Chinese Journal of Aeronautics, (2014),27(4): 977–985

Chinese Society of Aeronautics and Astronautics
& Beihang University

Chinese Journal of Aeronautics

cja@buaa.edu.cn
www.sciencedirect.com

Human factors quantification via boundary identification of flight performance margin

Yang Changpeng, Yin Tangwen, Zhao Weina, Huang Dan, Fu Shan *

School of Aeronautics and Astronautics, Shanghai Jiao Tong University, Shanghai 200240, China

Received 19 July 2013; revised 11 November 2013; accepted 14 January 2014
Available online 17 March 2014

KEYWORDS

Computational pilot model;
Flight performance;
Human factors quantification;
Monte Carlo simulation;
Pattern recognition

Abstract A systematic methodology including a computational pilot model and a pattern recognition method is presented to identify the boundary of the flight performance margin for quantifying the human factors. The pilot model is proposed to correlate a set of quantitative human factors which represent the attributes and characteristics of a group of pilots. Three information processing components which are influenced by human factors are modeled: information perception, decision making, and action execution. By treating the human factors as stochastic variables that follow appropriate probability density functions, the effects of human factors on flight performance can be investigated through Monte Carlo (MC) simulation. Kernel density estimation algorithm is selected to find and rank the influential human factors. Subsequently, human factors are quantified through identifying the boundary of the flight performance margin by the k-nearest neighbor (k-NN) classifier. Simulation-based analysis shows that flight performance can be dramatically improved with the quantitative human factors.

1. Introduction

The safety of aviation activities, a critical issue in the aviation domain, is influenced by multiple potential factors and interactions between these factors. Human factors play an essential role in these factors that lead to poor flight performance, aviation incidents, and even disasters.[1,2] Thus, study of the relationship between human factors and flight performance or safety related activities is important for aircraft design, selection of pilots and operational environments.

Human factors analysis methods[3] such as task analysis techniques, cognitive task analysis techniques, and mental workload assessment analysis techniques are used to assess various aspects of operator behavior. These time consuming methods generally lead to subjective and qualitative results. In the last few decades, several computational human factors models have been developed to evaluate the effects of human factors such as physical limitations and cognitive constraints on pilot behaviors and flight performance. McRuer and Jex[4] have developed a crossover model which is expressed by two human factor parameters: the gain, which is the ratio of output velocity to perceived error, and the effective time delay, described as the continuous analog of the human operator's

* Corresponding author. Tel.: +86 21 34205668.
E-mail addresses: chpyang@163.com (C. Yang), sfu@sjtu.edu.cn (S. Fu).

Peer review under responsibility of Editorial Committee of CJA.

Production and hosting by Elsevier

http://dx.doi.org/10.1016/j.cja.2014.03.016

discrete reaction time. This model expressed by transfer function has been proved successful in analyzing the dynamic stability and handling quality of piloted aircraft. An optimal control model, restricted by two kinds of human factors: time delay and noise, is introduced to account for different operator strategies performance.[5] Recently, Hess and Marchesi[6,7] develops a pilot model that takes visual, proprioceptive, and vestibular limitations into account to simulate the operator's pursuit control. The model can be used for the analytical assessment of flight simulator fidelity. A multichannel perception and control human model that mainly includes parameters on vestibular, visual and neuromuscular activities is introduced.[8] Five pilot performance models are applied to predict pilot performance and behaviors in the National Aeronautics and Space Administration Human Performance Modeling (NASA HPM) Project.[9] These five models are built under the limitations of human information processing, such as biases, memory deficits and scan patterns. All of these models have emerged as powerful tools for evaluation of human factors on the human-machine interface.

A critical drawback of these models is that they are only developed to account for the sensitiveness of human factors, namely, investigating the effects of human factors on flight safety related criteria. However, there are many situations in which we are more interested in the value range of a set of human factors under certain criteria of human-aircraft performance. For example, in order to reach 10^{-9} accident rate, it is a normal practice to consider what kind of pilots should be selected for the newly designed system or what skill levels a pilot should acquire in training. If the allowable ranges of these human factors which greatly influence the flight performance are identified and quantified, the criteria for pilot selection and training will be defined more precisely, and the design of human-machine interface and flight control system will also be enhanced.

The present paper attempts to explore a novel method that directly quantifies the human factors based on the flight performance margin—a threshold value to reflect the quality of flight performance that is typically measured in terms of error. Two critical procedures are included in this method, namely, building a pilot model that rigorously represents the characteristics of a group of pilots, and identifying and quantifying the influential human factors by using the classical Monte Carlo (MC) simulation[10] and pattern recognition method. MC simulation is one of the most powerful nonintrusive uncertainty analysis tools for fast data generation that reflects the influences of various combinations of uncertain input parameters. The pilot model in this research mainly emphasizes the modeling approaches that unify many kinds of human factors into one single computational model. Three critical components are incorporated into the pilot model to represent the process of information perception, decision making, and action execution. A set of human factors that represent the characteristics of human pilots are selected and coupled with these three components. These human factors affect each phase of information processing and ultimately will influence human behavior. By choosing a suitable probability density function (PDF) for each human factor, the characteristics and attributes of a group of pilots can be incorporated in one model. Once the pilot model is integrated with an external environment model consisting of an aircraft dynamic model, human-machine display, and automation equipment, the influences of human factors on flight performance can be fast simulated. Two tractable pattern recognition algorithms, kernel density estimation (KDE) algorithm[11] and k-nearest neighbor (k-NN) classification algorithm,[12] are combined to rank and quantify the influential human factor parameters through boundary identification of the flight performance margin.

2. Specification of proposed pilot model

As previously mentioned, the pilot model has three primary components: information perception, decision making, and action execution. These three components are integrated with a set of human factors, which specify the characteristics of a group of pilots, to form a tight cognitive loop. A block diagram of the model is shown in Fig. 1. This section will describe each component, the integration of these components with human factors, and how these human factors influence each

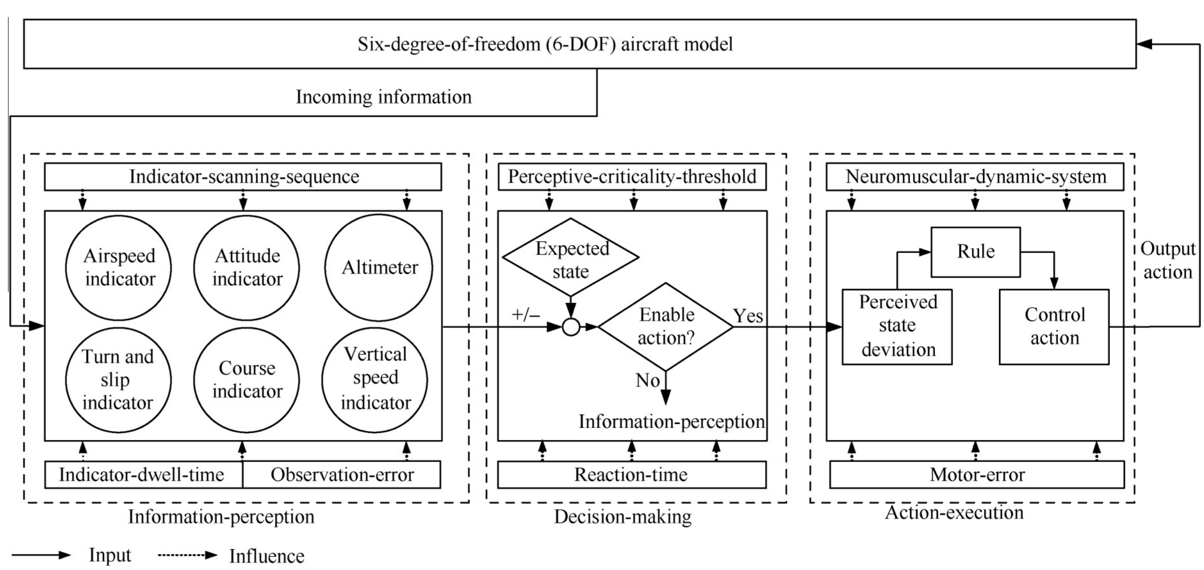

Fig. 1 Schematic representation of the pilot-aircraft model.

of the information processing components. The definition of flight performance is given at the end of this section.

2.1. Selection of human factors

When faced with a dynamic environment, individual natural reaction is often constrained or affected by a set of human factors. Research and experiments on human factors in aviation are increasingly carried out, and some major aspects of human factors with significant impacts on flight safety are identified.[3,13–15] Human factors influencing flight performance and safety include but are not limited to the following:

(1) Pilot's control time and control precision.
(2) Visual scene of cockpit and out-of-window area.
(3) Pilot's scan pattern and dwell time.
(4) Pilot's fatigue and fatigue related error.
(5) Pilot's prediction on parameter variation.
(6) Pilot's situation awareness.
(7) Pilot's fast recognition on unacceptable conditions.
(8) Pilot's detection and isolation of state transition.

Literature review indicates that a great many human factors can be classified according to their effects on the flight performance. However, from the view of computer simulation, it is not practical to consider more than a handful of human factors; consequently, a limited number of factors with explicit definition should be selected. Three rules are used to guide the selection of human factors in this research. Firstly, the human factor should play a tangible role in affecting the pilot behavior. Accordingly, those factors having indirect influences on the pilot's response are excluded. Secondly, each factor can be easily quantified and precisely interpreted into computer rules that govern the pilot behavior in different contexts. As a result, those descriptive and qualitative factors are excluded, for example, fatigue is a crucial factor affecting the operator's performance, but the difficulties in quantification of such a factor make it impossible to be simulated. Finally, with the consideration of validation, these factors should be easily obtained from flight or simulator experiments.

Due to time and resource limitations, this research does not attempt to implement all the human factors in the current pilot model. Instead, a small subset of factors that represent limitations and constraints of the operator are selected. Namely, indicator-dwell-time (IDT), observation-error (OE), motor-error (ME), perceptive-criticality-threshold (PCT), indicator-scanning-sequence (ISS), and reaction-time (RT). All these human factors are coupled with the information processing components to influence the pilot behavior.

2.2. Information perception model

The information perception of the pilot model handles the continual maintenance of situation awareness. For the pilot in a flying environment, information perception critically focuses on awareness of the state of the aircraft. In particular, the pilot samples the information on subsets of cockpit instruments such as the attitude indicator, altimeter, vertical speed indicator, etc.

The process of visual scanning consists of saccades such as the jerky eye movements when the eye fixation jumps from one indicator to the other. Location and dwell time are characteristics associated with eye fixation.[16] Fixation sequence and dwell time used by the pilot in information perception are given by

$$Q = \{ d_1, \quad d_2, \quad \cdots, \quad d_n \} \tag{1}$$

$$T_{\mathrm{IDT}} = \{ t_{d_1}, \quad t_{d_2}, \quad \cdots, \quad t_{d_n} \} \tag{2}$$

where Q is indicator-scanning-sequence, T_{IDT} is the indicator-dwell-time sequence associated with Q, d_i is each scanned indicator, and t_{d_i} is the indicator-dwell-time of d_i.

During visual sampling, the pilot moves his attention to get the flight states. Each indicator consists of several flight states, which is given by

$$d_i = \{ x_{i,1}, \quad x_{i,2}, \quad \cdots, \quad x_{i,m} \} \tag{3}$$

where $x_{i,j}$ is the jth flight state on indicator d_i.

During the interval of indicator-dwell-time, the operator does not exert any control on the aircraft besides "looking" at the associated indicator. After the visual sampling of one indicator, the pilot might repeat the scanning activity or make a decision based on the perceived flight state.

Due to display resolution, calibration or human sensitiveness, there are various sources of error when the pilot interprets the states of the aircraft from the indicators. Additionally, there are some other latent or unmolded errors induced by the external dynamic environment. To sufficiently represent these errors, a random variable called observation-error is modeled in the pilot model. Each observed parameter on a different indicator is associated with an observation-error. The observation-error set of each indicator can be defined as

$$E_{d_i} = \{ e_{x_{i,1}}, \quad e_{x_{i,2}}, \quad \cdots, \quad e_{x_{i,m}} \} \tag{4}$$

As a matter of fact, the perceived flight state $x_{i,j}^{\mathrm{pec}}$ is given by

$$x_{i,j}^{\mathrm{pec}} = x_{i,j} + e_{x_{i,j}} \tag{5}$$

The process of information perception is a discrete event in the simulation; an implementation algorithm of this process on one display is given as follows:
Algorithm: information perception

1. select a display d_i from Q
2. create a timer with interval t_{d_i}, named as ipTimer
3. void ipTimer_Tick(){
4. for each $x_{i,j}$ on d_i {
5. $x_{i,j} \leftarrow$:current flight state on d_i
6. $x_{i,j}^{\mathrm{pec}} \leftarrow: x_{i,j} + e_{x_{i,j}}$;}
7. select next display d_{i+1} for scanning according to Q;
8. ipTimer. interval $\leftarrow: t_{d_{i+1}} = \mathrm{IDT}d_{i+1}, T_{\mathrm{IDT}}\}$

As explained previously, this process is influenced by three human factors: indicator-scanning-sequence, observation-error, and indicator-dwell-time. These three human factors will have a significant impact on pilot behavior. First of all, the higher is the value setting of T_{IDT}, the longer time will the pilot use to get the dynamic aircraft state; as a result, the output will no longer line up with the input. The induced error between input and output will grow with the increase of T_{IDT}. Often more seriously, this time delay of T_{IDT} might lead to instability in the pilot-aircraft system. Secondly, indicator-scanning-sequence enables the frequency and order of scanned indicators to be different from each other; ultimately this will have an effect on the result of information perception. Finally, the observation-error exerts influences on the decision making through affecting the precision of the perceived information.

2.3. Decision making model

The decision making component of the pilot model uses the information gathered in information perception and the expected aircraft state mentally to determine whether any decisions should be made. During the actual flight task, a common decision making opportunity arises in the determination of whether to change the flight routine, configure the aircraft, and control the attitude. To simplify the process of decision making, the decision of the current pilot model only involves the changes of altitude. Specifically, the pilot determines whether to adjust the control surface of the aircraft according to the perceived difference of the current and expected state.

Two human factors, reaction-time and perceptive-criticality-threshold, influence the process of decision making. In the real piloted aircraft flight, the perceived flight states will be translated by the operator into a control response in a finite amount of time. During this period of time, perceived signals from the displays are sent to the brain for information processing and decision making. Such information processing time and decision making time are approximated in the pilot model by a reaction-time, T_{RT}. The influence of T_{RT} on pilot behavior is the same as T_{IDT}. Another human factor perceptive-criticality-threshold establishes the sensitive threshold for detecting the criticality of the system state. The difference between the pilot perceived information value and expected information value is calculated in each cognitive loop; if the difference excesses the perceptive-criticality-threshold, the pilot will conclude that a transition of system state occurs. The setting value of perceptive-criticality-threshold will significantly influence the pilot behavior. For example, the pilot might not quickly feel the transition of aircraft state and hence delay the action execution if perceptive-criticality-threshold is denoted with a high value.

The decision making process can be expressed by the following simple equation:

$$f_{\mathrm{DM}}(x_i^{\mathrm{pec}},\ x_i^{\mathrm{exp}},\ \mathrm{PCT}_i) = \begin{cases} 1 & |x_i^{\mathrm{pec}} - x_i^{\mathrm{exp}}| \geqslant \mathrm{PCT}_i \\ 0 & \text{Otherwise} \end{cases} \tag{6}$$

where $f_{\mathrm{DM}}(x_i^{\mathrm{pec}}, x_i^{\mathrm{exp}}, \mathrm{PCT}_i)$ is the decision making function, PCT_i is perceptive-criticality-threshold of the flight state x_i, x_i^{pec} and x_i^{exp} are respectively the perceived and expected flight state. If the result of decision making is 1, the pilot will take action; otherwise, the pilot will keep scanning the indicators.

2.4. Action execution model

The action execution of the pilot model maps the perceived information gained from information perception and expected information in mind to quantitatively control the output. As the aim of the pilot model is trying to build a linkage between human factors and flight performance, mimicking the actual and real pilot behavior is not within the scope of this study. Consequently, a basic compensatory control model is chosen to represent and simulate the pilot control strategy. Since only altitude tracking task is simulated in the model, the pilot simply performs the elevator deflection to change the aircraft altitude through scanning the attitude indicator and altimeter. The following equation governing the pilot control rules shows in which way the elevator is computed from the perceived altitude (h^{pec}) and pitch angle (θ^{pec}):

$$\delta e^{\mathrm{exp}} = K_{p_\theta}(\theta^{\mathrm{pec}} - \theta_{\mathrm{c}}) + K_{i_\theta}(\theta^{\mathrm{pec}} - \theta_{\mathrm{c}})T_{\mathrm{RT}} \tag{7}$$

$$\theta_{\mathrm{c}} = K_{p_h}(h^{\mathrm{pec}} - h^{\mathrm{exp}}) + K_{i_h}(h^{\mathrm{pec}} - h^{\mathrm{exp}})T_{\mathrm{RT}} \tag{8}$$

where $K_{p_\theta}, K_{i_\theta}, K_{p_h}$, and K_{i_h} are gains, δe^{exp} is implies the expected elevator deflection, and h^{exp} is expected altitude.

The actual output of elevator deflection will be constrained by the human neuromuscular dynamic system and motor-error. The neuromuscular dynamic system is used to reflect the position characteristic of hand movement due to the acceleration of the mass of the hand, and the spring stiffness and damping of muscular response. When faced with the same flight condition, each pilot will have his or her own way of responses. For example, a pilot may adopt different control strategies, smooth or hard, to complete a height tracking task. To represent such effects, it is necessary to build a neuromuscular dynamic system in the pilot model. A first order system with a time constant of 0.1–0.2 is used in the pilot model to simulate the muscular response.[5,17] The mathematical model of the neuromuscular system can be expressed by the following transfer equation:

$$\frac{1}{\tau_{\mathrm{NS}}s + 1} \tag{9}$$

where τ_{NS} is the time constant of the neuromuscular dynamic system, and s is the Laplace variable.

Additionally, motor-error represents the natural factors such as physical instability and mental distraction that affect pilot action execution. This type of error may cause the response of the neuromuscular system to overshoot or undershoot. This error occurs when the pilot tries to move the stick to adjust the deflection of the control surface. The actual elevator deflection is governed by the following equation:

$$\delta e = f_{\mathrm{NS}}(\delta e^{\mathrm{exp}}) + e_{\delta e} \tag{10}$$

where $f_{\mathrm{NS}}(\cdot)$ is the neuromuscular dynamic system expressed by Eq. (9), and $e_{\delta e}$ denotes the motor-error of elevator deflection is a deterministic variable specified by certain PDF.

In simulation, the pilot directly deflects the elevator to change the aircraft altitude. So far, in our study, the pilot model has been accomplished by coupling three information processing components with a set of human factors, indicator-scanning-sequence, observation-error, motor-error, reaction-time, perceptive-criticality-threshold, and indicator-dwell-time.

2.5. Definition of flight performance

As the flight task only involves the altitude tracking, root mean square error (RMSE) of trajectory deviation can be used as the flight performance index (FPI):[16,18]

$$\mathrm{FPI} = \frac{\sqrt{\sum_{i=1}^{N}(h_{\mathrm{pilot},i} - h_{\mathrm{ref},i})^2}}{N} \tag{11}$$

where $h_{\mathrm{pilot},i}$ and $h_{\mathrm{ref},i}$ are actual and reference altitudes in each sample point, respectively. N is the total sample number.

It is necessary to determine the flight performance level (FPL) for the human factor quantification procedure. With the definition of FPI, the FPL can be defined as

$$\mathrm{FPL} = \begin{cases} \text{Good} & 0 \leqslant \mathrm{FPI} \leqslant \mathrm{FPM} \\ \text{Poor} & \text{Otherwise} \end{cases} \tag{12}$$

where FPM is a threshold value to reflect the quality of flight performance.

3. MC Simulation

To investigate and ultimately quantify the effects of human factors on flight performance, the pilot is placed in an altitude tracking scenario. This section will discuss the setting of human factors in MC simulation, and the selected scenario.

3.1. Setting of human factor variables

As mentioned before, a probabilistic approach denoting the quantitative human factors as random variables with a suitable PDF can be used to study the flight performance due to the interactions of these factors.

However, it is impossible to use the same PDF to specify these variables in simulation due to the different attributes of human factors. For example, the reaction-time has the following characteristics. The smaller the parameter is, the better the pilot is considered to be as he will take less time to make a decision. However, in the real life, the probability of finding the best or worst performing pilot is small. To truly reflect this characteristic, a shifted version of Rayleigh distribution[19] instead of a Gaussian distribution is used to specify the time variables. The PDF of the shifted Rayleigh is

$$f(x) = \frac{x - x_0}{\sigma^2} \exp\left(\frac{x - x_0}{2\sigma^2}\right) u(x - x_0) \tag{13}$$

where $u(x)$ denotes the unit step function, whose value is 1 for $x \geqslant 0$ and 0 for $x < 0$, and x_0 is the amount of shift. As the equation indicates, the shifted Rayleigh PDF is determined by two variables, x_0 and σ.

By similar arguments, a shifted Rayleigh PDF is used to represent the probabilistic distribution of indicator-dwell-time, and Rayleigh PDF is selected to specify the probabilistic distribution of perceptive-criticality-threshold. Observation-error and motor-error are considered as noise variables denoted by Gaussian distribution.

The setting values of the human factor variables in the MC simulation are listed in Table 1. These values of random variables are chosen based on the results available in the literature or the intuition of authors.[19,20] For example, the indicator-dwell-time (T_{IDT}) of each indicator and reaction-time (T_{RT}) of the pilot are denoted by a shifted Rayleigh distribution, which corresponds to the reported values 0.5 and 0.15–0.3 in Refs.[21,5] It is noted that the indicator-dwell-time of indicators t_{di} are set with same distribution t_d during simulation. Observation-error (e_θ, e_h) and motor-error ($e_{\delta e}$) are assumed to be Gaussian random variables with a zero mean that generates values within the confidence intervals of 95%. Specifically, the variances of the observation noise in the pitch angle and height are selected such that the maximum deviations are equal to 0.04 rad and 4 m, which are possible cases in actual flight tasks. Perceptive-criticality-threshold for height (PCT_h) is denoted by a Rayleigh distribution with a scalar value of 5 m such that its mean value is about 6 m. In simulations, human factor variables are set with larger regions such that different extreme conditions are considered to examine the consequences. No attempt has been made to determine the true probabilistic nature of these parameters in the current work and this is left as a topic for future study.

It is noted that the pilot scans the indicators with a fixed indicator-scanning-sequence, Q = {Attitude, Altimeter, Attitude, Airspeed, Attitude}, which corresponds with the scanning sequence pilots are taught in a training school.[21] Although the airspeed indicator is part of the scanning cycle and the time is reserved in the MC simulation, it will not be used to perform any velocity correcting action since the velocity is controlled by the autothrottle during the simulation. The airspeed scanning activity is just used to mimic the real scanning sequence used by a pilot during the altitude tracking task. The time constant τ_{NS} of the neuromuscular dynamic system is set to 0.2.

3.2. Flight scenario

A typical flight scenario is shown in Fig. 2. The pilot is commanded to track a reference trajectory in this scenario. The experiment begins at A where the aircraft is balanced with

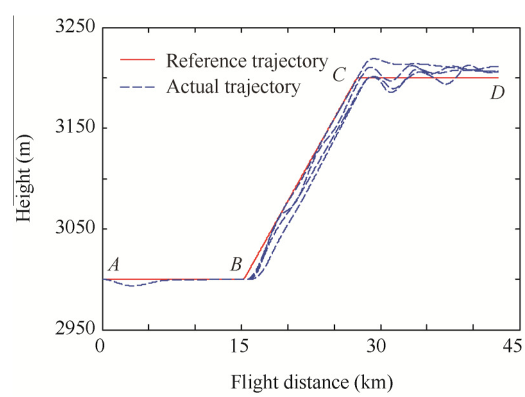

Fig. 2 Flight scenario for MC simulation.

Table 1 Setting values of human factors of pilot model in MC simulation.

Human factor parameter	Distribution type	Shift value	Deviation
t_d (s)	Shifted Rayleigh	0.05	0.2
e_θ (rad)	Normal	0	0.02
e_h (m)	Normal	0	2
PCT_h (m)	Rayleigh	0	5
T_{RT} (s)	Shifted Rayleigh	0.05	0.1369
$e_{\delta e}$ (°)	Normal	0	2

velocity of 263 m/s and altitude of 3000 m. Before reaching *B*, the aircraft is controlled by the autothrottle and autopilot. On the location of *B*, the autopilot is disengaged and the human pilot is required to control the deflection of the elevator so as to track the reference trajectory. After reaching *C*, the pilot is commanded to hold a level flight. Finally, the MC simulation ends when the aircraft is at *D*. It is noted that the autothrottle is engaged during the task.

3.3. Aircraft model

A 6-DOF rigid-body aircraft model is used in this research.[22] This model consists of 13 first-order nonlinear equations governing the engine dynamics, saturation and rate limits of the actuators. Additionally, this model is equipped with an autothrottle and altitude hold control system, and it is assumed that the real-time aircraft state is displayed on six indicators without time delay and distortion.

4. Results and discussion

Several typical results of 500 MC simulation are illustrated in Fig. 2 with the parameters setting in Section 3. Because of the randomness and uncertainty of input human factors, each flight trajectory is different with the other. Although the relationship between input and output can be investigated through analyzing a series of trajectories, the results are often qualitative. This section will discuss how to use the pattern recognition method to analyze the large amount of recorded data for establishing an objective and quantitative relationship between input human factors and flight performance.

4.1. Sensitivity analysis

Variations of FPI due to the human factor variables are presented in the form of a Tornado diagram and displayed with increasing order in Fig. 3. The diagram is developed based on baseline ±20% of the human factors, as shown in Table 2.

Fig. 3 shows that all of these six human factors are sensitive to the flight performance in different degrees. In particular, e_θ is the most influential one, while PCT_h is the least sensitive one.

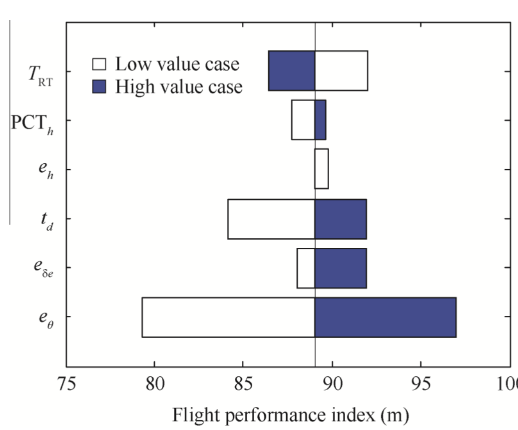

Fig. 3 Variations of flight performance indices due to variations of human factors.

Table 2 Setting values of human factors in sensitivity analysis simulations.

Human factor parameter	Low value	Baseline	High value
t_d (s)	0.4	0.5	0.6
e_θ (rad)	0.016	0.020	0.024
e_h (m)	1.6	2.0	2.4
PCT_h (m)	3.2	4.0	4.8
T_{RT} (s)	0.24	0.30	0.36
$e_{\delta e}$ (°)	1.6	2.0	2.4

These relationships successfully indicate the effectiveness of the selections of human factors and thus make the quantification of human factors possible.

4.2. MC simulation results analysis

All the rewards come from the analysis of the large number of results generated by the MC simulation. The selection of the analysis method is a critical step for analyzing the effects of human factors on flight performance. Traditionally, statistical methods[23] like modern design of experiment (MDOE), analysis of variance (ANOVA), are mainly used as sensitivity analysis of all the output parameters in contrast to input parameters; however, these methods are unable to reveal the quantitative relationship between the input variables and output variables. A pattern recognition method which combines KDE and k-NN classifier provides a systemic way to concretely rank and quantify the influential factors that directly influences the flight performance in this research.

KDE is a non-parametric density estimation method to estimate the PDF of any design variables and it indicates that all the variables can be compared without normalizing the raw data or manipulating the data in any way. This method is useful for understanding the MC simulation results when the KDE is calculated for the two levels of performance data. Fig. 4 shows the co-plotting and both curves can easily highlight which human factors are the best discriminators between poor and good performance runs. Similar trends of density estimation curves indicate that these factors, such as T_{RT} and e_h, have very similar effects on the two classes of flight performance, whereas the factors that have significantly different curves imply the inconsistent contributions to the flight performance and are usually our main concern. The factors are then ranked according to the difference between the two curves. Fig. 4 shows the selected human factors in the order of their rankings. Obviously, the single most influential factor is e_θ. However, contributions of e_h to these two flight performance classes are almost equal. Although the result is encouraging, there is still no clear boundary between the good and poor performance data with respect to each single human factor. In other words, we still cannot get the quantitative human factors. However, the combination of these factors contains a relatively discernible boundary. Fig. 5 shows the flight performance region with respect to the first three influential human factors in the spatial coordinates; fortunately, there is a specific spatial pattern in this case. There is a spatial boundary between the good performance region labeled by dots and poor performance region labeled by circles. This boundary is the exact boundary of flight performance margin. When the human factors are limited into this boundary, the performance

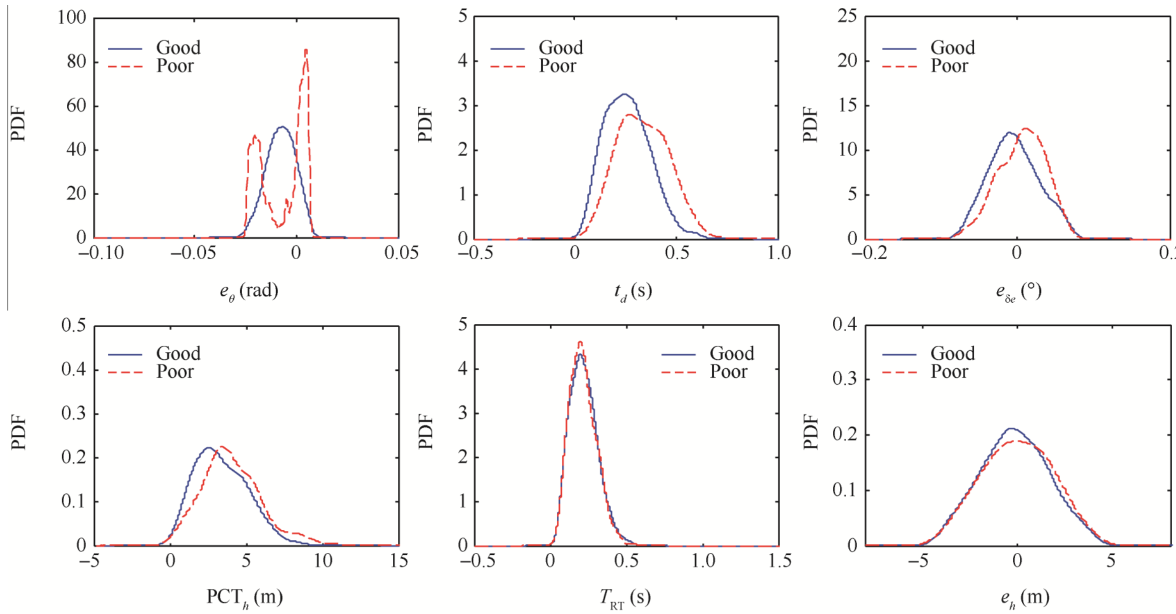

Fig. 4 Kernel density estimation for each single human factor.

is considered to be good. Thus, the problem of human factors quantification is simplified into the identification of this boundary.

Subsequently, the k-NN algorithm is used to determine the boundary between the good and poor performance data. For these six human factors, the first three influential factors are selected to illustrate the process of boundary quantification and the overall process is shown in Figs. 6 and 7. Fig. 6(a) and Fig. 7(a) show the MC data in 2D projection view from Fig. 5. The classification typically involves partitioning samples into training and testing categories. Let the MC data be the training sample and then create a map of 2D region as the testing sample. The detailed process of k-NN algorithm is discussed in Ref.[12]. Fig. 6(b) and Fig. 7(b) illustrate the results of classification. In these figures, good performance regions are labeled with dots, and poor performance regions are labeled with circles, and the boundary regions are labeled with asterisks. Hence, the good performance region is completely separated from the poor performance region. The plot clearly points out the boundary of the human factors when the flight performance is considered to be good. For example, Fig. 7(b) shows that if the human factors are constrained in

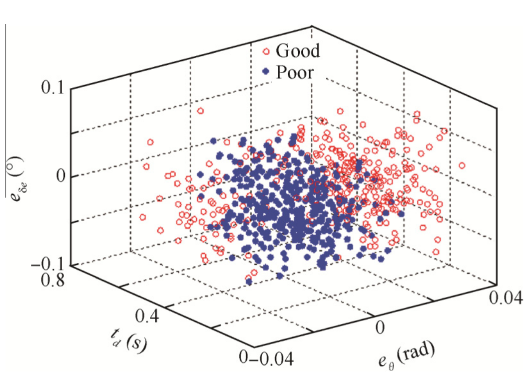

Fig. 5 Flight performance region with respect to the first three influential human factors.

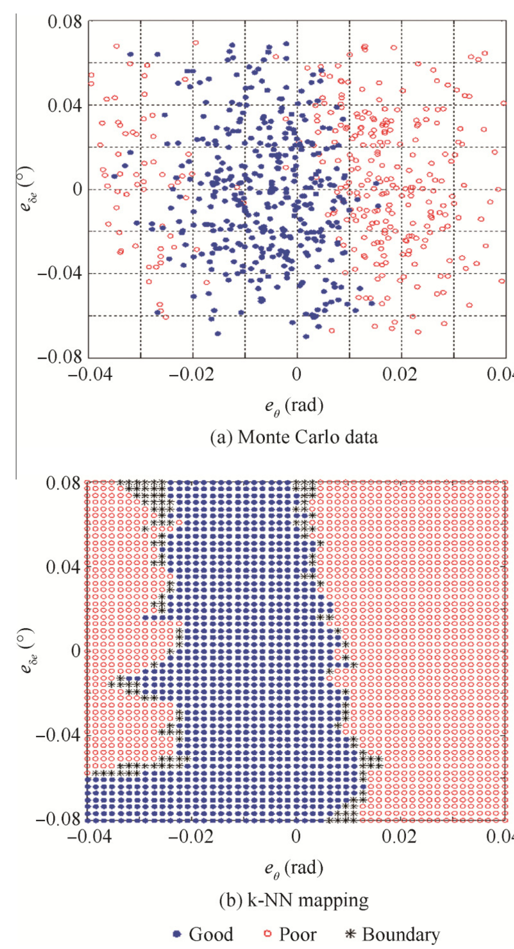

Fig. 6 Flight performance region with e_θ and $e_{\delta e}$.

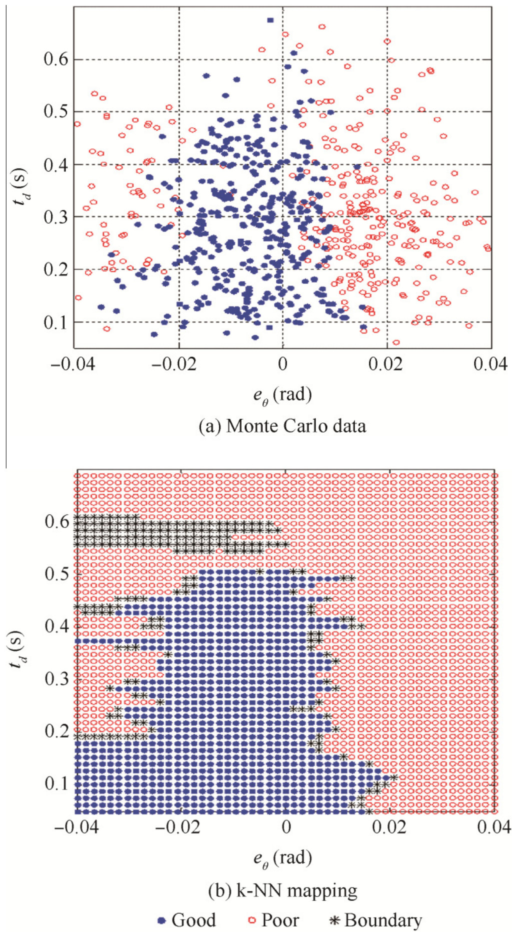

Fig. 7 Flight performance region with e_θ and t_d.

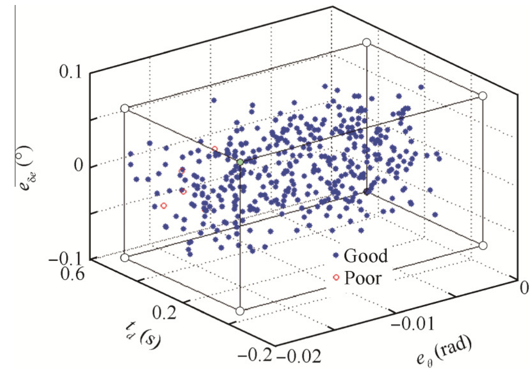

Fig. 8 Results of validation simulation and the boundary of input human factors.

the boundary, the contributions of e_θ and t_d to poor performance will be dramatically diminished. So far, the quantification of human factors that greatly influence the flight performance has been accomplished through building a pilot model, simulating by MC simulation, and recognizing the boundary of the flight performance margin by using the pattern recognition method.

4.3. Experiment of validation

Given the goal of the research is to quantify the human factors with consideration of the flight performance margin; the method requires validation with the analysis results. We here select a sub-region from the dot region in Fig. 6(b) and Fig. 7(b), for example, $e_\theta \in [0, 2]$ rad, $t_d \in [0.05, 0.45]$ s, $e_{\delta e} \in [-0.08°, 0.08°]$, and set up a new MC simulation using these specific limitations of the above three human factors as inputs, illustrated by the cuboid in Fig. 8. The other random input human factor variables are still expected to follow the setting in Table 1. The results of 500 MC simulations and the input boundary of the three human factors are shown in Fig. 8. It is seen that only six simulation labeled circles are in the region of poor performance. The appearance of unexpected simulations is mainly due to the fact that the limitations are only applied to the three most influential human factors and the "good" region is only effective in statistics. The dramatical improvement of good performance ratio indicates the effectiveness of this approach.

5. Conclusions

(1) A novel approach is proposed to quantify the human factors based on flight performance margin. Two procedures are included in this approach: building a pilot model, and analyzing the MC data by a pattern recognition method that combines KDE algorithm and k-NN algorithm.
(2) An implementation of the pilot model for a simple altitude tracking task is used to demonstrate its effectiveness and practicability. The results indicate that all these human factors are influential to the flight performance. Furthermore, three factors are the best discriminators between poor and good performance. The problem of human factors quantification is simplified into the identification of the flight performance margin by pattern recognition method.
(3) The new method is validated through a new MC simulation experiment with the setting of human factors in the "good" range. This method can be used to quickly analyze human factor related activities such as the objective and quantitative evaluation on the handling quality, flight safety, and ergonomics.

Acknowledgment

This work was supported by the National Basic Research Program of China (No. 2010CB734103).

References

1. Salas E, Jentsch F, Maurino D. *Human factors in aviation: an overview*. 2nd ed. Oxford: Elsevier Press; 2010. p. 1–23.
2. Shappell S, Detwiler C, Holcomb K, Hackworth C, Boquet A, Wiegmann DA. Human error and commercial aviation accidents: an analysis using the human factors analysis and classification system. *Hum Factors* 2007;**49**(2):227–42.
3. Stanton NA, Salmon PM, Rafferty LA, Walker GH, Baber C, Jenkins DP. *Human factors methods: a practical guide for engineering and design*. 2nd ed. Surrey: Ashgate Publishing Company; 2013. p. 39–486.

4. McRuer DT, Jex HR. A review of quasi-linear pilot models. *IEEE Trans Hum Factors in Electronics* 1967;**8**(3):231–49.
5. Kleinman DL, Baron S, Levison WH. An optimal control model of human response part I: theory and validation. *Automatica* 1970;**6**(3):357–69.
6. Hess RA, Marchesi F. Analytical assessment of flight simulator fidelity using pilot models. *J Guid Control Dyn* 2009;**32**(3):760–70.
7. Hess RA. Modeling the pilot detection of time-varying aircraft dynamics. *J Aircraft* 2012;**49**(6):2100–4.
8. Nieuwenhuizen FM, Zaal PMT, Mulder M, van Paassen MM, Mulder JA. Modeling human multichannel perception and control using linear time-invariant models. *J Guid Control Dyn* 2008;**31**(4):999–1013.
9. Foyle DC, Hooey BL. *Human performance modeling in aviation*. Boca Raton: CRC Press; 2007. p. 4–376.
10. Rubinstein RY, Kroese DP. *Simulation and the Monte Carlo method*. 2nd ed. Hoboken: Wiley Publisher; 2011. p. 37–88.
11. Scott DW. *Multivariate density estimation: theory, practice, and visualization*. Hoboken: Wiley Publisher; 2009. p. 125–95.
12. Bishop CM. *Pattern recognition and machine learning*. New York: Springer; 2006. p. 13–49.
13. Byrne MD, Pew RW. A history and primer of human performance modeling. *Rev Humn Factors Ergon* 2009;**5**(1):225–63.
14. Melnik RVN. Coupling control and human factors in mathematical models of complex systems. *Eng Appl Artif Intell* 2009;**22**(3):351–62.
15. Dul J, Bruder R, Buckle P, Carayon P, Falzon P, Marras WS, et al. A strategy for human factors/ergonomics: developing the discipline and profession. *Ergonomics* 2012;**55**(4):377–95.
16. Wickens CD, Hollands JG, Parasuraman R, Banbury S. *Engineering psychology and human performance*. 4th ed. London: Pearson; 2012. p. 101–256.
17. Metz LD, Cyr B. Robust control performance of time-varying human controller models. *Automatica* 1985;**21**(4):473–8.
18. Corwin WH, Sandry-Garza DL, Biferno MH, Boucek GP Jr, Logan AL. Assessment of crew workload measurement methods, techniques and procedures. Volume 1. process, methods and results; 1989. Report No.: ADA217699.
19. Dogan A, Kaewchay K. Probabilistic human pilot approach: application to microburst escape maneuver. *J Guid Control Dyn* 2007;**30**(2):357–69.
20. Kaewchay K, Dogan A. Design of a probabilistic human pilot: application to microburst escape maneuver; 2005. Report No.: AIAA-2005-6031.
21. Heiligers M, van Holten T, Mulder M. Predicting the safety of airport approaches from the pilot's perspective based on flight mechanical considerations. 2007; Report No.: AIAA-2007-1056.
22. Zipfel PH. *Modeling and simulation of aerospace vehicle dynamics*. Reston: AIAA; 2000. p. 367–481.
23. Howell DC. *Fundamental statistics for the behavioral sciences*. 7th ed. Stamford: Cengage Learning; 2010. p. 184–465.

Yang Changpeng is a M.S. student in control science and engineering at the School of Aeronautics and Astronautics, Shanghai Jiao Tong University, Shanghai, China. His research interests include aviation human factors and flight dynamics.

Fu Shan is a professor and Ph.D. supervisor at the School of Aeronautics and Astronautics, Shanghai Jiao Tong University, Shanghai, China. His research interests include aviation human factors and optical metrology.