Chapter 11
Robust Observer Based Model Predictive Control of a 3-DOF Helicopter System

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Abstract Helicopter systems are characterized by highly nonlinear dynamics, multiple operating regions, and significant interaction among state variables. In this paper, an observer based model predictive control (MPC) scheme with successive linearization is presented, for a 3 degree of freedom (DOF) helicopter system. All control simulations were performed under the conditions of noisy measurements. To illustrate the advantage by using unscented Kalman filter (UKF) as the observer, the performance of UKF based MPC is compared with those of MPC algorithms using linear filters and extended Kalman filter (EKF). The simulation results have shown that for this application the UKF-based MPC has superior performance, in terms of the disturbance rejection and set-point tracking.

Keywords Nonlinear systems · Helicopter dynamics · MIMO systems · Model predictive control · Kalman filter

11.1 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 [6]. Based on the obtained linear models, classical single-input single-output (SISO) techniques with a PID controller are widely used [7, 9, 18] Of course, this approach will require multi-loop controllers, which

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makes their design inflexible and difficult to tune. Hence, the development of MIMO controller design approaches has received more and more attention. For example, successful implementation of LQR design for a helicopter system has been presented in [2]. Also, Koo and Sastry [8] 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 [15]. More MIMO control approaches for helicopter maneuver are presented in [11, 13, 20, 21].

In the past two decades, model predictive control has been widely used in industrial process control [3, 10, 16]. 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 [23, 24]. Many researchers utilized linear MPC to control helicopter systems [12, 22]. 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. The applications of MPC by using nonlinear internal model (NMPC) directly can be found in petrochemical industry due to the slow update rate of control input. The time limitation for the necessary online computation does not need to be taken into consideration. For a helicopter system, the equations which accurately describe the nonlinear dynamics can be derived by the knowledge of aerodynamics. However, a typical rate on in helicopter control is every 0.1 s, and given such small time interval, it is very difficult to for micro-controller to produce a control input using NMPC scheme. This study is principally concern with the control of a 3DOF helicopter using model predictive control scheme. To make the control scheme have better performance and meet online computational requirement, successive linearization (SL) on a known nonlinear helicopter model is applied to obtain the linear internal model for MPC. The harsh operation environment of helicopter is a challenge to the stability of control system. For a control scheme based on the helicopter model with high order, the derivatives terms, such as angle velocity and acceleration, are usually obtained by analytical or numerical differentiation, which would amplify the effects of measurement noise. To increase the stability of MPC scheme, the unscented Kalman filter is employed to estimate the system states and disturbances from the available measurements. To demonstrate the advantage brought by UKF, the performance of proposed control scheme is compared with those achieved by other filter based MPC, such as linear filter, extended Kalman filter.

This paper is organized as follows. In Sect. 11.2, the mathematical model of 3-DOF helicopter system used in this work is introduced. The MPC with successive linearization and state estimation algorithms are covered in Sect. 11.3. In Sect. 11.4, simulation results are presented showing the performance of different observers based MPC for the control on elevation and travel of the 3-DOF helicopter. Section 11.5 concludes this paper with a few closing remarks.

11.2 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 lab 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 [2].

The system dynamics can be described by the following highly nonlinear state model [2]:

$$\dot{x} = F(x) + [G_1(x), G_2(x)]u \tag{11.1}$$

where

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

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

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

$$G_1(x) = [\,0, \quad p_4 \cos\theta, \quad 0, \quad p_8, \quad 0, \quad p_{10}\sin\theta\,]^T$$
$$G_2(x) = [\,0, \quad p_4 \cos\theta, \quad 0, \quad -p_8, \quad 0, \quad p_{10}\sin\theta\,]^T$$

$$p_1 = \left[-\left(M_f + M_b\right)gL_a + M_c g L_c\right]/J_\varepsilon \quad p_2 = \left[-\left(M_f + M_b\right)gL_a \tan\delta a + M_c g L_c \tan\delta_c\right]/J_\varepsilon$$
$$p_3 = -\eta_\varepsilon/J_\varepsilon \qquad p_4 = K_m L_a/J_\varepsilon$$
$$p_5 = \left[-\left(M_f + M_b\right)gL_h\right]/J_\theta \qquad p_6 = -\left(M_f + M_b\right)gL_h \tan\delta_h/J_\theta$$
$$P_7 = -\eta_\theta/J_\theta \qquad p_8 = K_m L_h/J_\theta$$
$$P_9 = -\eta_\phi J_\phi \qquad p_{10} = -K_m L_a/J_\phi$$
$$\delta_a = \tan^{-1}\{(L_d + L_e)/L_a\} \qquad \delta_c = \tan^{-1}\{L_d/L_c\} \qquad \delta_\eta = \tan^{-1} L_e/L_h$$

and, the symbols used above are model parameters.

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, ϕ, are chosen as the controlled variables, i.e.,

$$y = [\varepsilon, \quad \phi]^T \tag{11.2}$$

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

$$u = \left[V_f, \quad V_b\right]^T \tag{11.3}$$

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.

11.3 Model Predictive Control Algorithm

In [5], it has been shown that the nonlinear model described in Sect. 11.2 captures the essential dynamic behavior of a lab helicopter, and therefore, it is used in this work to describe the Quanser lab helicopter system and to design the MPC scheme.

11.3.1 Linearized Model by Successive Linearization

The nonlinear system in Sect. 11.2 can be written as:

$$\dot{x} \cong f(x_k, u_k) + A(x - x_k) + B(u - u_k) \tag{11.4}$$

$$y \cong g(x_k, u_k) + C(x - x_k) + D(u - u_k) \tag{11.5}$$

where,

$$A = \left.\frac{\partial f}{\partial x}\right|_{x_k, u_k}, B = \left.\frac{\partial f}{\partial u}\right|_{x_k, u_k}$$

$$C = \left.\frac{\partial g}{\partial x}\right|_{x_k, u_k}, D = \left.\frac{\partial g}{\partial u}\right|_{x_k, u_k}$$

are matrices of the appropriate sizes. At a given time sample t_k, x_k and u_k represent the current state and control vectors, respectively. Using Eqs. (11.1), (11.4), (11.5), these system matrices can be obtained as follows:

$$A = \begin{bmatrix} 0 & 1 & 0 & 0 & 0 & 0 \\ -p_1 \sin\varepsilon + p_2 \cos\varepsilon & p_3 & -p_4 \sin\theta\left(V_f + V_b\right) & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & -p_5 \sin\theta + p_6 \cos\theta & p_7 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & p_{10} \cos\theta\left(V_f + V_b\right) & 0 & 0 & p_9 \end{bmatrix} \tag{11.6}$$

$$B = \begin{bmatrix} 0 & 0 \\ p_4 \cos\theta & p_4 \cos\theta \\ 0 & 0 \\ p_8 & -p_8 \\ 0 & 0 \\ p_{10} \sin\theta & p_{10} \sin\theta \end{bmatrix} \qquad C = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \end{bmatrix} \tag{11.7}$$

$$D = \begin{bmatrix} 0 & 0 \\ 0 & 0 \end{bmatrix}$$

According to Eqs. (11.6) and (11.7), at every instance, the nonlinear model can be linearized at the current state and the control input. Then, the obtained linear model is used in MPC scheme. The advantage of utilizing this kind of successive linearization (SL) technique is that, the updated model can catch the change of system dynamics, and produce accurate prediction on future behavior. MPC scheme with SL is therefore more robust against the external disturbances. Theoretically, MPC based on the nonlinear model in Eq. (11.1) is possible. However, the introduction of such nonlinear model would result in nonlinear programming (NLP) problem that need to be solved online by, for example, *sequential quadratic programming* (SQP) technique that is a very computationally expensive algorithm. Given the computational power of the micro-controllers used in this application, the helicopter dynamics is too fast to implement such SQP technique. Therefore, 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 hardware requirement of a real-time control system.

11.3.2 Model Predictive Control with Successive Linearization

Figure 11.1 below depicts the structure of closed-loop observer based MPC on a 3DOF helicopter system, with successive linearization.

In Fig. 11.1, sp_k stands for the set point value at sample time t_k, u_k the control input, y_k the measurement and $\hat{x}_k$ the current estimate of system states. At sample time t_k, MPC controller can obtain a linear model of system using u_k and $\hat{x}_k$. This linear model can be used as an internal model of a predictive controller. The model

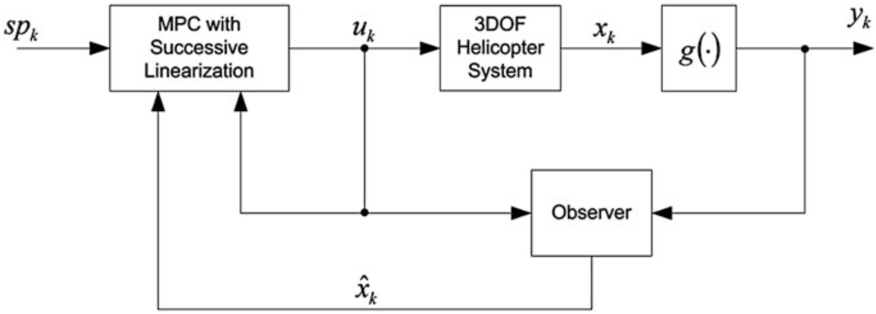

Fig. 11.1 Structure of model predictive control with observer

generates predictions of future process output over a specified prediction horizon, which is then used to minimize the following MPC objective criterion:

$$\min_{u_k} \sum_{i=1}^{P} e_{y,i}^T Q e_{y,i} + \sum_{j=1}^{M} j^T R \Delta u_j, \quad k = 0, 1, \ldots, M-1 \tag{11.8}$$

s.t.,

$$u_L \leq u_k \leq u_U$$

$$u_k = u(t_k) = u(t), \quad t \in [t_0, t_p]; \quad e_{y,i} = y_i - r_i, \in [1, P]; \quad \Delta u_j = u_{j+1} - u_j, \quad j \in [1, M]$$

where M and P are the control and prediction horizons respectively, $Q \in R^{n_e \times n_e}$ and $R \in R^{n_{\Delta u} \times n_{\Delta u}}$ are the weighting matrices for the output error and the control signal changes respectively, and $n_e = P \times n_y, n_{\Delta u} = M \times n_u . r_k \in R^{n_e}$ is the output reference vector at t_k, and u_L and u_U are constant vectors determining the input constraints as element-by-element inequalities [1]. By minimizing the objective function in Eq. (11.8), the MPC algorithm generates a sequence of control inputs u_k and $k = 0, 1, \ldots, M-1$. 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 [4, 14].

11.3.3 State Estimation

In the 3DOF helicopter system, two encoders mounted on these axes allow for measuring the elevation and travel of the arm. The helicopter body is mounted at the end of the arm. The helicopter body is free to swivel about a "pitch" axis. The pitch angle is measured via a third encoder. Therefore, the measurement model is

$$\mathrm{y_m} = Hx \quad with \quad \mathrm{H} = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix} \tag{11.9}$$

which means only the positions of three angles—elevation ε, pitch θ, travel ϕ, are available by direct measurements. In this case, angle velocities—$\dot{\varepsilon} \quad \dot{\theta} \quad \dot{\phi}$ need to be estimated to have a full-state vector for MPC.

11.3.3.1 Unscented Kalman Filter

The unscented Kalman filter used in this study is a straightforward extension of the unscented transformation (UT) to the recursive estimation on system states, where the system state vector is augmented as the concatenation of the original state and noise variables: $\mathrm{X_k^a} = \begin{bmatrix} x_k^T & v_k^T & n_k^T \end{bmatrix}^T$. Then, the UT sigma point selection scheme is applied to this new augmented state vector to calculate the corresponding sigma matrix, $\boldsymbol{X}_k^a$. The UKF algorithm is given as following:

Initialize with

$$\hat{x}_0 = \mathbb{E}[x_0] \tag{11.10}$$

$$\mathbf{P}_0 = \mathbb{E}\left[(x_0 - \hat{x}_0)(x_0 - \hat{x}_0)^T\right] \tag{11.11}$$

$$\hat{x}_0^a = \mathbb{E}[x^a] = \begin{bmatrix} \hat{x}_0^T & \mathbf{0} & \mathbf{0} \end{bmatrix}^T \tag{11.12}$$

$$\mathbf{P}_0^a = \mathbb{E}\ \left[\left(x_0^a - \hat{x}_0^a\right)\left(x_0^a - \hat{x}_0^a\right)^T\right] = \begin{bmatrix} \mathbf{P_0} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{R^V} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \mathbf{R^n} \end{bmatrix} \tag{11.13}$$

For $k \in \{1, \ldots, \infty\}$

Calculate sigma points:

$$\boldsymbol{X}_{k-1}^a = \begin{bmatrix} \hat{x}_{k-1}^a & \hat{x}_{k-1}^a + \gamma\sqrt{\mathbf{P}_{k-1}^a} & \hat{x}_{k-1}^a - \gamma\sqrt{\mathbf{P}_{k-1}^a} \end{bmatrix} \tag{11.14}$$

Time update:

$$\boldsymbol{X}_{\mathrm{k|k-1}}^x = \mathbf{F}\left[\boldsymbol{X}_{\mathrm{k|k-1}}^x, \quad \mathbf{u}_{k-1} \quad \boldsymbol{X}_{\mathrm{k|k-1}}^v\right] \tag{11.15}$$

$$\hat{x}_k^- = \sum\nolimits_{i=0}^{2L} W_i^{(m)} \boldsymbol{X}_{i,\mathrm{k|k-1}}^x \tag{11.16}$$

$$P_k^- = \sum_{i=0}^{2L} W_i^{(c)} \left[\boldsymbol{X}_{i,\,\mathrm{k|k-1}}^x - \hat{x}_k^- \right] \left[\boldsymbol{X}_{i,\,\mathrm{k|k-1}}^x - \hat{x}_k^- \right]^T \tag{11.17}$$

$$\boldsymbol{Y}_{\mathrm{k|k-1}} = H\left[\boldsymbol{X}_{\mathrm{k|k-1}}^x, \boldsymbol{X}_{\mathrm{k-1}}^n \right] \tag{11.18}$$

$$\hat{y}_k^- = \sum_{i=0}^{2L} W_i^{(m)} \boldsymbol{Y}_{\mathrm{i,k|k-1}}^x \tag{11.19}$$

Measurements update equations:

$$\mathbf{P}_{\tilde{\boldsymbol{y}}_k \tilde{\boldsymbol{y}}_k} = \sum_{i=0}^{2L} W_i^{(c)} \left[\boldsymbol{Y}_{i,k|k-1} - \hat{y}_k^- \right] \left[\boldsymbol{Y}_{i,k|k-1} - \hat{y}_k^- \right]^{\boldsymbol{T}} \tag{11.20}$$

$$\mathbf{P}_{\boldsymbol{x}_k \boldsymbol{y}_k} = \sum_{i=0}^{2L} W_i^{(c)} \left[\boldsymbol{X}_{i,k|k-1} - \hat{x}_k^- \right] \left[\boldsymbol{Y}_{i,k|k-1} - \hat{y}_k^- \right]^{\boldsymbol{T}} \tag{11.21}$$

$$\boldsymbol{K}_k = \mathbf{P}_{\boldsymbol{x}_k \boldsymbol{y}_k} \mathbf{P}_{\tilde{\boldsymbol{y}}_k \tilde{\boldsymbol{y}}_k}^{-\mathbf{1}} \tag{11.22}$$

$$\hat{x}_k = \hat{x}_k^- + \boldsymbol{K}_k \left(y_k - \hat{y}_k^- \right) \tag{11.23}$$

$$\mathbf{P}_{\mathrm{k}} = P_k^- - \boldsymbol{K}_{\mathrm{k}} \mathbf{P}_{\tilde{\boldsymbol{y}}_k \tilde{\boldsymbol{y}}_k} \boldsymbol{K}_{\mathrm{k}}^T \tag{11.24}$$

where, $\mathrm{X^a} = [x^T \quad v^T \quad n^T]T$, $\boldsymbol{X}^a = \left[(\boldsymbol{X}^{\mathrm{x}})^T (\boldsymbol{X}^{\mathrm{v}})^T (\boldsymbol{X}^{\mathrm{n}})^T \right]^T$, $\gamma = \sqrt{(L+\lambda)}$, λ = composite scaling parameter, L = dimension of augmented state, $\mathrm{R^v}$ = process noise cov., $\mathrm{R^n}$ = measurement noise cov., $\mathrm{W_i}$ = weight as calculated as following:

$$W_0^{(m)} = \frac{\lambda}{(L+\lambda)}, \quad W_0^{(c)} = \frac{\lambda}{(L+\lambda)} + \left(1 - \alpha^2 + \beta \right) \tag{11.25}$$

$$W_i^{(m)} = \quad W_i^{(c)} = \frac{1}{\{2(L+\lambda)\}} \qquad i = 1, \ldots, 2\mathrm{L}. \tag{11.26}$$

The constant α *determines the spread of the sigma points around x and is usually set to a small positive value.* β *is used to incorporate prior knowledge of the distribution of x. For Gaussian distributions,* $\beta = 2$ *is optimal.*

The tracking performance and robustness of MPC scheme based on different filters were investigated in this study, and would be shown next.

11.4 Results

In this work, the control algorithm described earlier is applied to the nonlinear helicopter model using MATLAB. The voltages V_f and V_b of the two motors are assumed to be changeable in the range $[0\mathrm{V}, 5\mathrm{V}]$. The nominal values of the physical constants in the helicopter test-bed are as follows [5]:

$J_{\varepsilon} = 0.86\,\mathrm{kg\,m^2}$, $J_{\theta} = 0.044\,\mathrm{kg\,m^2}$, $J_{\phi} = 0.82\,\mathrm{kg\,m^2}$,
$L_a = 0.62\,\mathrm{m}$, $L_c = 0.44\,\mathrm{m}$, $L_d = 0.05\,\mathrm{m}$, $L_e = 0.02\,\mathrm{m}$, $L_h = 0.177$,
$M_f = 0.69\,\mathrm{kg}$, $M_b = 0.69\,\mathrm{kg}$, $M_c = 1.69\,\mathrm{kg}$, $K_m = 0.5\,\mathrm{N/V}$, $g = 9.81\,\mathrm{m/s^2}$,
$\eta_{\varepsilon} = 0.001\,\mathrm{kg\,m^2/s}, = 0.001\,\mathrm{kg\,m^2/s}, \eta_{\phi} = 0.005\,\mathrm{kg\,m^2/s}$

The reference signals for the elevation and travel angles in this simulation are changed between $-20°$ to $20°$ to simulate the demands given by the pilot as shown in Figs. 11.2, and 11.3. Also, the sampling time for control and simulation time used are 0.1 and 200 s, respectively.

The design parameters used in MPC with successive linearization are given in Table 11.1:

The EKF and UKF parameter are $\hat{x}_0 = X_0 + [10^{-3} \quad 10^{-3} \quad 10^{-3} \quad 10^{-3} \quad 10^{-3} \quad 10^{-3}]^T$, and $\mathrm{P}_0 = diag\left[10^6 \quad 10^6 \quad 10^6 \quad 10^6 \quad 10^6 \quad 10^6\right]$. The process noise was not considered, which means: $\mathbf{Q} = \mathrm{diag}\{\mathbf{0} \quad \mathbf{0} \quad \mathbf{0} \quad \mathbf{0} \quad \mathbf{0} \quad \mathbf{0}\}$. In simulations, the sampling rate for measurement is 100 Hz that is 10 time higher than that of control action. The measurements ARE corrupted by zero mean white noise with covariance for the test: $R = diag\left\{10^{-2} \quad 10^{-2} \quad 10^{-2}\right\}$. This is an extreme case, in which the measurement noise on three angles is very significant, and linear filter based MPC, and EKF based MPC all failed to guarantee the stability of this control system. The corresponding simulation crashed after a few seconds. However, the UKF based algorithm continues operating satisfactorily. According to the noise magnitude, the test was completed, and the control results of UKF based MPC are shown in Fig. 11.4.

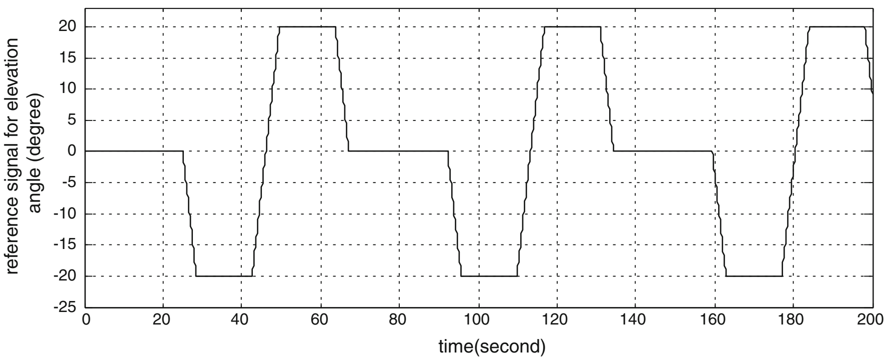

Fig. 11.2 Reference signal for the elevation angle

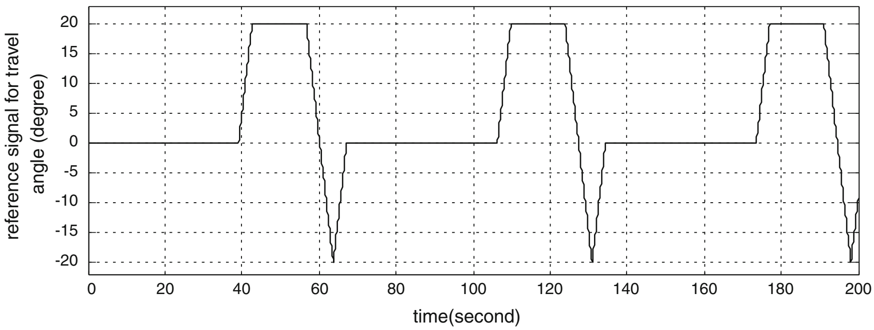

Fig. 11.3 Reference signal for the travel angle

Table 11.1 Design parameters MPCSL

Initial Conditions	$\varepsilon = \theta = \phi = \dot{\varepsilon} = \dot{\theta} = \dot{\phi} = 0,\ V_f = 1.8865,\ V_b = 1.936$
P	10
M	5
Q	$10{*}I_p$
R	$0.01{*}I_M$

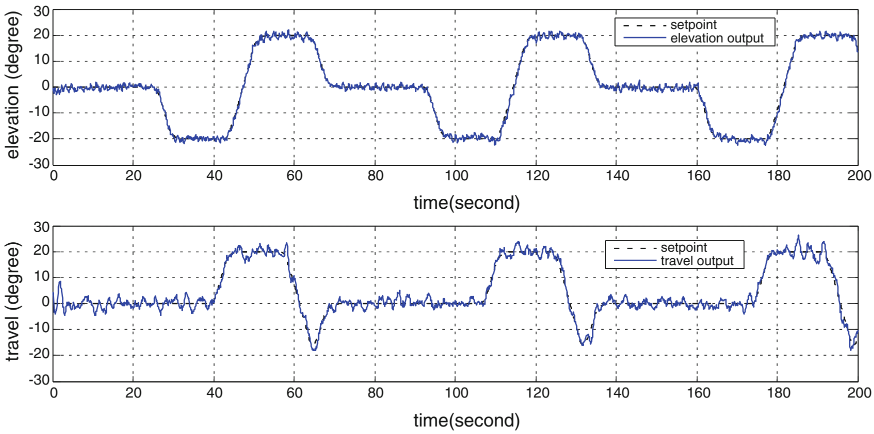

Fig. 11.4 Simulation results of UKF based MPC

11.5 Conclusion

This paper describes the application of observer based model predictive control with successive linearization for a 3-DOF helicopter system. The simulation has shown satisfactory tracking performance on elevation and travel. It was shown that, in the presence of significant measurement noise, the UKF based MPC performed very well on controlling such highly nonlinear and fast dynamics helicopter system. In the proposed MPC scheme, the system robustness is enhanced greatly by the implementation of unscented Kalman filter.

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