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Identification and control of a small-scale helicopter*

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Abstract: Designing reliable flight control for an autonomous helicopter requires a high performance dynamics model. In this paper, a nonlinear autoregressive with exogenous inputs (NLARX) model is selected as the mathematical structure for identifying and controlling the flight of a small-scale helicopter. A neural network learning algorithm is combined with the NLARX model to identify the dynamic component of the rotorcraft unmanned aerial vehicle (RUAV). This identification process is based on the well-known gradient descent learning algorithm. As a case study, the multiple-input multiple-output (MIMO) model predictive control (MPC) is applied to control the pitch motion of the helicopter. Results of the neural network output model are closely match with the real flight data. The MPC also shows good performance under various conditions.

Key words: Dynamics model, System identification, Black box, Small-scale helicopter, Neural networks (NNs), Control design

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1 Introduction

A common problem in designing a high performance controller for an unmanned aerial helicopter is obtaining a fidelity dynamics model. There are two main approaches to modeling: one is known as the first principle modeling and the other is known as the system identification approach. The first principle modeling is based on the direct physical understanding of forces and moments balancing a vehicle, which has been applied by Nugroho and Taha (2005) to develop a nonlinear small-scale helicopter model. Budiyono *et al*. (2007) analyzed the development of a linear model based on the first principle method for an X-Cell 60 helicopter.

Helicopters are commonly known to have complicated dynamics models. Their dynamics models are, therefore, usually obtained through system identification techniques using experimental data. The US Army and the National Aeronautics and Space Administration (NASA) have developed a technique named CIFER (comprehensive identification from frequency response) to identify a full size rotorcraft dynamics model. Mettler *et al*. (1999) applied this technique to a small size Yamaha R-50 helicopter platform and successfully obtained a linear model. By minimizing the quadratic error between the predicted output and the experimental data, the prediction error method (PEM) was used as an estimation algorithm for establishing dynamics system parameters by Shim *et al*. (2000).

The use of artificial intelligence is well-known for its ability in system identification (rather than control design) of a dynamic system (Narendra and Parthasarathy, 1990). A genetic algorithm has been used to identify a nonlinear dynamics model of a helicopter (Tahersima and Fatehi, 2007).

Different types of control have been developed for small-scale helicopters including conventional, intelligent, and vision controls. For example, a linear control design includes the use of a multi-loop proportional-integral-derivative (PID) control (Kim and Shim, 2003). State feedback control was used to

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control motion stability of a small scale helicopter by Dharmayanda *et al*. (2007).

Sanchez *et al*. (2007) proposed a flight control structure combining PID, fuzzy, and regulation control, using the nonlinear multiple-input and multiple-output (MIMO) model for an X-Cell mini-helicopter platform. They had also proposed a mathematical model to design a hybrid intelligent control. Fuzzy flight controllers were presented by Kadmiry and Driankov (2004) as achieving the stability and maneuverability of an unmanned helicopter. A learning machine algorithm was applied to an autonomous helicopter flight problem for learning trajectory (Coates *et al*., 2008). Amidi *et al*. (1999) presented a visual odometer for an autonomous helicopter flight, which estimating the helicopter's position by visually locking on to and tracking ground objects. Saripalli *et al*. (2003) designed and implemented a real-time vision algorithm for the guided landing of an unmanned aerial vehicle (UAV).

Predictive control strategies, such as the model algorithmic control (MAC) (Richalet *et al*., 1978) and the dynamic matrix control (DMC) (Cutler and Ramaker, 1979), are advanced control strategies based on predictions of linear convolution models. Therefore, the model predictive control (MPC) is not a specific control strategy but a wide class of optimal control-based algorithms that use an explicit process model to predict the behavior of a linear plant.

In this paper, a neural network (NN) structure to learn and estimate a black box nonlinear autoregressive with exogenous inputs (NLARX) model is proposed. This model is then used to identify the dynamics model of the helicopter. We used a longitudinal model as a control example. To control the pitch motion of the helicopter, the MPC was used as a controller.

2 System identification

For this study, initial experiments were conducted on a Hirobo Sceadu 50 radio-controlled (R/C) helicopter, which was first used as an experimental platform by Chen *et al*. (2006) for sensors configuration. Due to its payload capability and manoeuvrability, the upgrade of autopilot systems, sensors and communication devices is easy to perform with a UAV helicopter. The Hirobo Sceadu helicopter actuation is performed by five onboard servo actuators. To execute all the swash plate movements (collective, aileron, and elevator), three of these servos are connected to the swash plate via the cyclic collective pitch mixing (CCPM) method.

The centre piece of the helicopter onboard system includes: (1) a PC/104, used as data storage memory; (2) a inertial measurement unit (IMU), connected directly to the flight computer through a special serial port; (3) a diamond GPIO-MM counter/timer card; and, (4) a hobby helicopter. Table 1 presents the specifications of this helicopter.

Table 1 Specification of the Hirobo Sceadu 50 helicopter

Parameter	Value
Rotor diameter (mm)	1348
Gross weight (kg)	3.9
Gear ratio	8.7:1:8.7
Engine type	OS 50 Class

Fig. 1 shows the connective components of the UAV helicopter system used to collect flight data. This system contains three main parts: a hobby helicopter, an onboard system and a ground station. The R/C receiver receives the command signal from the

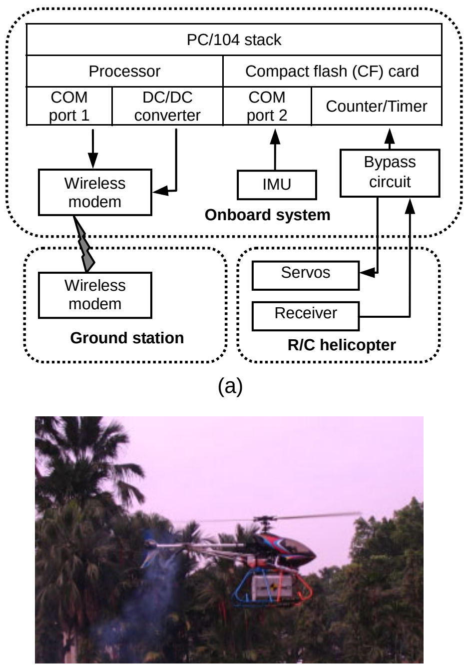

Fig. 1 Principle diagram of rotorcraft unmanned aerial vehicle (RUAV) onboard system (a); photograph of experimental collecting data (b)

transmitter and sends pulse width modulation (PWM) signals to the actuators. The PWM signals generated in R/C receiver are captured by the counter/timer device. The IMU sends the airframe signals which are accelerations (a_x, a_y, a_z), angular rates (p, q, r), and Euler angles ($Ø$, θ, φ). Signal data from both the counter/timer device and the IMU are recorded and stored in the compact flash (CF) card.

Using a human operator to pilot the craft, a number of experimental flights were conducted to collect flight data. During the flight data test, the IMU sends the airframe data of the vehicle back to the PC/104, while the counter/timer captures the PWM signals generated by the R/C receiver.

Fig. 2 shows the overall system identification procedure. The identification block consists of setting the hardware used to collect the flight data. To select the optimal hovering flight data, the helicopter was in stand-still hovering mode for several trials. Hovering flight data were selected based on the assumption that, in these conditions, the system is linear. Collected data, first, requires pre-processing to screen out noises. To perform this task, a moving average filter was used in this study. The NLARX model is selected as a mathematical black box model to be identified for an autonomous helicopter. To avoid excess computation at the overhead, we divided the model into three principal components: the longitudinal, lateral, and heave sub-models. Each of these sub-models is identified separately. The data contains 800 input-output data samples in near-hovering mode, generated at a sampling rate of 0.03 s. This data was then split into two subsets for estimating and validating the dynamics model, respectively. The control input vector contains the duty cycles of the five actuators, which are set up according to the swash plate layout. The output vector contains nine variables: Euler angles (°), angular rates (rad/s), and translation velocities (m/s) along the x, y, z axes.

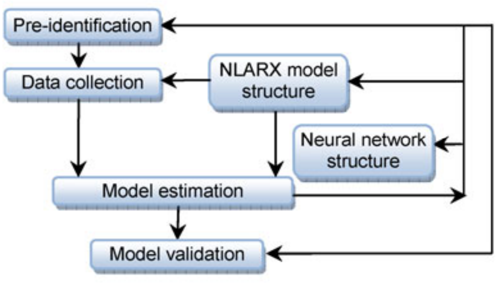

Fig. 2 System identification procedure

2.1 Swash plate setup

The helicopter is actuated by five electromechanical servos controlled by PWM signals. The throttle servo, which is the engine governor, is considered as lacking dynamic and, therefore, identified as a constant. One servo is used to control the tail rotor, and the three remaining servos are attached to the swash plate in a 120° CCPM layout. The three command inputs are described as

$$\text{S1}=\text{Collective}+\text{Aileron}+0.5\times\text{Elevator}, \tag{1}$$
$$\text{S2}=\text{Collective}-\text{Elevator}, \tag{2}$$
$$\text{S3}=\text{Collective}-\text{Aileron}+0.5\times\text{Elevator}, \tag{3}$$

where the factor 0.5 ($\sin 30°$) comes from resolving the position of the diagonal servos, Aileron is the control surface that influences rotation of the aircraft along its roll axis, Elevator is the control input that allows the helicopter rotates along its pitch axis, while the collective control allows the helicopter to perform a vertical movement, and S1, S2 and S3 are the commanded servo positions. The collected data of the servos are in duty cycles, and need to be converted into position angles. The relationship between Eqs. (1) and (3) is identified as

$$\text{S1}+\text{S3}=2\times\text{Collective}+\text{Elevator}. \tag{4}$$

By replacing the obtained relationships in Eqs. (1) and (2), the three main aeronautic inputs to the swash plate platform can be obtained as follows:

$$\text{Collective}=1/3\times(\text{S1}+\text{S2}+\text{S3}), \tag{5}$$
$$\text{Aileron}=1/2\times(\text{S1}-\text{S3}), \tag{6}$$
$$\text{Elevator}=1/3\times(\text{S1}+\text{S3})-2/3\times(\text{S2}). \tag{7}$$

2.2 Proposed model

A standard NLARX discrete time nonlinear multivariable model system with m outputs and r inputs, which is a general parametric form for modeling black box nonlinear systems (Zhang and Ljung, 2004) with a one-step-ahead prediction, can be described by

$$\begin{aligned}\hat{\boldsymbol{y}}_m(t) = N[&\boldsymbol{y}_m(t-1), \boldsymbol{y}_m(t-2), ..., \boldsymbol{y}_m(t-\boldsymbol{n}_a),\\ &\boldsymbol{u}_r(t), \boldsymbol{u}_r(t-\boldsymbol{n}_k), ..., \boldsymbol{u}_r(t-\boldsymbol{n}_k-\boldsymbol{n}_b+1)] + \boldsymbol{e}_m(t),\end{aligned} \tag{8}$$

where $\boldsymbol{y}_m(t)=\begin{bmatrix} y_1(t) \\ y_2(t) \\ \vdots \\ y_m(t) \end{bmatrix}, \boldsymbol{u}_r(t)=\begin{bmatrix} u_1(t) \\ u_2(t) \\ \vdots \\ u_r(t) \end{bmatrix}, \boldsymbol{e}_m(t)=\begin{bmatrix} e_1(t) \\ e_2(t) \\ \vdots \\ e_m(t) \end{bmatrix}$

(m=1, 2, …, 8, r=1, 2, …) are the outputs and the inputs systems respectively. $\boldsymbol{n}_a$ and $\boldsymbol{n}_b$ are the matrices of the past outputs and inputs involved in the system, $\boldsymbol{n}_k$ is a matrix of the inputs delays from each input to output, $e_m(t)$ represents the modeling error, and t is time step. $N(\,)$ represents an unknown nonlinear function, which is estimated by the NN training in our case. The order of the system [$\boldsymbol{n}_a$ $\boldsymbol{n}_b$ $\boldsymbol{n}_k$] is defined by the following matrices:

$$\boldsymbol{n}_a=\begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1m} \\ a_{21} & a_{22} & \cdots & a_{2m} \\ \vdots & \vdots & \vdots & \vdots \\ a_{m1} & a_{m2} & \cdots & a_{mm} \end{bmatrix}, \quad \boldsymbol{n}_b=\begin{bmatrix} b_{11} & b_{12} & \cdots & b_{1r} \\ b_{21} & b_{22} & \cdots & b_{2r} \\ \vdots & \vdots & \vdots & \vdots \\ b_{m1} & b_{m2} & \cdots & b_{mr} \end{bmatrix}, \quad \boldsymbol{n}_k=\begin{bmatrix} k_{11} & k_{12} & \cdots & k_{1r} \\ k_{21} & k_{22} & \cdots & k_{2r} \\ \vdots & \vdots & \vdots & \vdots \\ k_{m1} & k_{m2} & \cdots & k_{mr} \end{bmatrix}. \tag{10}$$

The recurrent outputs and inputs that are fed back with the delay steps $\boldsymbol{n}_k$ and $\boldsymbol{n}_k-\boldsymbol{n}_b$ can be manipulated using the Matlab toolbox.

2.3 Neural networks architecture

NNs commonly have two layers connected together as shown in Fig. 3. The networks structure has nonlinear transfer functions in its hidden layer and linear functions in its output layer. The general relationship between input-output of the ith node (neuron) in the lth layer is defined as

$$n_i^{(l)}=\sum_{j=1}^{n_{l-1}} w_{ij}^{(l)} x_i^{(l-1)}+b_i^{(l)}. \tag{11}$$

The output of the jth neuron is given by

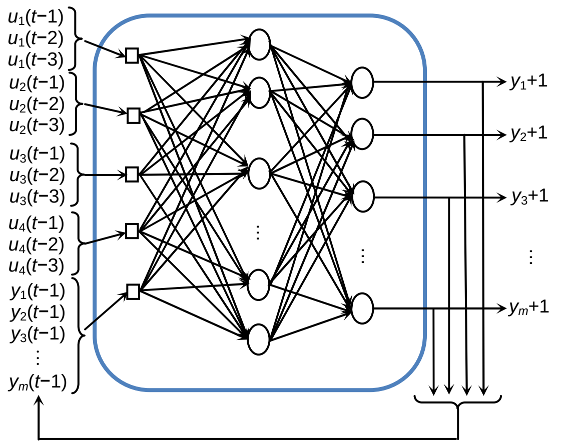

Fig. 3 The proposed nonlinear autoregressive with exogenous inputs (NLARX) model

$$y_j^{(l)}=\sigma_j(n_i^{(l)}). \tag{12}$$

From the above two relations the networks outputs are then updated to

$$\hat{y}_j(w_{ij},w_{jl})=\left(F_j\sum_{j=1}^{m} w_{jl}\sigma_j\left(\sum_{i=1}^{n} w_{ij}\boldsymbol{x}_i+b_i\right)+b_j\right), \tag{13}$$

where b_i and b_j are the input and the output layers biases respectively, $\boldsymbol{x}_i$ is the ith node input vector, F_j is the lth node linear activation function of the output layer, w_{jl} is the weight from the jth neuron in the hidden layer to the lth neuron in the output layer, and w_{ij} is the weight from the ith neuron in the input layer to the jth neuron in the hidden layer. The nonlinear transfer function σ_j given by

$$\sigma_j(x)=\frac{1+\mathrm{e}^{-ax}}{1-\mathrm{e}^{-ax}} \tag{14}$$

is the hidden layer activation function of each unit.

The strategy applied in this study is the prediction error approach based on the sum square error (SSE) criterion, which is given by

$$E=\frac{1}{n}\sum_{t=1}^{n}(y_\mathrm{d}-y_j)^2, \tag{15}$$

where y_j is the output of the model from the networks, y_d represents the desired output at index time t, and n

is the number of input-output training samples which are split into estimation and validation data. The idea of the algorithm here is to obtain an approximation for the gradient descent that minimizes the error between the desired outputs and the networks outputs.

Based on the conventional gradient descent back propagation (BP) algorithm using supervised NNs learning (Kadmiry and Driankov, 2004), the algorithm adjusts the weights to minimize the cost function (E) through the following equation:

$$W(t+1)=W(t)-\propto\frac{\partial E}{\partial W},\quad 0\le\propto\le 1, \tag{16}$$

where $\propto$ is the learning rate.

3 Control design

Before designing the controller, the identified NLARX models need to be linearized and transformed into linear-time invariant system.

The longitudinal linearized multivariable autoregressive with exogenous input (ARX) model is obtained as

$$\begin{aligned}&\boldsymbol{A}_0\times y_m(t)+\boldsymbol{A}_1\times y_m(t-T)+\ldots+\boldsymbol{A}_n\times y_m(t-nT)\\&=\boldsymbol{B}_0\times u_r(t)+\boldsymbol{B}_1\times u_r(t-T)+\ldots\\&\quad+\boldsymbol{B}_m\times u_r(t-mT)+e_r(t),\end{aligned} \tag{17}$$

where T is the sampling time,

$$\boldsymbol{A}_0=\begin{bmatrix}1&0&0\\0&1&0\\0&0&1\end{bmatrix},\quad \boldsymbol{B}_0=\begin{bmatrix}0&0&0&0\\0&0&0&0\\0&0&0&0\end{bmatrix},$$

$$\boldsymbol{A}_1=\begin{bmatrix}-1.0472&-1.2221&-0.0508\\0.0008&-1.0051&0.0002\\0.0645&0.8764&-0.9569\end{bmatrix},$$

$$\boldsymbol{B}_1=\begin{bmatrix}3.1857&-2.0299&-0.2027&-0.0273\\0.0344&-0.0093&-0.0410&0.0010\\-0.5353&0.0801&0.3961&-0.0096\end{bmatrix},$$

$$\boldsymbol{B}_2=\begin{bmatrix}-4.0407&2.1067&-0.4069&0.0110\\-0.0366&0.0089&0.0330&0.0002\\-0.0392&0.1835&-0.1175&0.0091\end{bmatrix},\quad\text{and}$$

$$\boldsymbol{B}_3=\begin{bmatrix}0.9620&-0.1524&0.6141&-0.0027\\0.0184&-0.0047&-0.0026&-0.0011\\0.1309&-0.1016&-0.1561&0.0022\end{bmatrix}.$$

The linear time-invariant (LTI) system can be described by

$$\begin{cases}x(t+1)=\boldsymbol{A}x(t)+\boldsymbol{B}_u u(t),\\ y_m(t)=\boldsymbol{C}_m x(t)+\boldsymbol{D}_u(t),\end{cases} \tag{18}$$

where $\boldsymbol{A}$, $\boldsymbol{B}_u$, $\boldsymbol{C}_m$, and $\boldsymbol{D}_u$ are the state space matrices, $x(t)$ is the state variables of the obtained model, $u(t)$ is the manipulated variables which are the model inputs, and $y_m(t)$ is the observed outputs.

The proposed MPC scheme is depicted in Fig. 4. The basic idea of the MPC approach is to control the longitudinal dynamics model of the helicopter obtained from system identification earlier, and to generate the required control signals (Ulon, Ulat, Ucol, and Uped) in order to stabilize the helicopter longitudinal motion in terms of pitch angle, translation velocity, and angular rate. From the set-point (reference) the controller will predict how much the output deviate.

$$y_m(t)=\sum_{i=1}^{P}\sum_{j=1}^{N_y}\left(w_j^y\left(r_j(t+j)-y_j(t+i)\right)\right),\ N_y=3, \tag{19}$$

where y_m is the model output, N_y is the outputs number, j is one specific output of the model, w_j^y is the adjustable weight for the output y_j, P is the prediction horizon, and $\left(r_j(t+j)-y_j(t+i)\right)$ is the predictive deviation for the output j at the future instant $t+i$.

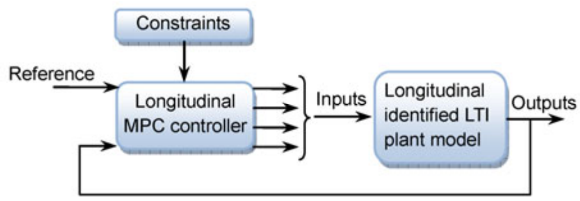

Fig. 4 Diagram of MPC implemented to a longitudinal MIMO plant model

The generalized single-input single-output (SISO) formula of the predictive control performance defined by Constantin (2003) for a MIMO system can be rewritten as

$$J_j=\sum_{i=1}^{P}\left(r_j(t+i)-y_j(t+i)\right)^2+\sum_{i=1}^{N}\sum_{k=1}^{N_u}\rho\left(\Delta u_k(t+i-1)\right)^2,$$
$$j=1,2,\ldots,N_y, \tag{20}$$

where N_u is the inputs numbers of the system, respectively, P is the prediction horizon, N is the control horizon, ρ is the control penalty factor, and $\Delta u_k(t+i-1)$ is the control increment.

For each input and output signals, the constraints are defined as follows: $u_{\min}\leq u_{t+k}\leq u_{\max}$, $y_{\min}\leq y_{t+j}\leq y_{\max}$.

4 Simulation results

The MPC technique is applied to the MIMO longitudinal motion of the small-scale helicopter. From Section 2, the longitudinal model is obtained by the NN training algorithm and is linearized as an LTI model. Also, an MPC is designed for this model structure. These two models form the main parts of a Simulink model as shown in Fig. 5. The reference model generates the trajectory signals (angular rate, translation velocity and the pitch angle) to be followed. The longitudinal MPC that generates the control signals (Ulon, Ulat, Ucol, and Uped) for the LTI longitudinal plant model whose output is fed back to the MPC.

4.1 Identification results

The proposed NLARX model have the structure with order *nn*=[onces[3,3], 3×onces[3,4], onces[3,4]] for the longitudinal model, *nn*=[2×onces[3,3], 3×onces[3,4], onces[3,4]] for the lateral model and *nn*=[onces[2*x*2], 3×onces[2,4], onces[2,4]] for the heave dynamics of nonlinear small-scale helicopter. All of the models consists one delayed output $y_j(t)$, $y_j(t-1)$ and three delayed inputs $u_k(t)$, $u_k(t-1)$, $u_k(t-2)$, $u_k(t-3)$. The nonlinearity of each submodel is estimated by NN structure. It contains four input (Ulon, Ulat, Ucol, and Uped) on its input layer, and ten nonlinear activation (units) functions in the hidden layer and the output layer were treated as a single output. As the number of the output set, the training algorithm plays the role of multi-input single-output (MISO) system. Thus, each of the output parameters was estimated separately. For each model, the difference in output between the measured system and the simulated model are plotted against the number of samples. Figs. 6–8 compare the longitudinal, lateral, and heave states variables which are the angular rates, translation velocities, and the Euler angles along *x*, *y*, and *z* axes by the identified models, respectively. It can be seen that there is a close match with the real flight data.

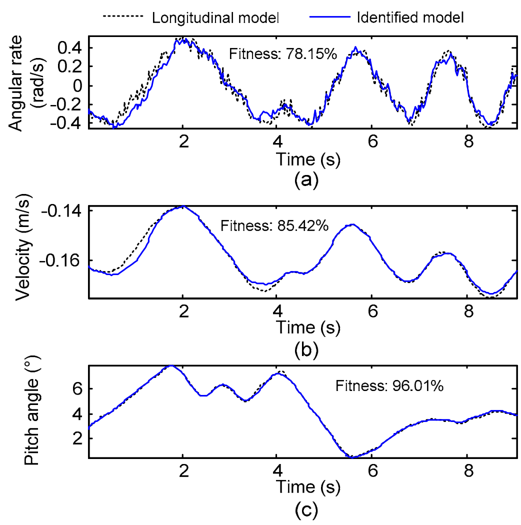

Fig. 6 Identification results of (a) angular rate, (b) velocity, and (c) pitch angle along *x* axis of longitudinal model and identified model

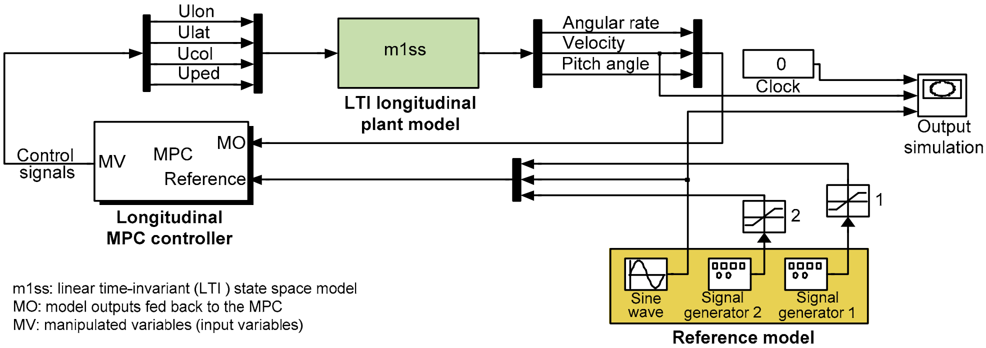

Fig. 5 Simulink model for small-scale helicopter longitudinal motion control using MPC controller

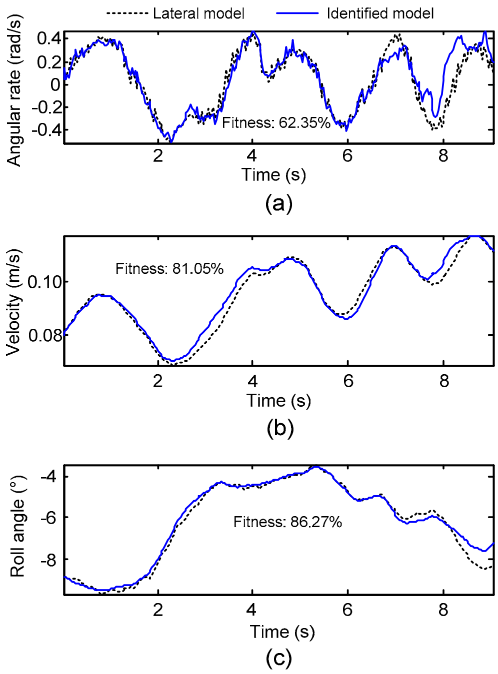

Fig. 7 Identification results of (a) angular rate, (b) velocity, and (c) roll angle along *y* axis of lateral model and identified model

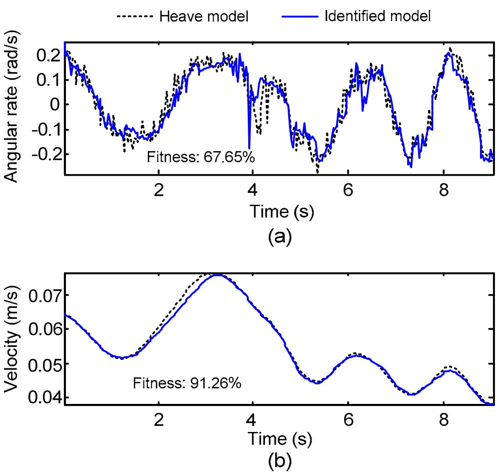

Fig. 8 Identification results (a) angular rate and (b) velocity along *z* axis of heave model and identified model

4.2 Results of control design and Simulink model

To assess the performance of the MPC, a series of simulation cases were performed. A study was carried out to assess the performance of the MPC controller implemented on the longitudinal dynamics model of the helicopter platform. The first case evaluated the step set-point trajectory tracking capability of the controller with white disturbance. The second case assessed the controller with trajectory of square wave. The third case compared the controller with a half sinusoidal wave trajectory. The predictive controller in the study involved the parameters setting as the controller factor ρ=0.8 with horizon value as P=10 and N=2. Fig. 9 shows the MPC simulation with step response reference for the longitudinal model parameters (pitch angle, angular rate, and translation velocity). Fig. 10 shows the Simulink model results of the controller tracking a square signal for longitudinal model parameters. It can be seen that the MPC follows very closely to the reference signals. Moreover, a half sine wave has tested with the MPC for the angular rate angle.

5 Conclusions

In this paper, a combination of NLARX and NNs approaches to model small-scale helicopter black box plant is proposed. The black box structures of all

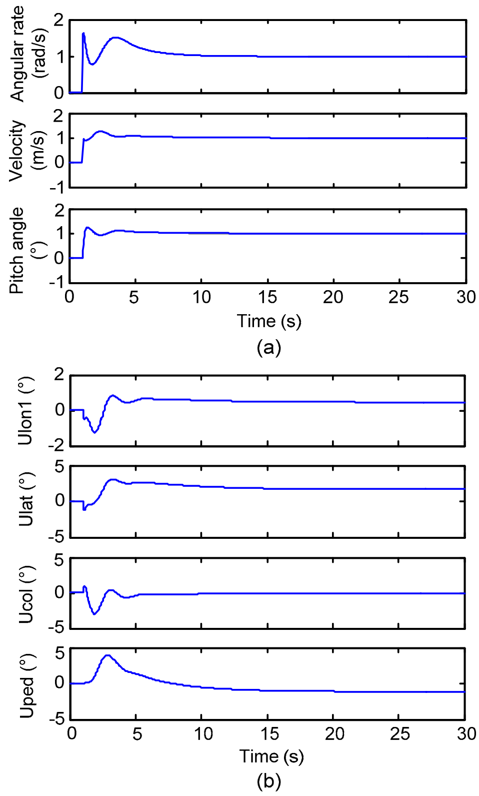

Fig. 9 Designing control simulation results of MPC tracking step set-points

(a) Tracking of step trajectory for angular rate, translation velocity, and pitch angle along *x* axis; (b) Required inputs generated by the MPC to track steps trajectory

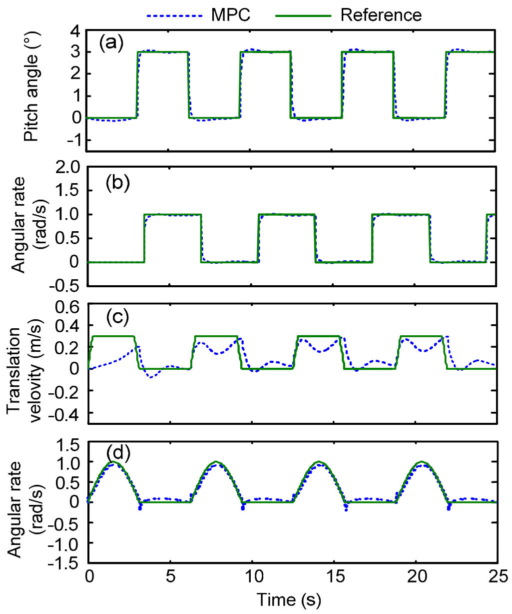

Fig. 10 Tracking a square signal for (a) pitch angle, (b) angular rate, (c) translation velocity; and, (d) tracking a half sine wave signal for angular rate

sub-models (longitudinal, lateral, and heave) were identified as nonlinear models from test flight data. In order to design the flight control, it was necessary to linearize the identified models. The tracking control for different set-points is designed using MPC. This control was used for the longitudinal dynamics model of the RUAV. The performance of the MPC shows good tracking performance in the presence of white noises. These results may have practical significance in the analysis of the helicopter dynamics model and may lead to more efficient intelligent flight control strategies.

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