Pilot Control Modeling With Stochastic Periodical Discrete Movement

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This paper proposes a novel pilot control model which reflects the following three characteristics of the pilot control behavior: stochastic, periodical, and discrete movement. The focus is on the final descent phase when the pilot controls the aircraft manually based on the flight director commands. The proposed model is developed based on an existing model as well as highly experienced pilot's comments. A flight simulator experiment is conducted and three pilots' landing data are obtained. The parameters of the pilot model are tuned via a genetic algorithm. The simulation result reveals that the proposed model captures well the characteristics of the data obtained in the simulator experiment and shows a good accordance with actual command tracking capability. The obtained parameters also identify the difference of control strategies between the pilots.

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I. INTRODUCTION

Nowadays, pilots control aircraft manually less often than they used to due to the sophistication of the aircraft systems and equipment. Although autopilot is almost entirely used during the enroute phase, the take-off and landing are often operated manually. Indeed, an autoland system has been developed, but it has its constraints, such as aircraft special redundant system, airport system equipment, special pilot license, and wind limits. As for take-off, there is no existing auto take-off system for civil aircraft. Therefore, manual control is still necessary, especially during the ascent and descent phase.

During the landing phase, aircraft often use instrument landing system (ILS) which provides precise navigation for safe landing. ILS is a radio beam transmitter installed at the airport, which provides horizontal and vertical guidance. However, even if the aircraft uses ILS, the aircraft can deviate from the nominal path due to aircraft dynamics, wind disturbances, navigation errors, and the pilot/autopilot command tracking errors. Therefore, to install the ILS landing procedure at one airport, a "protection area" must be considered [1]. Safe separation between the aircraft and the ground obstacles (such as trees, buildings, etc.) needs to be established so that such ground obstacles do not get into the protection area. The criteria of the protection area are described in PANS-OPS certified by International Civil Aviation Organization (ICAO) so that the probability of collision to the ground obstacles per landing is less than 1.0×10^{-7} [2]. The current criteria were developed in 1970s based on statistical analysis of actual landing data [2], but recent aircraft can track the path more precisely. In addition, an alternate system called ground-based augmentation system (GBAS) landing system (GLS) has been developed and already available at some airports in the world [3]. GLS is a GPS-based landing system, which offers more precise navigation guidance than ILS, but the criteria of the protection area are the same as those of ILS. Therefore, if the protection area is evaluated and eventually shrunk, new GLS procedures can be installed at the airports where the current criteria do not meet the requirement of the protection area. The final goal of this study is to establish a method to evaluate the protection area reflecting the capabilities of the modern aircraft systems.

Simulation is a straightforward approach to calculate the protection area and there are such ongoing projects in ICAO [4]. However, to calculate the protection area, the pilot manual control model is a key component, because this is the predominant control during the descent phase.

Pilot modeling has a long history, and various pilot models have been proposed. Most models are based on a linear system approximation, such as Tustin model [5], quasi-linear model [6], optimal control model [7], and precision model [8]. These pilot models describe the average pilot model, and have been used to design the aircraft flight control system [9], assess the flight simulator fidelity [10], or evaluate the handling quality [11]. However, the target of this study is to determine a very low probability deviation contour from the nominal path. The control executed by the pilot differs from that of an automatic controller, since the human control changes with the pilot's fatigue, for example. These characteristics are difficult to be modeled by the linear system. In addition, the linear system assumes that the pilot can obtain the information continuously and control accordingly. However, it is well known that the human tracking task has discrete features [12], so the linear system tends to track the target more precisely than the human pilot. In addition, the pilot model in this paper is expected to be used for the simulation to obtain the aircraft deviation characteristics, but past pilot models have not been evaluated from this aspect, so it has not been validated whether the existing pilot models can simulate the deviation characteristics. Therefore, this paper proposes a new pilot model with the same deviation characteristics as human pilots based on an existing model (Belyavin's model) [13], [14], which was developed considering perception process of a human pilot.

In Section II, the characteristics of the pilot manual control which should be modeled are described. The existing pilot models are also presented, and the difference with the proposed model is clarified. In Section III, a new pilot model is developed. The proposed model is based on Belyavin's model, so this model is first introduced, followed by a description of the model development. Since several parameters have to be optimized to represent the obtained pilot's control data, the parameter optimization method is also described. In Section IV, the proposed model with optimal parameters are validated with various aspects. The result of the proposed model is compared to several existing pilot models. Section V concludes this paper. A preliminary work on this study has been presented at the past IEEE SMC conference [15].

II. CHARACTERISTICS OF PILOT MANUAL CONTROL

A. Literature Review

The modeling of pilot control behavior has been a major research topic in aviation. Most research works focus on the landing control, because the control in this phase is known to be difficult, and yet most landings are still operated manually. In the early years, various types of pilot models were developed based on a linear system of either single loop or multiloop systems [5], [6], [8]. Among them, the most famous model is a quasi-linear pilot model developed by McRuer. The quasi-linear pilot model is described in the following form:

$$\frac{K(1+T_L s)}{(1+T_I s)(1+T_N s)}\exp(-\tau s). \tag{1}$$

Pilot equalization characteristics are represented by the time-lead parameter (T_L), and the time lag parameter (T_I). The pilot reaction time and neuromuscular delay are represented by τ and T_N, respectively. Their extensions are also found in many papers [16], [17].

Another approach is the optimal control model [7]. This model assumes that a highly experienced pilot always acts in an optimal manner while remaining subject to inherent psycho-physical limitations. The cost function of the optimal control model is usually defined as follows:

$$E\left\{\lim_{\eta\to\infty}\frac{1}{\eta}\int_0^\eta\left(y^T\mathbf{Q}y+u^T\mathbf{R}u+\dot{u}^T\mathbf{S}\dot{u}\right)\right\} \tag{2}$$

where y and u represent the observed variable and control inputs, respectively. **Q**, **R,** and **S** indicate the weight matrixes. The optimal control model has mainly been applied for the analysis of time delay effects on aircraft handling qualities [18]. In respect to data matching of experimental data, the optimal control model is not necessarily superior to the linear model, but its extension models [19], [20] are also proposed.

Based on these models, further improvements have been proposed such as development of nonlinear control models by switching multiple models [21]–[23], time-dependent parameters using wavelet transform [24], parameters identification in real flight [25], discrete step-like control model [26], and consideration of motion cues [27], [28]. Also, there are some recent approaches not based on the classical models, such as neural network [29]–[31], auto-regressive models [32], or fuzzy system [33], [34].

However, as noted in Section I, all these models assume that the pilot always perceives the current status and controls accordingly. On the other hand, the purpose of this study is to evaluate the deviation characteristics under manual control, and the above assumptions might underestimate the deviation characteristics. Besides, the above models are all deterministic, while the human pilot does not repeat the same control exactly, even if the flight situation is the same. This stochastic component of human pilot is also important to evaluate the deviation characteristics.

Furthermore, it is reported that the human pilot control includes several independent processes, such as "perception," "decision," and "response" [35]. There are several approaches to model the pilot control in a descriptive manner [13], [14], [36], [37]. Among them, Belyavin's model is developed based on the linear model, and it is revised to follow the human's perception process. In addition, this model already includes stochastic components, and is easy to be extended to have additional control characteristics, which will be explained in detail later. Therefore, this paper develops a new pilot control model based on the existing Belyavin's model.

B. Target of This Study

The focus of this study is on the final descent phase, because the protection area of ILS or GLS approach is set around the final descent path. In the final descent, the aircraft has captured both vertical and lateral guidance (called glideslope and localizer), and flies straight following a constant descent angle. During this phase, the pilot usually controls the control stick (called control column or column) manually to track the flight director (FD). Fig. 1 shows the primary flight display the pilot follows during the descent. The horizontal and vertical magenta bars are the FD bars.

Fig. 1. Primary Flight Display.

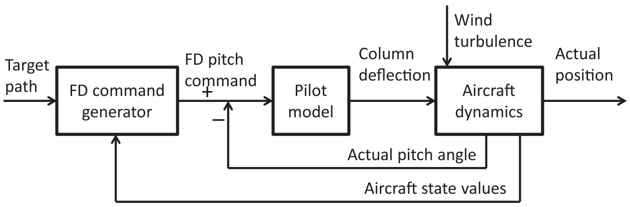

Fig. 2. Pilot control flow.

The FD bars show the target pitch and roll angles, and they intersect at the center when both the pitch and the roll angles are the same as the target angles. Note that this paper considers the pitch direction only. Here, the following two values are defined for clarity. “FD pitch command” refers to the target pitch angle provided by FD, and “FD command” refers to the difference between the FD pitch command and the current pitch angle, i.e., the relative FD pitch command to the current pitch angle.

The flow of pilot manual control is shown in Fig. 2. First, an FD command generator provides a target pitch angle which has to be kept for the aircraft to follow the flight path. Second, the pilot controls the column based on the FD command. Therefore, the pilot control is basically a simple activity: control the column to adjust the pitch angle to the target (FD pitch command). Finally, the aircraft moves based on the aircraft dynamics and the wind disturbance. The aircraft dynamics are calculated based on 6 degree of freedom nonlinear aircraft equation of motion, which is the most common model in the aviation field [38].

FD command generator is developed based on PID control theory, and parameters are tuned so that the pilot can control the aircraft based on FD command. The details of the FD command generation are out of scope of this research, and not mentioned here.

C. Observed Characteristics of Pilot Manual Control Based on Obtained Data

Flight simulator tests are conducted to identify the characteristics which need to be reflected by the pilot model.

TABLE I
Wind Patterns

Wind	Steady wind	Turbulence (created by Von Karman model [40])
(i)	10 kt from 45° direction	Light
(ii)	10 kt from 45° direction	Moderate
(iii)	0 kt	None

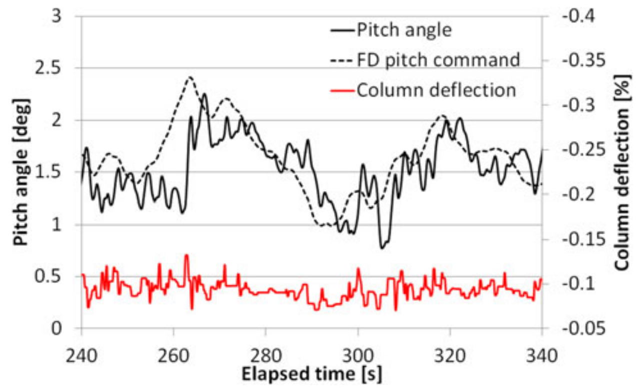

Fig. 3. Time histories of flight data of Data A-(i)-1.

The aircraft model is Dornier 228-202, which is a small-size turbo-prop aircraft with a control wheel. The aircraft used here is an experimental aircraft owned by Japan Aerospace Exploration Agency (JAXA) [39]. This flight simulator can create the counter force on the column, and the pilot actually flying with the modeled aircraft has confirmed that realistic data can be obtained with this simulator. Three test pilots have collaborated in this experiment. Pilot A is a retired captain pilot with experience of B747-400. Pilot B is a first officer of B767-300 with about 10 years flight experience. Pilot C is also a first officer of B737-800 with less than 2 years flight experience. New-Chitose Airport (RJCC) Runway 01L is assumed in the simulation, and three wind patterns are used as summarized in Table I. Each pilot is asked to control the aircraft four times, twice for wind 1), once for wind 2), and once for wind 3). The pilot control starts before capturing localizer and glideslope. A total of 12 datasets are obtained, which are described as “Data A-(i)-1.” The final descent starts at 2000 ft, and assumes 3° glideslope angle.

Fig. 3 shows the time histories of Data A-(i)-1. Other data also show similar trends, so here only the result of Data A-(i)-1 is shown. This figure shows several characteristics of the pilot control.

First, the pitch angle oscillates around the target pitch angle, because the human pilot can track the target pitch angle only roughly. Overshooting the pitch angle against the target is also observed around 305 s. This means that the pilot control includes noise. In addition, the tracking capability is not the same throughout the simulation. While the actual pitch angle is delayed from the target pitch angle by about 7 s around 260 s, the delay is small around 280 s. Such behavior can be considered as stochastic tracking capability, which should also be present in the pilot model.

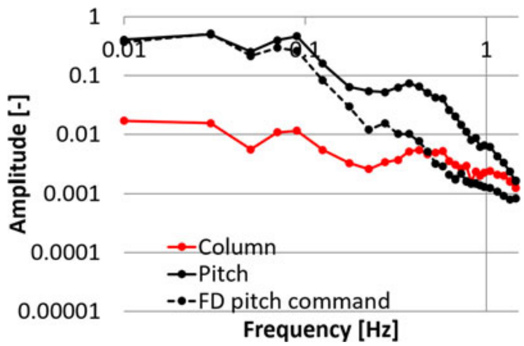

Fig. 4. Frequency analysis. (Data A-(i)-1).

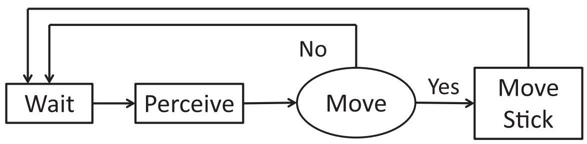

Fig. 5. Flow of Belyavin's model.

Second, the control is discrete and periodical. Fig. 3 shows that the pilot control does have a discrete movement as reported in another reference [12]. In addition, periodical control is also observed. Periodical control is characterized by short-term oscillation of both pitch angle and column movement. This periodical control is observed throughout the experiment. Fig. 4 shows the frequency analysis of the obtained data. The most interesting point is that both the pitch angle and the column deflection have an amplitude peak around 0.4–0.5 Hz (2–2.5 s), while the FD pitch command does not have a peak around this frequency. This means that the periodical pilot control does not come from the FD pitch command, but is a self-excited oscillation. The details will be discussed later in Section III-B.

These characteristics are identified based on a single flight only, but they are also observed in other datasets too. These two characteristics, the stochastic tracking capability and discrete periodical control, are not represented in Belyavin's model. These characteristics are to be modeled in the following section.

III. DEVELOPMENT OF PILOT MANUAL CONTROL MODEL

A. Introduction to the Existing Model

This section discusses how the new pilot model should express the characteristics explained in the last section. Here, the pilot model proposed by Belyavin is introduced, which matches this study the most as explained in Section II-A. Belyavin's model includes a discrete and a partially stochastic movement. Fig. 5 shows the flow of the model. First, it is assumed that it takes some time for the human pilot to detect or react the current situation, so the pilot has to wait for a while at the beginning at "wait" state. After that, the pilot perceives the current situation, such as the target pitch angle and the current pitch angle at "perceive" state. Based on this information, the pilot decides whether he should move the control stick or not at "move" state. If the pilot decides to move the control stick, he will control the control stick then go back to "wait." If he decides not to move the control stick, he will go back to "wait."

At move state, the pilot model calculates the required amount of column movement ($\Delta\delta$) by the following expression:

$$\Delta\delta = \frac{\mu\left(d + \eta\dot{d}\right)}{1 + \gamma\delta^2} - \lambda\delta \tag{3}$$

where d denotes FD command, in other words, the FD bar position from the center. δ is the current column position. μ, η, γ, λ are the parameters. Based on $\Delta\delta$, the probability that the pilot decides to move the control stick (p) is calculated by the following expression:

$$p\left(\Delta\delta\right) = \frac{1}{1 + \exp\left(-\sigma\left(|\Delta\delta| - \tau\right)\right)} \tag{4}$$

where σ, τ are parameters. When the pilot decides to move the control stick, the new column position is calculated by the following expression:

$$\delta + \Delta\delta + e \tag{5}$$

where e expresses the human noise, which follows normal distribution with 0 average and Σ standard deviation.

This model can describe the discrete control and stochastic movement to some extent, but the periodical movement and stochastic tracking capability are not modeled.

B. Expression of Periodical Control

First, the reason of approximately 2 s periodical control is discussed. An experienced pilot provided the following insight:

The pilot has a target pitch angle in mind (which is not necessarily the same as the FD pitch command), and he tries to keep the desired pitch angle by a control series. To track the target pitch angle in mind, he tries to move the column to the desired direction first. When the pitch angle approaches the target pitch angle in mind, he moves the column to the opposite direction to stop the movement of the pitch angle. This is a control series. The target pitch angle in mind is not continuously changed, and it changes discretely only when the control series is completed.

Here, such a control series is important. The pilot moves the column forward first then backward next (or opposite), which seems to result in a 2 s periodical control. This control series can affect the pitch tracking capability, which affects the vertical deviation from the nominal path.

According to the comment, the first movement is to track the pitch angle in mind, and the second movement is to break the pitch movement. This control flow is modeled and shown in Fig. 6. The transfer probability between states is written in blue.

First, the pilot starts with the "perceive 1" state. The perceive 1 state happen with the interval of t_{int1} to perceive the current situation like the "wait" in Belyavin's model. At "perceive 1" state, the pilot updates the target pitch angle in

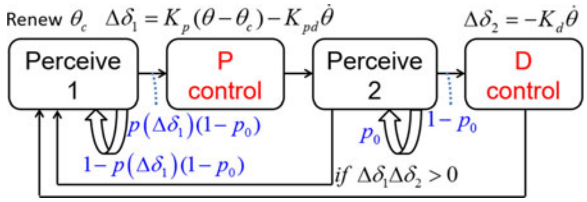

Fig. 6. Control flow of the proposed model.

mind, denoted by θ_c, based on FD pitch command. The way to decide on θ_c will be explained in the following section. Next, the pilot calculates the required control movement denoted by $\Delta\delta_1$ with the following expression:

$$\Delta\delta_1 = K_p(\theta - \theta_c) - K_{pd}\dot{\theta} \tag{6}$$

where K_p and K_{pd} are the parameters. Based on $\Delta\delta_1$, the pilot decides whether he should move the control stick or not. Its probability is calculated with (4). However, since a human pilot sometimes does not react to situational changes, the pilot maintains the "perceive 1" state with probability. In total, the pilot moves to "P control" with the probability of $p(\Delta\delta_1)(1 - p_0)$, otherwise the pilot stays at "perceive 1" state. If the pilot stays at "perceive 1" state, the same perceive 1 process goes again with an interval of t_{int1}. Here, if he decides to move the control stick, he moves to the "P control" state and the new column position is calculated by (5), then he moves to the "perceive 2" state. "Perceive 2" state also happens with the interval of t_{int2}. Once the pilot goes to "perceive 2" state, he moves to "D control" state unless $\Delta\delta_1\Delta\delta_2 > 0$. $\Delta\delta_1\Delta\delta_2 > 0$ means that P control and D control have the same direction of control, and D control is not a brake to P control. In such a case, D control is skipped and the pilot moves to "perceive 1" state. In addition, like the perceive 1 state, the pilot stays at "perceive 2" state with probability of p_0. At "D control" state, the required column movement is calculated in the following equation:

$$\Delta\delta_2 = -K_d\dot{\theta} \tag{7}$$

where K_d is the parameter. The new column position is calculated by (5). After D control, he goes back to the "perceive 1" state. This control series results in about 2 s periodical control.

C. Expression of Stochastic Control

Belyavin's model also includes a stochastic control characteristic, but it cannot change the tracking capability during the simulation. This tracking capability affects the deviation from the nominal path very much, so it should also be simulated. An experienced pilot also provided the following interesting comments.

The pilot usually tracks the FD pitch command (θ_{FD})*, but if he tries to track FD pitch command too aggressively, it sometimes causes "over control." To avoid this, "half control" is recommended. "Half control" means that the pilot moves only half the amount of control he thinks he will need.*

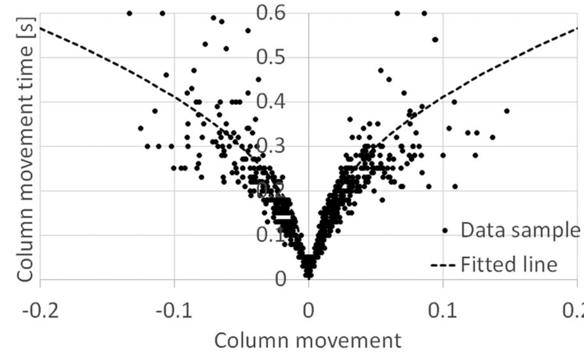

Fig. 7. Relationship between column movement and column movement time for pilot A.

In other words, the target pitch angle in mind is set between the current pitch angle and the FD pitch command. This "half control" can also be confirmed clearly from the data. In Fig. 3 around 265 s, the pitch angle increases from about 1.2° to about 1.9° when the target FD pitch command is about 2.4°. The pilot seems to make the target pitch angle in mind around half of the current pitch angle and the target FD pitch command. This half control can be expressed by the following equation:

$$\theta_c = \theta + \alpha\left(\theta_{\text{target}} - \theta\right) \tag{8}$$

where α is the control parameter, which should be 0.5 for the exact "half control," but actually α can vary. When α is small, the tracking capability is poor, and vice versa. By changing α, the variation of tracking capability is achieved.

D. Expression of Discrete Control

In addition to the two characteristics explained above, one more characteristic is implemented in the model. According to Fig. 3, even though the overall pilot control seems discrete, there are also some components which are not strictly discrete. Therefore, from the obtained data, a single column movement is isolated and the relationship between the column movement and the corresponding column movement time is examined as shown in Fig. 7. The negative column movement means the pull of the column. As seen in the figure, the column movement time increases linearly with the column movement range when the column movement range is small, but the column movement time becomes relatively faster as the column movement range increases. No difference in regard to column movement direction is found. Therefore, once the column movement amount is decided based on either (6) or (7), the column movement time is calculated based on the following equation:

$$x|\Delta\delta|^y \tag{9}$$

where x, y are the parameters. The fitted line is also shown in Fig. 7, and it seems to fit well. Since this relationship differs with the pilot, different parameters are used for each pilot. Using the obtained column movement time, the column is moved in "P control" and "D control" state. In addition, once the pilot moves the control stick, a minimum

TABLE II
Required Parameters in the Proposed Pilot Model

Parameters	Explanations	Constant
σ, τ	Parameter of state transition probability at perceive 1 state.	Yes
K_p	Proportional gain in P control state	Yes
K_{pd}	Derivative gain in P control state	Yes
K_d	Derivative gain in D control state	Yes
t_{int1}	Interval of perceive 1 state	No
t_{int2}	Interval of perceive 2 state	No
Σ	Standard deviation of control noise e	Yes
p_0	Probability of failure of state transition at perceive states	Yes
α	Parameter of "half control"	No
x	Parameters to decide column movement time	No
y	Parameters to decide column movement time	Yes
$\Delta\delta_{\min}$	Minimum column movement	Yes

movement seems to exist. Such a minimum movement is defined as $\Delta\delta_{\min}$.

E. Summary of the Proposed Model Flow and the Required Parameters

The flow of the proposed model explained before is summarized as follows.

1) At perceive 1 state, the pitch command in mind is updated based on (8) and waiting for t_{int1}.
2) The required control movement is calculated based on (6), and the pilot decides whether he will move the column or not with the probability of $p(\Delta\delta_1)(1 - p_0)$. ($p(\Delta\delta_1)$ can be calculated by (4).)
3) If he decides to move the column, the new column position will be applied by (5) and moved to perceive 2 state. Otherwise, he will go back to perceive 1 state.
4) Perceive 2 state is triggered every t_{int2}. The required control movement is calculated based on (7). If $\Delta\delta_1\Delta\delta_2 > 0$, he moves back to perceive 1 state. Otherwise, he moves to D control state or stays with a probability of p_0.
5) At D control state, the new column position is applied by (5). After that, he moves back to perceive 1 state.

Many parameters are required for the calculation as summarized in Table II. "Constant" means that there is a single constant parameter in the pilot model and the same parameter is used throughout a single landing simulation. Not constant parameters are randomly distributed by the following rules.

1) t_{int1} and t_{int2} follow a normal distribution with an average of $t_{\text{int1\_ave}}$ and $t_{\text{int2\_ave}}$ respectively, and a standard deviation of $t_{\text{int1\_sig}}$ and $t_{\text{int2\_sig}}$, respectively.
2) $\alpha_{\text{center}} - \alpha$ follows a gamma distribution with a shape parameter a and a scale parameter b. α is also limited between –1 and 1.
3) x follow a normal distribution with average of x_{ave}, and standard deviation of $x_{\text{ave}}\sigma_x$.

This control loop is applied to FD tracking landing control, but according to the pilot, the same control strategy is applied to most aircraft controls such as visual landing and level flight. Therefore, this model can be easily extended to other flight phases, other types of control sticks (such as the joystick type), and other types of aircraft. In addition, the proposed model has a low computational burden, so it can be used in Monte Carlo simulations to calculate the deviation at very low probability.

F. Parameter Estimation Method

Based on the discussions in the last subsection, a total of 18 parameters should be tuned. 2 parameters (x_{ave}, y) can be obtained directly from the data, so the remaining 16 parameters should be estimated. These parameters are set to fit the actual pilot control data. The key component of the proposed model is the periodical control, so the frequency analysis is included in the objective function. The objective function consists mainly of the mean square errors of the amplitude of control column movement and FD command movement between 0.04 Hz and 1 Hz. This frequency range is decided based on Ref. [13]. This model focuses on the FD tracking, so too low a frequency range is highly affected by the stochastic component, and too high a frequency range is affected by high frequency noise with little effect on tracking capability. The objective function g is described by the following equation,

$$\begin{aligned} g = \sum_i \log\left(\frac{\omega_{i+1}}{\omega_i}\right) \Big\{ & w_1 \left(\log\left(f_{\text{act}}^{\text{column}}(\omega_i)\right)\right. \\ & \left. -\log\left(f_{\text{model}}^{\text{column}}(\omega_i)\right)\right)^2 \\ & + w_2\left(\log\left(f_{\text{act}}^{\text{FD}}(\omega_i)\right) - \log\left(f_{\text{model}}^{\text{FD}}(\omega_i)\right)\right)^2 \\ & + w_3(\text{FD}_{\text{act}} - \text{FD}_{\text{model}})^2 \Big\} \end{aligned} \tag{10}$$

where w_1, w_2, w_3 are the weight parameters and $f(\omega)$ indicates the amplitude at frequency ω. FD indicates the root mean square error (RMSE) of FD command. The first term indicates the similarity of column movement, and the second term indicates the similarity of FD command. The last term indicates the similarity of FD tracking capability. By trial and error, three weight parameters are set as follows: $w_1 = 3$, $w_2 = 2$, $w_3 = 5$. Since the proposed model has a stochastic component, 50 runs (landings) of simulations are conducted and both the average and the best case result are included in the objective function. The reason is that some parameters include the degree of stochastic behavior, and if the average only is used, the stochastic parameters will converge to zero. Finally, the objective function is used with the parameter β. β is set to 0.5.

$$\beta g_{\text{best}} + (1 - \beta) g_{\text{average}}. \tag{11}$$

When conducting a simulation using the pilot model, the initial altitude is set to 1850 ft, and the other initial conditions (e.g., pitch angle, vertical deviation from glideslope) are set the same as in the actual data. The simulation data correspondent to an altitude between 1800 ft and 500 ft is extracted, and the objective function is calculated within

TABLE III
Parameter of RCGA.

Parameters	Values
Populations	100
Number of generations	500
Selections	MGG [41]
Crossover	Simplex [42]
Number of crossover	6 × (number of parameters)

this altitude range for both actual data and the pilot-model simulation data. A single pilot model is made with a single landing data, so in total 12 pilot models are created. The obtained pilot models are named after the obtained data, like "pilot model A-(i)-1" During the simulation, the lateral and speed controls are given by the autopilot and autothrottle, and only the pitch control (elevator control) is exerted by the proposed model. The autopilot is also developed based on PID control for the purpose of comparison. The frequency analysis result can differ depending on the wind turbulence, so the exactly same wind is used between the obtained data and simulation. The parameters are optimized via Real-Coded Genetic Algorithm (RCGA). The parameters of RCGA are summarized in Table III.

G. Model Comparison

To evaluate the performance of the proposed pilot model, other pilot models are also applied and parameters are estimated based on the same data. This time, two pilot models are chosen for comparison. The first pilot model is the Belyavin's pilot model, which is base of the proposed model. The overall explanation of the Belyavin's model was already provided in Section III-A. Due to the limited space in the paper, details are not described here. The 10 parameters are used as described in Ref. [13]. The second model is McRuer's model as expressed in (1). This is the linear system with 5 parameters. This model does not include remnant, and there are several ways proposed to describe remnant in linear system [6], [43], [44]. Here, the noise expressed by the following equation is added to the FD command input.

$$\frac{K_n}{s^2 + 3^2} \tag{12}$$

where K_n is the magnitude of the noise. In total, there are 6 parameters in McRuer's model. To obtain the parameters in each model to fit the human control data, the method described in Section III-F is applied.

IV. SIMULATION RESULTS

A. Comparison of the Objective Function and the Tracking Capability

Since the objective function mainly consists of the frequency data, Fig. 8 shows an example of the frequency analysis result of two terms (column movement and FD command) in the objective function for data A-(i)-1 and corresponding three pilot models. As for the column movement, all three models tend to have the similar trend to the actual data including the peak around 0.5 Hz. The McRuer model has low amplitude at high frequency, which is due to the noise expression described in (12). (12) means that low amplitude is expected at high frequency, so the amplitude of the column movement at high frequency is also small. As for FD command, the proposed model matches the actual data very well, while the other two models differ from the actual data. This might be due to bad modeling capability.

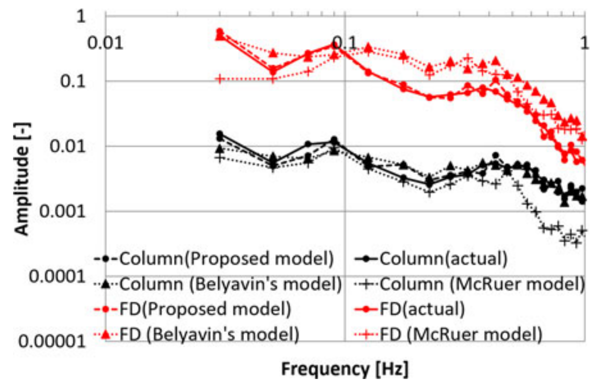

Fig. 8. Frequency analysis of flight data and three pilot models for data A-(i)-1.

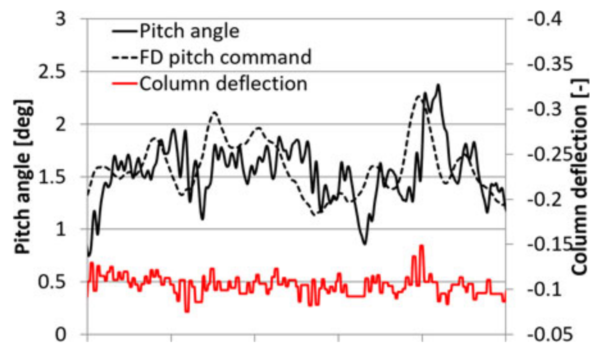

Fig. 9. Time sequences of pitch angle, FD pitch command, and column position with the proposed pilot model based on data A-(i)-1.

Next, the pitch command tracking capability and the corresponding column position based on data A-(i)-1 are shown. Fig. 9 shows the result with the proposed model, Fig. 10 with Belyavin's model, and Fig. 11 with McRuer model. All models include a stochastic component, so these figures show just one case of the results. As for the proposed model, the simulation result includes the periodical column movement and the corresponding pitch periodical oscillation characteristics perceived in the actual data too. In addition, the pitch angle usually follows the FD pitch command, but it is sometimes delayed to the FD pitch command, e.g., around 115 s, which is also the case with the actual data. As for the Belyavin's model, the result looks similar to the one by the proposed model in terms of discrete control. However, the tracking capability in this model looks worse than the actual data. Also, not like the proposed model, discrete control is performed separately, not pull and push periodical control. As for McRuer model, discrete control

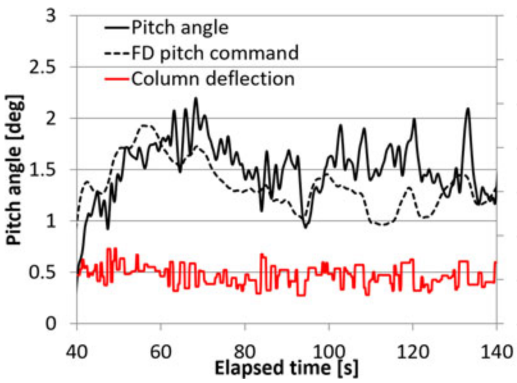

Fig. 10. Time sequences of pitch angle, FD pitch command, and column position with Belyavin's pilot model based on data A-(i)-1.

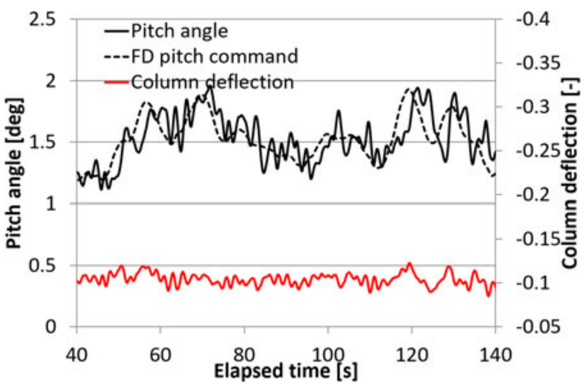

Fig. 11. Time sequences of pitch angle, FD pitch command, and column position with McRuer pilot model based on data A-(i)-1.

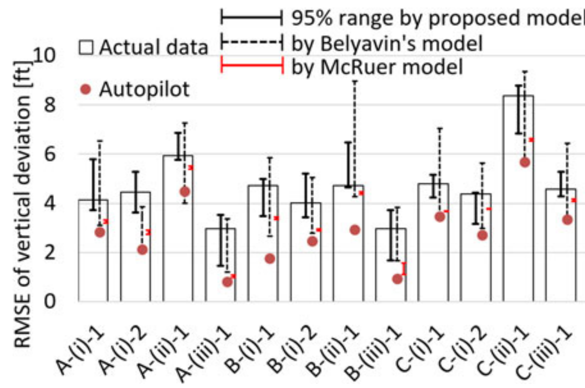

Fig. 12. Summary of RMSE of vertical deviation between actual data, autopilot, and various pilot models.

is not modeled because McRuer model is linear. Pitch oscillation is observed, but column oscillation does not follow the actual data. The tracking capability looks better than the actual data, and the large tracking delay is not observed.

Considering these results, the proposed model can imitate the pilot characteristics, such as periodical discrete stochastic movement, and the similarity to the actual data is the best in the proposed model.

B. Comparison in Vertical Deviation

The degree of vertical deviation is the main scope of the research, and this subsection considers the deviation aspect. The degree of vertical deviation is affected by various factors, such as pilot pitch tracking capability and wind effect. The vertical deviation can be evaluated by RMSE of the vertical aircraft position from the glideslope nominal path, which is not directly included in the objective function of the pilot model.

Fig. 12 shows RMSE of vertical deviation of each actual data and the 95% range of RMSE of the vertical deviation of each pilot model. For reference purposes, the red spot indicates RMSE of the vertical deviation by autopilot. Since all pilot models are stochastic, a different result is made in each simulation, so the simulation is conducted 100 times each, and 95% range is shown in the figure in each model. As for the proposed model, in all 12 cases, the actual RMSE of the vertical deviation falls within the 95% range of RMSE of the vertical deviation by the pilot model. This means that each pilot model can represent the vertical deviation characteristics. In the Belyavin's model, the 95% range of RMSE of the vertical deviation includes the actual RMSE except case A-(i)-2. This implies that the Belyavin's model also represents the characteristics of the vertical deviation. However, the 95% range by Belyavin's model is larger than that by the proposed model in most cases, which means that the Belyavin's model is more general and does not represent the control characteristics of each case. The 95% range is similar between the proposed model and the Belyavin's model for cases A-(iii)-1 and B-(iii)-1. These cases are both under no wind, so these cases may include just simple control characteristics, which can be modeled well by the Belyavin's model as well. On the other hand, as for McRuer model, the 95% range of the vertical deviation is below the actual vertical deviation in all cases. This means that McRuer model tracks the FD command better than the actual pilot. In addition, the 95% range is much smaller than that by the other two models. Even if the McRuer model includes remnant, the model always performs to track the FD command and never degrades the control characteristics.

As for the cases difference, as expected, the vertical deviation tends to be small under no wind, and large under moderate turbulence for actual data, autopilot, and pilot models simulation results. Also, the actual RMSE of the vertical deviation is 1-3 ft larger than the result by autopilot, which means that the pilot control tracking capability is worse than that by autopilot. Since the pilot can track the FD command only roughly compared to an autopilot, the worse tracking capability of glideslope in pilot model or pilot actual data is not surprising.

Considering the above discussions, the proposed model describes the pilot control characteristics the most accurately. Also, the linear model seems inappropriate to evaluate the deviation characteristics.

C. Parameter Difference Between Pilots

In the previous subsections A and B, it was verified that the proposed pilot model capture well the various pilot control characteristics. This subsection investigates the

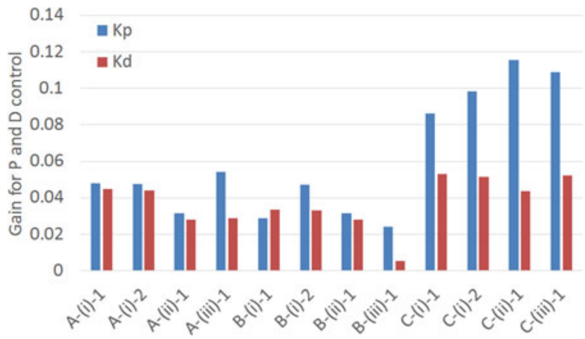

Fig. 13. Summary of K_p and K_d.

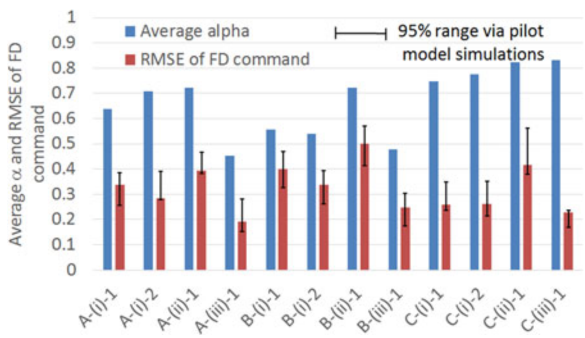

Fig. 14. Summary of average α and RMSE of FD command.

difference of pilot control characteristics via pilot model parameters. There are many parameters, so only the key parameters are compared.

First, Fig. 13 shows K_p and K_d which denote gains for P control and D control. The gain magnitudes differ among the pilots. Pilot A and Pilot B have similar gains between K_p and K_d. Both K_p and K_d gains of Pilot C are larger than those of the other pilots, and K_d is almost half of K_p in all cases. The difference in gains among various wind cases is not significant, and no clear trend is observed. The difference in gains seems to be due to randomness.

Next, Fig. 14 shows the average $\alpha(= \alpha_{\text{center}} - ab)$ in each pilot model and RMSE of FD command of both actual data and pilot model simulation. The first parameter denotes the parameter for "half control", and the second parameter is FD command tracking capability. As for the first parameter, the large α means that the pilot tries to track FD command more accurately, and the pitch tracking performance and the path tracking performance is expected to be improved, and vice versa. On the other hand, half control is recommended to avoid over-control, so a large average α is not necessarily a good human control strategy. In reality, the average α is somewhere between around 0.4 and 0.8, but in most cases the value exceeds 0.5. This means that the actual FD tracking capability is better than the so-called "half control". The variation of α also has a trend between wind cases. Under strong turbulence (A-(ii)-1, B-(ii)-1), the average α tends to be larger than the other cases in Pilots A and B, while smaller average α is observed under no wind (A-(iii)-1, B-(iii)-1) in Pilots A and B. The exception is Pilot C, where similar large average α values are observed regardless of wind conditions. Actually, RMSE of FD command in Pilot C is the smallest on average due to high average α, but the difference is not significant. Pilots A and B seem to change their control strategy by changing average α, and large average α (i.e., good FD command tracking) is applied only when needed (large turbulence). The author argues that good FD command tracking control increases the pilot's workload, so both Pilots A and B increase their workload when necessary only.

From these results, the following conclusion is made: even though there is a high degree of similarity among the parameters in all cases (pilots and wind conditions), some parameters are different which can identify the control strategy differences between cases. This also means that the proposed model works well and the parameter tuning is also appropriate.

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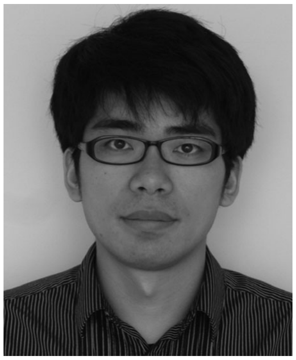

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