JOURNAL OF AIRCRAFT
Vol. 46, No. 5, September–October 2009

# Neural Network Modeling of Lateral Pilot Landing Control

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DOI: 10.2514/1.42576

**Human pilot landing control has been analyzed by the authors using neural network modeling. Although the previous research considered only longitudinal control, analysis of the lateral control is the focus of this paper. The lateral control can be quite difficult under crosswind conditions, because the combination of two lateral control methodologies (crab method and wing-low method) is needed for a successful landing. To analyze lateral control, this paper makes a first step: a lateral pilot control model is established. The necessary visual cues for lateral control are defined, and neural network models for aileron and rudder controls are constructed. The adequacy of the proposed neural network model is checked by Monte Carlo simulations.**

## I. Introduction

RECENT commercial aircraft not only have an autopilot system, but they also have an automatic landing system, so that the aircraft can land at the airport automatically and safely. While cruising, the autopilot system is widely used, and the main task of the human pilot is monitoring instrument panels and checking the aircraft states for any abnormality. On the other hand, during approach and landing, the automatic landing system is rarely used. Compared with the cruising autopilot, the automatic landing system has many requirements. For example, the airport needs to be equipped with an advanced instrument landing system (such as CAT III), and the captain pilot and the aircraft have to be specially certified. The weather condition can also form restrictions for autolanding. In addition, if the pilots rely on autolanding excessively, it might result in a decline of their control skills. Manual pilot control will always be required as backup in case of failure of the automated system. Taking all these points into consideration, it is not surprising that the landing maneuvers are performed manually in most cases.

The landing is more difficult than other operations for airline pilots. The pilot has to perceive the continuous change of the situation and control the aircraft accordingly. During the final landing, he cannot afford to watch instrument panels and gets the necessary information mainly from the out-the-window view. The characteristics contained in this view will be referred to as *visual cues*. The authors have examined the relationships between visual cues and pilot control (e.g., how he times his control and what cue the pilot focuses on as time goes by). We have developed a method for the mathematical modeling of pilot control using a neural network (NN), and we have applied the obtained model to analyze a pilot's control, using contribution and sensitivity analyses [1,2] to quantitatively examine the pilot's points of attention and his subsequent reactions during flight. The difference in control strategy between veteran and freshman pilots can pinpoint any shortcomings of the freshman pilot, which makes the pilot training more effective. The ultimate goal is to develop a pilot training tool that can be used by airlines.

The authors' team considered only longitudinal motion in the past research [1,2]. In other words, only the elevator and throttle deflection were analyzed. The effectiveness of the applied analysis method was verified through simulator tests [1,2] and real flight experiments [3]. To follow up, this paper considers the lateral control. The lateral control requires two additional control devices (aileron and rudder), and there is a characteristic difficult control called *decrab* under crosswind condition. The pilot workload increases under critical flight conditions, and it is considered that the differences between pilots can be found more clearly with the analysis of lateral control. In this paper, longitudinal modeling method of the previous study is adapted to include lateral motion. In Sec. II, landing control in a visual approach is explained in detail, and the characteristic controls (flare and decrab) are introduced. In Sec. III, NN structure for longitudinal control modeling is explained first. Although the basic modeling methods were established in the previous works [1,2], there were several modeling problems. For example, the learning was time-consuming, because several NN parameters such as initial weights and biases were optimized by a genetic algorithm to assure convergence of the training error. Thus, an enhanced modeling method is detailed in this paper. In particular, the NN inputs are strictly selected, and the objective function for NN learning is refined. Next, NN models of a pilot's lateral landing control are constructed using training data obtained with a B747 simulator owned by the authors' laboratory. In Sec. IV, the adequacy of the constructed network is verified. In other words, it is confirmed that the network can obtain the characteristic of the pilot control through Monte Carlo simulations. The obtained NN models control the simulator instead of the pilot, and the flight trajectories and the time histories of aircraft states are compared. In Sec. V, this paper is concluded.

## II. Visual Landing Control

### A. Characteristics of Landing Control

This paper considers manual landing control of a simulated B747. For longitudinal control, a flare maneuver is difficult to control. The flare maneuver is a lifting-the-nose control just before the landing. Its purpose is twofold: to decrease the sink rate at the landing and to land at the main gear first. The timing of the flare maneuver is not fixed and depends on the situation. During the landing, numerous tasks have to be completed in a short time, which leads to a high workload. That is why the longitudinal control has been analyzed first in previous research. The lateral control at landing should also be considered. The lateral control is more difficult than the longitudinal control, because the lateral motion comprises two attitudes (roll and yaw), whereas longitudinal motion comprises only one attitude (pitch). The number of parameters that should be adjusted at the landing also increases. For lateral control, the additional parameters at landing are lateral position and roll and yaw angles. Although keeping the roll angle low is important to prevent touching the runway with the wingtip, the yaw angle is also an important factor. If the aircraft lands with a high yaw angle, the lateral loads on the undercarriage will be high, which might lead to damage.

Received 5 December 2008; revision received 19 January 2009; accepted for publication 19 January 2009. 

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Fig. 1 Visual information.

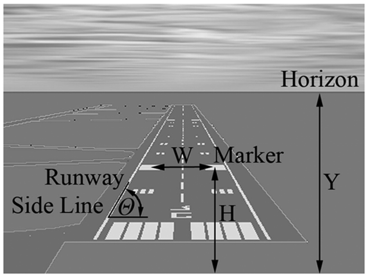


Fig. 2 Longitudinal visual cues.

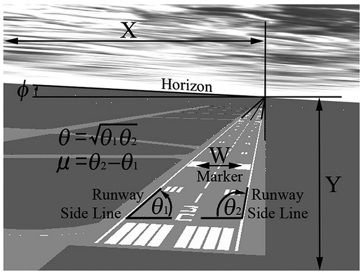


Fig. 3 Lateral visual cues.

To prevent damage in crosswind landings, the pilot changes the approach style before the touchdown. Under crosswind conditions, there are two approach styles. The first one is the so-called *crab landing method*, in which the aircraft nose is turned windward. This landing allows the pilot to keep the aircraft stable relatively easily and thus provides comfort for the passengers. However, the big difference between the direction of the aircraft and the runway may cause damage of the undercarriage.

The other approach style is called *wing low*, in which the aircraft is slightly banked windward to minimize the difference between the direction of the aircraft and the runway. In this case, it is difficult to keep the aircraft stable, resulting in a high workload for pilots and discomfort for passengers. The main advantage of the wing-low method is that the aircraft is aligned with the runway. In practice, at normal landings under crosswind, the crab approach is used first, and at a certain moment, before the touchdown, the style is shifted to the wing-low method. This maneuver is called *decrab* and it is recognized as being quite difficult for freshman pilots. This is why the pilot control analysis is extended to lateral motion in this paper.

### B. Visual Cues During the Final Landing Phase

Figure 1 shows one example of out-the-window views at final landing. During the final approach, the pilot obtains most necessary information for landing from the out-the-window views. The reasons that the pilot uses the visual information at landing are as follows:

1) It is easier to perceive small changes in aircraft movement than from instruments.

2) Visual information is more reliable and gives faster response than with the instruments.

Although motion cues are also considered to be important for landing control, they are mainly used to detect acceleration of the aircraft, not to identify the aircraft position and attitude [4]. Thus, in this paper, motion cues are not considered. According to pilot comments, below 500 ft, the pilot mainly uses the visual information for landing control and only checks the instrument panel to monitor airspeed. At the visual approach, it is considered that the pilot perceives several cues of visual information and converts them to aircraft state values such as pitch angle and altitude. The optical flow of visual cues, such as the position of the horizon or the runway shape, can help the pilot estimate the current aircraft state values [5]. According to the pilot's comment, other objects around the airport (buildings, trees, etc.) are not used as cues, and so they are not considered in this paper.

In the past research, only longitudinal control was considered. The corresponding necessary information was assumed to be only longitudinal aircraft states values (in particular, altitude, pitch angle, and the distance to the runway). Based on the pilot comments, the necessary visual cues to estimate such aircraft states were defined as 1) inclination of runway sidelines $\theta$, 2) position of the horizon $Y$, and 3) marker positions $H$ and $W$, as shown in Fig. 2.

In this paper, the visual information for lateral control is considered in the same manner. The lateral control consists of aileron control and rudder control. Information for lateral control is considered to be the lateral aircraft position from the runway centerline, roll angle, and yaw angle. This information can also be estimated from visual cues, which are the runway shape and inclination of the horizon, according to the pilot. Based on these comments, it is concluded that the three necessary state values can be obtained from the two pieces of visual information: position and yaw from the runway location and the asymmetry of its shape and roll from the inclination of the horizon. They are quantified as shown in Fig. 3. The longitudinal cues are redefined to match 3-dimensional movement. The three longitudinal cues and three lateral cues have strong mathematical relationships to specific aircraft states, which are summarized in Table 1.

## III. Construction of the NN Pilot Model

### A. Neural Network

In our research, a neural network [6,7] is used for modeling a pilot to analyze the characteristics of the pilot's control. A NN is a mathematical model of a biological nervous network, and it is composed of a large number of small computing units called *neurons*. The operation of a neuron is very simple: it acts only when the sum of weighted inputs is higher than a threshold value (bias). A mathematical neuron normally uses a sigmoid or tan-sigmoid function as the activation function, and in this research, the tan-sigmoid function is used for the hidden-layer neurons. The adopted network structure has three layers (input layer, hidden layer, and output layer). The connections between neurons are called *weights*, and these weights

Table 1 Relationship between visual cues and related aircraft state values

| Visual cues | Related aircraft state values |
|---|---|
| $Y$ | Pitch angle |
| $\theta$ | Altitude |
| $H$ | Pitch angle and longitudinal distance to the runway |
| $W$ | Longitudinal distance to the runway |
| $\phi$ | Roll angle |
| $\mu$ | Lateral position from the runway centerline and yaw angle |
| $X$ | Yaw angle |

and the biases of the neurons are the parameters of the network. In this research, the NN is used as a pilot model, which means that the NN is trained to imitate the pilot control. The pilot control can be analyzed through analysis of the NN, because the pilot and the NN eventually work in the same manner.

To construct a pilot model network, sets of inputs and output data are prepared, which are referred to as *teaching data* in this paper. In this case, the visual cues are chosen as inputs, and the pilot controls such as the elevator are chosen as outputs. The parameters of the network (weights and biases) are renewed iteratively to learn to imitate the relation between inputs and outputs. This process is called *learning*. The backpropagation method is used as the learning scheme. In this paper, a scaled conjugate gradient algorithm [8] is applied, which uses an advanced conjugate gradient method.

### B. Network Structures

In the last section, several important elements in the visual scene have been defined. However, the careful selection of NN inputs is very important. If as many NN inputs as possible are selected, whether containing necessary or unnecessary information, the NN learning does not work well, which means that an unwanted mapping is constructed. Relatively unimportant inputs can work as an important part of the network. Therefore, in the current study, a refined learning scheme is used to prevent overlearning. One of the refined points is the selection of inputs. To decrease the inputs' correlations, the derivatives of visual cues are added to the input, and the time-delayed visual cues are removed. This new selection of inputs can also decrease the number of inputs. In addition, $H$ (height of markers) was used as a visual cue in the previous study, but it has a close relationship with $Y$ (height of the horizon), and so $W$ (the width of the markers) is currently used to recognize the distance to the runway instead of $H$. Note that $\log W$, not $W$, is used as NN inputs because of the scaling problem. The pilot thinks that the distance to the runway is recognized from the size and position of the markers. It is considered that this change of the defined cues is not contradictory with any of the obtained pilot comments on the used cues.

Based on these considerations, the applied network inputs for longitudinal control are shown in Fig. 4. Separate networks are created for different outputs to refine the input selection. For the throttle output, the airspeed is added as input based on the pilot comment. All inputs have a 0.2 s time delay, which accounts for the delay of human response.

Another refined point is the NN learning flow. Overlearning is mainly caused by modeling noise. The authors have proposed a new learning method based on regularization to make the learning robust against noise. The regularization method [9] is one of the noise-deleting methods. For normal NN learning, the objective function consists of the average error between the modeled outputs and NN outputs. Using the regularization method, the objective function also includes the size of the network (i.e., the squared weights) as

$$F = \gamma \sum^{N} \frac{(x_{\mathrm{NN}} - x_{\mathrm{teach}})^2}{N} + (1-\gamma) \sum^{n} \frac{w_{ij}^2}{2n}$$

where $N$ is the number of teaching data, $n$ is the total number of network weights, and $\gamma$ is a regularization parameter. The networks generated according to the preceding description were checked through simulation tests, and the results indicated that the pilot control was imitated with sufficient generalization for the proposed analysis [10].

In the same way, the lateral pilot model is considered. The defined three lateral visual cues are used as NN inputs. Like the longitudinal network, every input includes a 0.2 s time delay, and time derivatives of the cues are also added as NN inputs. Moreover, the timing of decrab depends on the altitude, according to the pilot comment, and so $\theta$ (which is related to the altitude) is also added as NN input. In addition, the rudder pedal control is relatively smooth. As an excessive number of inputs leads to overlearning, $\varphi$ (which is relatively less important for yaw control) is removed from the inputs. Figure 5 shows the proposed NN inputs for the lateral motion. The adequacy of these networks is verified in the next section.

## IV. Verification of the Adequacy of the Networks

### A. Experiment Condition

To confirm the adequacy of the networks, a simulator experiment was carried out. The flight simulator is owned by the authors' laboratory and shown in Fig. 6. The aircraft simulated was a B747, and the experiment was conducted in collaboration with a retired B747 pilot. The initial flight condition is summarized in Table 2. The initial altitude is 1000 ft, and the longitudinal position is on the glide slope. The pilot was asked to land the aircraft without any further restriction or demand. To analyze the decrab control, the experiment was conducted 3 times each under a no-wind condition and under a 10-kt-crosswind condition. A constant crosswind is assumed.

Using the obtained data, the NN models are constructed. For both flight conditions (no wind/crosswind), the four NNs for elevator, throttle, aileron, and rudder are constructed. Of all three sets, the landing data under a 200 ft altitude are used as teaching data for both flight conditions, because this research focuses on the flare maneuver

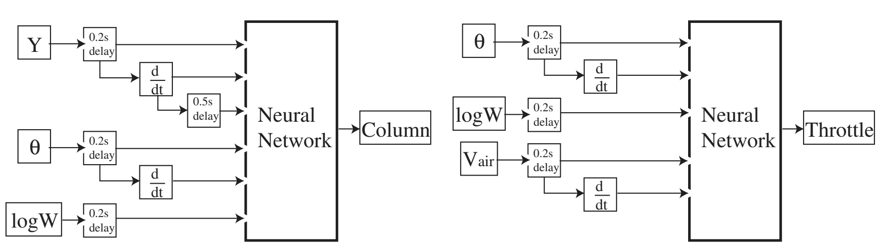


**Fig. 4 Longitudinal network structures.**

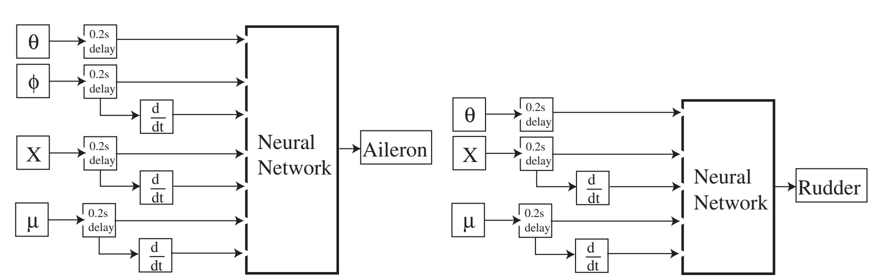


**Fig. 5 Lateral network structures.**

**Fig. 6 Flight simulator.**

and decrab control. The values of visual cues have been calculated from the relative position between the aircraft and runway.

### B. Obtained Flight Data

Figure 7 shows the time sequences of the obtained flight data (altitude, pitch angle, lateral position from the runway centerline, roll angle, and yaw angle). The horizontal axis indicates the longitudinal position from the runway, and 0 ft indicates the front edge of the runway. The yaw angle is defined as 0 when parallel to the runway. As seen from these graphs, just before the landing, the pitch angle increases. This is the flare maneuver, performed to decrease the sink rate. The big difference between the two cases is observed in the time histories of the yaw angle. Under no wind, the yaw angle is around 0. On the other hand, under crosswind, the yaw angle is about $-4$ deg at first and diminishes to $-2$ deg at $-500$ ft. This is the decrab control. In normal decrab, the yaw angle does not reach zero deg, but just half of the crab yaw angle. In other words, a combination of the crab and wing-low methods is applied. The other difference is that the landing positions under crosswind are a little windward. This is due to the fact that once the aircraft is swept away downwind, it is difficult to take the aircraft windward again, and so the pilot tries to keep the aircraft slightly windward. It is recognized that the pilot performs decrab control, and there are some differences between the wind conditions.

### C. Monte Carlo Simulations

To check the adequacy of the proposed networks, Monte Carlo simulations are performed. In these simulations, the constructed NNs are used as automatic controllers. That is to say, the NNs control the aircraft instead of the pilot. Initial flight conditions are mainly based on the teaching data at 200 ft altitude, with the addition of a few random values. In this simulation, path angle, airspeed, three attitudes, lateral and longitudinal position, and sideslip angle are distributed uniformly. The ranges of these distributions are given in Table 3. The simulations are carried out repeatedly, and the trends of the simulation results are analyzed.

Figure 8 shows the simulation results under the no-wind case. From the top, lateral position, roll angle, and yaw angle are shown. In this paper, we focus on the lateral network, and so only the lateral results are shown. In most cases, the aircraft can land on the runway with low roll and yaw angle. The roll angle is unsteady and oscillating in the teaching data (solid lines), which can also be seen in the simulation results (dotted lines). When the aircraft starts from a shifted lateral position in Monte Carlo simulations, the aircraft goes straight and the landing position is slightly shifted from the centerline. During the experiment, once the aircraft is stabilized under no wind, the adjustment of lateral position is not necessary. This means that the teaching data contain a low ability to adjust lateral position. That is why the NNs trained with a no-wind condition are unable to correct the lateral position. It is considered that this result is due to the teaching data and not due to the network input variables or training method.

These results are confirmed more clearly in crosswind simulations. The NNs trained with a no-wind condition are used for

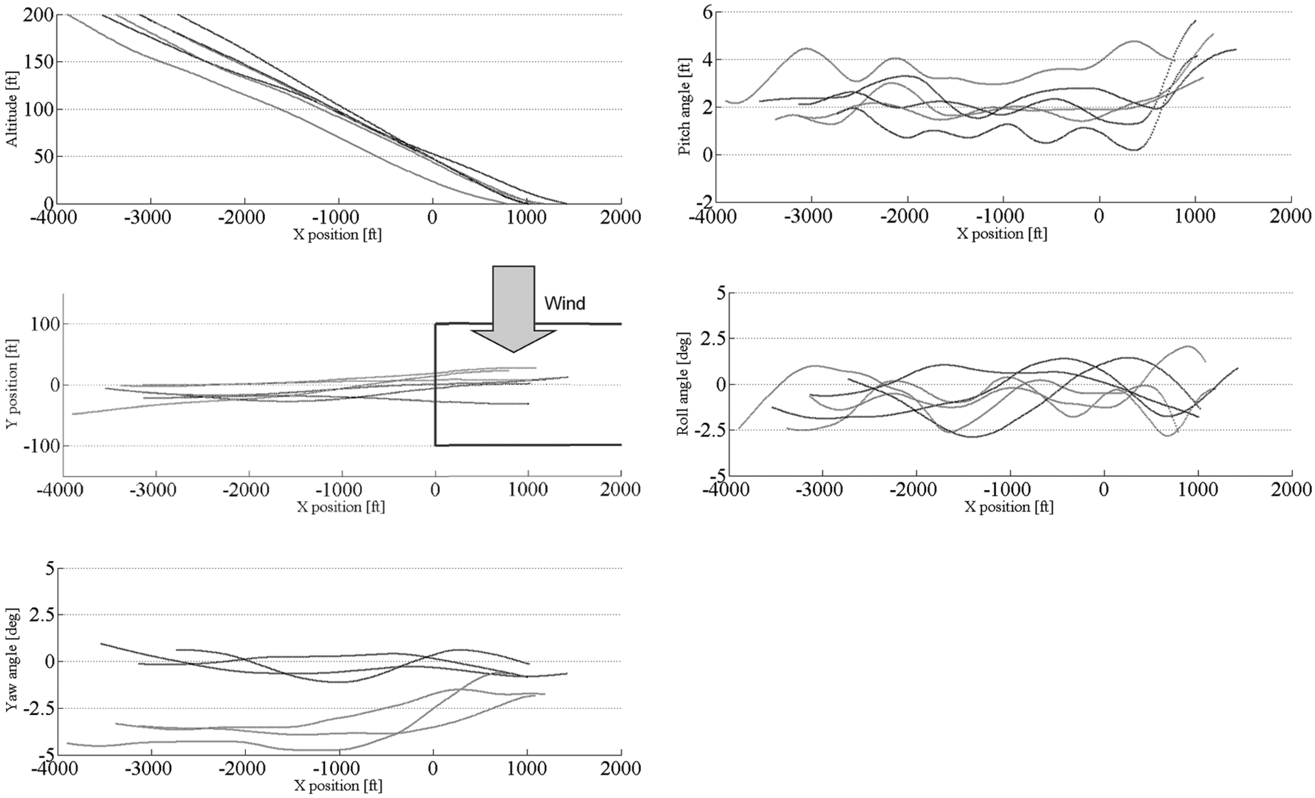


**Fig. 7 Obtained flight data: no wind (dotted lines) and crosswind (solid lines).**

**Table 2 Initial flight conditions**

| | |
|---|---|
| Weight | 564,000 lb |
| Initial altitude | 1000 ft |
| Initial path angle | −3 deg |
| Initial airspeed | 260 ft/s |
| Initial longitudinal position | On glide slope |
| Initial lateral position | 0 ft |
| Initial attitude | Trimmed |

**Table 3 Range of random values**

| | |
|---|---|
| Path angle | ±0.5 deg |
| Airspeed | ±5 ft/s |
| Roll angle | ±1 deg |
| Pitch angle | ±0.5 deg |
| Yaw angle | ±0.5 deg |
| Lateral position | ±30 ft |
| Longitudinal position | ±200 ft |
| Sideslip angle | ±0.5 deg |

Monte Carlo simulations under crosswind. The simulation results are shown in Fig. 9. These NNs are trained under no-wind conditions, and so decrab control is not trained. The time histories of yaw angle are kept around −2.5 to −5 deg, in which no decrab control is observed but the yaw angle is kept steady. The time histories of roll angle also seem steady, as under the no-wind condition. However, as for the time histories of lateral position, the aircraft sometimes deviates from the runway. This implies that the NNs trained under a no-wind condition lack the ability to adjust the lateral position.

Figure 10 shows the simulation results under the crosswind case. The figures are allocated in the same manner as for the no-wind case. Under this wind condition, without proper control, the aircraft is swept away downwind about 200 ft. Nevertheless, the NN can land the aircraft on the runway. In addition, between −2000 and −1000 ft, the yaw angle is changed to get closer to 0 deg. The yaw angle at the landing is mostly smaller than −2.5 deg. This means that the NN trained with crosswind-condition data can simulate decrab control. Moreover, the lateral landing points are slightly windward, which is characteristic for the crosswind case.

Considering these results, it is confirmed that the selection of visual cues, the NN modeling, and the learning methods are adequate for modeling human pilot landing control.

## V. Conclusions

The neural network modeling approach for pilot control has revealed the pilot's information processing flow. In the previous research, only longitudinal control had been analyzed. In this paper, the target of analysis was extended to lateral motion. The visual cues that are needed for lateral control were defined, and the lateral neural networks were constructed. To deal with the lateral control and increase the learning performance, the selection of inputs was refined. In particular, the derivative of visual cues was used instead of

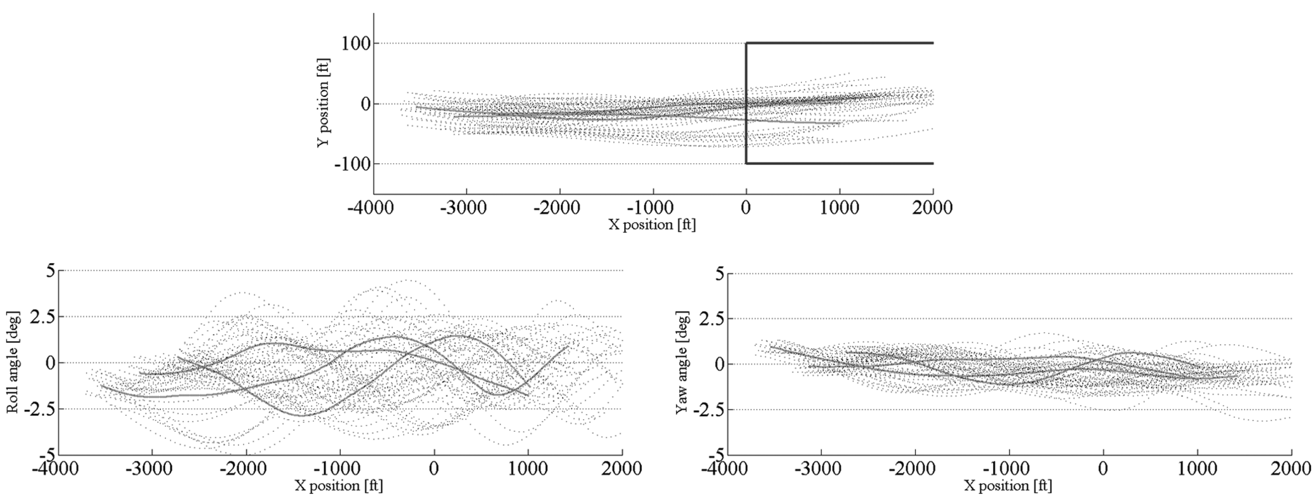


**Fig. 8 Monte Carlo simulation results under no wind: teaching data (solid lines) and simulation (dotted lines).**

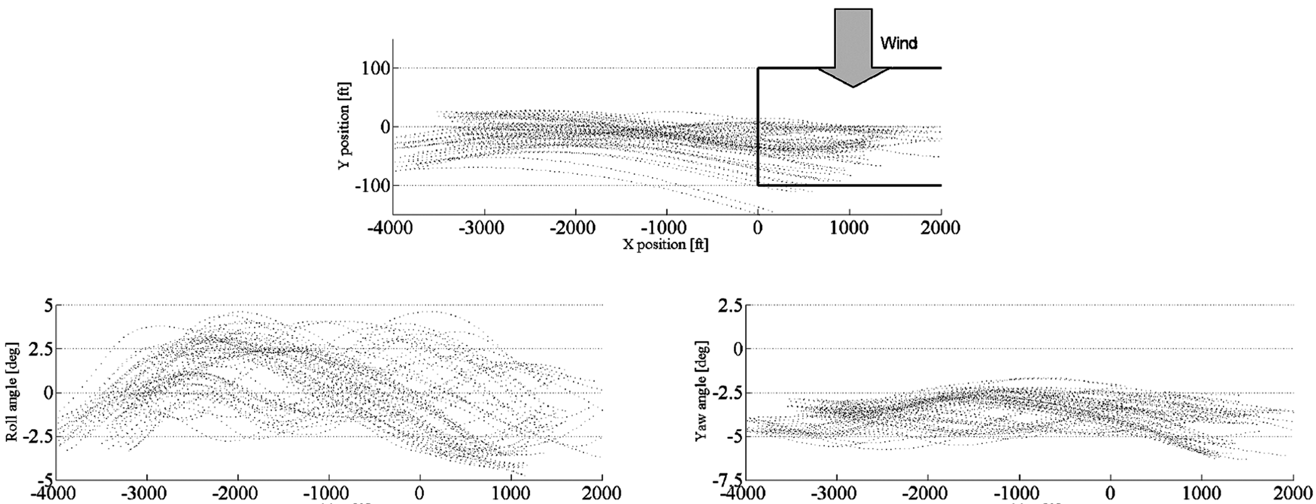


**Fig. 9 Monte Carlo simulation results under a crosswind with NNs trained by a no-wind condition.**

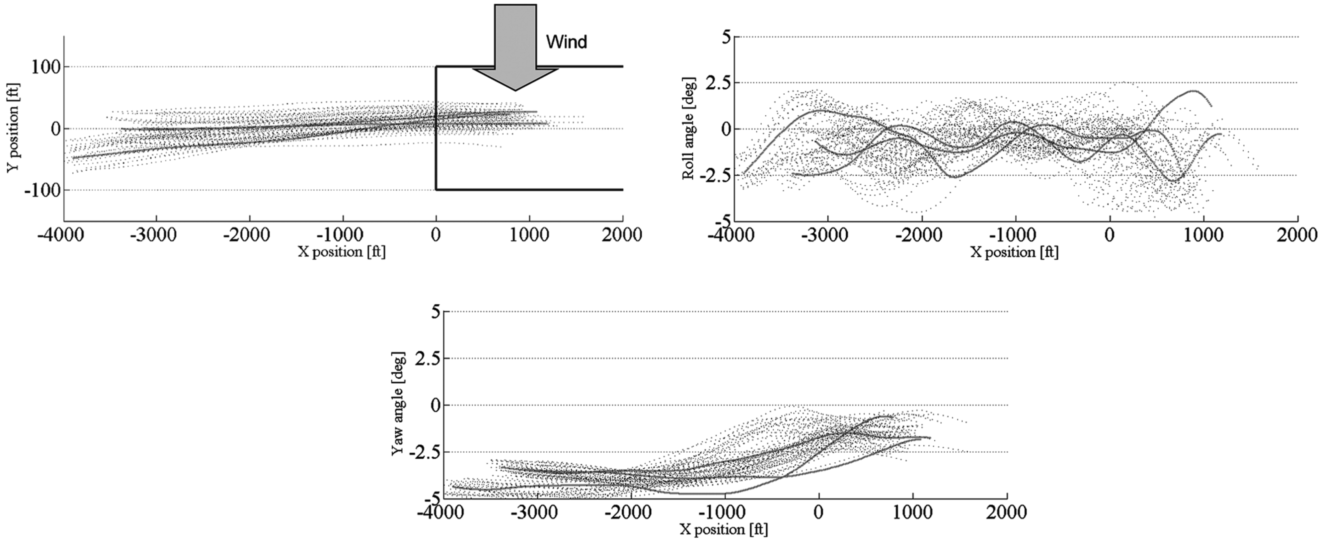


**Fig. 10 Monte Carlo simulation results under a crosswind: teaching data (solid lines) and simulation (dotted lines).**

time-delayed visual cues, and one visual cue is redefined to prevent interference of visual cues. At the same time, the learning method was refined, as the objective function now includes the size of the network. Using this method, the NN models of pilot landing control were constructed for both no-wind and crosswind conditions using data obtained with a B747 simulator. By using Monte Carlo simulations, it was confirmed that the proposed networks captured some pilot control characteristics under both wind conditions. In a future study, the pilot controls will be modeled with NNs and analyzed under crosswind conditions, and the differences in control strategies will be examined with contribution ratio and sensitivity analyses.

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