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Model predictive control of a 3-DOF helicopter system using successive linearization

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Abstract

Helicopter dynamics are in general nonlinear, time-varying, and may be highly uncertain. Traditional control schemes such as proportional–integral–derivative (PID) control, linear quadratic regulator (LQR), and eigen-structure assignment are usually not effective when a linearized model is used and the helicopter moves away from the design trim point. This paper presents a nonlinear model predictive control (NMPC) method to control the elevation and travel of a three degree of freedom (DOF) laboratory helicopter using successive linearization to approximate the internal model of the system. The developed algorithm is evaluated by simulation, and its performance is compared with that achieved by linear model predictive control (LMPC).

Keywords: nonlinear systems, helicopter dynamics, MIMO systems, model predictive control, successive linearization

1. Introduction

Helicopters have severe nonlinearities and open-loop unstable dynamics as well as significant cross-coupling between their control channels, which make the control of such multiple-input multiple-output (MIMO) systems a challenging task. Conventional approaches to helicopter flight control involve linearization of these nonlinear dynamics about a set of pre-selected equilibrium conditions or trim points within the flight envelop (Kim, 1993). Based on the obtained linear models, classical single-input single-output (SISO) techniques with a PID controller are widely used (Reiner *et al*, 1995; Kim *et al*, 1997; Lee *et al.*, 2005). Of course, this approach will require multi-loop controllers, which makes their design inflexible and difficult to tune. Hence, the MIMO controller design approaches have received more and more attention. For example, successful implementation of LQR design for a helicopter system has been presented in (Apkarian, 1998). Also, Koo *et al* (1998) used dynamical sliding mode control to stabilize the altitude of a nonlinear helicopter model in vertical flights. Later, neural network based inverse control of an aircraft system was presented in (Prasad *et al*, 1999). More MIMO control approaches for helicopter maneuver are presented in (Sira-Ramirez *et al.,* 1994; Mahony *et al.*, 2004; Marconi *et al.*, 2007, Tao *et al.*, 2010).

In the past two decades, model predictive control (MPC) has been widely used in industrial process control (Lee *et al.*, 1994; Ricker *et al.*, 1995; Qin *et al.*, 2003; Dua *et al.*, 2008). With the development of modern micro-processors, it has been possible to solve the optimization problems associated with MPC online effectively, which makes MPC applicable to systems with fast dynamics (Wang *et al.*, 2010; Zhai *et al.*, 2010). Many researchers utilized linear MPC to control helicopter systems (Witt *et al*, 2007; Maia *et al.*, 2008). However, as the linearized model is valid only for small perturbations from its equilibrium or trim point, the control performance can degrade severely if the helicopter does not operate around the design trim point.

In this paper, a nonlinear model predictive control based on successive linearization (MPCSL) of the nonlinear helicopter model is applied to a laboratory helicopter system to achieve acceptable performance over a wide flight envelope. The performance of the applied control technique is illustrated and compared to that of LMPC by comparing the steady state error, rise time, and overshoot. This paper is organized as follows. First the dynamical model of a laboratory helicopter system is presented, followed by a description of the applied successive linearization based NMPC used to control the elevation and travel of the helicopter. Then, simulation results are presented to illustrate the effectiveness of the proposed control algorithm. Finally, conclusions are drawn in the last section.

2. Helicopter system dynamics

It is economical for both industrial and academic research to investigate the effectiveness of an advanced control system before putting it into practical application. The research presented in this paper is based on a mathematical model of a 3-DOF laboratory helicopter system from Quanser Consulting, Inc. The 3-DOF helicopter consists of a base upon which an arm is mounted. The arm carries the helicopter body on one end and a counter weight on the other end. The arm can pitch about an elevation axis as well as swivel about a vertical (travel) axis. Encoders that are mounted on these axes allow measuring the elevation and travel of the arm. The helicopter body is mounted at the end of the arm and is free to swivel about a pitch axis. The pitch angle is measured via a third encoder (Apkarian, 1998). Due to hardware restrictions, the movement range of the elevation and pitch angles are constrained within [-1, +1] rad (Ishitobi *et al.*, 2010). Two DC motors with propellers mounted on the helicopter body can generate a force proportional to the voltages applied to the DC motors. The force generated by the propellers can cause the helicopter body to lift off the ground. The purpose of the counterweight is to reduce the power requirements on the motors. The helicopter experimental system is shown in Figure 1 (Quanser, 2010).

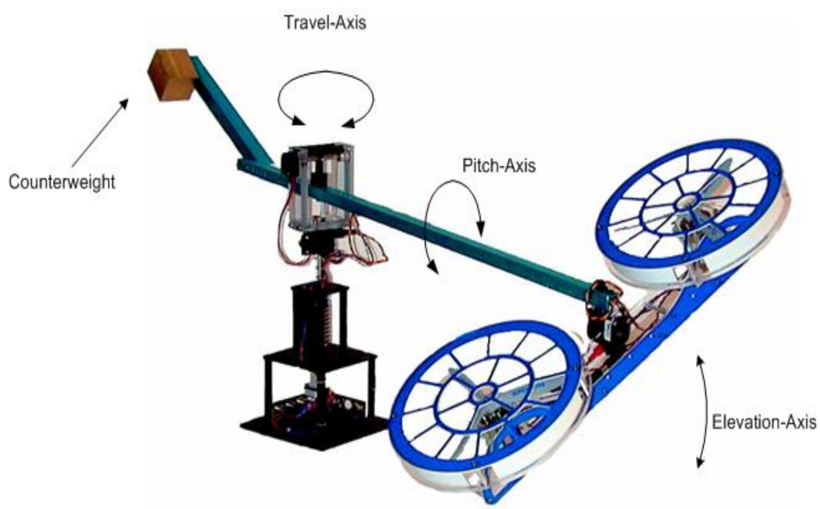

Figure 1: Laboratory Helicopter from Quanser Consulting, Inc.

The system dynamics can be described by the following highly nonlinear state model (Apkarian, 1998):

$$\dot{x} = F(x) + [G_1(x), G_2(x)]u \tag{1}$$

where

$$x = [\varepsilon \quad \dot{\varepsilon} \quad \theta \quad \dot{\theta} \quad \phi \quad \dot{\phi}]^T$$

$$u = [V_f \quad V_b]^T$$

$$F(x) = \begin{bmatrix} \dot{\varepsilon} \\ p_1 \cos\varepsilon + p_2 \sin\varepsilon + p_3\dot{\varepsilon} \\ \dot{\theta} \\ p_5 \cos\theta + p_6 \sin\theta + p_7\dot{\theta} \\ \dot{\phi} \\ p_9\dot{\phi} \end{bmatrix}$$

$$G_1(x) = [0 \quad p_4\cos\theta \quad 0 \quad p_8 \quad 0 \quad p_{10}\sin\theta]^T$$

$$G_2(x) = [0 \quad p_4\cos\theta \quad 0 \quad -p_8 \quad 0 \quad p_{10}\sin\theta]^T$$

$$p_1 = \left[-\left(M_f + M_b\right)gL_a + M_c gL_c\right] / J_\varepsilon \qquad p_2 = \left[-\left(M_f + M_b\right)gL_a \tan\delta_a + M_c gL_c \tan\delta_c\right] / J_\varepsilon$$
$$p_3 = -\eta_\varepsilon / J_\varepsilon \qquad p_4 = K_m L_a / J_\varepsilon$$
$$p_5 = \left(-M_f + M_b\right)gL_h / J_\theta \qquad p_6 = -\left(M_f + M_b\right)gL_h \tan\delta_h / J_\theta$$
$$p_7 = -\eta_\theta / J_\theta \qquad p_8 = K_m L_h / J_\theta$$
$$p_9 = -\eta_\phi / J_\phi \qquad p_{10} = -K_m L_a / J_\phi$$
$$\delta_a = \tan^{-1}\left\{\left(L_d + L_e\right)/L_a\right\} \qquad \delta_c = \tan^{-1}\left\{L_d / L_c\right\} \qquad \delta_h = \tan^{-1}\left\{L_e / L_h\right\}$$

and, the symbols used in the above model are described in Table 1.

Table 1. Notation and units used in the laboratory helicopter model

Symbols	Unit	Description
ε	Degree	Elevation angle
θ	Degree	Pitch angle
ϕ	Degree	Travel angle
V_f , V_b	Volt	Voltages applied to the front and back motor
M_f , M_b	kg	Mass of the front section of the helicopter, and mass of the rear section
M_c	kg	Mass of the count-weight
L_d	m	The length of pendulum for the elevation axis
L_c	m	The distance from the pivot point to the counter-weight
L_a	m	The distance from the pivot point to the helicopter body
L_e	m	The length of pendulum for pitch axis
L_h	m	The distance from the pitch axis to either motor
g	m/s^2	Gravitational acceleration
J_ε , J_θ , J_ϕ	kg m^2	Moment of inertia about the elevation, pitch and travel axes
η_ε , η_θ , η_ϕ	kg m^2 /s	Coefficient of viscous friction about the elevation, pitch and travel axes

In this research, a model predictive control algorithm with successive linearization is investigated for the control of the elevation and travel in the helicopter system by manipulating the voltages applied to the front and back motors. Therefore, elevation angle, ε, and travel angle, □, are chosen as the controlled variables, i.e.,

$$y = \left[\varepsilon \quad \phi\right]^T \tag{2}$$

and the two voltages, V_f and V_b, are chosen as the manipulated variables, i.e.,

$$u = \left[V_f \quad V_b\right]^T \tag{3}$$

For such dynamical system with severe nonlinearities, the direct MIMO control is challenging; however, this challenge can be overcome using successive linearization as described in the next sections.

3. NMPC using successive linearization

Ishitobi *et al.* (2010) have shown that the nonlinear model described in Section 2 captures the essential dynamic behavior of a laboratory helicopter, and therefore, it is used in this work to describe the Quanser laboratory helicopter system and to design the

MPCSL scheme. At every instance, the nonlinear model is linearized at the current state and the control input. Then, the obtained linear model is used in MPC. This successive linearization makes the predictive model represent the latest operating condition of the helicopter. In addition, if compared with conventional MPC, the use of a linearized model reduces the computational effort in solving the MPC optimization problem significantly, and makes the developed control algorithm more realistic to meet the requirement of a real-time control system. The remainder of this section describes the MPCSL algorithm in more detail.

3.1. Model Linearization

The nonlinear system in section 2 can be written as:

$$\dot{x} = f(x,u) \ , \quad x \in \Re^{n_x} \ , \ u \in \Re^{n_u} \tag{4}$$

and,

$$y = g(x,u) \qquad y \in \Re^{n_y} \tag{5}$$

where n_x , n_u and n_y are the dimensions of state vector, manipulated variables and controlled variables, respectively. The equations (4) and (5) can be linearized as follows:

$$\dot{x} \cong f(x_0,u_0) + A(x - x_0) + B(u - u_0) \tag{6}$$

$$y \cong g(x_0,u_0) + C(x - x_0) + D(u - u_0) \tag{7}$$

where,

$$A = \left.\frac{\partial f}{\partial x}\right|_{x_0,u_0} , \ B = \left.\frac{\partial f}{\partial u}\right|_{x_0,u_0}$$
$$C = \left.\frac{\partial g}{\partial x}\right|_{x_0,u_0} , \ D = \left.\frac{\partial g}{\partial u}\right|_{x_0,u_0}$$

are matrices of the appropriate sizes. At a given time sample, x_0 and u_0 represent the current state and control vectors, respectively. Using equations (1), (6), (7), these system matrices can be obtained as follows:

$$A = \begin{bmatrix} 0 & 1 & 0 & 0 & 0 & 0 \\ -p_1 \sin\varepsilon + p_2 \cos\varepsilon & p_3 & -p_4 \sin\theta (V_f + V_b) & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & -p_5 \sin\theta + p_6 \cos\theta & p_7 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & p_{10} \cos\theta (V_f + V_b) & 0 & 0 & p_9 \end{bmatrix}$$

$$B = \begin{bmatrix} 0 & 0 \\ p_4 \cos\theta & p_4 \cos\theta \\ 0 & 0 \\ p_8 & -p_8 \\ 0 & 0 \\ p_{10} \sin\theta & p_{10} \sin\theta \end{bmatrix}$$

$$C = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \end{bmatrix} \qquad D = \begin{bmatrix} 0 & 0 \\ 0 & 0 \end{bmatrix}$$

After linearization, the linearized model is discretized and the discrete model is used in MPC as described next.

3.2 MPC algorithm

The diagram below depicts the structure used by the model predictive controller.

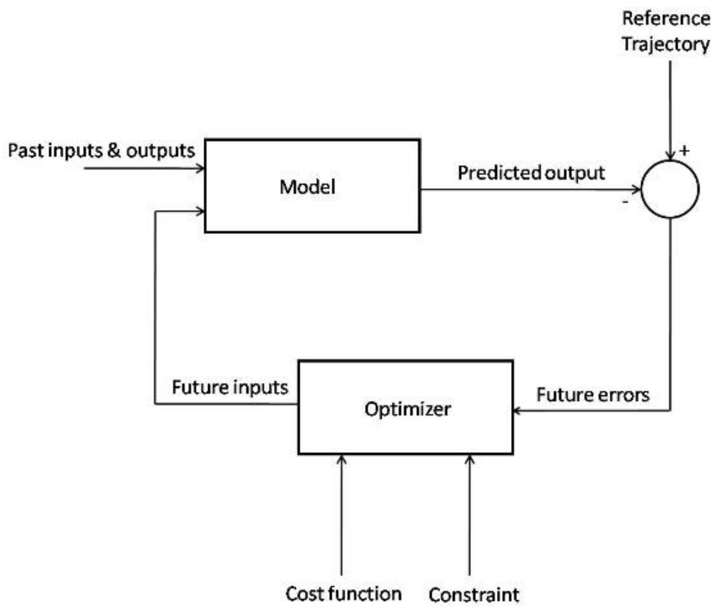

Figure 2: The structure of model predictive controller

As shown in Figure 2, once the model has been obtained, it can be used as an internal model of a predictive controller. The model generates predictions of future process outputs over a specified prediction horizon, which are then used to minimize the following MPC objective criterion:

$$\min_{u_k} \sum_{i=1}^{P} e_{y,i}^T Q e_{y,i} + \sum_{j=1}^{M} \Delta u_j^T R \Delta u_j , \quad k = 0,1,\cdots,M-1 \tag{8}$$

s.t.,

$$u_L \le u_k \le u_U$$
$$u_k = u(t_k) = u(t),\ t \in [t_0, t_P]$$
$$e_{y,i} = y_i - r_i,\ i \in [1, P]$$
$$\Delta u_j = u_{j+1} - u_j$$

where M and P are the control and prediction horizons respectively, $Q \in \Re^{n_e \times n_e}$ and $R \in \Re^{n_{\Delta u} \times n_{\Delta u}}$ are the weighting matrices for the output error and the control signal changes respectively, and $n_e = P \times n_y$, $n_{\Delta u} = M \times n_u$. $r_k \in \Re^{n_e}$ is the output reference vector at t_k , and u_L , u_U are constant vectors determining the input constraints as element-by-element inequalities (Al Seyab *et al*, 2008). By minimizing the objective function in equation (8), the MPC algorithm generates a sequence of control inputs u_k and $k = 0,1,\cdots,M-1$, as illustrated in Figure 3 (Qin *et al.*, 2003).

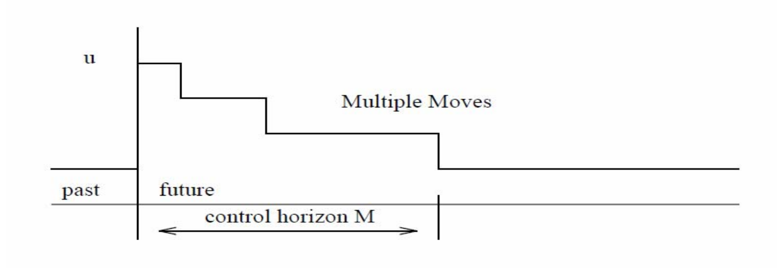

Figure 3: Manipulated variable profile

Then, only the first element in this control sequence is implemented and the whole procedure is repeated at next sampling instant. In this research, the internal model used by the model predictive controller is a linear model that is obtained by linearizing the nonlinear helicopter model at each sampling instant. Therefore, the optimization problem above is a standard quadratic programming problem (QP) which can be solved by any modern QP solvers. Given the medium size of optimization problem in this application, the active set method is used here to efficiently solve this online optimization problem (Fletcher, 2000; Nocedal *et al.*, 2006).

4. Simulated Example

In this example, the MPCSL control algorithm described earlier is applied to the nonlinear helicopter model using MATLAB/SIMULINK. The voltages V_f and V_b of the two motors are assumed to be changeable in the range $[0V, 5V]$. The nominal values of the physical constants in the helicopter test-bed are as follows (Ishitobi, *et al.*, 2010):

$J_\varepsilon = 0.86kg \cdot m^2$, $J_\theta = 0.044kg \cdot m^2$ $J_\phi = 0.82kg \cdot m^2$,

$L_a = 0.62m$, $L_c = 0.44m$, $L_d = 0.05m$, $L_e = 0.02m$, $L_h = 0.177m$,

$M_f = 0.69kg$, $M_b = 0.69kg$, $M_c = 1.69kg$, $K_m = 0.5N/V$, $g = 9.81m/s^2$,

$\eta_\varepsilon = 0.001kg \cdot m^2/s$, $\eta_\theta = 0.001kg \cdot m^2/s$, $\eta_\phi = 0.005kg \cdot m^2/s$,

In this simulation, the reference signals for the elevation and travel angles are changed between -20^o to 20^o to simulate the demands given by the pilot as shown in Figures 4, and 5. Also, the sampling time and simulation time used are 0.1 and 200 seconds, respectively.

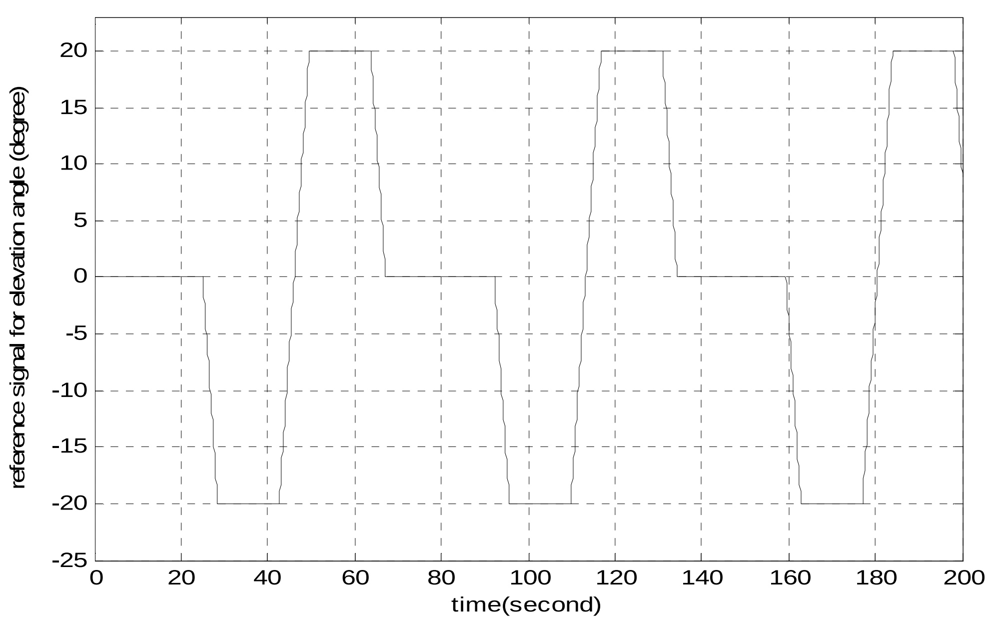

Figure 4: Reference signal for the elevation angle

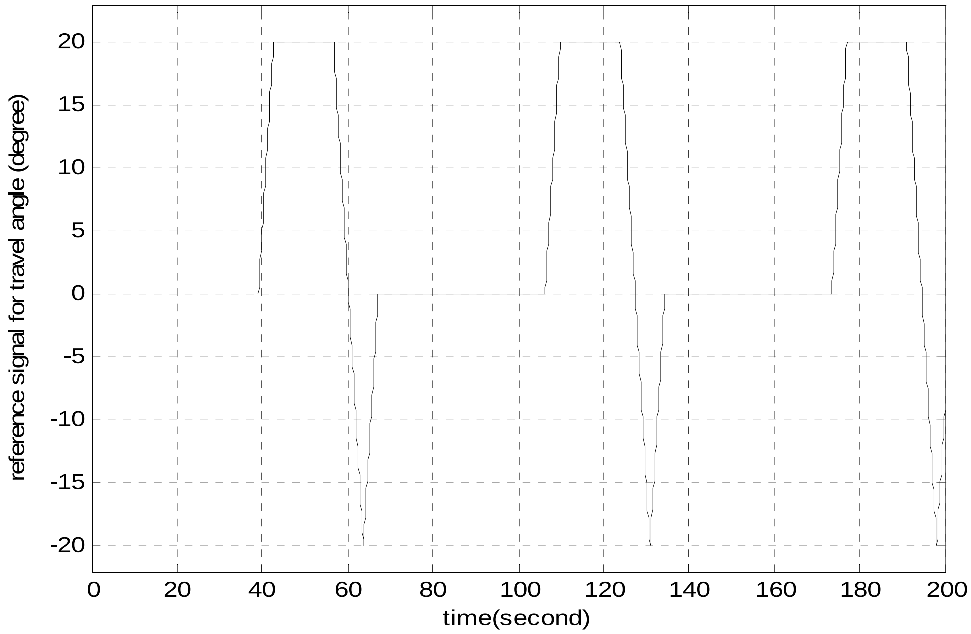

Figure 5: Reference signal for the travel angle

In order to show the advantages of the MPCSL method when used to control this helicopter system, the control results are compared with those of LMPC, which is well tuned using the linearized model at the helicopter hovering condition, i.e., $[\varepsilon \quad \theta \quad \phi] = [0 \quad 0 \quad 0]$. The design parameters used in these two MIMO approaches are given in Table 2.

Table 2: Design parameters used in LMPC and MPCSL

Initial Condition	$\varepsilon = \theta = \phi = \dot{\varepsilon} = \dot{\theta} = \dot{\phi} = 0$, $V_f = 1.8865$, $V_b = 1.9366$
P	10(MPCSL); 20(LMPC)
M	5(MPCSL); 5(LMPC)
Q	$10*I_P$ (MPCSL); $10*I_P$(LMPC)
R	$0.01*I_M$(MPCSL); $0.01*I_M$(LMPC)

The simulation results for the MPCSL and LMPC are shown in Figures 6 and 7, and the corresponding voltage signals applied to the rotors are shown in Figures 8 and 9.

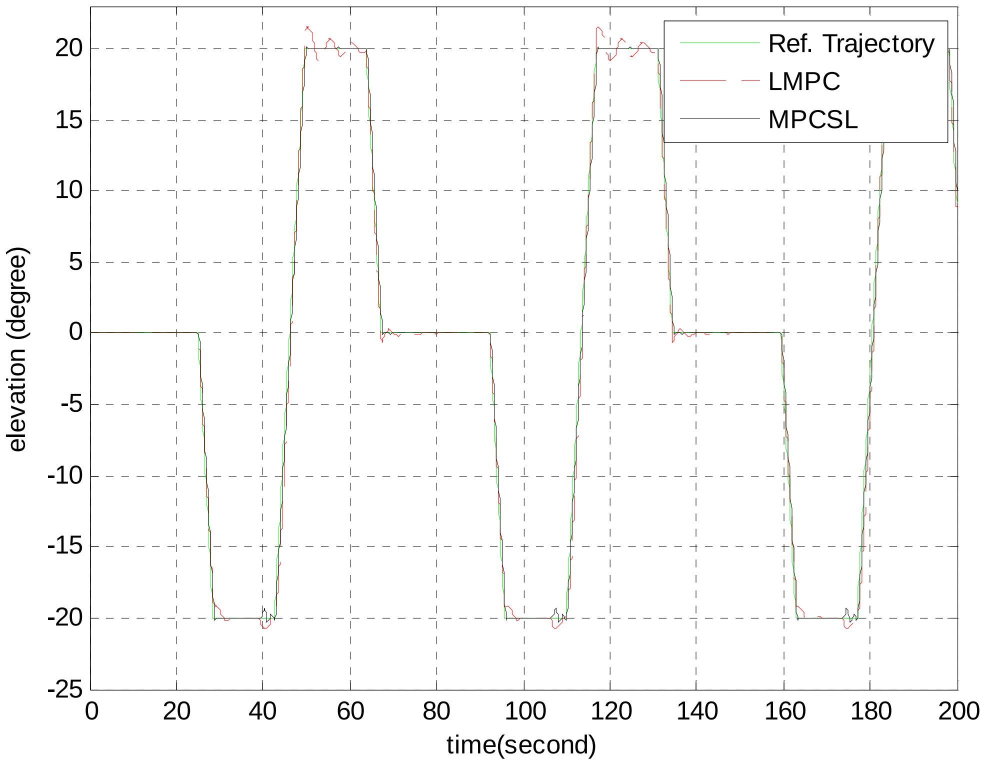

Figure 6: Control simulation results for the elevation angle

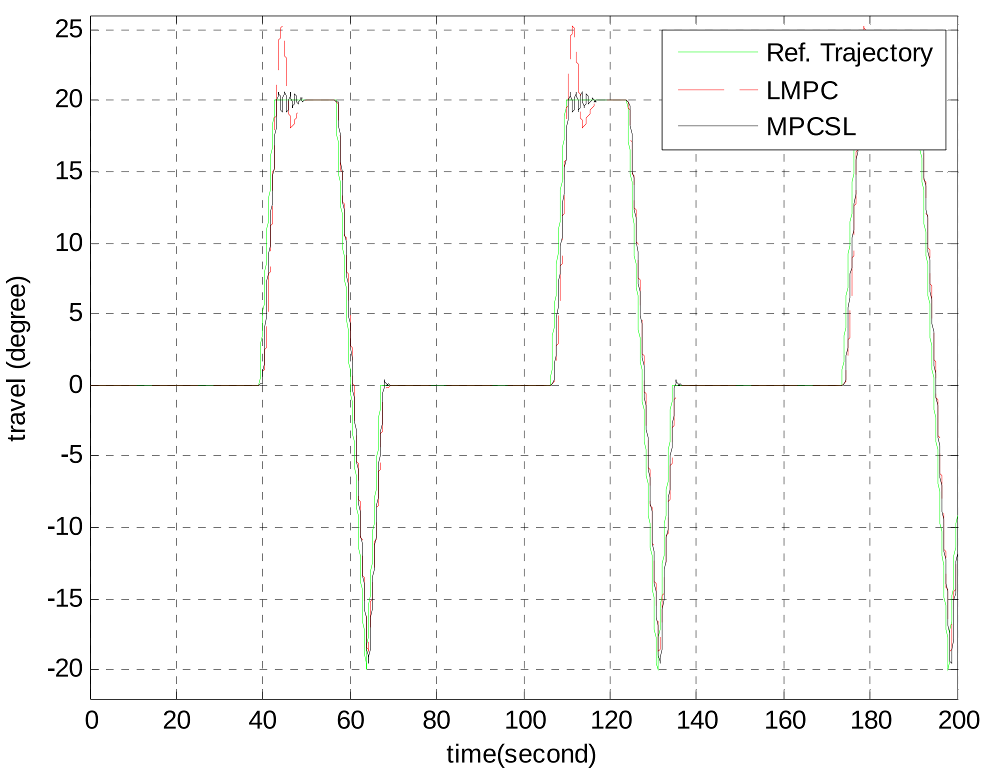

Figure 7: Control simulation results for the travel angle

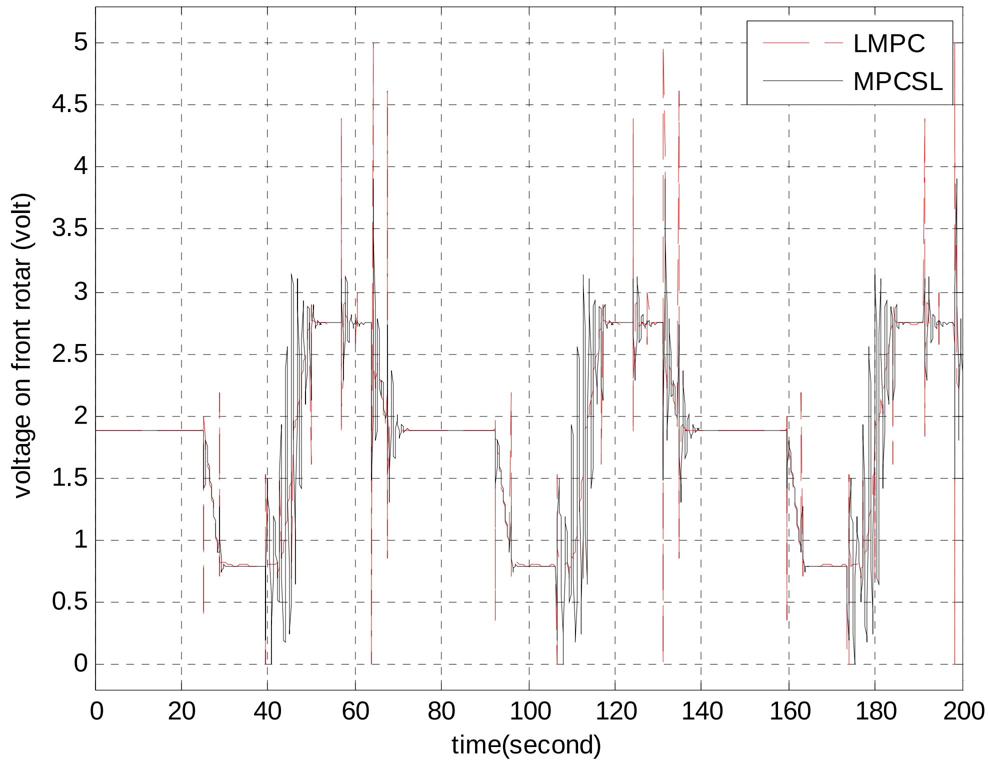

Figure 8: Voltage applied on the front rotor

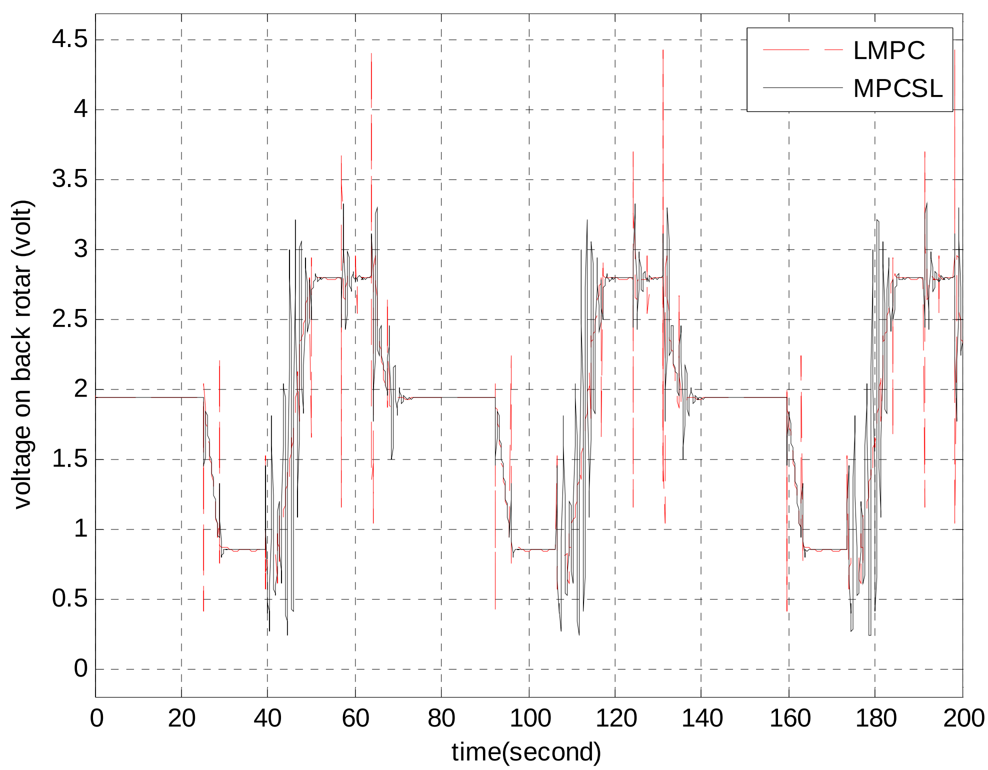

Figure 9: Voltage applied on the back rotor

It can be seen from the Figures 6 and 7 that when the helicopter is operating in a wide range of its flight envelope, the tracking performance of LMPC looks acceptable; however, large overshoot is not avoidable due to the inaccuracy of the internal model used in prediction. Also, compared with LMPC, the MPCSL approach results in smaller overshoot and shorter settling time for both the elevation and travel angles, which is a considerable improvement in performance. This is shown in Tables 3, 4, and 5, which compare the tracking mean absolute errors (MAE), percent overshoot, and settling time (using a band of $\pm 2\%$ of the total change in the controlled variables), for the two control algorithms.

Table 3: MAE for elevation and travel control

MAE (degree)	LMPC	MPCSL
Elevation	0.4114	0.2122
Travel	0.9346	0.5909

Table 4: Overshoot for elevation and travel control

Percentage Overshoot	LMPC	MPCSL
Elevation	7.5%	0%
Travel	25%	5.3%

Table 5: Settling time for elevation and travel control

Settling Time (seconds)	LMPC	MPCSL
Elevation	7.5	1.1
Travel	8.9	6.4

5. Conclusion

This paper presents a nonlinear model predictive control method that is based on successive linearization to control the elevation and travel of a laboratory helicopter system. The performance of the developed algorithm is illustrated and compared to that of linear model predictive control, and the results show a considerable improvement for the developed algorithm in term of tracking error, overshoot and settling time.

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Biographical notes

Dr. Yujia Zhai received his M.Sc and Ph.D. from University of Liverpoo and Liverpool John Moores University, UK, in 2004 and 2009, respectively. He is currently working as a post-doctoral researcher in the Chemical Engineering Program, Texas A&M University at Qatar. His research interests include Dynamical System Identification and Control, Artificial Neural network, Nonlinear Optimization, and Model Predictive Control

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Yasser Al-Hamidi is currently working as a Technical Laboratory Coordinator in the Mechanical Engineering Program at Texas A&M University at Qatar since 2007. He is specialized in instrumentation, controls and automation. He worked as a Lab Engineer in the College of Engineering, University of Sharjah for seven years before joining TAMUQ. His other experiences include Laboratory Supervisor/Network Administrator at Ajman University of Science and Technology (Al Ain Campus), Maintenance Engineer at AGRINCO, Electrical Engineer at Ministry of Culture (National Theater Project, Damascus) and also as a Novel Network Supervisor (NetWare 3.12) in a medical and agricultural services company, Damascus. Yasser's professional interests include precision mechatronics, real-time control systems design, networked control systems.

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