ANALYSIS OF HUMAN PILOT MANEUVER USING NEURAL NETWORK MODELING

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Keywords: *man-machine system, neural network, human operation*

Abstract

The purpose of this paper is to analyze human pilot maneuver at landing phase of Visual Approach. A Neural Network Modeling approach is newly applied to analyze the information processing flow from visual cues to pilot maneuvers. Flight data that contain aircraft state variables and pilot's maneuver are obtained by using the flight simulator, and then are used as learning data for Neural Networks. The Genetic Algorithms approach is developed to determine the Neural Network structure and it's parameters. The contribution ratios and sensitivities of each visual cue and control input to pilot's maneuver are estimated by analyzing the obtained Neural Network Models. The obtained results reveal the characteristics of the skill in each pilot's maneuver.

1 Introduction

Landing is perhaps the most difficult maneuver for airline pilots in normal operations. Except fully automated landing systems such as CAT III C, pilots have to change an ILS approach to a visual approach at a final landing phase. In a visual approach, pilots have to perceive the states of an airplane, e.g., airspeed, descent rate, altitude, and pitch angle by mainly using visual cues. It is considered that the estimation skill of pilots has an important effect on smooth landing. Since it is very difficult to analyze the cognitive process in a human brain, there is a strong demand to develop analysis tools that can be utilized for pilot trainings.

It has been widely reported that visual cues have major roles when pilots capture the states of an airplane at landing phase. In 1940's, Gibson investigated the landing skill of pilots from psychological approach and proposed that the optical flow of visual cues was utilized to perceive the states of landing airplanes[1]. Recently, this hypothesis was confirmed by mathematical modeling of human brain nervous system[2], i.e., the states of a moving body could be estimated from the optical flow information by using simple neurological processes. Additionally, the optimal state estimation using Kalman Filter techniques reveals that visual cues are more important than motion cues when the effect of observation errors is minimized[3.4].

This paper proposes the application of a Neural Network (NN) Modeling for analyzing information process flows from visual cues to pilot maneuvers. Artificial Neural Networks (NN) are mathematical models that emulate biological nervous systems and are composed of a large number of highly interconnected processing elements like neurons[5,6]. The elements are tied together with weighted connections that are analogous to synapses. The synaptic connections are adjusted by learning process in biological systems. In Artificial Neural Network, a learning data set of input/output data is used for training several parameters. After the learning, the obtained Neural Network can present the input/output relationship. The Neural Network has been applied to automatic recognition systems and automatic control systems of complicated problems with high nonlinearly. Some attempts have been applied to analyze a human operation in automobile driving[7] and throttle operation of landing airplanes[8]. Authors have been applying the NN modeling to analyze an airplane pilot operation at a landing phase[9,10]. In our analysis, flight data obtained by using a flight simulator were used for the NN learning. Input data for NN are selected some visual cues, e.g., runway geometries and the horizon, and control stick input. Output data from NN are control stick deflections and throttle lever deflections. The sensitivity from input to output data and the contribution ratio of each input are computed to analyze pilot maneuvers. It is widely recognized that the most difficult problem in creating NN models is the selection of network structures and its initial parameters for learning. Authors have proposed the use of the Genetic Algorithms to search the optimal structure of Neural Network models and its parameters in order to increase the robustness characteristics[10].

This paper will present the outline of the method and demonstrate some experimental results. Especially, the comparison of veteran pilot's results and freshman pilot's results will reveal the effectiveness of our approach.

2 Neural Network and Its Training

2.1 Neural Network

An Artificial Neural Network is the information process model that is inspired by the way biological nervous system's information process. The network is composed of a large number of interconnected processing elements, i.e., neurons working in unison to solve problems[11]. When a neuron receives excitation inputs that are summed up a certain level, it sends a spike of electrical activity down to adjacent neurons. This process is modeled as shown in Fig.1 where the sigmoid function represents the threshold level of spike ignition. Arbitral nonlinear mapping functions from input data to output data can be generated from the network of a large number of neurons if an appropriate hidden layer is selected (Fig. 2).

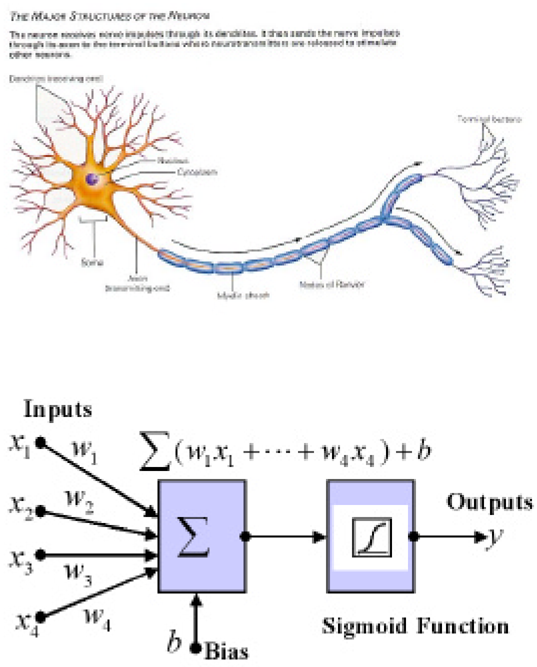


Fig. 1. Nueron[11] and Its Mathematical Model

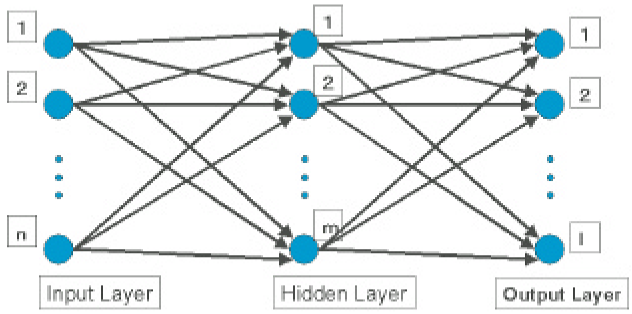


Fig. 2. 3 Layers Neural Network

A Neural Network has some parameters, e.g., weight values, and bias levels. Those parameters are determined from leaning process which minimizes the difference between the output data and computed results by the Neural Network with specified input data. This paper utilizes a kind of an efficient backward propagation method, the Levenberg-Marquardt method.

2.2 GA Approach for Determining Neural Network

The parameters in NN are trained by using flight data recorded in flight simulators as shown later. This paper newly presents the use of the Genetic Algorithms to determine appropriate network structures and some parameters.

The most difficult problem in making NN models is the determination of its structures, e.g., the number of layers and the number of nodes in hidden layers. The inappropriate choice of these numbers leads the lack of applicability of the NN for data that are slightly different from learning data. Additionally, initial values of parameters in NN are important to obtain the global optimal model since inappropriate choice of initial parameters may lead to a local minimum solution. This paper proposes the use of Genetic Algorithms (GA) for determining the NN structure and the initial parameters to increase the robust characteristics of NN.

The GA is one of optimization methods, which uses search procedures based on the mechanics of natural genetics, which combines a Darwinian survival-of-the-fittest strategy to eliminate unfit characteristics and uses random information exchange[6]. Firstly, the number of hidden layers, the initial values of parameters those are weights and bias for each neuron are coded into a binary string. Initial population is selected at random and the population is successively transformed by the use of probabilistic rules from generation to generation. Secondly, the value of a fitness function of each string is evaluated. The definition of a fitness function used in our research will be described later.

Thirdly, reproduction process is intended to select good strings with higher fitness values by using the survival-of-the-fittest concept. While the several methods are proposed in the reproduction process, this paper uses a tournament method in which strings selected at random are compared to select the string with a highest fitness. This tournament selection is repeated until the next population is obtained. Crossover and mutation following reproduction are introduced to give GA probabilistic search characteristics. In crossover process, the strings generated from reproduction are paired together at random and based on probability of crossover, the paired strings swap their bit patterns at a position selected at random. Mutation is a simple alternation of a bit in a string based on a probability of mutation. When mutation is used sparingly with reproduction and crossover, it helps in avoiding a local minimum through search iterations.

The above process is repeated until the convergence is obtained as shown in Fig. 3. Since this method requires a lot of computation time, a parallel processing approach is applied to drastically reduce the computation time.

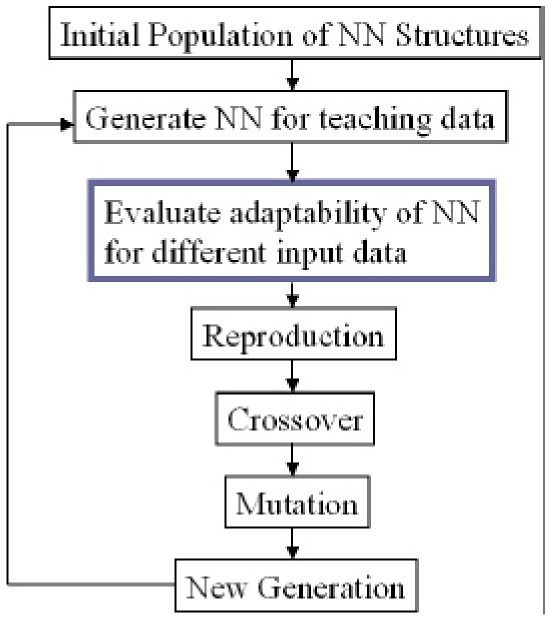


Fig. 3. Flow Chart of GA

3 Experiments and Date Analysis

3.1 NN Modeling

The B767 flight simulator (Fig.4) for airline pilot training is used to obtain an input/output data set. Input data are both visual cues and pilot maneuvers recorded in the simulator flight (Fig.5), and the output data of the Neural Network are the deflection angles of the control yoke and the throttle lever. In our analysis, the visual cues used by a pilot are modeled as shown in Fiq.6, where *Y*, *H*, and q are the height of the horizon, the marker on a runway from the glare shield, and the angle of the sideline of a runway, respectively.

Figure 7 illustrates the Neural Network model where the present and sampled past visual cues and the sampled past deflection angle of the control yoke are input data and the deflection angles of the control yoke and the throttle lever are the output data. The data are recorded in every 1/30 second and the data from the 100 ft height to touchdown are utilized for the learning process of the Neural Network.

Figure 8 shows the learning scheme of the Neural Network. The mean square error between the recorded control data and the output data from the NN is minimized to adjust weights and bias data in NN. This learning process assumed the Neural Network structure and the initial values of parameters. It should be noted that the NN determined from a simple learning might lack of the robustness. The authors are proposing the use of the GA approach to optimize the NN structure and the initial values of the parameters in order to increase the robustness of the NN model.

The fitness function in the GA is determined in the following manner. Two sets of input data are prepared for the GA process as shown in Fig. 9. The learning data are selected at intervals of 4/30 seconds. While the NN is learned by using this input data, the different sampling data (test data) as shown in Fig. 9 are used to evaluate the fitness function in GA. Then, the fitness function of each string is defined as follows:

$$f_i = \max(e_1, e_2, ..., e_N) - e_i \qquad (1)$$

where e_i is a mean square error between the recorded data and the NN output generated from the different sampling data (test data).

Fig. 4. B767 Flight Simulator

Fig. 5. Visual Screen on B767 Flight Simulator

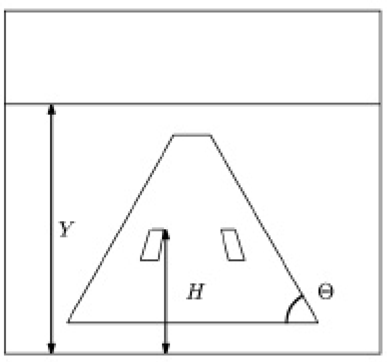


Fig 6. Visual Cue Model

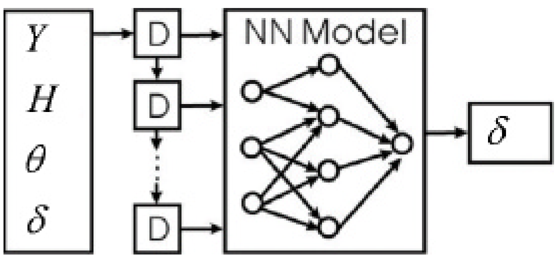


Fig. 7. Neural Network Model

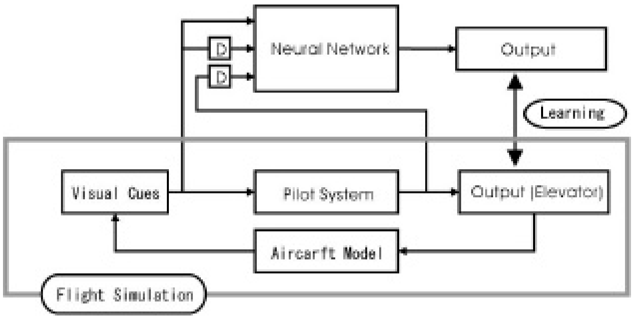


Fig. 8. Learning of the Neural Network

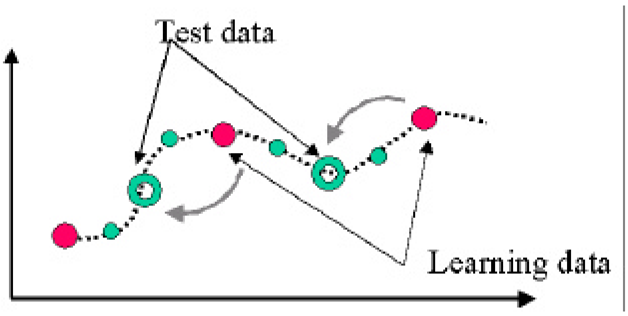


Fig. 9. Learning data in NN and Test data in GA

Figure 10 demonstrates the time history of the column angle. Blue and green lines show recorded data and the NN output data, where the NN was learned from the recoded data. While the two data indicates the excellent agreement, the simple NN may lose the adaptability for noises in input data. Figure 11 (a) indicates that the similar data of the simple NN deviate the recorded data when the test data with different sampling data is applied as the input data of the obtained NN. However, the NN optimized with GA approach improves the applicability to a large extent as shown in Fig. 11(b).

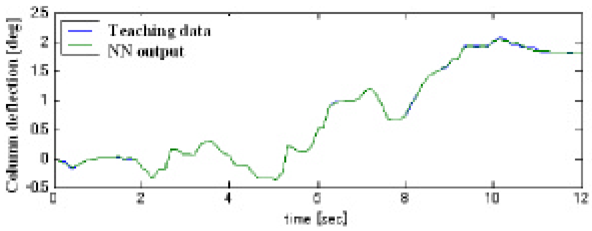
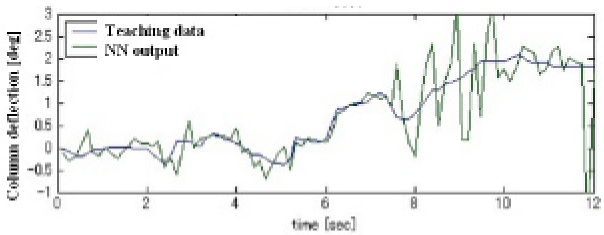
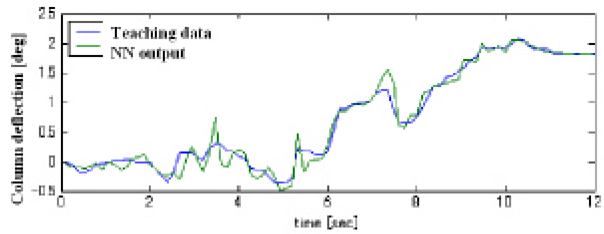


Fig. 10. Recorded data vs NN output data



(a) Simple NN



(b) NN optimized with GA approach

Fig. 11. NN output data with different input data (test data)

3.2 Analysis of Pilot Maneuver

The obtained Neural Network can be utilized to analyze the information processing done by a pilot, where several cues are utilized to make suitable maneuver. The authors developed the contribution analysis and the sensitivity analysis that indicate the contribution and the sensitivity of each input to output data. Figures 12 and 13 show the recorded data of a veteran pilot and the contribution in the column control. This indicates that the pilot increased the attentiveness to the horizontal line information just before the touch down. This coincides well with the pilot impression.

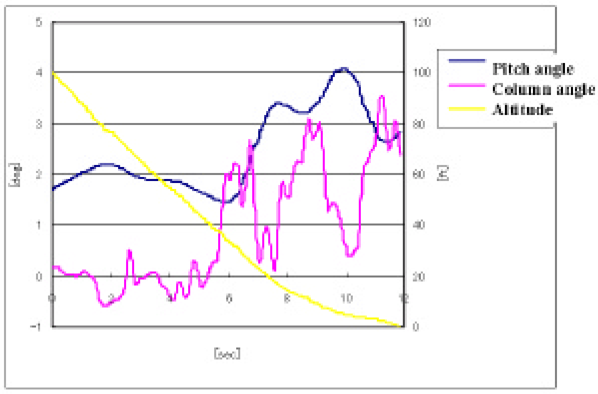


Fig. 12. Recorded flight data (Veteran Pilot)

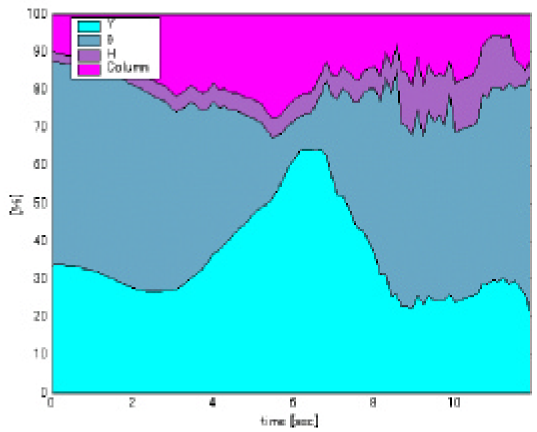


Fig. 13. Contribution analysis (Veteran Pilot)
(Y: horizontal line, q : runway inclination, H: marker position)

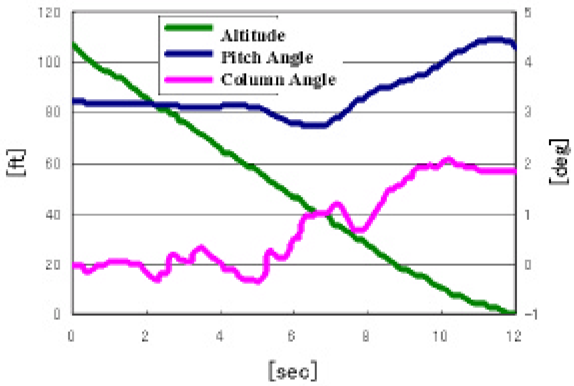


Fig. 14. Recorded flight data (Freshman Pilot)

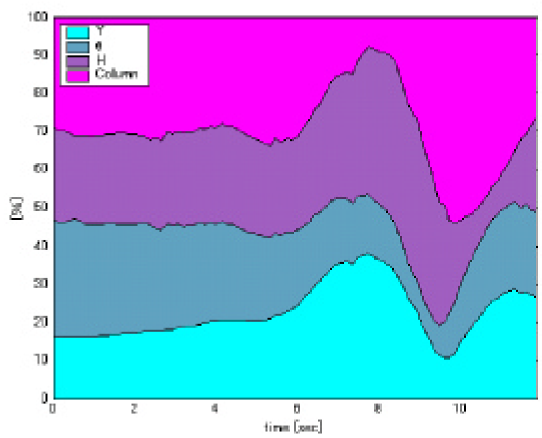


Fig. 15. Contribution analysis (Freshman Pilot)
(Y: horizontal line, q : runway inclination, H: marker position)

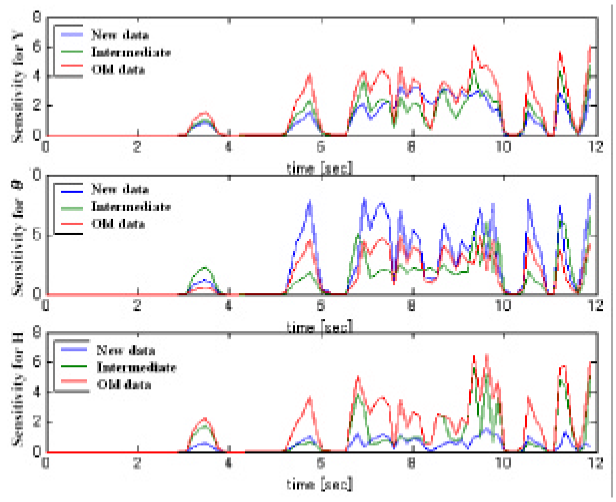


Fig. 16. Sensitivity Analysis (Veteran Pilot)

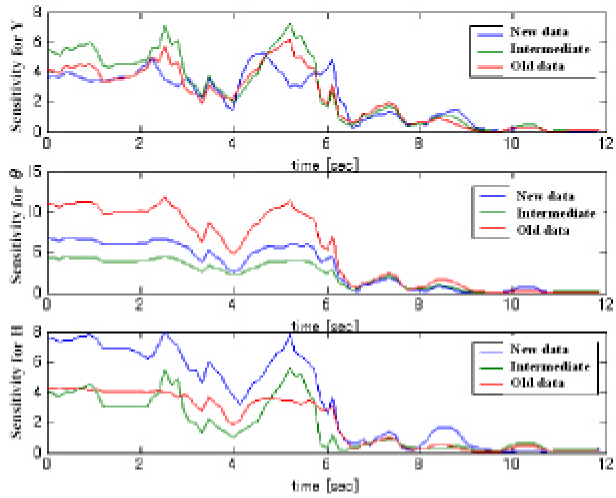


Fig. 17. Sensitivity Analysis (Freshman Pilot)

Figures 14 and 15 indicate the flight data and the contribution ratio of a freshman pilot. By comparing with the flight data of a veteran pilot in Fig. 12, the column control of the freshman pilot was moderate and slow. The conscious control of the attentiveness to visual cues is unclear in comparison with the results of the veteran pilot. The difference in two pilots operation is shown more clearly in sensitivity analysis. Figures 16 and 17 show the sensitivity for three input data to the column control. The sensitivity data are categorized as new (present to 0.27 sec), intermediate (0.27 to 1.1 sec) and old (1.1 to 1.9 sec) input data. Figure 16 means that the veteran pilot was relax just bore the flare phase and suddenly increased his sensitivity. On the other hand, Fig. 17 indicates the different pattern. Although the freshman pilot held high sensitivity during the approach phase, he lost sensitivity after the flare phase. It implies that he could not control consciously in the final phase. Two pilots' impressions support the analyzed results. It is confirmed that our approach can access the information process flow of each pilot during the visual landing phase.

4 Summary

It is considered that the proposing Neural Network analysis has a potential that can reveal information processing flow of visual cues used by a pilot at visual landing phase. The difficulties in determination of the Neural Network structure and of the initial parameters are solved by applying the Genetic Algorithms. Neural Network models are obtained by learning process for recorded simulator flight data that contains visual cues and control history. The obtained models are used to estimate the contribution ratio and the sensitivity for each input to column input. Since the model is obtained for each pilot and for each flight, obtained results can reveal the characteristics of each pilot or of each flight individually. The comparison of veteran pilot's data and freshman pilot's data clarifies the skill of each pilot. This approach is planning to be utilized in airline pilot training[12].

References

[1] Gibson J J. *The Perception of the Visual World*, Houghton Mifflin, Boston, 1950.

[2] Okamoto H, Kawakami S, Saito H, Hida E, Odajima K, Tamanoi D, and Ohno H. MT neurons in the macaque exhibited two types of bimodal direction tuning as predicted by a model for visual motion detection. *Vision Research*, 39 (20) pp 3465-3479, 1999.

[3] David K S, et al. Modeling Human Perception And Estimation Of Kinematic Responses During Aircraft Landing, AIAA, 88-4186-CP, 1988.

[4] Kuriki Y, Suzuki S, Uemura T, and Kitaki Y, Research on State Estomation of Pilot in Landing Aircraft (in Japanese), *J. of the Japan Society for Aeronautical and Space Sciences*, 49(571), pp 246-254, 2001.

[5] Arbib M A. Brains, *Machines and Mathematics*, 2nd Ed. Springer Verlag, New York, 1987.

[6] Holland J, *Adaptation and Natural and Artificial System*, Univ. of Michigan Press, Ann Arbor, MI, 1975.

[7] Kageyama I, Arai A. Research on Driver's Information Process at Accident-prone Area (in Japanese), *The 7th Transportation and Logistics Conference 2003*, pp227-230, 1998.

[8] Martens D. Neural networks as a tool for assessment of human pilot behavior in wind shear, *Aerospace Science and Technology*, 1, pp. 39-48, 1999.

[9] Hayashi K, Suzuki S, and Uemura T, Analysis of Human Pilot Behavior at Landing with Neural Network (in Japanese), *J. of the Japan Society for Aeronautical and Space Sciences*, 49(564), pp 21-26, 2001.

[10] Suzuki S, Hayashi K, and Uemura T. Analysis of Human Pilot Behavior at Landing with Neural Network 2nd report (in Japanese), *J. of the Japan Society for Aeronautical and Space Sciences*, 51(590), pp 109-113, 2003.

[11] Anthony, A.W., Introduction to Psychology http://inside.salve.edu/walsh/psychology100.html

[12] Takahara H, Kondo T, and Suzuki S. Study of Landing Technique During Visual Approach, *ICAS2004 paper*