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HANDLING QUALITIES PREDICTION BASED ON ADAPTIVE OPTIMAL CONTROL PILOT MODEL

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Abstract

The traditional optimal control pilot model (OCM) is based on Kalman filter which cannot reveal the pilot behavior in time varying disturbance of unknown environment. To overcome the omissions, a Modified Optimal Control Pilot Model based on Adaptive State Estimate (AOCM) is developed. The pilot models are utilized to reproduce the flight test by pilot-aircraft closed-loop simulation. In frequency domain, the AOCM is testified by magnitude and phase comparison. In time domain, some unknown disturbance is led into the simulation, the attitude tracking results show that AOCM performs better than OCM. Both the evaluations in frequency domain and time domain show the merit of AOCM, and reflect the pilot character of environment adaption. AOCM and OCM are utilized in Handling Qualities(HQ) prediction, in all the four HQ test cases, with modified weighting matrixes, AOCM gets more accurate HQ rating prediction than OCM, it's identical to the flight test pilot rating. The result shows the HQ prediction is critical corresponded to the ratio of $\boldsymbol{Q}_y/\boldsymbol{R}$. *Accurate HQ prediction is based on the precisely* $\boldsymbol{Q}_y/\boldsymbol{R}$ *ratio chosen. And* $\boldsymbol{Q}_y/\boldsymbol{R}$ *ratio is corresponded to the aircraft dynamics, as the aircraft dynamics degrades the value of* $\boldsymbol{Q}_y/\boldsymbol{R}$ *should increase. It denotes that the pilot will pay more attention in flight observation while he keeps the same attention in controlling as before. Thus, the heavier mental workload degrades the pilot rating. Yet this assumption is still need to be testified.*

1 Introduction

Handling qualities (HQ) evaluation plays an important role in aircraft design [1-2]. The current handling qualities assessment methods can be divided into theoretical criteria and pilot evaluation methods. The criteria, such as the control anticipation parameter, Neal-Smith, bandwidth (BW), and low-order equivalent systems are used as guidelines [3], based on previous experiences with already existing aircraft. These criteria are very useful since they correlate handling qualities to a limited number of quantifiable parameters. However, the handling quality level can be mispredicted: for instance, due to deviations of the type of aircraft on which the criterion was based, the limitations of the applied human operator model, the omission of the influence of the feel system, or debatable assumptions such as a fixed BW or fixed stability margins [4].

Pilot evaluation methods include the Cooper-Harper rating (CHR),"Paper pilot", Optimal Control Pilot model rating (OCM)[5], pilot-in-the-loop testing method and the handling qualities during tracking (HQDT) method[6]. The first method evaluates the flying qualities incorporating all aspects of a realistic task, but it sometimes fails to reveal hidden deficiencies due to the inability to evaluate the full handling qualities envelope. The HQDT method tries to evaluate the full handling qualities envelope by prescribing a forced high-gain and high-BW control technique, but pilots regard this technique as highly unnatural [4]. The OCM method with Kalman filter fails to reveal the procedure of inference and adaptation in unknown disturbance. Thus, the OCM could not be used in real flight evaluation only if the following conditions are fulfilled in the same time [7].

1) The pilot should be perfect and fully experienced and

2) The statistics characteristics of disturbance should constant values and

3) The flight test must sustain as long time as the pilot evaluate the character of the aircraft and disturbance precisely.

However, the requirements above can hardly be satisfied simultaneously, therefore parts of the OCM rating do not coincide with the pilot rating in flight test.

The method proposed in this article is an adaptive optimal control evaluation method (AOCM) capable of evaluating the handling qualities in unknown environment. The new method tries to overcome the omissions of the OCM and is complementary of the theoretical criteria method.

2 Adaptive Optimal Control Pilot Model

In AOCM, modified noise model and adaptive state estimation method are added into the original OCM. The process of optimal control gains calculation and other parts that same as OCM will not be reviewed, one can go to the detail in Ref.[5]. This article will introduce the modification of AOCM. The merits of the modification are as follows:

1) Multi-variable Lyapunov formula solving is avoided.

2) In physical scene, the pilot does not need to evaluate the disturbance based on the unknown future. The new noise models reflect the pilot's behavior and thinking process in real flight.

3) With adaptive state estimation, the AOCM can be used in time varying disturbance, this characteristic is especially important when describe the pilot's behavior in real flight with unknown disturbance.

2.1 Modification of observation noise model

In OCM, the variance of observation is solved by Lyapunov equation, in this article, $\sigma_{y_i}^2$ is a statistic value based on the recent observation history, it is a time varying value. The AOCM observation variance based on recent history is

$$\sigma_{yi}^2 = \mathrm{var}([y_{i.1}, y_{i.2}, \cdots, y_{i.t_p}]) \tag{1}$$

The subscripts 1 to t_p represent the recent sample time points. And the single axis covariance of the observation noise can be acquired as

$$V_{y_i} = \frac{\pi \rho_{y_i} \sigma_{y_i}^2}{f_{y_i}} \tag{2}$$

In this equation ρ_{y_i} is the nominal full-attention observation signal-to-noise ratio, f_{y_i} is the fraction of total attention spent on the i^{th} observation channel, and $\sigma_{y_i}^2$ is the variance of the i^{th} observation variable. Single-axis manual tracking control tasks have shown that, on the average, $\rho_{y_i} = 0.01$, which corresponds to normalized observation noise of -20dB [5]. Supposed that the noise of different observation axes are independent, then the intensity of the noise can be acquired as

$$\boldsymbol{V}_y = \mathrm{diag}(V_{y_i}) \tag{3}$$

2.2 Modification of control noise model

In the traditional OCM the variance σ_{ui}^2 is solved by the Lyapunov Equation. And the covariance of $\boldsymbol{V}_{\mathrm{u}}$ is calculated by iteration of desired signal to noise ratio. Furthermore, when the noise intensity is achieved, it will be treated as a constant value in the following application in OCM. In this article, the variance of control σ_{ui}^2 is calculated based on the recent control history, same as the observation variance; it is a time varying value

$$\sigma_{ui}^2 = \mathrm{var}([u_{ci.1}, u_{ci.2}, \cdots, u_{ci.t_m}]) \tag{4}$$

the subscripts 1 to t_{p} represent the recent sample time points, i is the i^{th} control channel. Supposed all the control channel are independent, one can obtain the current motor noise intensity by

$$\boldsymbol{V}_u = diag(\boldsymbol{V}_{u_i}) \tag{5}$$

Analyses of single-axis manual tracking control task experiments have shown that the typical value of ρ_{u} is 0.003, which corresponds to the normalized control noise ratio of -25 dB

[5]. In this article, in the multi-axis problem we suppose that the control noise ratio is in proportion to the number of control channels.

2.3 Adaptive state estimation

In AOCM, Adaptive Kalman filter[8] is added into the model, the time varying noise estimator is

$$\hat{\boldsymbol{q}}(k) = \hat{\boldsymbol{q}}(k-1) + d_{k-1}\hat{\boldsymbol{Q}}(k-1)\boldsymbol{D}(k)\boldsymbol{\varepsilon}(k) \tag{6}$$

$$\begin{aligned}\hat{\boldsymbol{Q}}(k) = \hat{\boldsymbol{Q}}(k-1) + d_{k-1}\hat{\boldsymbol{Q}}(k-1)\boldsymbol{D}(k)[\boldsymbol{\varepsilon}(k)\boldsymbol{\varepsilon}^T(k) - \\ \boldsymbol{H}(k)\boldsymbol{P}(k\,|\,k-1)\boldsymbol{H}^T(k) - \hat{\boldsymbol{R}}(k-1)]\boldsymbol{D}^T(k)\hat{\boldsymbol{Q}}(k-1)\end{aligned} \tag{7}$$

$$\begin{aligned}\hat{\boldsymbol{r}}(k) &= (1-d_{k-1})\hat{\boldsymbol{r}}(k-1) \\ &+ d_{k-1}\left[\boldsymbol{Y}(k) - \boldsymbol{H}(k)\hat{\boldsymbol{X}}(k\,|\,k-1) - \boldsymbol{D}_{dis}\boldsymbol{u}(k)\right]\end{aligned} \tag{8}$$

$$\begin{aligned}\hat{\boldsymbol{R}}(k) &= (1-d_{k-1})\hat{\boldsymbol{R}}(k-1) \\ &+ d_{k-1}\{[\boldsymbol{I} - \boldsymbol{H}(k)\boldsymbol{K}(k)]\boldsymbol{\varepsilon}(k)\boldsymbol{\varepsilon}^T(k) \\ &\times[\boldsymbol{I} - \boldsymbol{H}(k)\boldsymbol{K}(k)]^T + \boldsymbol{H}(k)\boldsymbol{P}(k\,|\,k)\boldsymbol{H}^T(k)\}\end{aligned} \tag{9}$$

where d is the gradually forgetting coefficient

$$d_{k-1} = (1-b)/(1-b^k) \tag{10}$$

b is the forgetting factor, $0<b<1$. $\boldsymbol{D}(k)$ is the recursion operator

$$\begin{aligned}\boldsymbol{D}(k) = \boldsymbol{E}_{dis}^T\boldsymbol{H}^T(k)[\boldsymbol{H}(k)\boldsymbol{P}(k\,|\,k-1)\boldsymbol{H}^T(k) \\ +\boldsymbol{R}(k-1)]^{-1}\end{aligned} \tag{11}$$

And the adaptive Kalman filter is

$$\begin{aligned}\hat{\boldsymbol{X}}(k\,|\,k-1) = \boldsymbol{\varphi}(k-1)\hat{\boldsymbol{X}}(k-1\,|\,k-1) \\ +\boldsymbol{B}_{dis}\boldsymbol{u}(k-1) + \boldsymbol{E}_{dis}\hat{\boldsymbol{q}}(k-1)\end{aligned} \tag{12}$$

$$\begin{aligned}\boldsymbol{P}(k\,|\,k-1) = \boldsymbol{\varphi}(k-1)\boldsymbol{P}(k-1\,|\,k-1)\boldsymbol{\varphi}^T(k-1) \\ +\boldsymbol{E}_{dis}\hat{\boldsymbol{Q}}(k-1)\boldsymbol{E}_{dis}{}^T\end{aligned} \tag{13}$$

$$\begin{aligned}\boldsymbol{\varepsilon}(k) = \boldsymbol{Y}(k) - \boldsymbol{H}(k)\hat{\boldsymbol{X}}(k\,|\,k-1) \\ -\boldsymbol{D}_{dis}\boldsymbol{u}(k) - \hat{\boldsymbol{r}}(k-1)\end{aligned} \tag{14}$$

$$\begin{aligned}\boldsymbol{K}(k) = \boldsymbol{P}(k\,|\,k-1)\boldsymbol{H}^T(k) \\ \times\left[\boldsymbol{H}(k)\boldsymbol{P}(k\,|\,k-1)\boldsymbol{H}^T(k) + \hat{\boldsymbol{R}}(k-1)\right]^{-1}\end{aligned} \tag{15}$$

$$\boldsymbol{P}(k\,|\,k) = [\boldsymbol{I}_n - \boldsymbol{K}(k)\boldsymbol{H}(k)]\boldsymbol{P}(k\,|\,k-1) \tag{16}$$

$$\hat{\boldsymbol{X}}(k\,|\,k) = \hat{\boldsymbol{X}}(k\,|\,k-1) + \boldsymbol{K}(k)\boldsymbol{\varepsilon}(k) \tag{17}$$

Through equation (6) to equation (17), $\boldsymbol{\varphi}$, $\boldsymbol{B}_{dis}$, $\boldsymbol{H}$, $\boldsymbol{D}_{dis}$, $\boldsymbol{E}_{dis}$ are the coefficient matrixes of the discrete state equation, $\hat{\boldsymbol{X}}$ is the estimation of the state vector, $\boldsymbol{Y}$ is the observation vector, $\boldsymbol{u}$ is the pilot control output, $\boldsymbol{P}$ is the prediction error covariance, $\hat{\boldsymbol{q}}$ is the mean disturbance estimation, $\hat{\boldsymbol{Q}}$ is the disturbance intensity estimation, $\hat{\boldsymbol{r}}$ is the mean estimation of observation noise, $\hat{\boldsymbol{R}}$ is the intensity estimation of observation noise, $\boldsymbol{\varepsilon}$ denotes the innovation process, and $\boldsymbol{K}$ is the filter gain.

All above are the modifications of AOCM, by proper algorithm implementation, it will reveal the pilot's behavior in unknown disturbance.

2.4 AOCM Algorithm Implementation

The algorithm implementation of AOCM is almost the same as OCM's. It is organized into four main parts. The first part involves augmentation of the plant and disturbance dynamics with a Pade approximation of the pilot's effective time delay. The second part is the calculation of the pilot's control gains, where iteration on the cost function control-rate weighting is usually required to achieve the desired value of pilot's neuromotor time constant. The third part is the calculation of the pilot's estimation gains. This requires the calculation of observation and control noise covariances by Eq.(1) to Eq.(5). The fourth part is discrete conversion and adaptive state estimation, then the pilot-aircraft closed-loop simulation can carry on. The algorithm implementation of AOCM is shown in Figure 1.

3 Model Evaluation

In this section, the experimental results is based on the analysis of the closed-loop performance of a pilot in a tracking task presented in Ref.[9] and it is used as a benchmark to determine the merits of the AOCM in frequency domain. Besides, to show the pilot's behavior of environment adaption, some unknown disturbance is added into the simulation, once the result shows the AOCM tracking error is smaller than OCM, then the characteristic of environment adaption is confirmed.

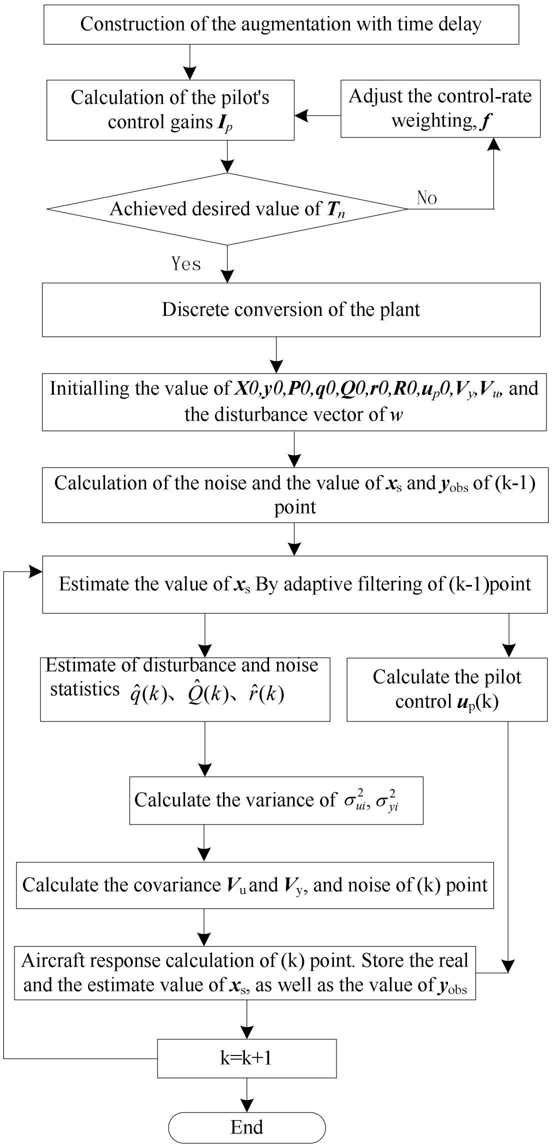


Fig. 1 Computational flow for AOCM

3.1 Frequency domain characters comparison

In evaluation examples, the dynamics model and measurement data is derived in flight test in reference [9]. The flight test was conducted by a five-member team from the USAF Test Pilot School in Calspan Corporation, Buffalo, New York from Oct 8 to Oct 11, 1993. The Calspan Variable-Stability Lear II was used as the research vehicle for the test. The basic aircraft is shown in figure 2.

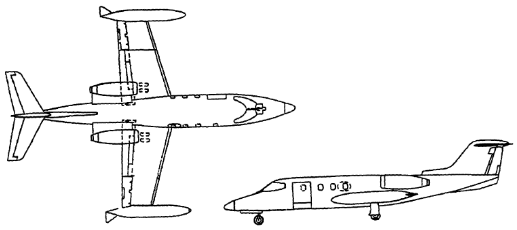


Fig. 2 Two Plan View of Lear 25B

The aircraft dynamics parameter is shown in Table 1.

Tabal 1 Aircraft Parameters

Dynamics Parameters	Values
Longitudinal Dynamics of Baseline Aircraft	$\frac{\theta}{\delta_e}=\frac{20(s+1.8)e^{-0.04s}}{s(s^2+8.4s+36)}$
Actuator Dynamics	$\frac{70^2}{s^2+2(.7)(70)s+70^2}$
Stick Dynamics	$\frac{16^2}{s^2+2(.7)(16)s+16^2}$
Stick Force Gradient	6lb/in
Stick Breakout force	0.75lb
Stick Force per g	7lb/g
Control gearing	8deg/in

3.1.1. Flight test simulation

The pitch axis dynamics of the aircraft is

$$\frac{\theta}{\delta_{es}}=8\cdot\frac{70^2}{[.7,70]}\cdot\frac{5.5(s+1.8)e^{-0.04s}}{s[.7,6]} \tag{18}$$

Tracking task is used in the flight test. The tracking task forcing function is modeled by a second order Butterworth filter

$$\frac{\theta_c}{w}=\frac{\sqrt{2}}{6.25s^2+3.54s+1} \tag{19}$$

w is the zero mean Gaussian white noise. To get the standard form which used in AOCM, turn the pitch axis function and task forcing function into state space form as shown below

$$\begin{cases}\dot{\boldsymbol{x}}_\theta=\boldsymbol{A}_\theta\boldsymbol{x}_\theta+\boldsymbol{B}_\theta\delta_{es}\\ \theta=\boldsymbol{C}_\theta\boldsymbol{x}_\theta+\boldsymbol{D}_\theta\delta_{es}\end{cases} \tag{20}$$

$$\begin{cases}\dot{\boldsymbol{x}}_c=\boldsymbol{A}_c\boldsymbol{x}_c+\boldsymbol{B}_c w\\ \theta_c=\boldsymbol{C}_c\boldsymbol{x}_c+\boldsymbol{D}_c w\end{cases} \tag{21}$$

$\boldsymbol{A}_\theta,\boldsymbol{B}_\theta,\boldsymbol{C}_\theta,\boldsymbol{D}_\theta$ are pitch dynamic matrixes, δ_{es} is the stick deflection, θ is the attitude response, $\boldsymbol{A}_c,\boldsymbol{B}_c,\boldsymbol{C}_c,\boldsymbol{D}_c$ are the command dynamic matrixes, θ_c is the pitch command. And the tracking error is

$$e=\theta-\theta_c=\boldsymbol{C}_\theta\boldsymbol{x}_\theta+\boldsymbol{D}_\theta\delta_{es}-\boldsymbol{C}_c\boldsymbol{x}_c+\boldsymbol{D}_c w \tag{22}$$

Simultaneous Eq. (20) to Eq.(22), the dynamics augmented is given by

$$\begin{cases} \begin{bmatrix} \dot{\boldsymbol{x}}_\theta \\ \dot{\boldsymbol{x}}_c \end{bmatrix} = \begin{bmatrix} \boldsymbol{A}_\theta & \boldsymbol{0} \\ \boldsymbol{0} & \boldsymbol{A}_c \end{bmatrix} \begin{bmatrix} \boldsymbol{x}_\theta \\ \boldsymbol{x}_c \end{bmatrix} + \begin{bmatrix} \boldsymbol{B}_\theta \\ \boldsymbol{0} \end{bmatrix} \delta_{es} + \begin{bmatrix} \boldsymbol{0} \\ \boldsymbol{B}_c \end{bmatrix} w \\ y = \begin{bmatrix} \boldsymbol{C}_\theta & \boldsymbol{C}_c \end{bmatrix} \begin{bmatrix} \boldsymbol{x}_\theta \\ \boldsymbol{x}_c \end{bmatrix} + \boldsymbol{D}_\theta \delta_{es} - \boldsymbol{D}_c w \end{cases} \tag{23}$$

By the calculation, $\boldsymbol{D}_c = \boldsymbol{0}$, that Eq. (23) gets the standard form which can be used in AOCM.

$$\begin{cases} \dot{\boldsymbol{x}} = \boldsymbol{A}\boldsymbol{x} + \boldsymbol{B}\boldsymbol{\delta} + \boldsymbol{E}\boldsymbol{w} \\ \boldsymbol{y} = \boldsymbol{C}\boldsymbol{x} + \boldsymbol{D}\boldsymbol{\delta} \end{cases} \tag{24}$$

Suppose that the pilot puts the same attention into state observation and aircraft control, then the Pilot-Aircraft system performance index is

$$J = E_\infty \left\{ e^2 + \delta_{es}^2 + f \dot{\delta}_{es}^2 \right\} \tag{25}$$

Thus, the weighting matrix $Q_y = 1, r_u = 1$, set other pilot model input parameters as table 2.

Table 2 Pilot Model Input Parameters

Parameter	Value
Effective time delay τ	0.25s
Neuromotor lag, τ_n	0.08s
Observation noise ratio, ρ_y	20dB
Motor noise ratio, ρ_u	25dB
Objective function observation weights, Q_y	1
Objective function control weights, r_u	1

Then, make pilot-aircraft close-loop simulation as the flight test in AOCM procedure; it results the pilot gain and other calculation which are shown in table 3, the aircraft response and stick deflection are shown in figure 3 and figure 4. In figure 4, OCM results a bigger tracking error than AOCM, this shows the merit of AOCM.

Table 3 Pilot Model Calculation Results

Paramter	Pilot model	Value
f	AOCM	0.0113
I_p	AOCM	[0.2656,0.2649,0.2346,0.4243,0.7640,0.6130,2.040,-0.0959,-0.1625,0.5853,80.073]
f	OCM	0.0113
I_p	OCM	[0.2656,0.2649,0.2346,0.4243,0.7640,0.6130,2.040,-0.0959,-0.1625,0.5853,80.073]
$F_{Filtergain}$	OCM	[-0.0601;0.3304;0.154;-.033;2.377;6.4969;0.6934;-1.95×10^{-16};4.97×10^{-16};-1.8301×10^{-6};1.441×10^{-7};1.214×10^{-5}]
V_u	OCM	6.077×10^{-5}
V_y	OCM	0.0014

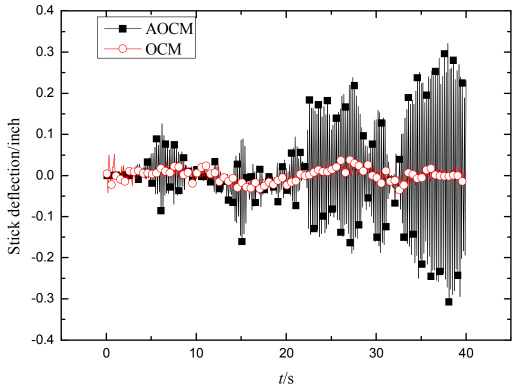


Fig. 3 Stick deflection comparison of AOCM and OCM

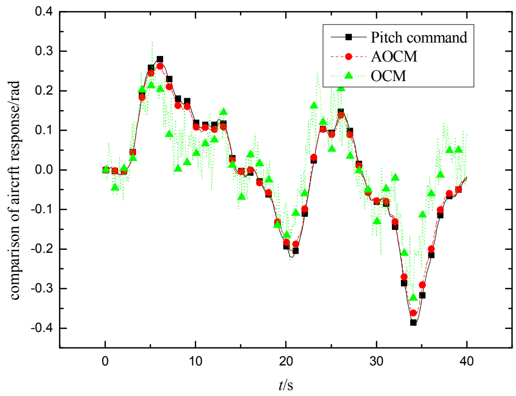


Fig. 4 Pitch angle tracking of AOCM and OCM

3.1.2. Frequency domain character comparison

Utilized AOCM and OCM to simulate the pilot control, we got series discrete points of stick deflection δ_{es} and pitch response θ as shown in figure 3 and figure 4. Make a frequency transforming in matlab toolbox, we got the frequency response shown in figure 5 and figure 6. The results can show AOCM fit the measurements in main trends. As the flight test is a kind of stochastic test affected by pilot and atmosphere disturbance, so the simulation frequency data and the measurement are not fitted in every points.

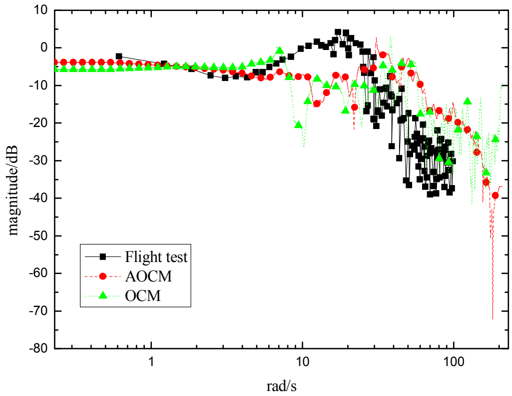


Fig. 5 Magnitude comparison of measurement in flight test and simulations of AOCM and OCM

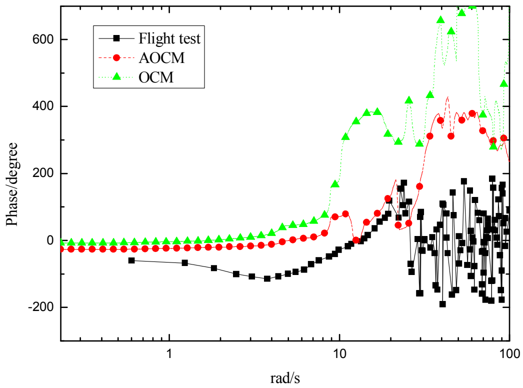


Fig. 6 Phase comparison of measurement in flight test and simulations of AOCM and OCM

In addition, in figure 5 and figure 6, AOCM fits the measurements better than OCM especially in phase comparison; this shows the merit of AOCM. Based on the measurements comparison, AOCM can reflect the pilot's behavior more practical.

3.2 Time domain characters comparison

In time domain evaluation, we set an unknown time varying disturbance in tracking task, once the OCM results a bigger tracking error, then also shows the merits of AOCM. The unknown disturbance is set as

$$w_{unknown} = 0.1 \cdot t \cdot w + w \tag{26}$$

Replace the white noise w with unknown disturbance $w_{unknown}$, after the pilot-aircraft close-loop simulation; the results of the pitch command and aircraft response in control of AOCM and OCM are shown in figure 7. It is obvious that AOCM gets the smaller tracking error, it performs better than OCM, the merit of AOCM is clear to see, and also proves that AOCM can reflect pilot's characteristic of environment adaption.

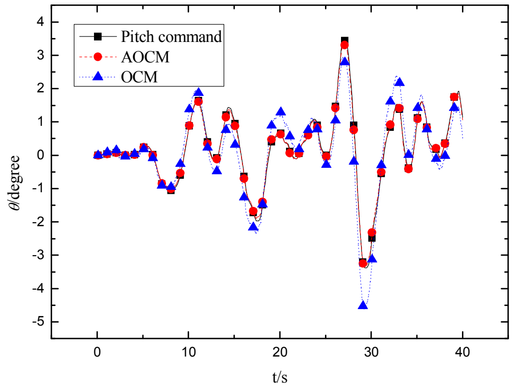


Fig.7 Tracking error comparison in unknown disturbance

4 Handling Qualities Prediction Based on AOCM

4.1 Handling Qualities Prediction Flight Test

The flight test data from Ref.[9] are used To evaluate the AOCM in handling qualities prediction. The flight test aircraft pitch dynamics is

$$\frac{\theta}{\delta_{es}} = 8 \cdot \frac{4900}{s^2 + 98s + 4900} \cdot \frac{5.5(s+1.8)}{s(s^2 + 12\xi s + 36)} e^{-\tau_D s} \tag{27}$$

In this equation ξ is the short period damping, τ_D is the time delay. Through Case1 to case4 four level of handling qualities prediction subject formed with different values of ξ and τ_D are shown in table 4.

Table 4 Case Definition Table

Case	ξ	τ_D
1	0.7	0.04
2	0.4	0.04
3	0.7	0.24
4	0.4	0.24

To make the handling qualities prediction in tracking task, the pitch command forcing function is modeled by Eq. (19). To avoid the rating dispersion caused by pilot delay, the flight data from pilot Darcy Granley was especially extracted. Both the pilot information and the flight test rating are shown in table 5. t_p is the pilot delay, PR is the pilot rating. In case 3, the pilot shows different ratings, which may caused by unknown disturbance in airborne test. Thus AOCM of this paper is specially fit to this situation.

Table 5 Flight test information

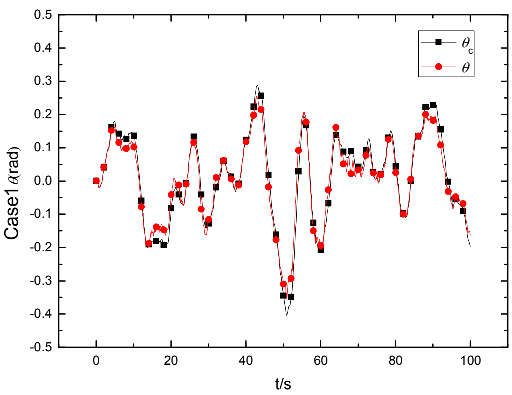
case	pilot	t_p	Iteration (sortie)	PR[9]
1	Darcy Granley	0.26	1(1)	2
1	Darcy Granley	0.26	3(5)	2
2	Darcy Granley	0.25	3(5)	2
3	Darcy Granley	0.26	3(5)	3
3	Darcy Granley	0.26	1(1)	4
4	Darcy Granley	0.31	1(1)	4

4.2 Pilot-aircraft close-loop simulation

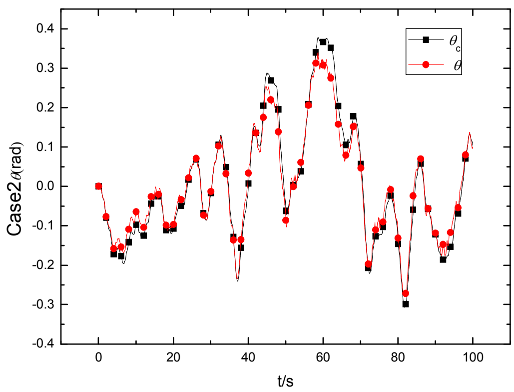
Use the pilot input parameter of table 6 to pilot-aircraft close-loop simulation, the four cases tracking results are shown in figure 8.

Table 6 Pilot Model Input Parameters

parameter	value
Neuromotor lag, τ_n	0.11s
Observation noise ratio, ρ_y	-20dB
Motor noise ratio, ρ_u	-25dB
Objective function observation weights, Q_y	0.30
Objective function control weights, R	1
Noise statistic time t_h	5s
Forgeting factor b	0.995



(a)



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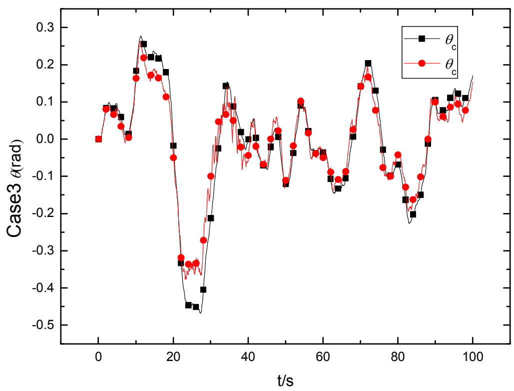

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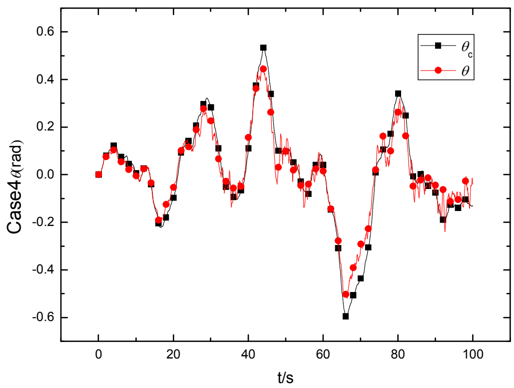

(d)

Fig. 8 Aircraft response of Lear 25B in HQ prediction

4.3 Handling Qualities Prediction

Each case was simulated one hundred times and 150 seconds long each time, the statistic rating parameters were calculated in table 7.

Then, the handling qualities prediction can be figured out by following equation

$$Rating = 5.5 + 3.7 \cdot \log_{10}\left(\frac{J}{\sigma_c^2 \omega_w^2}\right) \qquad (28)$$

where J is the performance index, it denotes the pilot physical workload and mental workload, σ_c^2 is the root mean square magnitude of task error, ω_w^2 is the forcing function bandwidth.

Table 7 Handling Qualities Prediction in AOCM

Case	Mean value of J	RMS error of J	σ_c^2	ω_w^2	Mean value of rating	RMS of rating error
1	0.0235	2.73e-4	0.9646	0.16	2.1784	0.6268
2	0.0218	2.68e-4	0.9358	0.16	2.1340	0.7876
3	0.0821	0.0152	1.8856	0.16	2.8579	0.8372
4	0.1384	0.0572	2.9462	0.16	2.9571	0.6797

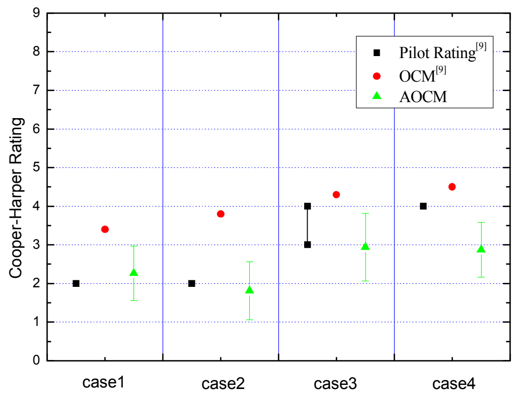

Fig. 9 Rating Prediction in AOCM of Q_y/R=0.3

In figure 9, it compares the flight test pilot rating, AOCM rating and OCM rating. The comparison shows that either the OCM or AOCM does not fit the measurement precisely. We suppose the reason is the weighting matrixes are not chosen properly. Thus, the weighting matrix effects are discussing below.

4.4 Discussion of weighting matrixes

In Ref.[10], the weighting matrixes $\boldsymbol{Q}_y$ and $\boldsymbol{R}$ are constant values, they are

$$\begin{cases} \boldsymbol{Q}_y = diag([q_1, \cdots q_n]) \\ \boldsymbol{R} = diag([r_1, \cdots r_n]) \end{cases} \qquad (29)$$

The matrixes elements are corresponding to the errors, are scaled to given approximate equal weights to standard deviations, they are calculated by

$$\begin{cases} q_i = 1 \big/ \sigma_{y_i}^2 \\ r_i = 1 \big/ \sigma_{u_i}^2 \end{cases} \qquad (30)$$

But, in this article, we found that, C-H rating is mainly corresponded to the value of $\boldsymbol{Q}_y/\boldsymbol{R}$. In table 8, we set different values but the same ratio of $\boldsymbol{Q}_y$ and $\boldsymbol{R}$, and the rating prediction shows that, once the same ratio of $\boldsymbol{Q}_y$ and $\boldsymbol{R}$ are resulted, the C-H rating is approximately the same. It proves the assumption of $\boldsymbol{Q}_y/\boldsymbol{R}$'s relationship and C-H rating.

Table 8 Relationship analysis of $\boldsymbol{Q}_y/\boldsymbol{R}$ and C-H rating

$\boldsymbol{Q}_y/\boldsymbol{R}$	Mean value of Rating	RMS of rating error	$\boldsymbol{Q}_y$	$\boldsymbol{R}$	Mean value of Rating	RMS of rating error
0.1	1.4887	0.9107	1	10	1.5254	1.0779
0.1	1.4887	0.9107	0.2	2	1.4665	1.0047
0.2	3.1963	0.9275	2	10	3.2916	0.9345
0.2	3.1963	0.9275	1	5	3.2307	1.0286
0.3	2.6282	0.9976	3	10	2.5300	1.0391
0.3	2.6282	0.9976	30	100	2.4624	1.0232

Eventually, the relationship of $\boldsymbol{Q}_y/\boldsymbol{R}$ and C-H rating is analyzed. In figure 10, HQ prediction by AOCM with changing value of $\boldsymbol{Q}_y/\boldsymbol{R}$ shows that, once the value of $\boldsymbol{Q}_y/\boldsymbol{R}$ increases, the C-H rating will decrease. It indicates that if the pilot pays more attention in flight observation while he keeps the same attention in controlling, he will make lower rating. In the four cases, if the ratio of $\boldsymbol{Q}_y/\boldsymbol{R}$ are same as the value in table 9, AOCM makes the most precisely prediction. It may denote that while the aircraft dynamics character changes, the pilot will allocate his attention in different way. From the cases studied in this article, while the aircraft dynamics degrades, the pilot will pay more attention in flight observation. Thus, the heavier mental workload will degrade the pilot rating, however, it is hard to measure the attention allocation in observation and controlling [11], thus this assumption is still need to be testified and deeply researched.

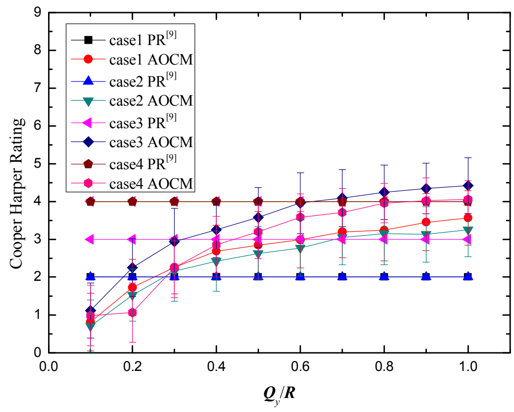

Fig. 10 Influence of the index weight ratio in rating prediction

Table 9 HQ Prediction in AOCM with modified weightings

Case	Q_y/R	PR[9]	Mean value of AOCM rating	RMS of rating error
1	0.25	2	2.0567	0.7115
2	0.28	2	2.0020	0.7135
3	0.46	3-4	3.5697	0.8052
4	0.80	4	4.0172	0.6094

The HQ prediction is recalculated with modified weighting matrixes; the result is shown in table 9 and Figure11. It shows that, with the modified weighting matrixes, AOCM generates more accurate HQ rating prediction than OCM; it is more identical to the flight test pilot rating than before.

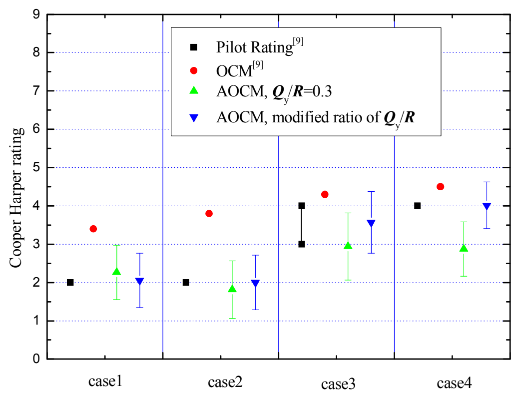

Fig. 11 HQ prediction with modified weighting matrixes

5 Conclusion

1) The traditional optimal control pilot model (OCM) is based on Kalman filter which cannot reveal the pilot's behavior in time varying disturbance of unknown environment. To overcome this omissions of OCM, a Modified Optimal Control Pilot Model based on Adaptive State Estimate (AOCM) is developed.

2) Utilized the pilot models in pilot-aircraft closed-loop simulation to reproduce the flight test. In frequency domain, the AOCM is testified by magnitude and phase comparison. In time domain, some unknown disturbance was added into the simulation, the attitude tracking results show that AOCM performs better than OCM, both the evaluations in frequency domain and time domain proves the merit of AOCM, and reflect the pilot's characteristic of environment adaption.

3) AOCM and OCM are utilized in HQ prediction, in all the four HQ test cases, with modified weighting matrixes, AOCM has a more accurate HQ rating prediction than OCM, it is more identical to the flight test pilot rating.

4) In OCM, the weighting matrixes $\boldsymbol{Q}_y$ and $\boldsymbol{R}$ are constant values. The conclusion of this article shows that the PR prediction is critical corresponded to the ratio of $\boldsymbol{Q}_y/\boldsymbol{R}$. An accurate PR prediction is based on the precisely $\boldsymbol{Q}_y/\boldsymbol{R}$ ratio chosen, and $\boldsymbol{Q}_y/\boldsymbol{R}$ ratio is corresponded to the aircraft dynamics, as the aircraft dynamics degrades the value of $\boldsymbol{Q}_y/\boldsymbol{R}$ increases. It denotes that if the pilot keeps the same attention in controlling then he will pay more attention in flight observation, while the aircraft dynamics degrades. Thus, the heavier mental workload will degrades the pilot's rating. Therefore, the weighting matrixes choosing principle and the relationship between aircraft dynamics and the weighting matrixes should be researched particularly.

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