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Use of Neural Networks in Control of High-Alpha Maneuvers

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A method is presented by which an appropriately constructed artificial neural network can be "trained" to predict the force and moment coefficients of a 70-deg sweep delta wing during a high-angle-of-attack excursion. The angle-of-attack time history is a sinusoidal motion from 0 to 90 deg and returning to 0 deg. Experimental data are used to train the network, and it is demonstrated that the network has indeed learned to model the behavior of the delta wing over a range of frequencies of this type of angle-of-attack time history. The longitudinal equations of motion for a delta wing aircraft are integrated for three sinusoidal angle-of-attack time histories using the predicted network aerodynamic data. This integration generates the longitudinal control deflection time histories required to produce these maneuvers. An exploration is then made as to whether a second artificial neural network can be trained as a neural stick gearing for such maneuvers. This is investigated by attempting to train a network to associate each required control deflection time history with a specified stick position schedule.

I. Introduction

MODERN tactical aircraft have to be able to fly well into the highly nonlinear poststall aerodynamic regimes. Advantages of high-angle-of-attack supermaneuvers, such as the example shown in Fig. 1, in close air tactical engagements have been pointed out in Refs. 1 and 2, among many. Such a supermaneuver can be thought of as a large-amplitude, long-period (low-frequency) oscillation in pitch. It has been shown that these maneuvers, performed at low speeds without exceeding the pilot load factor limits, can greatly increase the survival odds. However, to perform such maneuvers, the aircraft is placed into highly nonlinear transient aerodynamic states. Completely separated transient flow and its interactions with the inertia of the airplane preclude real-time analytical estimations of the aerodynamic forces and the resulting aircraft motion.

Traditionally, in the absence of alternatives, these forces have been estimated from the steady-state aerodynamics of the aircraft.[3] This procedure was deemed acceptable because of the small values of the reduced frequency associated with the aircraft pitching motion in such maneuvers. However, as shown in Ref. 4, even small reduced frequencies can have significant effects on the aerodynamic forces and moments and specifically on their hystereses.

On the other hand, although supermaneuvers do not impose undue load factors on the pilot, the rapid rates of motion can be beyond the pilot's control. Thus, an active controller between the pilot and the aircraft is required. Devising such a control system is further complicated by strong nonlinearities of the equations of motion during transient motion with large amplitudes. The rapid changes in the state of the aircraft preclude use of small-amplitude local linearization of the governing equations. Consequently, conventional adaptive control schemes, at best, degrade the performance and, at worst, fail to generate correct control inputs to the aircraft.

Artificial neural networks are promising tools for estimation and control of high-performance agile aircraft. They have the ability to accurately model highly nonlinear behavior and dynamically adapt to changing flight conditions. Using wind-tunnel data, these networks can be initially trained to provide real-time modeling of the nonlinear aerodynamic forces. This modeling can be used to train a neural controller to obtain acceptable pilot workload and handling qualities. Later, using actual data collected by onboard flight data recorders or interactively, the networks can be trained further for ever-improving flying characteristics.

It is the intention of this paper 1) to demonstrate the ability of a neural network to "learn" the aerodynamic characteristics of an aircraft during a specific type of transient motion and to accurately predict forces and moments for inputs not previously presented to the network, demonstrating that the network has learned to model the aerodynamics for this specific maneuver, and 2) to explore the ability of a neural network to associate a control stick motion with a maneuver and to provide correct control inputs to the aircraft: a type of neural stick gearing that associates a schedule of predetermined pilot stick inputs with the longitudinal control required to achieve each supermaneuver.

II. Method of Analysis

To demonstrate the aforementioned, a three-degree-of-freedom dynamic model is used along with experimental data provided in Ref. 4.

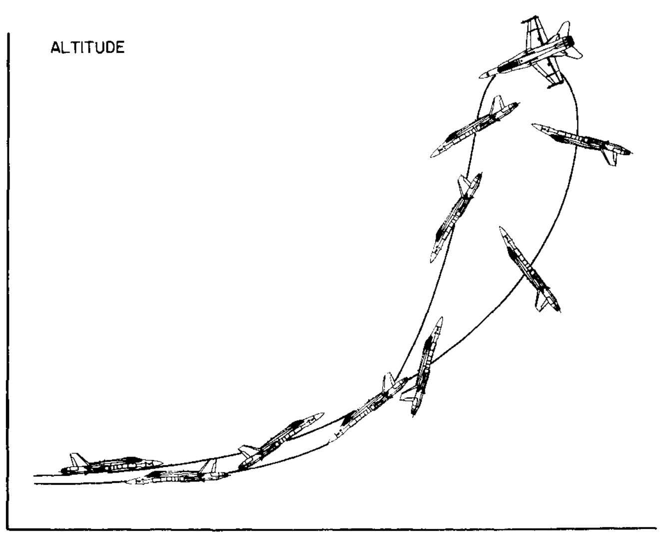

Fig. 1 Typical minimum turn-time high-alpha maneuver.

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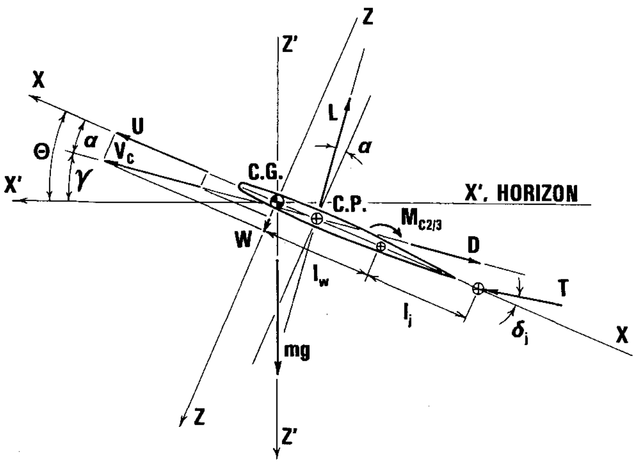

Fig. 2 Three-degree-of-freedom dynamic model.

A. Aircraft Model

1. Dynamic Model

A generic delta wing aircraft was used to model the dynamics of a supermaneuver. The aircraft closely resembled the delta wing of Ref. 4. The motion was limited to three degrees of freedom in the longitudinal mode. This was due to lack of any lateral directional aerodynamic data; however, it is believed that similar results can also be obtained in the lateral directional mode. Since the data of Ref. 4 pertained to a single wing alone, pitch control was assumed to be accomplished through thrust vectoring. Figure 2 shows the diagram of the forces and the moments acting on this model. The equations of motion of this model were developed using a body-fixed coordinate system. Limiting the motion to the longitudinal mode only, these equations were as follows:

$$M_{2C/3} - F_n l_w + T(l_j + l_w)\sin\delta_j = I_{yy}\ddot{\theta} \tag{1}$$

$$T\cos\delta_j + L\sin\alpha - D\cos\alpha - mg\sin\theta = m(\dot{U} + \dot{\theta}W) \tag{2}$$

$$T\sin\delta_j - L\cos\alpha - D\sin\alpha + mg\cos\theta = m(\dot{W} - \dot{\theta}U) \tag{3}$$

where in the body-fixed coordinates the angle of attack is defined by

$$\alpha = \tan^{-1}(W/U) \tag{4}$$

and where the climb angle is defined by $\gamma = \theta - \alpha$, δ_j is the thrust-deflection angle, and l_j and l_w are the distances defined in Fig. 2. The aerodynamic forces and moments are given in terms of the force and moment coefficients as

$$L = ½\rho(U^2 + W^2)SC_L \tag{5}$$

$$D = ½\rho(U^2 + W^2)SC_D \tag{6}$$

$$M_{2C/3} = ½\rho(U^2 + W^2)S\bar{C}C_{M_{2C/3}} \tag{7}$$

$$F_n = L\cos\alpha + D\sin\alpha \tag{8}$$

Equations (1-3) involve five variables: U, W, T, θ, and δ_j. Therefore, to solve these equations, two of the variables had to be defined a priori. In all cases, the time history of the thrust was assumed to be known. The equations were then solved with either a specified thrust-deflection-angle time history or angle-of-attack time history. Integration of these equations was performed using a four-step Runge-Kutta with standard weights and a time step of 0.001 s. Dimensions and the inertia of the aircraft were chosen so as to resemble a modern fighter aircraft. The pertinent data for this aircraft are shown in Table 1.

Table 1 Physical characteristics of the model

Parameter	Magnitude
Weight, mg, lbf	30,000
Moment of inertia, I_{yy}, slug-ft^2	80,000
Mean aerodynamic chord, $\bar{C}$, ft	20.0
Wing area, S, ft^2	45
Thrust moment arm, l_j, ft	15.0
Weight moment arm, l_w, ft	24.0

2. Aerodynamic Model

The aerodynamic data were obtained from Ref. 4. This reference gave experimentally obtained coefficients of lift, drag, and pitching moment for a delta wing with aspect ratio of 2. The wing, essentially a flat plate, was pitched in a sinusoidal motion from 0-deg angle of attack to 90 deg and back to 0. The sinusoidal motion is given by

$$\alpha(t) = (\pi/4)[1 - \cos(\omega t)] \tag{9}$$

where K is a reduced frequency defined as

$$K = \frac{\dot{\alpha}_{\max}\bar{C}}{2V_\infty} = \frac{\pi}{4}\cdot\frac{\omega\bar{C}}{2V_\infty} \tag{10}$$

The aerodynamic data of Ref. 4 are given in terms of this specific reduced frequency. Results for many different frequencies were presented in that paper. Five of those frequencies were used for aerodynamic modeling. Those aerodynamic data were used for solving the equations of motion as well as for training the neural network.

B. Neural Network

Reference 5 has discussed various methods by which an artificial neural network can be used to model dynamic systems. The method used in this paper was that of a discrete time sampled data state variable model. The aerodynamic forces and moments of the aircraft during a sinusoidal pitch oscillation were considered to be a nonlinear function of the angle of attack and angle-of-attack rate time histories. For example, the lift coefficient as a function of time during a supermaneuver was modeled as a function of the current value and two previous time sampled values of α and its time derivative:

$$C_L(t) = F[\alpha(t),\ \alpha(t-1),\ \alpha(t-2),\ \dot{\alpha}(t),\ \dot{\alpha}(t-1),\ \dot{\alpha}(t-2)] \tag{11}$$

For this equation, the time step at which the data were sampled was 0.10 s. This time increment is substantially longer than that used to integrate the equations of motion. The form of this equation was chosen based on the hypothesis that the time history of the aerodynamic coefficients are *only* a function of the first three derivatives of α. The presence of three consecutive values of the time derivative of α guarantees implicit modeling of such a dependence. Based on this consideration, the artificial neural network architecture shown in Fig. 3 was constructed to be an approximation to these models. This network was a feedforward network, each layer was fully connected to the following layer, and the network had 6 input neurons that were the current and delayed samples of angle of attack and angle-of-attack rate, 120 and 114 neurons in the two hidden layers, respectively, and 3 output neurons that were the aerodynamic force and moment coefficients of the aircraft. The input and output neurons had linear activation functions, the neurons in the hidden layers had the sigmoidal activation function

$$f(x) = 1 - \frac{2}{1 + e^x} \tag{12}$$

and the neurons were connected with simple multiplicative weighted connections. The 'activation' output signal of the ith neuron was given in terms of the sum of the signals from neurons j, weighted by w_{ij}, as

$$x_i = f_i\left(\sum_j w_{ij} x_j\right) \tag{13}$$

where f_i was the activation function of neuron i.

The network was trained by presenting it with many training pairs, each consisting of input data for the network and correct output obtained from the wind-tunnel data from Ref. 4. The training method used was a recursive least-squares form of standard backpropagation (gradient descent on the squared error at the output) implemented on an Intel iPSC/2 multicomputer (hypercube). This training method was discussed in detail in Ref. 6.

A similar artificial neural network model was used for generating the neural stick gearing for control during a sinusoidal supermaneuver. The thrust-deflection angle required at time t was assumed to be a function of current and delayed sample values of the stick deflection, angle of attack, angle-of-attack rate, pitch angle, pitch-angle rate, velocity, and thrust. The input was intentionally made redundant based on the following rationale. With current and future developments of proper neural hardware, this network would be placed on board the aircraft. The input data would be collected and the network would be continuously trained in real time. Under such conditions, significant amounts of noise would be present in the collected data. Indeed, some of the signals might periodically be lost entirely. The redundancy of the input is believed to make the network fault tolerant. Additionally, if the outputs are not a function of some of the inputs, the network would assign them very small weights. Therefore, with the exception of the CPU required for training, input redundancy is believed to have a positive effect on the final model. The neural network model used is shown in Fig. 4. It had 15 linear input neurons; 3 hidden layers with 120, 105, and 8 sigmoidal neurons, respectively; and 1 output neuron.

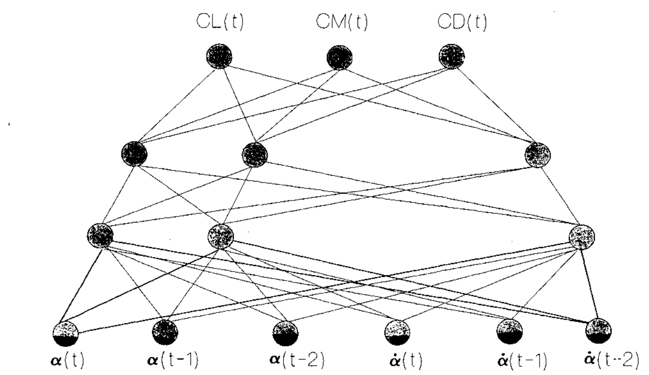

Fig. 3 Neural network architecture for delta wing aerodynamic model; data flow is from bottom to top.

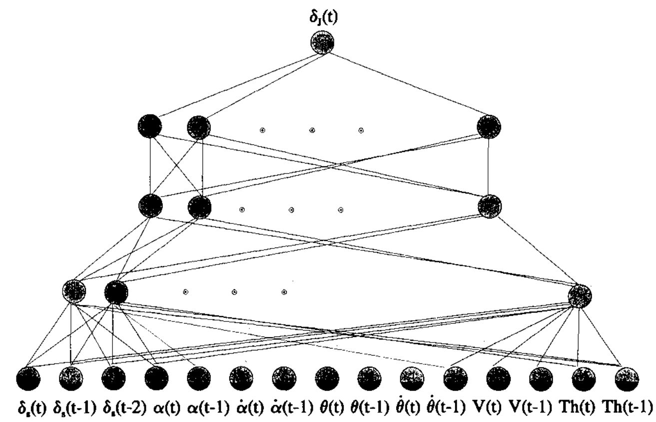

Fig. 4 Neural network architecture for neural stick gearing; data flow is from bottom to top.

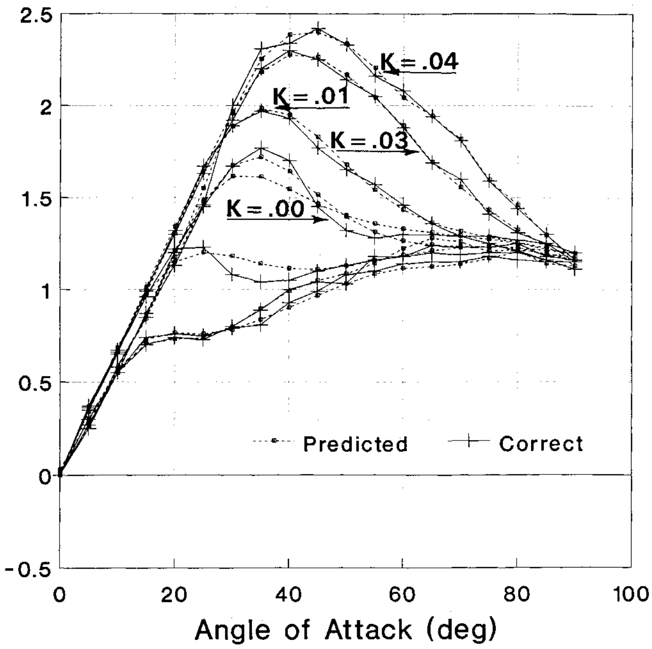

Fig. 5 Comparison between neural-network-predicted pitching moment coefficient and the correct data for the four sets of training data.

III. Results and Discussion

A. Aerodynamic Force Modeling

Reference 4 presented the coefficients of lift, pitching moment, and drag for a wide range of reduced frequencies. Five of these frequencies were deemed suitable for the maneuvers considered here. These were 0.0, 0.01, 0.02, 0.03, and 0.04.

To test the capabilities of the neural network, reduced frequencies of 0.0, 0.01, 0.03, and 0.04 were used for training. For each of the frequencies, 37 pairs of training data were used. Complete training required approximately 30 min of computation on the Intel iPSC/2 with 16 Intel 386 processors. Figure 5 shows the degree of agreement between the experimental results and those produced by the network, after training. This figure demonstrates how well the neural network could "learn" to model the aerodynamic behavior of this configuration. For the sake of brevity, only pitching moment coefficient is shown in this figure. However, similarly close results were also obtained for lift and drag coefficients. At this point, the network was used to predict, *without further training*, the aerodynamic coefficients for the reduced frequency of 0.02 that was absent in the training process. This is to demonstrate generalization by the network for this reduced frequency. For this reduced frequency, the angle-of-attack rate and the pitch rate time histories are different from those used for training. This gives novel combinations of the input current and past samples of the aircraft state, therefore demonstrating generalization. In addition, the input stick motion differs from those for which the network was trained. Figure 6 shows the comparison of the predicted results with those of the experiment. Although certain discrepancies are present between the two sets of data, the overall agreement between the two sets is remarkable. The degree of hysteresis is very well predicted for both coefficients. Similar agreement was also present for pitching moment coefficient.

To assess the effects of the previous discrepancies on the actual motion of the aircraft, the equations of motion were solved for this frequency, using both the experimental as well as the neural-network-predicted aerodynamic data. Here, the time history of angle of attack and thrust were specified, and the governing equations were solved for velocity, pitch angle, and the thrust-deflection angle required to produce the given angle-of-attack time history. The maneuver considered here was a rapid sinusoidal pitch up to 80-deg angle of attack, from trimmed level flight, and back to the initial state (the Cobra maneuver). Thrust was assumed to increase sinusoidally from that required for level flight by 20,000 lbf over a 2-s time span and to remain constant thereafter. Figure 7 shows the results. Although certain differences are present in the magnitude of the thrust-deflection angle, the resulting pitch angles are almost identical.

B. Neural Stick Gearing

At this point, it was decided to determine if the network could be trained to associate a given control stick motion with a predetermined pitch rate. The network would thus be providing a type of control "gearing" between the longitudinal stick and the thrust-deflection angle. This "neural gearing" associates longitudinal stick time histories with thrust-de-

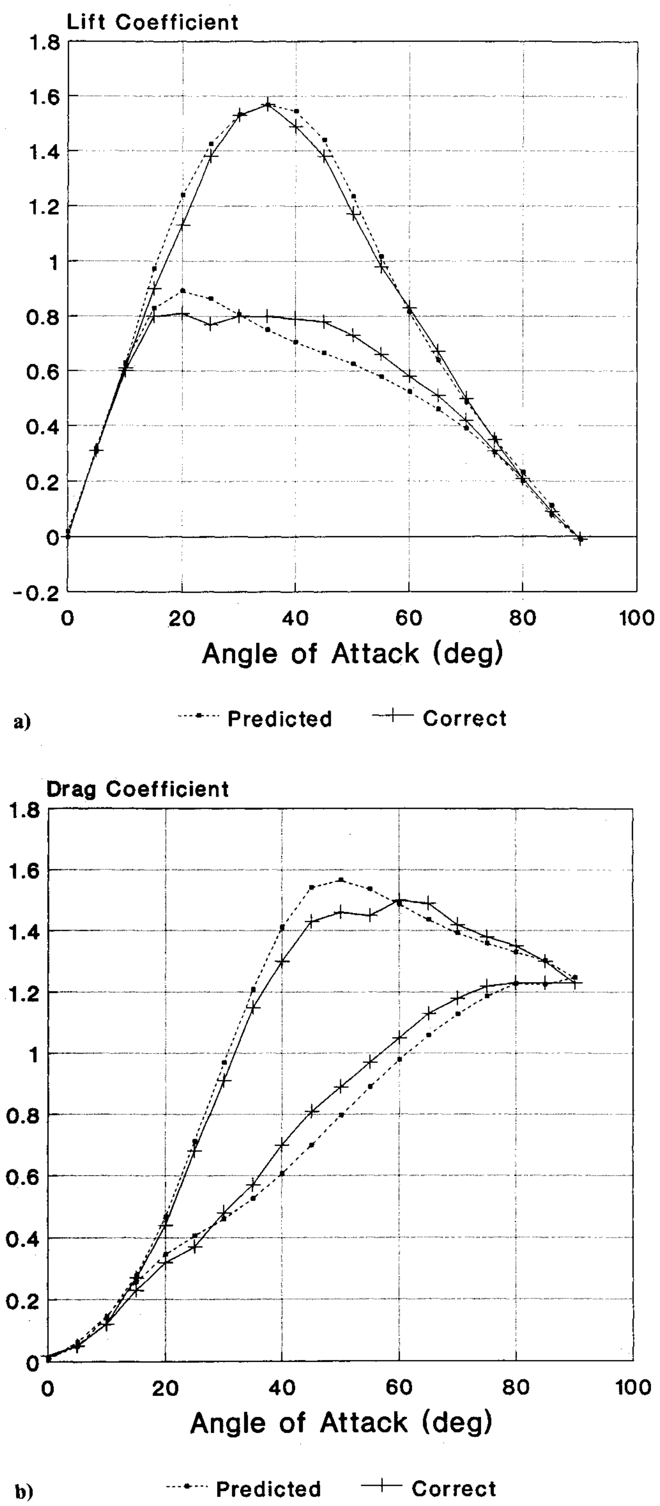

Fig. 6 Comparison between neural-network-predicted and correct data for the untrained case, $K = 0.02$: a) lift coefficient and b) drag coefficient.

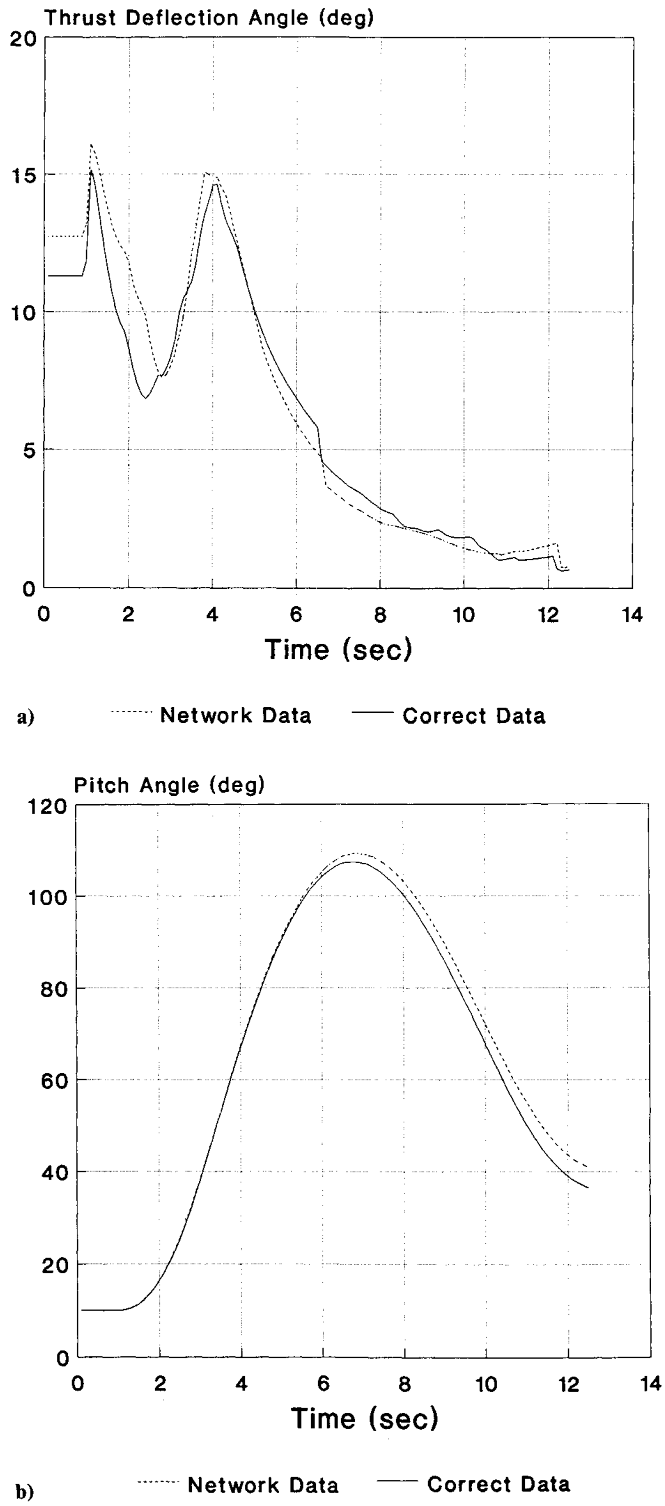

Fig. 7 Results from integrating the equations of motion using neural network and correct aerodynamic data for $K = 0.02$: a) required thrust deflection and b) pitch angle.

flection-angle time histories designed to produce specific supertype pitch maneuvers. Stick motion was composed of a sudden pull on the stick followed by a sinusoidal relaxation back to its initial position. The duration of the stick motion was matched to that of the angle-of-attack variation. The amplitude of motion of the stick was linearly connected with the magnitude of the desired frequency (i.e., degree of violence of the maneuver). The required thrust-deflection angles were calculated using the equations of motion and the experimental aerodynamic data. A network was then trained to associate each stick motion to one time history of the thrust-deflection angle. The angle-of-attack time history used for this training was 10 to 80 deg and back to 10 deg. The reduced frequencies used here were 0.01, 0.02, and 0.03. For each frequency, 200 pairs of training data were used. Complete training required approximately 4 h of computation on the Intel iPSC/2.

The results are shown in Fig. 8 for three reduced frequencies. Although the overall thrust-deflection history is predicted quite adequately, certain discrepancies are present. Primarily,

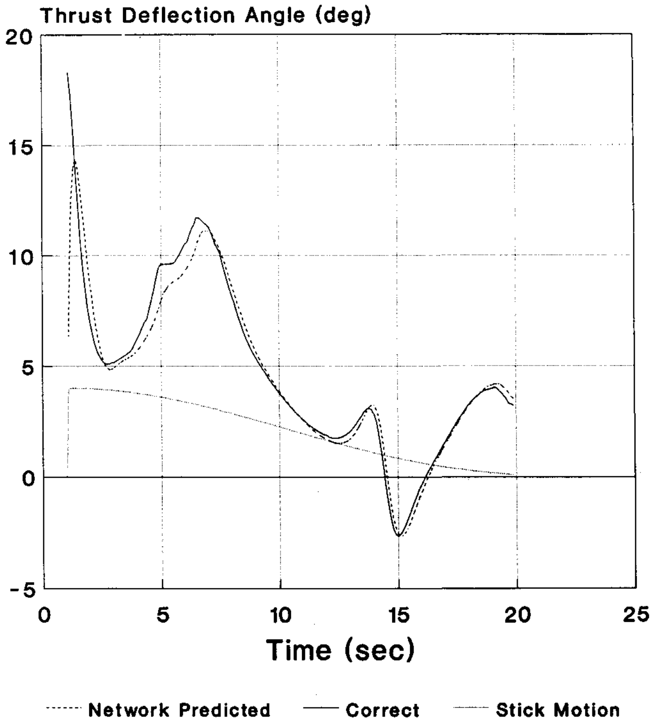

Fig. 8a Training results comparing correct and neural-network-generated thrust deflection required for the supermaneuver: $K = 0.01$.

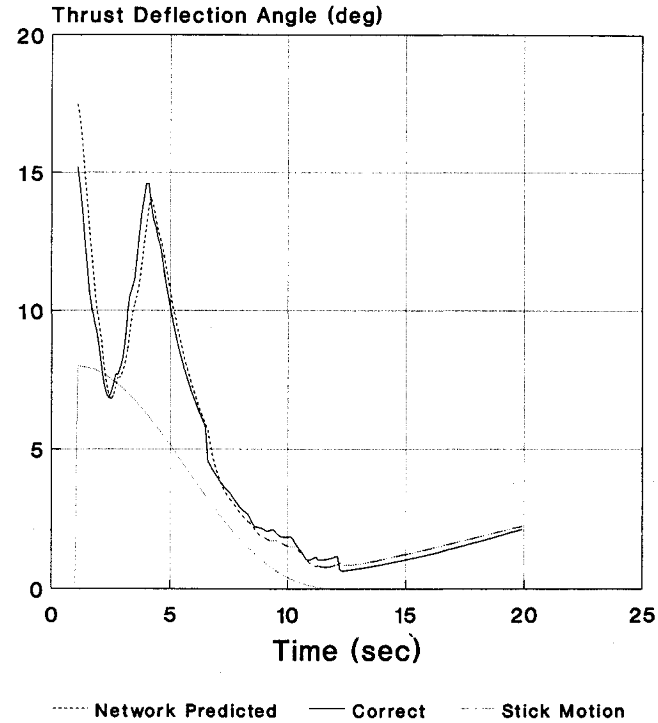

Fig. 8b Training results comparing correct and neural-network-generated thrust deflection required for the supermaneuver: $K = 0.02$.

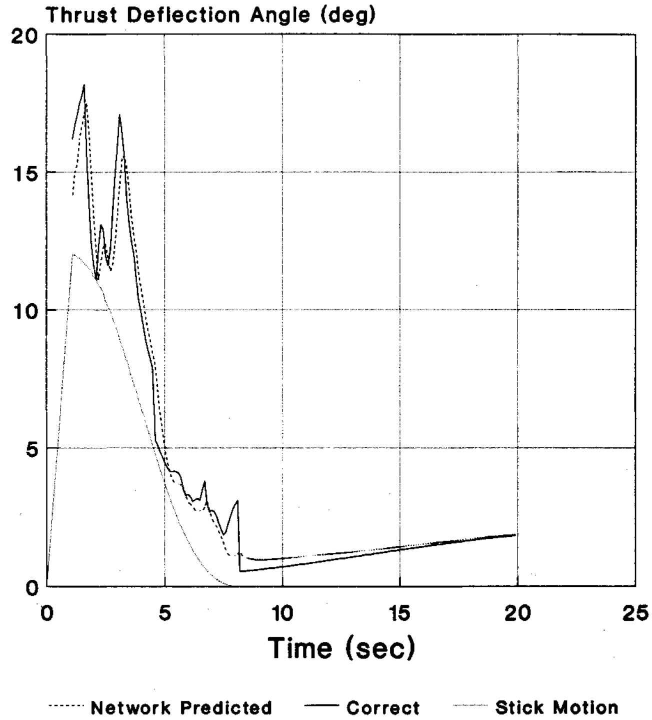

Fig. 8c Training results comparing correct and neural-network-generated thrust deflection required for the supermaneuver: $K = 0.03$.

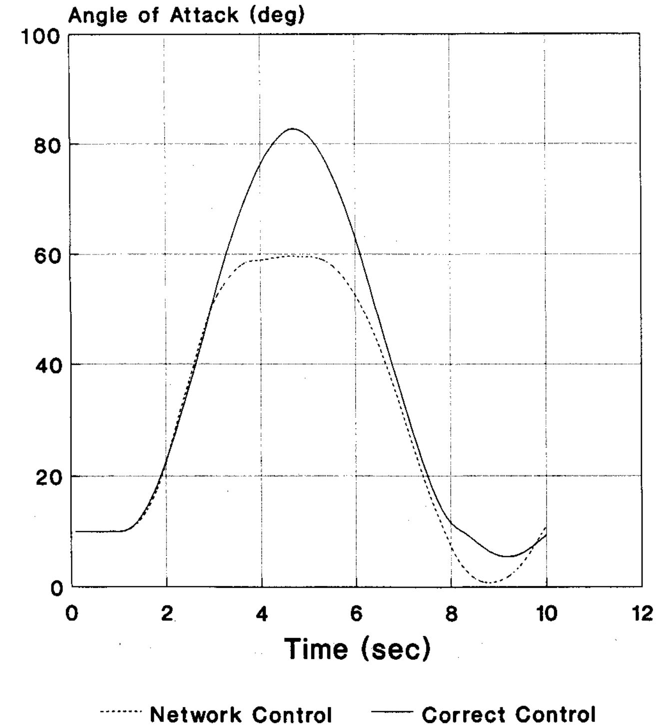

Fig. 9 Results from integrating the equations of motion using correct and neural-network-generated thrust deflections for $K = 0.03$.

it appears that the network predictions lag the correct control inputs. Also, at this point it has not been determined that the network is learning a global model for the control. The ultimate indication of accuracy was considered to be the response of the dynamic model to these predicted control inputs. Figure 9 shows the resulting angle-of-attack time history, predicted by the dynamic model, for reduced frequency of 0.03. It is quite evident from this figure that small discrepancies in thrust-deflection angle result in large differences in the angle of attack. Therefore, unlike the aerodynamic case, it appears that the neural network prediction of thrust-deflection angles does not possess sufficient accuracy to be used as control inputs to the aircraft.

IV. Conclusions

A method was presented by which a properly constructed neural network can be trained to predict the behavior of an aircraft performing a supermaneuver. The specific case of a 70-deg delta wing undergoing large-amplitude pitch oscillations was used as the test case. A hypothetical fighter aircraft was modeled using this wing.

In the first phase, the equations of motion for the three-degree-of-freedom longitudinal motion were solved using experimental as well as neural-network-predicted aerodynamic forces. It was demonstrated that a neural network could successfully learn the aerodynamic behavior of such a configuration.

In the next phase, the possibility of training a neural network to associate a specified stick motion to a predetermined control deflection schedule was explored. A second network was devised and trained by using numerically obtained data. It was demonstrated that the predicted time histories would be very much in agreement. However, because of the sensitivity of the dynamic model to control deflections, the resulting motions had unacceptable errors in angle of attack.

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