The Cascade Linear

By Mohammad Abu

The Cascade Linear Quadratic Gaussian (LQG) Controller for Automatic Landing Systems in Aircraft

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***Abstract*— In this note, we present the controller design by cascade LQG controller for automatic landing system. The problem in automatic landing system (ALS) is uncertain weather conditions which during take-off or landing can get stuck in turbulence and microburst conditions. We apply the LQG controller to overcome the noise caused by turbulence and microburst conditions. LQG controller is able to set the flight states according to the desired reference in noise conditions. The noise rejections are performed by Kalman filtering to estimate the state of the system dynamic. If the plant of automatic landing system is unstable system, the inner loop controller is performed by using pole placement technique solved by Ricati equation. The estimated state via the output of Kalman filtering becomes the state feedback of LQG controller. Based on the result of simulation LQG controller can be implemented in automatic landing system in which the noise composed to the system.**

Keywords*— automatic landing; Kalman filtering; LQG controller; pole placement; noise rejection.

I. Introduction

The automatic landing system for aircraft is the significant tool to guide landing for aircraft automatically. It is well known that taking off and landing is the most dangerous stages in flight, so it takes place to minimize the risk caused by human error at landing phase [1][2]. Automatic landing system is coupled with the Instrument Landing System (ILS) or Global Positioning System (GPS) to monitor state trajectory of flight tracking [3] [4]. The initial states requirement is need to perform automatic landing accurately to follow tracking reference trajectory and landing safely [5].

Automatic landing system give fairly satisfactory in performance when operate in normal conditions. However, in turbulence or microburst condition is a critical point in flight. Turbulence and microburst conditions are two disturbances that often occur in aircraft when the aircraft is going to landing or take-off. Wind shear can change direction horizontally or vertically [6]. Wind shift towards the vertical is called microburst or downburst which is very dangerous impact on the flight. Therefore, this problem is a very serious concern for both the pilot and the aviation industry [7].

Some researchers proposed the design of automatic landing system for aircraft using conventional PID controller [8] and neural-network based controller [9]. The design of automatic landing controller is derived under the radial basis function network that the controller called as minimal resource allocating Network (MRAN). The techniques are incorporated growing and pruning strategy by utilizing H∞ controller by feedback error learning mechanism [7]. The MRAN has been used for system identification, prediction, and deriving the control law for aircraft flight controller [10]. The robust controller was designed using H∞ technique under conventional controller with the inner-loop is replaced by PID controller [11] and model predictive control [12]. The adaptive control for the aircraft to control lateral movement was proposed using high order tuner of H∞ controller. However, the closed loop controller may become unstable with small level saturation. The control system is sensitive to parametric uncertainty of the external disturbances [13].

In this paper, we propose cascade LQG controller to track the reference trajectory of flight for landing automatically. LQG controller has two steps algorithm, 1) reject the noise by wind disturbances and 2) controller design using Linear Quadratic Regulator (LQR). The noise rejection is performed by Kalman filtering through estimate the state of system. The estimated state of the system is set as feedback controller. By solving Ricati equation, the gains of state feedback are obtained that is set as the gain of feedback controller. The inner loop system of cascade LQG controller is designed by pole placement technique to make the system become stable. By using pole placement technique, the characteristic of unstable system is manipulated by pole placement to keep the system becomes stable. Based on the stable system, we derive the controller by LQR algorithm via solving Ricati equation.

The estimated system is unstable shown by the state parameters of Kalman filtering. The poles of unstable system lie on the right half plan of imaginary axes. Thus, the inner loop is designed to make the system becomes stable by regulating the feedback gain using pole placement technique. As we know, Kalman filtering technique is the important tool for rejected the noise of the system and state estimation [14]. Based on Kalman filtering, we design the tracking filter and then the tracking of maneuvering targets for discrete-time control systems can be estimated [15]. Kalman filtering technique is performed to make the system become robust. Noise causes the system to become unstable. This is caused by the presence of state delay and missing measurement on the system [16]. Kalman filtering is used for nonlinear time varying system to become estimator and tracker sampled data applied for fault tolerance controller [17].

The cascade LQG controller is able to follow the target trajectory references by initial setting conditions of the system are determined. The performances of controller are

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measured by error trajectory and root mean square error (RMS). The noise of the system by wind disturbances are assumed that the noise signal is zero mean and the varying noise are assumed and calculated by source to noise ratio (SNR).

II. Problem Description and Formulation

A. Dynamic Modeling for Aircraft Landing System

The dynamic modeling of aircraft landing can be simplified as short period equations of motions stated as transfer function by [18],

$$\theta'(s) = \frac{K_s(T_s s+1)}{\left(\frac{s^2}{\omega_s^2}+\frac{2\eta s}{\omega_s}+1\right)}\delta(s),$$

$$h''(s) = \frac{C_F V}{(T_s s+1)}\theta'(s),$$

$$h(s) = \frac{1}{s^2}h''(s),$$

$$h(s) = \frac{C_F K_s V}{s^2\left(\frac{s^2}{\omega_s^2}+\frac{2\eta s}{\omega_s}+1\right)}\delta(s) \qquad (1)$$

Where the parameters of the aircraft are defined as the short period gain (K_s), the short period resonant frequency (ω_s), the short period damping factor (η), the path time constant (T_s), conversion factor (C_F) and V is the velocity of the aircraft. The controlled variable of aircraft presented in (1) are the pitch angle rate (θ'), the altitude (h) and the altitude acceleration (h'') and the input of controller by using elevator deflection (δ).

The dynamical model stated in (1) can be presented into state space model as,

$$\begin{bmatrix}\dot{x}_1\\ \dot{x}_2\\ \dot{x}_3\\ \dot{x}_4\end{bmatrix} = \begin{bmatrix}0 & 1 & 0 & 0\\ 0 & \frac{-C_F}{T_s} & \frac{C_F V}{T_s} & 0\\ 0 & 0 & 0 & 1\\ 0 & m_1 & m_2 & m_3\end{bmatrix}\begin{bmatrix}x_1\\ x_2\\ x_3\\ x_4\end{bmatrix} + \begin{bmatrix}0\\ 0\\ 0\\ \omega_s^2 K_s\end{bmatrix}\delta(t)$$

$$\begin{bmatrix}h(t)\\ \dot{h}(t)\\ \theta(t)\\ \dot{\theta}(t)\end{bmatrix} = \begin{bmatrix}1 & 0 & 0 & 0\\ 0 & 1 & 0 & 0\\ 0 & 0 & 1 & 0\\ 0 & 0 & 0 & 1\end{bmatrix}\begin{bmatrix}x_1\\ x_2\\ x_3\\ x_4\end{bmatrix} \qquad (2)$$

Where,

$$m_1 = \frac{1}{C_F V T_s^2} - \frac{2\eta\omega_s}{C_F V T_s} + \frac{\omega_s^2}{C_F V},$$

$$m_2 = \frac{2\eta\omega_s}{T_s} - \omega_s^2 - \frac{1}{T_s^2},$$

$$m_3 = \frac{1}{T_s} - 2\eta\omega_s.$$

Some requirements should be fulfilled in order to achieve safe and comfortable landing. Thus, the desired trajectory of altitude is stated as,

$$h_r = \begin{cases} 30\exp(-\frac{t}{5}), & 0 \le t \le 15 \\ 6-0.3t, & 15 \le t \le 20 \end{cases} \qquad (3)$$

Where the variable denoted as h_r and t are the desired trajectory of altitude and time. During landing time before touch-down, the pitch angle of the aircraft must be set that is lie in the range [0^0, 10^0]. The desired pitch angle at touchdown is equal to 2^0. The position of elevator is also set that is stated as in (4). Actually, the desired elevator deflection angle is equal to zero to minimize energy drive and control effort.

$$-35^0 \le \delta(t) \le 15^0, \quad 0 \le t \le t_f \qquad (4)$$

B. Cascade LQG Controller

The purposes of LQG controller are the same as LQR controller. Those are to get gain state feedback, so the response of the system controller is able to minimize the index performance. LQG controller use LQR algorithm as the step algorithm to get gain state feedback controller by solving Ricati equation. The other step of LQG controller design is to rejection the noise of the system by Kalman filtering. The output of the Kalman filtering is the estimated state of the system, it will become feedback with the gain feedback design are achieved by LQR algorithm. LQG controller is not able running well in unstable system, so the inner loop cascade with pole placement technique stabilize the system.

Tracking trajectory by LQG controller is to manage the response of controller in order to achieve the performance index that is to minimize the error and energy drive. The performance index of response controller is stated as,

$$J = \lim_{T\to\infty}\frac{1}{T}\int_0^T (X^T Q X + U^T R U)dt \qquad (5)$$

The minimum of J can be obtained by control signal u by,

$$u = K.X \qquad (6)$$

The K is the gain of state feedback expressed in (7) and X is the state of the system, in this LQG design state feedback is the estimated state from the output of Kalman filtering.

$$K(k) = R^{-1}B^T[P(k+1)^{-1} + BR^{-1}B^T]^{-1}A \qquad (7)$$

The P is the positive definite matrix achieved by solving Ricati equation stated as,

$$P(k)=Q+A^T P(k+1)A[I+BR^{-1}B^T P(k+1)]^{-1}A \qquad (8)$$

State of the system feedback expressed in (6) is the estimated tate by performing Kalman filtering. The problems in Kalman filtering are expressed by,

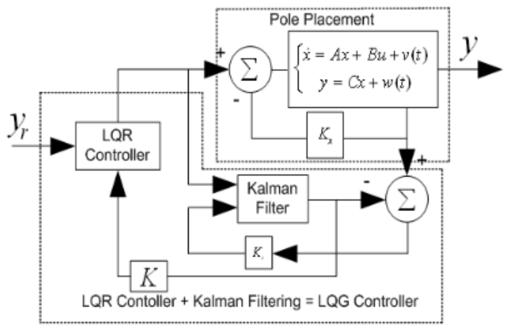

Fig. 1. The structure of Linear Quadratic Gaussian (LQG) controller

$$\begin{cases} \dot{x} = Ax + Bu + v(t) \\ y = Cx + w(t) \end{cases} \qquad (9)$$

The independent with noise are denoted bay $v(t)$ and $w(t)$ respectively. The noise properties is zero mean with the following properties E[$v(t)$]=0, E[$w(t)$]=0, A and C is the observable matrix. Kalman filtering is used to estimate the state of system called as state estimator whih the purpose is to minimize the estimated error covariance. The output Kaman estimator is denoted as $\hat{x}(t)$, and $x(t)$ denotes the state of system. The index performance of Kalman filtering for state estimator is expressed by,

$$J_e = E([x(t)-\hat{x}(t)]^T [x(t)-\hat{x}(t)]) \qquad (10)$$

Kalman filter is a state observer in which to calculate Kalman gain (Kalman filtering gain). The dynamical properties of Kalman filtering are describe as,

$$\begin{cases} \dot{\hat{x}} = A\hat{x} + Bu + K_e(y-\hat{y}) \\ \hat{y} = C\hat{x} \end{cases} \qquad (11)$$

The initial estimated state at $t=0$ ($\hat{x}(0)$) is given, the Kalman filter gain K_e can be calculated by,

$$K_e = P_e C^T R^{-1} \qquad (12)$$

The P_e is the positive definite solution by solving Ricati equation stated as,

$$P_e A^T + AP_e - P_e C^T R^{-1} CP_e + Q = 0 \qquad (13)$$

The dynamic modeling of automatic landing system is unstable systems and we create pole placement technique to stabilize the system by inner loop. The problem of pole placement is described as,

$$\begin{cases} \dot{x} = (A - BK_x^T)x \\ y = Cx \end{cases} \qquad (14)$$

The system (A,B,C) is unstable system, it can be replaced with the stable system by new dynamic state matrix in (14). The structure of LQG controller is depicted on Fig. 1.

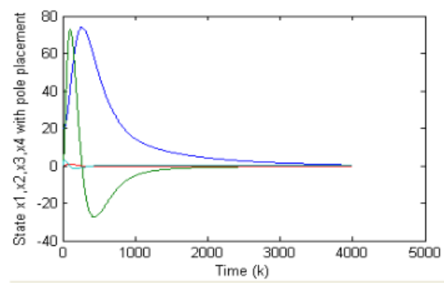

Fig. 2. The output state by pole placement technique

III. Implementation of LQG Controller

We will apply LQG controller to track automatic landing system described in (1) and (2). The parameters of dynamic modeling for aircraft are assumed as linear time invariant and the numerical value of the model parameters are determined as K_s = -0.95s^{-1}, T_s = 0.005 s, ω_s = -0.95 rad.s^{-1}, η = 0.5, C_F = 0.3048. The notation V is the velocity of aircraft is constant assumed as 78 ms^{-1}. Those parameters are substituted into (2), and the result is stated in (15). The stable system with pole placement technique is showed in (16). The conversion in (16) into discrete time with the sampling 0.005 is showed in (17).

The system in (15) is unstable system with the poles lay on [0, -61.64, 99.86+17i, 99.86-17i]. We arrange that the poles of the system are placed on [-2 -1 -3 -5]. The gains of the system state feedback of the pole placement technique are K_x = [1.47, -11083 -8566692 34778]. The system response of stable system with pole placement technique is showed in Fig. 2. The blue line is the altitude state x_1, green line is the altitude velocity x_2, red line is the state of pitch angle x_3, and cyan line is the state of pitch angle velocity x_4.

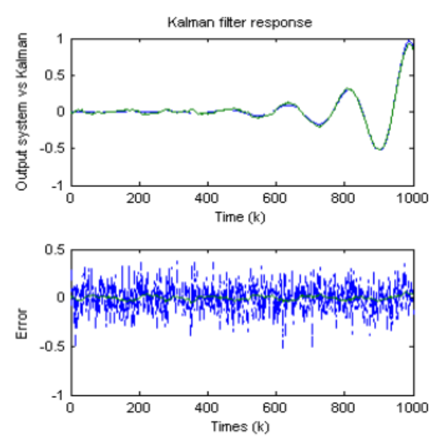

Fig. 3. The output altitude state of system and Kalman filtering

The noise of the system at input $w(t)$ and output $v(t)$ is assumed as zero means with the amplitude of the noise perturbations 2 percent, this noise is the same as 33.794 measured in SNR (source to noise ratio). The Kalman gains K_e by solution on (12) and (13) are [0.0264 0.071 0.00065 -0.017]. The state x_1 and $\hat{x}_1$ through Kalman filtering is showed on Fig. 3. In this case to show the performance of Kalman filtering, we perform the system and Kalman filtering system with the pseudo random binary sequence (PRBS) input. The output system vs Kalman filtering are presented by blue line is the system output and green line is the Kalman output. The error of system to measurement signal is showed by blue line and the error of system to Kalman filtering output is showed by green line.

$$\begin{bmatrix}\dot{x}_1\\ \dot{x}_2\\ \dot{x}_3\\ \dot{x}_4\end{bmatrix}=\begin{bmatrix}0 & 1 & 0 & 0\\ 0 & -60.96 & 4755 & 0\\ 0 & 0 & 0 & 1\\ 0 & -7.954 & -39810 & 199.1\end{bmatrix}\begin{bmatrix}x_1\\ x_2\\ x_3\\ x_4\end{bmatrix}+\begin{bmatrix}0\\ 0\\ 0\\ 0.00429\end{bmatrix}\delta(t);$$

$$\begin{bmatrix}h(t)\\ \dot{h}(t)\\ \theta(t)\\ \dot{\theta}(t)\end{bmatrix}=\begin{bmatrix}1 & 0 & 0 & 0\\ 0 & 1 & 0 & 0\\ 0 & 0 & 1 & 0\\ 0 & 0 & 0 & 1\end{bmatrix}\begin{bmatrix}x_1\\ x_2\\ x_3\\ x_4\end{bmatrix} \tag{15}$$

$$\begin{bmatrix}\dot{x}_1\\ \dot{x}_2\\ \dot{x}_3\\ \dot{x}_4\end{bmatrix}=\begin{bmatrix}0 & 1 & 0 & 0\\ 0 & -60.96 & 4755 & 0\\ 0 & 0 & 0 & 1\\ -0.0063 & 39.558 & -3086 & 49.96\end{bmatrix}\begin{bmatrix}x_1\\ x_2\\ x_3\\ x_4\end{bmatrix}+\begin{bmatrix}0\\ 0\\ 0\\ 0.00429\end{bmatrix}\delta(t);$$

$$\begin{bmatrix}h(t)\\ \dot{h}(t)\\ \theta(t)\\ \dot{\theta}(t)\end{bmatrix}=\begin{bmatrix}1 & 0 & 0 & 0\\ 0 & 1 & 0 & 0\\ 0 & 0 & 1 & 0\\ 0 & 0 & 0 & 1\end{bmatrix}\begin{bmatrix}x_1\\ x_2\\ x_3\\ x_4\end{bmatrix} \tag{16}$$

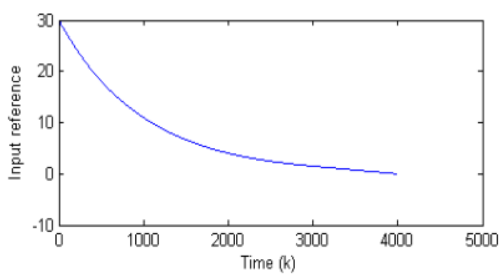

Fig. 4. The input reference of the system

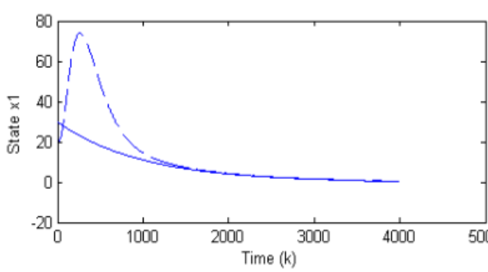

Fig. 5. The input reference vs the output of pole placement controller

The LQG controller is the same as LQR controller, but in LQG controller the state of the system is the estimated state by Kalman filtering output. The design of LQG controller are performed by solving Kalman filtering problem and minimize performance index stated as Ricati equation. The gain state feedback controller by solving Ricati equation in (7) and (8) are $K(k)$ = [112 922.5 -69467.8 1523 -0.96].

The gain of state of $\hat{x}_1$ = 112, $\hat{x}_2$ = 922.5, $\hat{x}_3$ = -69467.8, $\hat{x}_4$=1523, and gain servo integral controller -0.96. The input reference of the system is stated in (3) showed in Fig. 4. The output of the system by pole placement technique controller is showed on Fig. 5 and the output response of LQG controller is showed in Fig. 6. The RMS error of LQG controller is compared with pole placement technique depicted in Fig. 7. The solid line is the RMS error with pole placement technique and the dashed line is the RMS error with LQG controller.

$$\begin{bmatrix}x_1(k+1)\\ x_2(k+1)\\ x_3(k+1)\\ x_4(k+1)\end{bmatrix}=\begin{bmatrix}0 & 1 & 0 & 0\\ 0 & -60.96 & 4755 & 0\\ 0 & 0 & 0 & 1\\ -0.0063 & 39.558 & -3086 & 49.96\end{bmatrix}\begin{bmatrix}x_1(k)\\ x_2(k)\\ x_3(k)\\ x_4(k)\end{bmatrix}+\begin{bmatrix}0\\ 0\\ 0\\ 0.0043\end{bmatrix}\delta(t)'$$

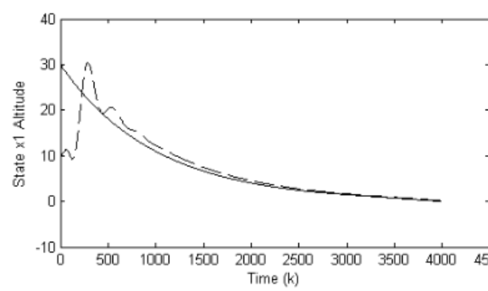

Fig. 6. The input reference vs the output of LQG controller

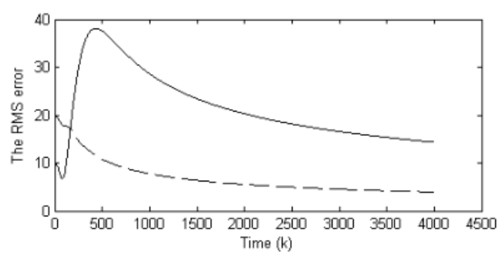

Fig. 7. The input RMS error of pole placement (-)vs LQG controller (- -)

$$\begin{bmatrix}h(k)\\ \dot{h}(k)\\ \theta(k)\\ \dot{\theta}(k)\end{bmatrix}=\begin{bmatrix}1 & 0 & 0 & 0\\ 0 & 1 & 0 & 0\\ 0 & 0 & 1 & 0\\ 0 & 0 & 0 & 1\end{bmatrix}\begin{bmatrix}x_1\\ x_2\\ x_3\\ x_4\end{bmatrix} \tag{17}$$

$$SNR = 20\log\left(\frac{A_{system}}{A_{noise}}\right) \tag{18}$$

The performance index of LQG controller are measured with RMS error expressed as,

$$RMS = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y^*(t) - y(t))^2} \quad (19)$$

Where N is the number of sampling, $y^*(t)$ is the input and $y(t)$ is the output response. The RMS error of the system with pole placement technique is 14.361, and the RMS error of the system with LQG controller is 3.9255.

IV. Conclusion

In this case we use LQG controller for tracking controller of automatic landing system. The problem of Automatic landing system is the noise rejection beside of creating controller problem. We use Kalman filtering with pole placement technique in inner loop for noise rejection and stabilize the system, then the controller is created with LQR algorithm, and we called cascade LQG controller. Based on the result of system simulation the cascade LQG controller can be implemented on automatic landing system.

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