PILOT LANDING CONTROL ANALYSIS USING NEURAL NETWORKS UNDER SEVERE FLIGHT CONDITIONS

Ryota Mori , Yukio Yamaguchi and Shinji Suzuki
University of Tokyo

Keywords: *Flight Simulator, Neural Network, Flare, Wind Shear*

Abstract

This research discusses analyzing the differences of control among pilots under critical flight conditions. Especially, it focuses on visual landing control. Several sets of landing data from simulator experiments are obtained and the human pilot control is modeled using neural network. Finally, the obtained neural networks are analyzed by contribution and sensitivity analysis. According to the analysis result, several differences of control strategy between the pilots are observed, which depends on the pilot experience.

1 Introduction

In the early morning of 23rd March 2009, a cargo aircraft failed to land at Narita airport, killing both crew members. The detailed reasons have not been revealed yet, but it is said that the aircraft encountered severe wind shear which caused the accident. In general, during the final landing phase, aircraft are usually controlled manually. The landing control is known to be one of the most difficult maneuvers for commercial aircraft especially under severe flight conditions like wind shear. In the case of the cargo aircraft mentioned above, the fatal accident might have been avoided if the pilot had opted for a different control.

Actually, pilots hardly face such severe flight conditions, and nobody knows in advance whether they can operate the aircraft properly. Each case is characterized by unique flight environment which makes the simulation of all possible scenarios practically impossible. We call skills, which can come into the open only in emergency, potential skills. They are difficult to obtain, depends on the pilots, and are the keys for the aircraft's safety in case of emergency.

The authors' team has developed a control skill evaluation method using neural network(NN) [1]. The pilot landing control is modeled by NNs, and is then studied by analyzing the obtained NNs. In the previous study, we focused on constructing a good pilot model [2] and verifying the effectiveness of our method [3]. However, currently the differences of pilots control are examined. This paper focuses on analyzing the differences between pilot controls under critical flight conditions like wind shear. This paper introduces the analysis result of the pilot control under wind shear in a simulator experiment.

2 Neural Network Modeling of Pilot Landing Control

2.1 Neural Network and Visual Cues

Artificial NNs[4] are analogous to the biological nervous systems, and have many applications as data mining tools and pattern recognitions. The NNs can make an appropriate mapping between inputs and outputs with nonlinearity, and such characteristics make it possible to model the complex human pilot control.

For reasons noted above, we focused on the landing control. We believe that it is a difficult phase because the pilot relies mostly on the out-of-the-window view, i.e. on visual cues. In order to consider the inputs of pilot sight, several visual cues are quantified as shown in Fig. 1.

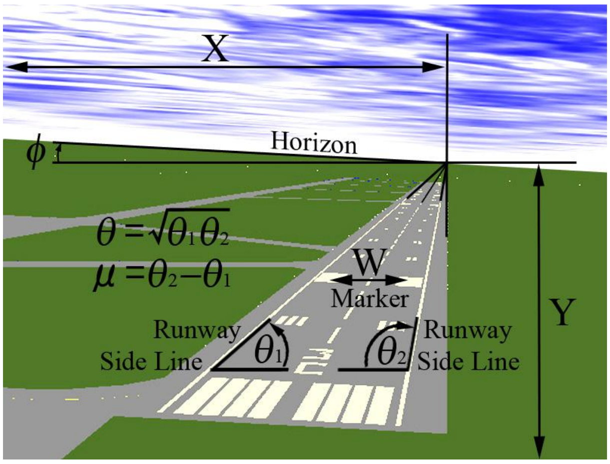

Fig. 1, Visual cues.

2.2 The Neural Network Structure

Using visual cues as inputs and pilot controls, such as column as output, the NN of pilot model is constructed. In order to simplify the model, inputs like motion cues are not taken into account. The simplified structure can easily pinpoint the difference of control strategies between pilots. The consideration of NN structures is the topic of the previous work, and an example where the column is the output is shown in Fig. 2. All inputs include 0.2 s or 0.5 s additional time delay, which corresponds to the delay of human response. We have considered the time derivatives of some visual cues to account for the derivative control. Monte Carlo landing simulations verified that these structures can imitate the pilot control.

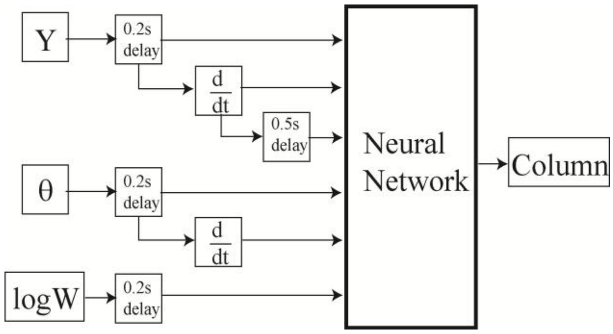

Fig. 2, NN structures for column.

NNs are trained through a supervised learning scheme based on scaled conjugate gradient algorithm[5], i.e. modeled inputs and outputs (called training data) are obtained in advance to train the model. After the training process, the NNs can be used as a model of the pilot's control behavior. A problem in training is the acquisition of good generalization, because training data contains several kinds of noise. However, the previous work showed how to overcome this problem based on weight decay method[6] and its improvement, and constructs a pilot model with good generalization automatically, without parameter tuning.

3 Analysis Methods

In order to analyze the pilot's control, among the various proposed analysis methods, this research adapts the contribution analysis and the sensitivity analysis.

As for the contribution analysis, we calculate how much the output depends on each input considering the magnitude of the weights which are the internal parameters of the NN.

Sensitivity means the partial differential of an output to an input, i.e. the degree of change of the output for small changes of inputs. A sensitivity corresponds how much sensitive a pilot is to the change of visual cue. In addition, the sensitivity has either a statistically stable direction or an unstable direction. For example, when the aircraft is banked slightly, the stable direction of aileron is to decrease the bank.

4 Experiment Condition

With the cooperation of All Nippon Airways, landing data under wind shear for three pilots are obtained with a B767 full-flight simulator. One of them is veteran captain pilot (named pilot A) and two are freshmen co-pilots (named pilot B and pilot C). In addition, experiment condition and pilots' total flight time are shown in Figs.3 and 4.

Runway	Haneda airport Runway 34R
Type of aircraft	B767-300
Weight	260000 lbs

Fig. 3, Experiment condition.

Pilot	Total flight time[s]
Pilot A	9000
Pilot B	600
Pilot C	750

Fig. 4, Pilots' total fight time.

We examine the relationship between flight experience and control strategy. Each pilot is asked to land the aircraft without go-around. Besides, we carry out the experiment under wind shear condition and standard condition at random and the pilots do not known in advance whether they encounter wind shear. In order to analyze the final landing control, the NN models are constructed using the data below around 250 ft altitude. Under wind shear, as the vertical control (column) is critical, only it is considered here.

Two types of the wind shear profile (called Wind shear 1 and Wind shear 2) are applied as shown in Fig. 5.

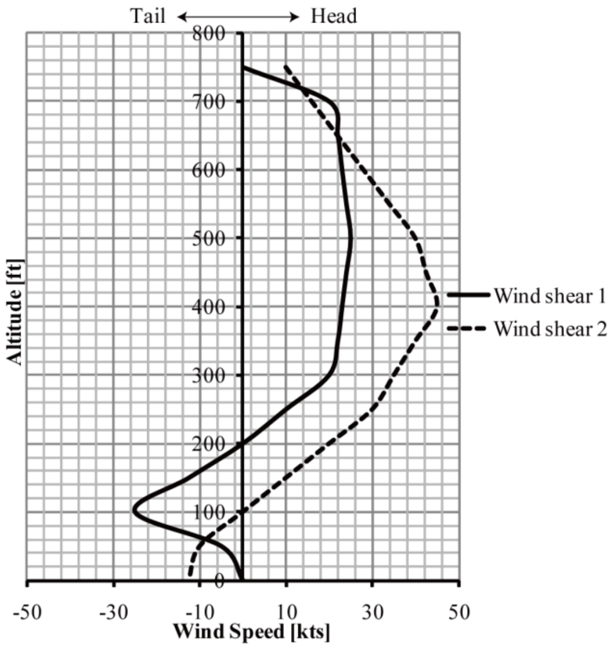

Fig. 5, Wind shear.

5 Analysis Result under Wind Shear

5.1 Flight Trajectories

First, flight trajectories are investigated. Figs. 6 and 7 show the flight trajectories in vertical direction in each pilot's case. The horizontal axis indicates the position of the direction of movement (defined X), and 0 ft indicates the edge of the touchdown zone marking. Therefore, it is preferred that the pilots land the aircraft around 0ft of X. The vertical axis indicates the altitude.

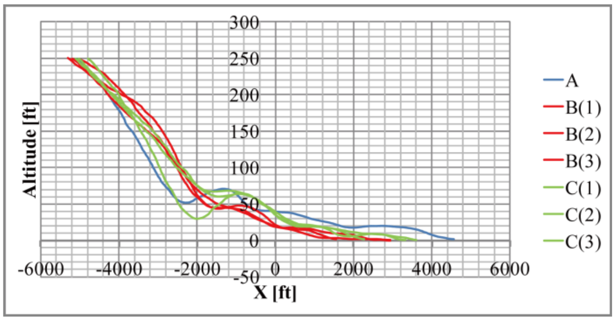

Fig. 6, Flight trajectory under Wind shear 1.

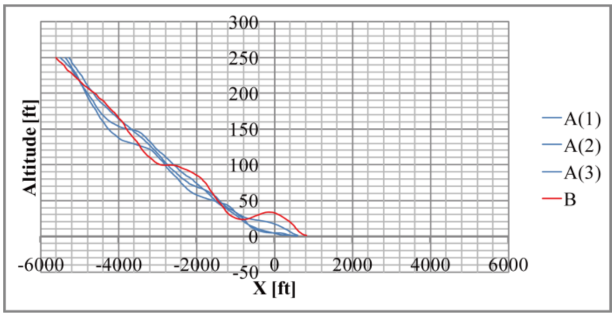

Fig. 7, Flight trajectory under Wind shear 2.

According to Fig. 6, all pilots land aircraft over the touchdown zone marking because of the heavy change of wind. On the other hand, in the case of Wind shear 2, the wind change made aircraft's attitude unstable. As a result, B's trajectory oscillated more severely than one under Wind shear1. However, we cannot examine the strategy of C's control under Wind shear 2 because we missed taking the data.

5.2 Contribution Analysis

We examine the relationship between flight experience and the factor which pilots pay most attention to. Figs. 8 and 9 show the result of the contribution analysis.

Under Wind shear 1, the factor which pilots focus on is different depending on flight experience. According to Fig. 8, All pilots deeply depend on θ (i.e. altitude), but pilot A pays less attention to dY/dt (i.e. the derivative of the pitch angle) than the others.

In the case of Wind shear 2, pilot A deeply depends on θ and W, and pilot B pays attention to θ. However, pilot B also relatively focuses on dY/dt. We think that it is because pilot B cannot help paying attention to the change of aircraft's attitude while pilot A can stabilize aircraft's attitude unconsciously.

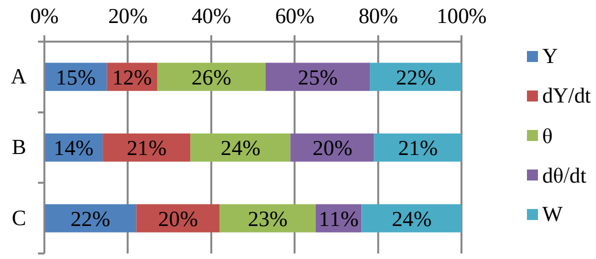

Fig. 8, Contribution analysis under Wind shear 1.

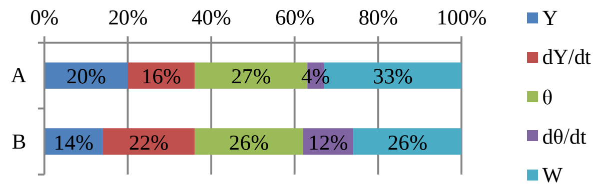

Fig. 9, Contribution analysis under Wind shear 2.

5.3 Sensitivity Analysis

Using the sensitivity analysis, We examine the relationship between flight experience and the response (i.e. column control) to the changes of visual cues. Then, Figs. 10-17 show the result of the sensitivity analysis and Figs. 18 and 19 show the change of pitch angle . In the graphs, blue markers show

A's sensitivity, red ones show B's and green ones show C's.

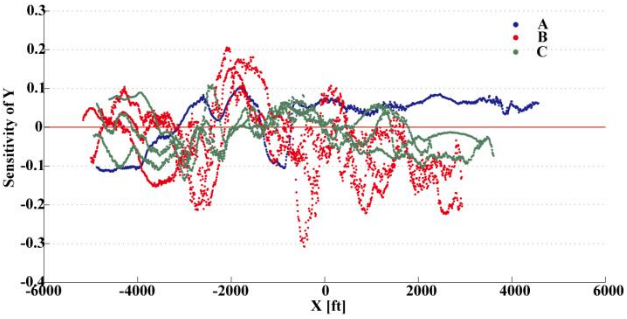

Fig. 10, Sensitivity of Y to column under Wind shear 1.

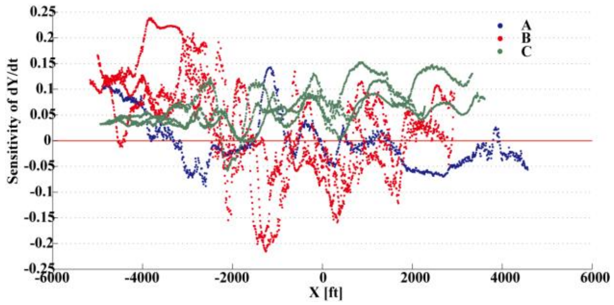

Fig. 11, Sensitivity of dY/dt to column under Wind shear 1.

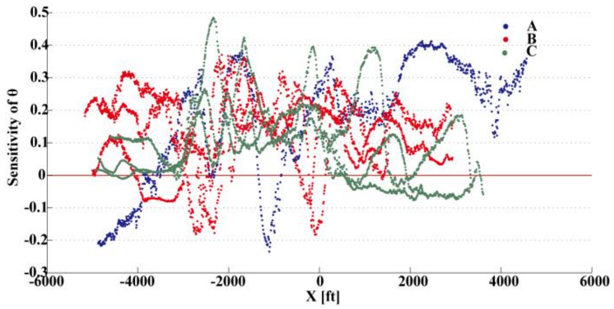

Fig. 12, Sensitivity of θ to column under Wind shear 1.

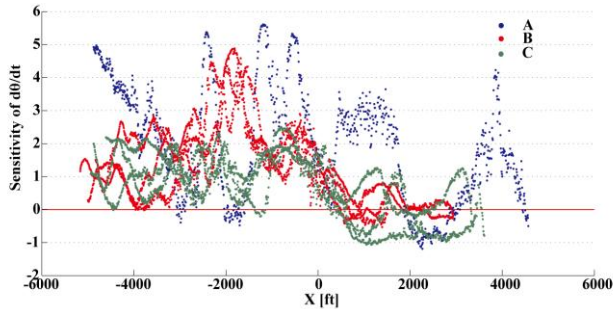

Fig. 13, Sensitivity of $d\theta/dt$ to column under Wind shear 1.

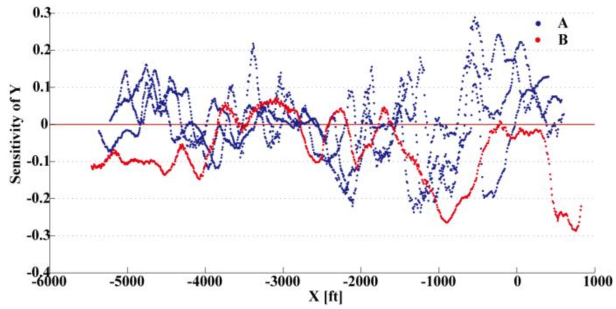

Fig. 14, Sensitivity of Y to column under Wind shear 2.

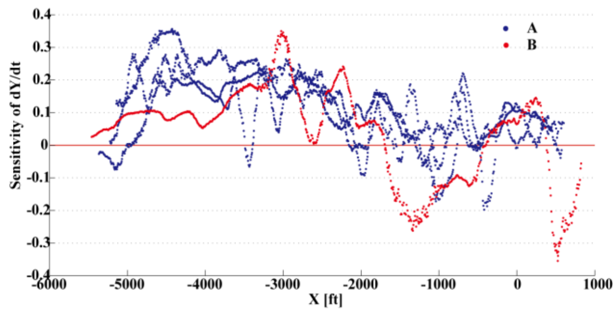

Fig. 15, Sensitivity of dY/dt to column under Wind shear 2.

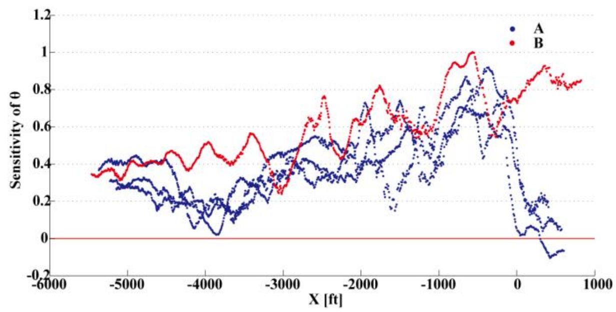

Fig. 16, Sensitivity of θ to column.

under Wind shear 2

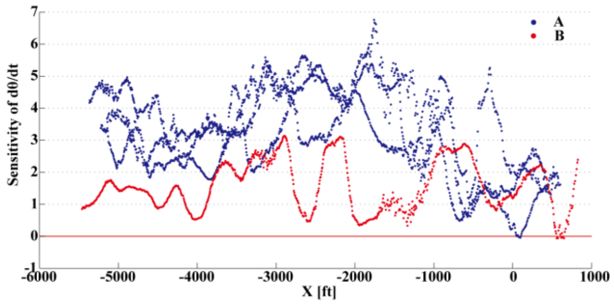

Fig. 17, Sensitivity of $d\theta/dt$ to column under Wind shear 2.

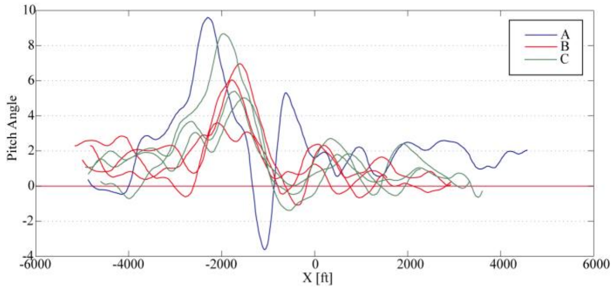

Fig. 18, Pitch angle under wind shear 1.

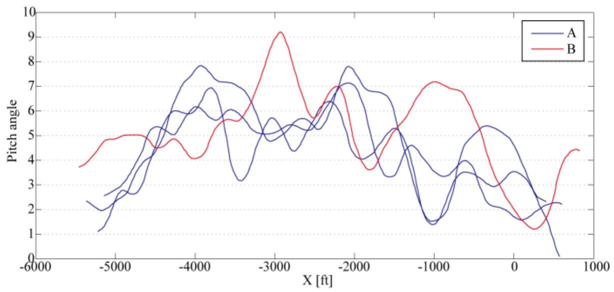

Fig. 19, Pitch angle under wind shear 2.

As regards Wind shear 1, pilot B and C are relatively sensitive to dY/dt, but A's sensitivity of $d\theta/dt$ and θ (not dY/dt) are great comparing with pilot B and pilot C. Pilot A tells that it is because while pilot B and C concentrate on the stability of the attitude, pilot A focuses on the altitude rather than the attitude.

In the case of Wind shear 2, every pilot is sensitive to dY/dt before X=-2000 [ft] because the strong wind and the heavy change of wind make aircraft's attitude more unstable than ones in the case of Wind shear 1. Besides, the closer the aircraft gets to the runway, the more sensitive to θ they sharply become. It is because they must pay attention to the altitude in order to avoid the crash to the runway. As for Fig. 17, it indicates that pilot A is obviously more sensitive to the change of the altitude than B when they encounter wind shear.

6 Conclusion

In this research, we investigated pilot landing maneuver under wind shear using NNs. The NNs were constructed to model the pilot control, and then the obtained NNs were analyzed by the contribution analysis and the sensitivity analysis. We found that there was the control difference between a captain pilot and co-pilots. They put the greatest emphasis on the different visual cues. Furthermore, when they encountered wind shear, the captain pilot was relatively sensitive to the altitude while the co-pilots were sensitive to the attitude.

For the future, we will reveal the control difference under various conditions and obtain some hints for safer controls collecting more control data. Finally, we appreciate the cooperation offered by All Nippon Airways.

References

[1] Suzuki S, Sakamoto Y, Sanematsu Y and Takahara H. Analysis of Human Pilot Control Inputs using Neural Network. *Journal of Aircraft*, Vol. 43, No. 3, pp 793-796, 2006.

[2] Mori R and Suzuki S. Neural Network Modeling of Lateral Pilot Landing Control. *Journal of Aircraft*, (in press).

[3] Mori R, Suzuki S, Sakamoto Y and Takahara H. Analysis of Visual Cues during Landing Phase by

using Neural Network Modeling. *Journal of Aircraft*, Vol. 44, No. 4, pp. 2006-2011, 2007.

[4] Shimizu T. *Neural Network and Control.* CORONA PUBLISHING CO.,LTD., 1997.

[5] Moller M F. A Scaled Conjugate Gradient Algorithm for Fast Supervised Learning. *Neural Networks*, Vol. 6, pp 525-533, 1993.

[6] Krogh A and Hertz J A. A Simple Weight Decay Can Improve Generalization. *Advances in Neural Information Processing Systems 4*, pp 951-957, 1993.

Contact Author Email Address

The author, R. Mori can be contacted by email at r-mori@enri.go.jp

Copyright Statement