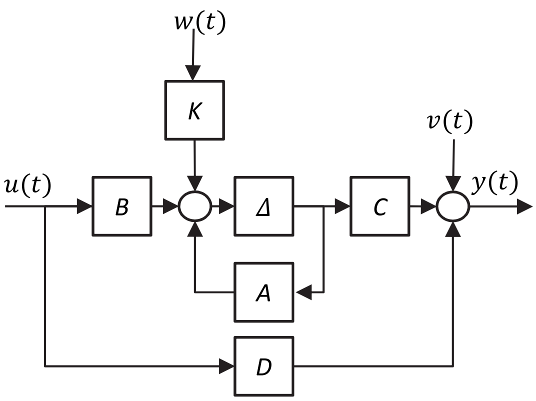

Figure 4: State space representation of the orientation dynamics in discrete time. Stochastic perturbations and measurement errors are included.

3.2 Nonlinear Model

A recurrent neural network (RNN) is the structure used for nonlinear representation of the system. This is shown in Figure 5.

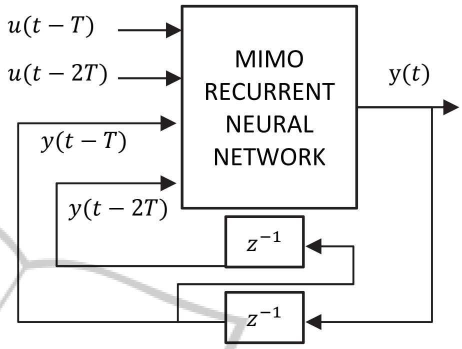

Figure 5: RNN used as nonlinear model.

Many practical systems are successfully described with Multilayer Perceptron (MLP) neural networks (Demuth and Beale, 1998). For this reason a MLP network is adopted in this research.

4 FLIGHT EXPERIMENTS

Unknown parameters of the models are determined from input-output data collected from the system. For this purpose the helicopter is flown in hover mode and variations around the trim value of the control are applied. Inputs and outputs are aligned after the flight by interpolation using the time stamps attached to each measurement. The alignment process is shown in Figure 6.

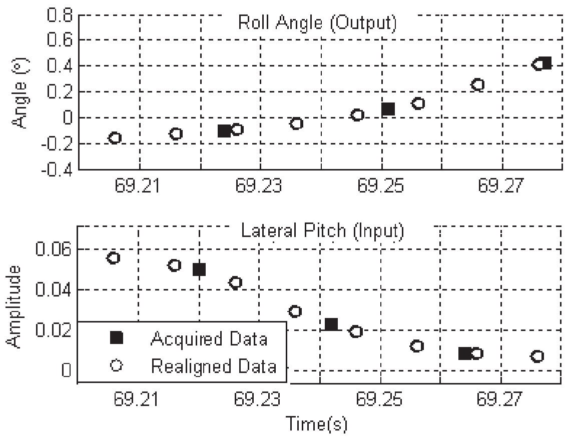

Figure 6: Inputs and outputs are acquired at different times (squares) and then uniformly interpolated (circles) as required for identification.

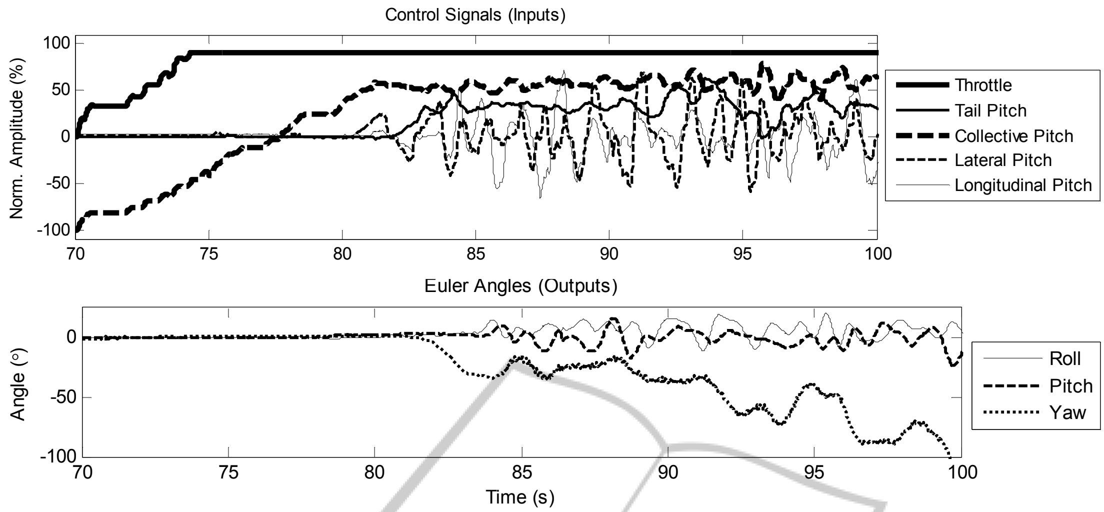

Figure 7: Data collected during test flight. The control signals of the helicopter including the inputs of the orientation models are shown in the top. The Euler angles (i.e. outputs) are presented in the bottom part.

After the data has been aligned, inputs and outputs can be presented at the same time instances as shown in Figure 6. The flight test starts by increasing the collective pitch to about 50% of its maximum value while keeping the throttle constant (~90%). When the collective pitch is high enough, the rotor produces sufficient thrust and the helicopter lifts off. The pilot applies small variations around the trim value of the lateral, longitudinal and tail pitch control signals to excite the dynamics of the helicopter while keeping it operating around hover mode.

The flight data is partitioned in two groups: one for model identification Z^N and other for model validation X^M. The indexes N and M refer to the number of points in each data set. The identification process is described next.

5 SYSTEM IDENTIFICATION

Identification refers to the process of determining the optimal mapping from the acquired data set Z^N to the set of parameters $\hat{\mathrm{P}}$ that specify the behaviour of the model.

$$Z^N = \{\, [u(t_k), y(t_k)] \mid t_k = T, \ldots, NT \,\} \rightarrow \hat{\mathrm{P}} \quad (3)$$

In this paper, the quadratic error $V_N(Z^N, \mathrm{P})$ between the model output $\hat{y}(t, \mathrm{P})$ and the system response $y(t)$ is chosen as the performance measure to study the accuracy of the model.

$$V_N(Z^N, \mathrm{P}) = \frac{1}{2N}\sum_{t=1}^{N}[y(t) - \hat{y}(t)]^T[y(t) - \hat{y}(t)] \quad (4)$$

$$\hat{\mathrm{P}} = \underset{\mathrm{P}}{\arg}\{\ \min[\,V_N(Z^N, \mathrm{P})]\ \} \quad (5)$$

More information on the identification process is presented in the next section.

5.1 Linear Model (State Space)

Identification of the State Space (SS) model consists of first determining the order of the model and then finding the matrices $\{A, B, C, D, K\} \leftrightarrow \hat{\mathrm{P}}$. Using Numerical algorithm for Subspace State Space Identification (N4SID) (Ljung, 1988), it was first verified that a 6th order model is sufficient to capture the orientation dynamics without overfitting the data. Figures 8 and 9 show the output of the identified model using the training data and validation data respectively.

5.2 Nonlinear Model (Neural Network)

In this case, the identified model parameters $\hat{\mathrm{P}}$ are the weights (i.e. $W_1 \in \mathbb{R}^{18\times30}, W_2 \in \mathbb{R}^{30}$) of the connections between neurons. The type of activation function in the neurons is motivated by the positive results reported in (Taha et al., 2010). Hyperbolic tangent activation function is used in the 18 neurons of the input layer and linear activation is used in the 30 neurons of the hidden layer. In Figures 10 and 11, the network outputs with the training data set and with an independent data set are presented, respectively.

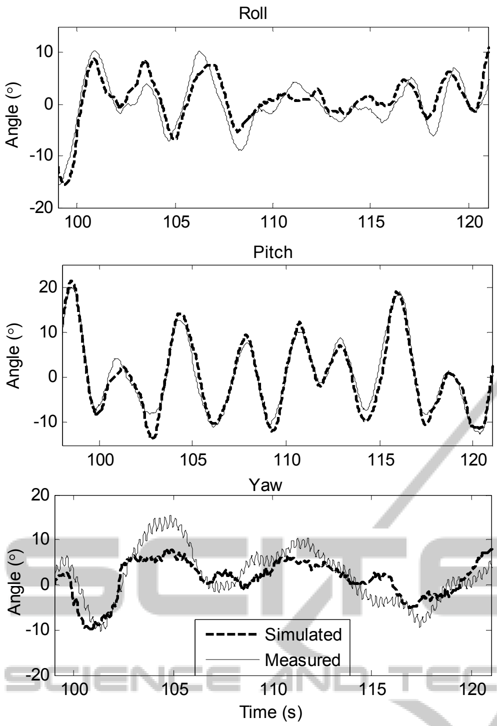

Figure 8: SS results with identification data set.

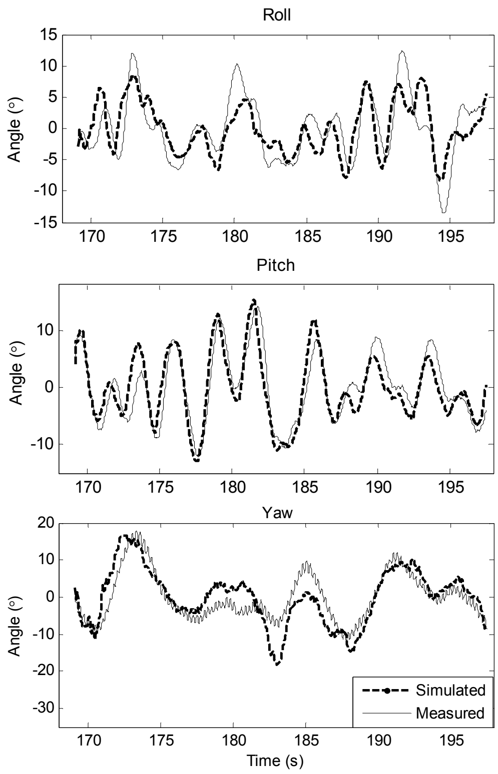

Figure 9: SS results with validation data set.

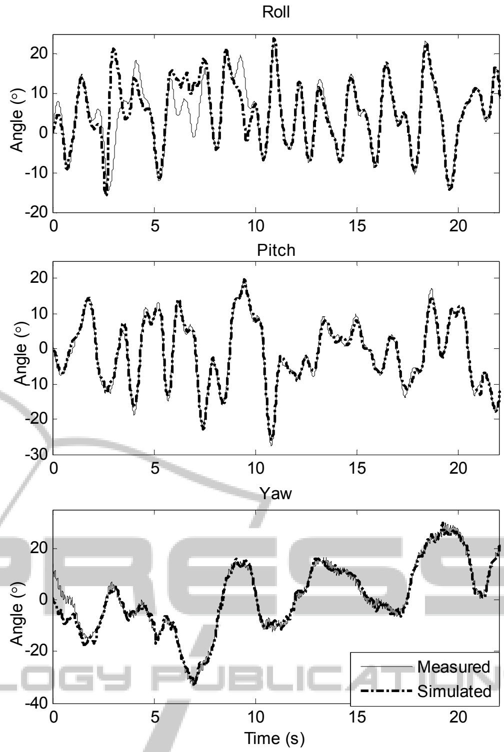

Figure 10: RNN results with training data.

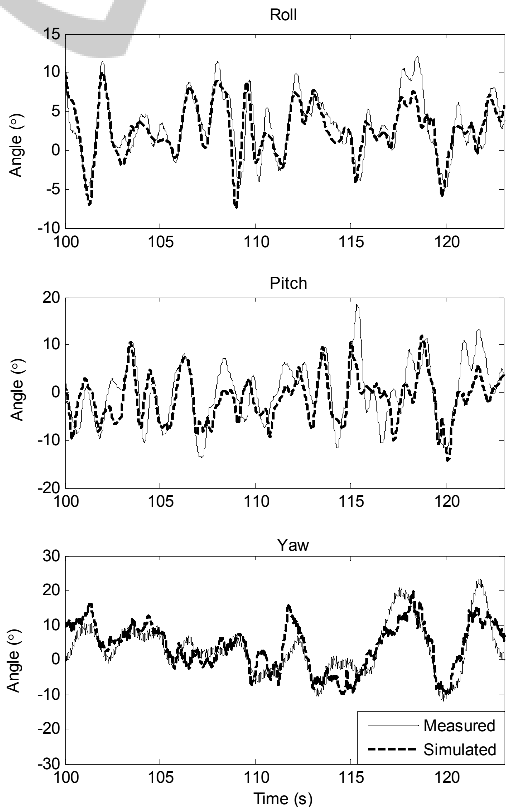

Figure 11: RNN results with validation data set.

6 PERFORMANCE ANALYSIS

The Root Mean Square Error (RMSE) between the models outputs and the measured outputs is used as a performance indicator. In Figures 12 (a) and (b) the RMSE of the RNN and the SS models with the identification and validation data sets are presented, respectively. Additionally, for each model the difference in performance between the validation and identification sets is presented in Figure 12-(c). Notice that on average (i.e. taking into account the three output channels: roll-pitch-yaw) the RNN is 0.99° more accurate than the SS model when they are evaluated with the identification data set. On the other hand, the RNN is on average 0.03° more accurate than the SS when an independent data set is used for evaluation. The average difference in the RMSE between identification and validation sets is 1.85° for the RNN and 0.90° for the SS model.

The results show that the RNN fits better the identification data compared to the SS.

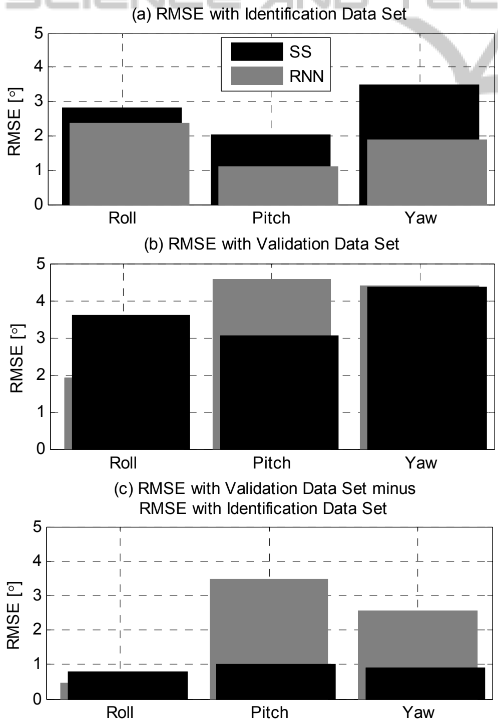

Figure 12: (Top) RMSE between the models outputs and the measured outputs using the identification data set; (Middle) the RMSE with validation data set; (Bottom) difference between RMSE with validation and identification data sets.

However, the RNN slightly outperforms the SS with the validation data set. The SS model shows a more consistent performance than the RNN between evaluations with different data sets.

7 CONCLUSIONS

The development of lightweight, low-cost instrumentation for a miniature helicopter was presented in this paper. Free flight experiments were conducted during which the control signals and the orientation in space of the helicopter were acquired. The rotorcraft was guided by an experienced pilot to hover while small variations around the trim value of the control signals were applied. A key contribution of this paper is the process for interpolating and generating the time synchronized data sets for identifying the mathematical model of the orientation dynamics of the helicopter in hover mode.

A State Space representation was used to describe the orientation dynamics of a miniature helicopter and the parameters of the model were identified from the flight data. The influence of perturbations, such as wind gusts and turbulences was also modelled. Inclusion of perturbations in the model is crucial because of the considerable effect that external forces have on miniature helicopters. Further, the model developed in this paper is also capable of predicting cross-axes dynamics that other models in the literature do not consider. A nonlinear model in the form of a recurrent neural network was also identified. The performance of both the linear and nonlinear models was quantitatively evaluated using the RMSE measure. The RNN described the identification data better than the SS model but both models had a similar performance with the validation data set.

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