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Neural Guidance Control for Aircraft Based on Differential Flatness

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Increasing air traffic density and new strict environmental regulations have been driving researchers to develop more advanced guidance systems for civil transportation aircraft to perform complex maneuvers. In this paper, a neural guidance control scheme is proposed to make an aircraft perform more complex trajectories. Based on differential flatness, the inertial position of the aircraft can be one of the flat outputs for its flight guidance dynamics such that the corresponding guidance control input can be derived from the desired flight trajectory. However, the flatness property of the guidance dynamics implies that the guidance control input cannot be obtained analytically from the information of reference trajectories. To tackle the numerical difficulty due to its implicit flatness, the neural network is employed to construct the relationship between the flat output and the guidance commands submitted to the autopilot system for the aircraft to track the reference trajectories. An additional adaptive capability is necessary to compensate for the model approximations, disturbances, and neural-network limitations.

Nomenclature

D	=	drag, N
g	=	gravitational acceleration, m/s^2
L	=	lift, N
M	=	Mach number
m	=	mass, kg
N_1	=	fan speed of turbofan jet engine, rpm
T	=	thrust, N
V_A	=	true airspeed, m/s
V_K	=	ground speed, m/s
X, U, Z	=	state vector, input vector, flat output vector
x, y, z	=	position of the center of gravity of aircraft in the inertial frame, m
α	=	angle of attack, rad
β	=	side-slip angle, rad
γ	=	flight-path angle, rad
θ	=	pitch angle, rad
μ	=	bank angle in aerodynamic axes, rad
ϕ	=	bank angle, rad
χ	=	heading angle, rad
Ω	=	shaft-rotational speed of propeller-driven engine, rpm

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I. Introduction

BECAUSE of the sustained increase of air transportation and stricter environmental regulations enforced near airports, air traffic control systems face numerous challenges. Aircraft maneuvering capabilities are expected to be reinforced to satisfy the performance requirements for the advanced air traffic control systems and procedures. For example, to reduce the noise level during approach over urban areas, pilots might be requested to begin the descent much closer to the airport and to land at a much higher angle of attack. Therefore, a more advanced guidance control approach should be introduced to deal with the increase in maneuvering trajectories.

Recently, nonlinear control techniques have been considered to develop more efficient flight control systems within a cost effective process. More specifically, the time-consuming and costly tuning process of linear flight control techniques should be avoided. This seems feasible because nonlinear controller designs are generally based on a single analytic model with a few parameters of the system to be controlled. However, because of the involved aerodynamics and thermodynamics of aircraft, it is not possible to obtain analytical models with sufficient accuracy. Moreover, many nonlinear control techniques assume that these dynamic models are partially invertible so that dynamic inversion-related control law can be made. Numerous considerable research efforts have been made for practical application. Azam and Singh have investigated the invertibility of nonlinnear maneuvers of aircraft [1]. Later, McConley and Frazzoli et al. also made significant achievement using the helicopter applications [2,3]. However, in most dynamic inversion problems, some restricted conditions or ignorance of some important nonlinearities exists to ensure the invertibility. The resulted control input are also the functions of numbers of different system variables, which possess their own constraints. This may lead to large complexity of the control system and difficulties of optimal control. In practice, the complexity of control systems increases the strong demand of computing capability and undesirable cost of flight computers. The complexity of control systems also hinders the advance application in civil transport aircraft due to the certification difficulties. Later, differential flatness gives the dynamic inversion problem another access and largely reduces the complexity of general dynamic inversion-related control system for better prospects of application.

Differential flatness, a property of dynamic systems introduced by Fliess et al., has given new access to designing advanced control schemes for nonlinear systems that have the same number of inputs and outputs [4,5]. In brief, a dynamic system holding differential flatness means that for a set of flat outputs with the same number of control inputs, the control input and the system state can be functions of the flat outputs and theirs successive derivatives until certain order. In other words, given a trajectory of a flat output, the corresponding control input can be derived with ease. Unlike the general dynamic inversion approaches, which often generate complex control input, the differential flatness turns the control law design problem into a trajectory planning problem of the flat output [6]. Namely, the differential flatness therefore largely reduces the complexity of control systems, and the trajectory of flat output is the only concern to ensure the dynamic inversion. In the differential geometric setting, Lie–Bäcklund equivalence explains the tight links between differential flatness and dynamic feedback linearization even though the two concepts are indeed distinct. It means that any dynamic system that holds differential flatness can be feedback linearized using endogenous dynamic feedbacks [7]. This simply provides a basis to transform the system, via dynamic feedback and appropriate changes of coordinates, to a single linear system for control purpose. Consequently, the differential flatness appears to be a practical approach to efficiently deal with the control problem of highly nonlinear flight dynamics.

Early in 1992, Martin showed the inertial position of aircraft to be the flat output for complete aircraft dynamics [8]. In 1997, Hauser presented flatnesslike results for aircraft dynamics [9]. Hauser adopted a simplified aircraft model and constructed a diffeomorphism between the chosen inertial position as the flat output and the required acceleration in the body axis as the control input. Later in 2003, Cazaurang applied the flatness approach on the linear-fractional-transformation problem of a simplified aircraft longitudinal model [10]. The differential flatness (or flat system) gives the basis of the research mentioned previously to deal with the control problem of aircraft dynamics. However, none of them specifically considered the flatness property of the flight guidance dynamics for a rigid aircraft and its potential applications.

In this study, the differential flatness of aircraft guidance dynamics is considered. Regarding the control input through pitch angle, roll angle, and one engine parameter fed into the basic autopilot system of aircraft, the spatial coordinate of aircraft in the inertial frame has been shown to be one set of flat outputs of the flight guidance dynamics [11]. Flatness of flight guidance dynamics exists if and only if the diffeomorphism exists between the flat output and the control input. For civil transport aircraft, the diffeomorphism exists while a basic autopilot system enables aircraft to stabilize the inner fast dynamics and to make a coordinate turn. Therefore, the guidance control input can be derived from the inertial coordinate of aircraft and its derivatives. However, due to the high nonlinearities of aerodynamics and thermodynamics involved in the aircraft guidance dynamics, the flatness is obviously implicit because the guidance control input cannot be simply obtained by algebraic operations from the flat output. Some numerical approaches should be used to tackle the implicit flatness and completely recover the input–output mapping for control purpose.

Neural networks, at first developed to mimic the human neural system, have shown their numerical capability in various domains. In mathematics, Cybenko and Funahshi have shown that neural networks can be made for function approximation with sufficiently significant data for both the input and the output [12,13]. In this study, neural networks are introduced as a numerical device to establish the mapping between the flat output and guidance control input, which are, respectively, the input and the output of a neural network. Theoretically, a well-trained neural network can be used to be a nonlinear guidance controller and to make aircraft perform smooth maneuvers to track any flyable trajectory. However, the numerical mapping based on neural networks cannot be perfect due to generalization problems from insufficient training data or modeling errors [14]. The quality of training data also severely affects the training time and the resulted mapping.

For control purpose, modeling errors and external disturbances degrade the performance of a neural guidance controller. So an additional closed loop is proposed by integrating a Luenberger observer to estimate the tracking errors and to correct the flat output.

This paper is organized as follows: The guidance dynamic model of aircraft is introduced in Sec. II. In Sec. III, the synthesis of flight guidance control law is discussed. The simulation results are presented in Sec. IV.

II. Aircraft Guidance Dynamic Model

The general guidance dynamic equations of aircraft expressed in the Earth-fixed inertial frame are

$$\dot{x} = V_K \cos\gamma \cos\chi \qquad \dot{y} = V_K \cos\gamma \sin\chi \qquad \dot{z} = -V_K \sin\gamma \tag{1}$$

where $V_K = \sqrt{\dot{x}^2 + \dot{y}^2 + \dot{z}^2}$. x, y, and z are, respectively, the components of the ground velocity V_K along the three axes in the fixed-Earth reference frame. γ, χ, and z are, respectively, the flight-path angle, the azimuth angle, and the altitude. Their dynamics can be expressed by the following equations:

$$\begin{aligned} \dot{V}_A &= -\frac{D}{m} + \left(\frac{T}{m}\right)\cos\alpha - g\sin\gamma \\ \dot{\gamma} &= \frac{L}{mV_A} - \left(\frac{T}{mV_A}\right)\sin\alpha - \left(\frac{g}{V_A}\right)\cos\gamma\cos\mu \\ \dot{\chi} &= -\frac{Y}{mV_A} + \left(\frac{g}{V_A}\right)\cos\gamma\sin\mu \end{aligned} \tag{2}$$

where V_A is the airspeed; D, L, Y, and T are, respectively, the drag, lift, lateral force, and propulsional force; and α and μ are, respectively, the angle of attack and the aerodynamic roll angle.

The aircraft are supposed to be inherently stable because civil transport aircraft are assumed to be equipped with a basic autopilot to efficiently deal with their fast dynamics and to control their attitude (θ, ϕ, β) as well as their propulsion regime (the rotational speed of the stage fan N_1 for a turbofan engine or the rotational speed of the engine Ω for a propeller-driven engine). The yaw damper is supposed to make aircraft perform perfect coordinate turns with negligible side-slip angle. If no wind condition is considered, the airspeed (V_A) can be regarded as the ground speed (V_K). In addition, if roll angle ϕ is small enough, we can have the following relationships:

$$\chi = \psi \qquad \alpha = \theta - \gamma \qquad \mu = \phi \tag{3}$$

Replacing the flight-path angle by the pitch angle and the angle of attack, the guidance dynamics expressed in Eq. (2) can be rewritten as

$$\begin{aligned} \dot{V}_A &= -\frac{D}{m} + \left(\frac{T}{m}\right)\cos\alpha - g\sin(\theta-\alpha) \\ \dot{\gamma} &= \frac{L}{mV_A} - \left(\frac{T}{mV_A}\right)\sin\alpha - \left(\frac{g}{V_A}\right)\cos(\theta-\alpha)\cos\phi \\ \dot{\psi} &= \left(\frac{g}{V_A}\right)\cos\theta\sin\phi \end{aligned} \tag{4}$$

To simplify the aerodynamics, the drag D and lift L are, respectively, assumed to be functions of altitude z, airspeed V_A, and angle of attack α. The thrust T of jet propulsion or propeller propulsion is generally a function of altitude z, airspeed V_A, and the engine regime (N_1 for the fan speed of jet propulsion or Ω for the engine shaft rotation speed of propeller propulsion).

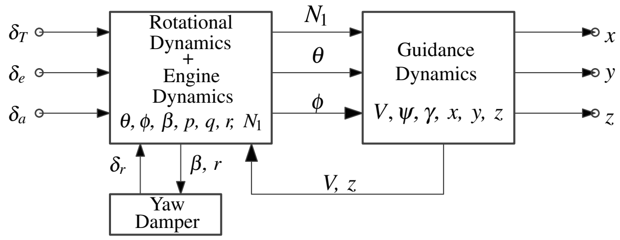

Fig. 1 Aircraft flight dynamics.

$$D = D(V_A, \alpha, z) \qquad L = L(V_A, \alpha, z) \qquad T = T(V_A, N_1, z) \quad (5)$$

From Eq. (4), the drag and the thrust are the main contributions to airspeed, with their long-period dynamics primarily dominated by the thrust, whereas the short-term dynamics depend on the pitch angle. To counteract the instant change of airspeed due to a wind gust, controlling the airspeed using the pitch angle inevitably works more efficiently than the manipulation of thrust. Moreover, due to the strong coupling effect between the airspeed and the angle of attack, the dynamics of angle of attack can be stabilized if the airspeed is well controlled, whereas the pitch angle has little effect on the slow dynamics of the airspeed. In addition, with the basic autopilot system stabilizing the attitude quickly, the angle of attack can be regarded instantly as a trim angle with respect to an airspeed at a certain thrust level. The dynamics of the flight-path angle are then mainly affected by the pitch angle rather than the airspeed, the angle of attack, and the thrust because their dynamics are much slower than the pitch angle. Therefore, the pitch angle θ can be taken as a control input of the flight-path angle. Considering the lateral dynamics, the heading angle dynamics is obviously determined directly by both the pitch angle and the roll angle.

Therefore, for guidance dynamics, the flight variables θ, ϕ, and N_1 can be taken as the inputs and also considered as the output variables for the fast dynamics of aircraft. Figure 1 illustrates the resulting structure for the entire flight dynamics.

III. Guidance Control Law Synthesis

A. Differential Flatness and Nonlinear Systems

Differential systems that exhibit dynamics with the properties of differential flatness were introduced to the control problem in early 1992 by Fliess et al. [5]. Here, two definitions of flatness are introduced: one relevant to systems for which causal relationships are displayed analytically, called explicit flatness, and the other, called implicit flatness, in which the causal relationships are introduced through implicit functions. The term differential is dropped in the remainder of this paper for brevity.

Definition 1: A general nonlinear system given by

$$\dot{X} = F(X, U) \qquad X \in \mathbf{R}^n, U \in \mathbf{R}^m \quad (6)$$

where F is a smooth mapping, is said to be explicitly flat with respect to the output vector Z, if Z is an m-order vector that can be expressed analytically as a function of the current state, the current input, and the successive derivatives of the current input such that the state and the input vectors can be expressed analytically as a function of Z and its derivatives. Then there exist smooth mappings F_X, F_U, and F_U such as

$$Z = G_Z(X, U, \dot{U}, \ldots, U^{(p)}) \qquad X = G_X(X, U, \dot{U}, \ldots, U^{(q)})$$
$$Z \in \mathbf{R}^m \qquad U = G_U(X, U, \dot{U}, \ldots, U^{(q+1)}) \quad (7)$$

where p and q are integers. Vector Z is called a flat output for the nonlinear system in Eq. (6).

Even though there is no systematical way to determine the flat output and its uniqueness, the flat output usually holds some physical meanings. The explicit flatness property is of particular interest for the solution of a control problem when a physically meaningful flat output can be related with its objectives. This means that the control problem of a dynamic system can be transformed into an output trajectory following problem using a flat output. In general, the flat output of Eq. (7) can be reduced, through state transformation, into a function of a single argument, the new system state itself:

$$Z = G_Z(X) \quad (8)$$

Generally, no complete analytical models are available for large numbers of dynamic systems to describe their complete dynamics. The theoretical and the experimental data are essential to numerically build the input–output relationship of a dynamic system. In these cases, available theory provides the main mathematical properties of these implicit functions, whereas experimental data is used to build accurate input–output numerical devices. This happens when flight dynamics modeling is considered either for control or simulation purposes because, in practice, the aerodynamic coefficients are obtained through interpolation across sets of lookup tables.

Definition 2: A nonlinear system given by a general implicit nth order state representation

$$F(X, \dot{X}, U) = 0 \qquad X \in \mathbf{R}^n, U \in \mathbf{R}^m \quad (9)$$

where F is a regular implicit mapping with respect to $\dot{X}$ such that the system holds implicit flatness over an interior nonempty domain $\Delta \subseteq \mathbf{R}^{n+m}$ if an mth-order vector Z can be found to meet the conditions of Eq. (7) and the condition

$$G(X, U, Z, \dot{U}, \ldots, U^{(r)}) \quad (10)$$

where G is locally invertible over Δ with respect to X and U, and r is an integer.

Furthermore, vector Z is said to be a flat output. The invertibility of G is guaranteed if the determinant of the Jacobian of G is not zero, according to the theorem of implicit functions, that is, if

$$\det\left(\frac{\partial G}{\partial(X, U)}\right) \neq 0 \quad (11)$$

Equations (9) and (10) imply that, given a trajectory of the flat output Z, it is possible to map it numerically into the input space to derive an adequate control law so that one of the more helpful properties of explicitly flat systems is still maintained. Furthermore, any established flatness of a dynamic system will also exist in numerical basis for explicitly flat systems because they can straightforwardly satisfy the relationship in Eq. (11).

B. Differential Flatness of Guidance Dynamics

By rearranging the kinematical Eq. (1), V_A, γ, and ψ can be expressed as

$$V_A = \sqrt{(\dot{x})^2 + (\dot{y})^2 + (\dot{z})^2} \qquad \gamma = -\sin^{-1}\left(\frac{\dot{z}}{V_A}\right)$$
$$\psi = \tan^{-1}\left(\frac{\dot{y}}{\dot{x}}\right) \quad (12)$$

According to Eq. (4), the state variables, V_A, γ, and ψ, can be functions of the inertial position of aircraft when the control variables, θ, ϕ, and N_1, satisfy the following relationships:

$$\dot{V}_A + \frac{D}{m} - \left(\frac{T}{m}\right)\cos\alpha + g\sin(\theta - \alpha) = 0$$
$$\dot{\gamma} - \frac{L}{mV_A} + \left(\frac{T}{mV_A}\right)\sin\alpha + \left(\frac{g}{V_A}\right)\cos(\theta - \alpha)\cos\phi = 0 \quad (13)$$
$$\dot{\psi} - \left(\frac{g}{V_A}\right)\cos\theta\sin\phi = 0$$

To simplify the notation of variables, the position coordinates of the center of gravity of the aircraft and the guidance control input can be defined as

$$Z = (x, y, z)^T \qquad U = (\theta, \phi, N_1) \tag{14}$$

Then, Eq. (13) can be regarded as implicit functions of the position vector Z of its first two derivatives with respect to time and of input U. They can be rewritten as

$$\begin{gathered} G_{N_1}(Z, \dot{Z}, \ddot{Z}, U) = 0 \qquad G_\theta(Z, \dot{Z}, \ddot{Z}, U) = 0 \\ G_\phi(Z, \dot{Z}, \ddot{Z}, U) = 0 \end{gathered} \tag{15}$$

These implicit functions can be locally invertible with respect to the input U because, for normal flight conditions, the determinant of their Jacobian is not zero:

$$\begin{vmatrix} \frac{\partial G_{N_1}}{\partial \theta} & \frac{\partial G_{N_1}}{\partial \phi} & \frac{\partial G_{N_1}}{\partial N_1} \\ \frac{\partial G_\theta}{\partial \theta} & \frac{\partial G_\theta}{\partial \phi} & \frac{\partial G_\theta}{\partial N_1} \\ \frac{\partial G_\phi}{\partial \theta} & \frac{\partial G_\phi}{\partial \phi} & \frac{\partial G_\phi}{\partial N_1} \end{vmatrix} \neq 0 \tag{16}$$

Then, the considered flight guidance dynamics can be concluded to hold implicit flatness with the inertial position of center of gravity of aircraft to be their flat output. According to the theory of differential flatness, and given the knowledge of a reference flight trajectory, it appears possible to find the corresponding control input for flight guidance dynamics.

IV. Neural Guidance System

A. Direct Neural Dynamic Inversion

Given a smooth reference trajectory for the flat output,

$$Z_c(\tau) = [x_c(\tau), y_c(\tau), z_c(\tau)]^T, \qquad \tau \in [t_0, t] \tag{17}$$

The corresponding reference input values at the instant t, $U_c(t) = [\theta, \phi, N_1]^T$, are the solutions of the equations

$$\begin{gathered} G_{N_1}(Z_c(t), \dot{Z}_c, \ddot{Z}_c, U_c(t)) = 0 \qquad G_\theta(Z_c, \dot{Z}_c, \ddot{Z}_c, U_c(t)) = 0 \\ G_\phi(Z_c, \dot{Z}_c, \ddot{Z}_c, U_c(t))R = 0 \end{gathered} \tag{18}$$

where $Z_c(t)$, $\dot{Z}_c(t)$, and $\ddot{Z}_c(t)$ are the current parameters. Because it is not possible to get an online numerical solution to this set of implicit equations, a neural network can be designed beforehand to build the previously described input–output mappings in which the current parameters are the inputs, and the components of the control vector are the outputs (see Fig. 2). Then, these input–output mappings will be available for online operation.

Multilayer neural networks (MLNN) have been proven to be able to perform function approximation with an adequate selection of the neural network structure and with a long enough learning process, although the selection of the structure and training algorithm still strongly depend on empirical rules from trial-and-error tests for different cases. A multilayer neural network can be trained through the minimization of a generalized mean-square error between field trajectory data and computed outputs.

$$\min_W \sum_{i \in I} \sum_{k \in K_i} \| U_{\mathrm{NN}}(W, Z(t_{ik}), \dot{Z}(t_{ik}), \ddot{Z}(t_{ik})) - U(t_{ik}) \|_Q^2 \tag{19}$$

where I is the set of training trajectories, K_i is the set of training points of the ith trajectory, and W is the matrix of the weights of the neural network. U_{NN} is the computed value for the input by the neural network. Here, matrix Q can be chosen as

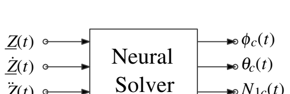

Fig. 2 Reference input generator by a neural network.

$$Q = \mathrm{diag}\{1/N_{1_{\max}}, 1/\theta_{\max}, 1/\phi_{\max}\} \tag{20}$$

Nowadays, many types of neural networks and training algorithms are available to improve the capabilities of neural networks. To achieve acceptable accuracy and generalization, sufficient training data without noise is necessary. Here, the training data is composed of sets of trajectories for both the flat output$Z$ and the guidance control input U, which can be obtained from either flight test data or simulation data of an aircraft dynamic model in which maneuvers are performed manually or by the autopilot with only basic attitude-holding capability. In general, the onboard navigation systems of modern transport aircraft are able to estimate the instant aircraft position, inertial speed, acceleration, and wind speed with good accuracy. Therefore, this information can be used for the training of the neural networks.

Figure 3 shows a possible flight guidance control structure, which integrates a neural-network solver. Tactical maneuvers can be generated from the comparison of the actual position and speed of the aircraft with its flight plan and from the intervention of the pilot through his control display unit. The neural-network solver, like a flight director, needs only the current position and tendency to the second order. To provide smooth reference values to the guidance system, these outputs can also be post processed by linear filters and checked by flight envelope control logic. Because the navigation loop is used with a discrete time scale, the drift resulting from modeling errors and perturbations will be compensated by introducing an updated reference trajectory at each current sampled time [15].

B. Closed-Loop Guidance Control

However, the direct implementation of the previously described approach will encounter increasing drift of trajectory with time because the resulting control scheme is open looped. The drifts may mainly come from the modeling errors (aerodynamic and thrust effects) and the generalization errors of a neural network. Furthermore, external perturbations (gusts and unsteady atmosphere) will also cause errors in trajectory tracking. To eliminate the drifts and errors, some measures should be taken to improve the open-looped neural guidance control scheme. An online training mechanism is often used to make the control scheme adaptive to counteract the adverse effects. It works well in many noncritical control problems. In the critical application of civil transport aircraft, the online training scheme has not yet been practical for implementation because it is still time consuming. In this study, an estimator for tracking errors is considered to close the guidance loop. To compensate for the modeling errors, the navigation equations can be written as

$$\begin{cases} \frac{\mathrm{d}Z}{\mathrm{d}t} &= \dot{Z} \\ \frac{\mathrm{d}\dot{Z}}{\mathrm{d}t} &= \ddot{Z}_c + E \end{cases} \qquad \text{with} \begin{cases} \frac{\mathrm{d}Z_c}{\mathrm{d}t} &= \dot{Z}_c \\ \frac{\mathrm{d}\dot{Z}_c}{\mathrm{d}t} &= \ddot{Z}_c + E \end{cases} \tag{21}$$

where $E = [e_x, e_y, e_z]^T$ is the acceleration error and is assumed to change slowly. Then, the trajectory drift by $\delta Z(t)$ can be defined as

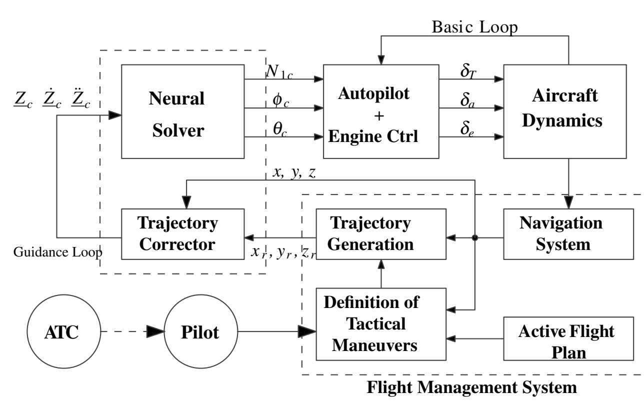

Fig. 3 A possible flight guidance control structure.

$$\delta Z(t) = Z(t) - Z_c(t) \tag{22}$$

which obeys the dynamics

$$\begin{cases} \frac{\mathrm{d}(\delta Z)}{\mathrm{d}t} & = \delta \dot{Z} \\ \frac{\mathrm{d}(\delta \dot{Z})}{\mathrm{d}t} & = E \end{cases} \tag{23}$$

assuming that E changes slowly, such that

$$\frac{\mathrm{d}E}{\mathrm{d}t} \approx 0 \tag{24}$$

Because the linear error system is observable from δZ and $\delta \dot{Z}$, a Luenberger estimator then can be built from measurements of Z and $\dot{Z}$. Therefore, the estimated error dynamics are given by

$$\dot{\hat{E}} = K_1(\delta Z - \delta \hat{Z}) \quad \text{with } \hat{E}(0) = 0 \tag{25}$$

where δZ and $\delta \dot{Z}$ are the other components of the estimation of the global state vector, and K_1 and K_2 are matrix gains, which are chosen such that nominal convergence of the estimator can be made, whereas the acceleration input of the neural-network structure can be given by

$$\ddot{Z}_{\mathrm{NN}}(t) = \ddot{Z}(t) - \hat{E}(t) \tag{26}$$

Therefore, the resulting correction scheme can be equivalent to an integral correction approach.

V. Simulation and Results

A. Simulation

A model of a general-aviation light aircraft called *Navion*, equipped with a basic autopilot system, was used through the whole study for training-data generation and simulation purposes. The training data from the nonlinear aircraft dynamics can largely avoid the noise of general flight data and expand the range of flight conditions. Then, the evaluation of the proposed guidance control scheme begins with the training of a single-layered neural network to construct an onput–output (I–O) mapping for guidance dynamics. Here, the I–O training data are gathered from the I–O relationship of the guidance dynamics of the aircraft, which exclude the physics of the autopilot, as shown in Fig. 4. The actuator dynamics are assumed to be fast enough to be negligible in this study. For better generalization, the trajectories corresponding to the training data are generated for diverse flight maneuvers shown in Fig. 5. Noted that, in this study, the training data do not cover the entire flight envelop of Navion aircraft. A batch of training data from simulation output is randomly sampled at 10 Hz from 200 trajectories of different roll angles, pitch angles, initial airspeeds, and altitudes lasting for two minutes with the original sampling rate of 100 Hz. To alleviate the load and shorten the training process, the sampling rate is reduced to 1 Hz. After evaluating the effects of different sampling rates, the training performance is kept with reduced sampling rate, and the training process is shortened significantly.

Second, a single-layered neural network of a selected number of neurons is constructed. The number of neurons should be selected empirically according to the quantity of training data and complexities of system dynamics. The *Error–Backpropagation* algorithm is

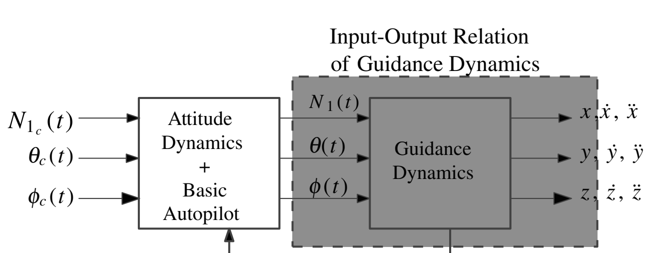

Fig. 4 I–O relationship of guidance dynamics.

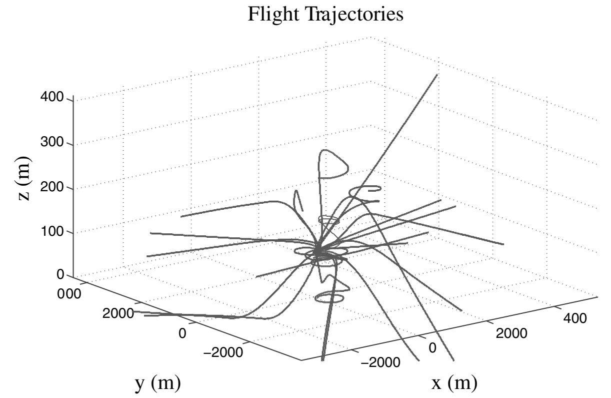

Fig. 5 Example of flight trajectories for training-data generation.

taken for training process. The *Levernberg–Marquardt* optimization algorithm is also adopted to accelerate the training process. The input of the neural network comprises seven components, which are the altitude, three components of inertial velocity, and three components of inertial acceleration. The outputs are the pitch angle command θ, roll angle command ϕ, and one engine command Ω for a propeller-driven piston engine. For a set of given training data, a neural network can be built after the inevitable trial-and-error tuning of the neural-network parameters and training process shown in Fig. 6.

At the third stage, the neural network is evaluated in the guidance control scheme. An additional observer-based closed loop with selected gains is designed to eliminate the drift due to the modeling errors or external perturbations.

B. Results

Figures 7 and 8 indicate the drift of altitude by direct application of neural guidance control only with regard to a maneuver in the vertical plane. By closing the control loop with an observer, the tracking performance is significantly improved with slight positional bias in the horizontal plane, as shown in Figs. 9 and 10.

Figures 11 and 12 also demonstrate the capability of the proposed neural guidance control approach for coupling 3-D maneuvers. They indicate the proposed closed-loop control scheme, effectively overcoming the modeling errors.

VI. Conclusions

A flatness-based neural guidance control scheme is proposed in this study. The theory of differential flatness provides a sound basis to introduce the neural-network technology into the architecture of flight guidance systems. With the combination of both the differential flatness and the neural networks, a simple and feasible generic guidance control system becomes possible to make aircraft perform accurate trajectory tracking maneuvers for nontraditional trajectories, complying with stricter air traffic requirements even

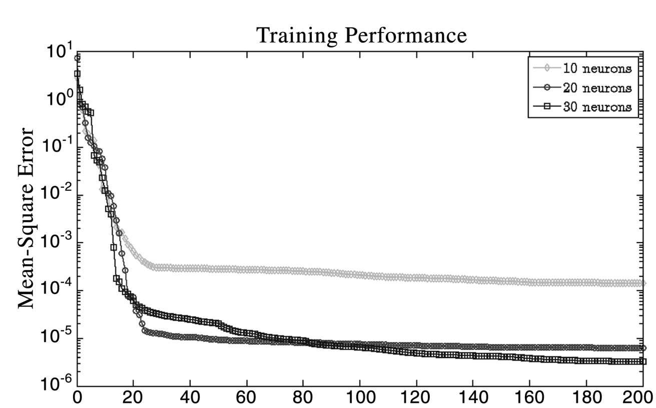

Fig. 6 Training performance using different numbers of neurons.

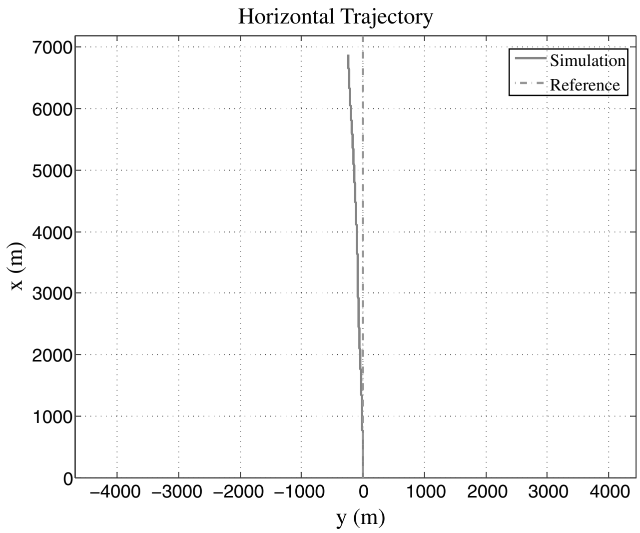

Fig. 7 Horizontal trajectory tracking by nominal guidance control directives.

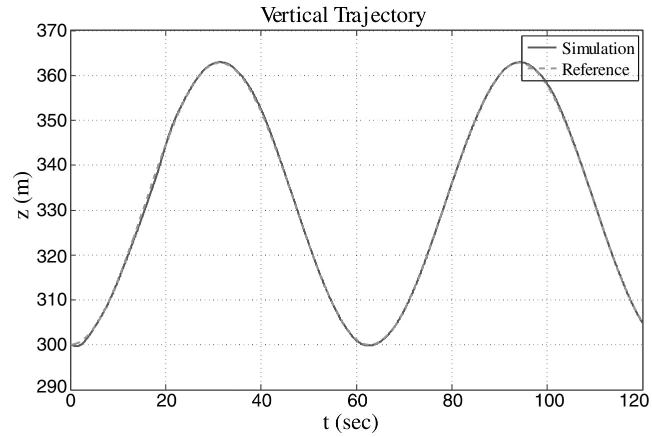

Fig. 10 Vertical tracking performance by neural guidance control with a closed loop.

though the robustness of the observer-based closed loop seems less effective to against the foreseeable gust or large turbulence. The aircraft with such a guidance system may be potentially able to realize 4-D guidance in real-time applications. This proposition and preliminary simulation results make it possible to transform the current mode-scheduling-based guidance system into trajectory-based tracking guidance. This may also lead to more efficient approaches and landing procedures, which can alleviate crowded air traffic around airports. Many issues still remain open, such as the generalization problem of neural networks devoted to guidance and

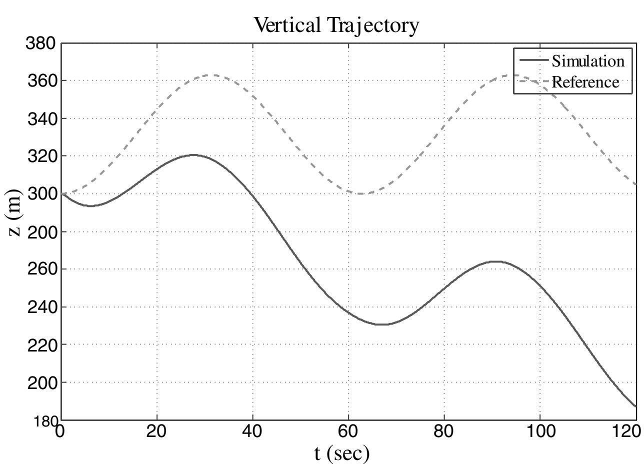

Fig. 8 Vertical trajectory tracking by nominal guidance control directives.

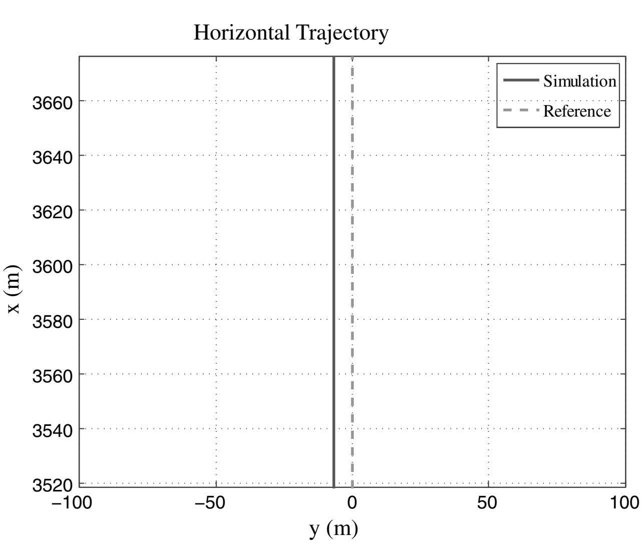

Fig. 9 Horizontal tracking performance by neural guidance control with a closed loop.

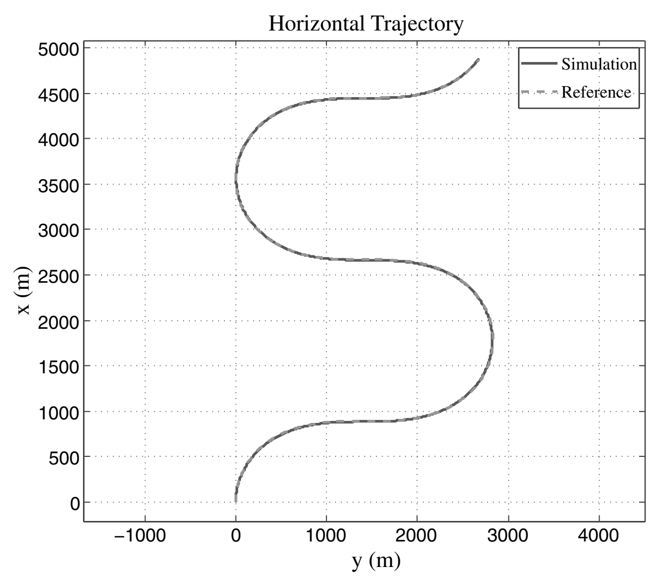

Fig. 11 Vertical trajectory tracking using nominal guidance control directives with a closed loop.

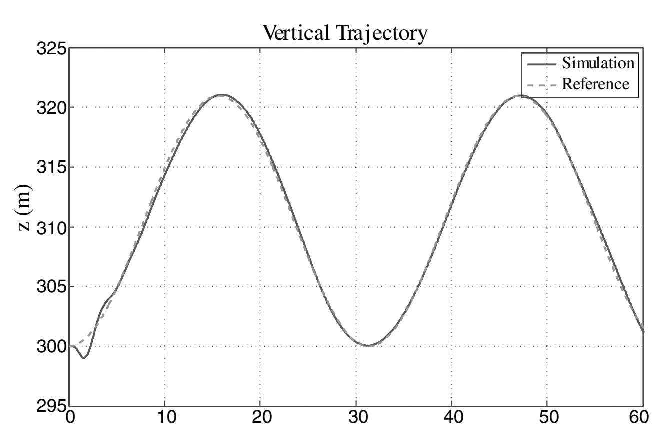

Fig. 12 Vertical trajectory tracking using nominal guidance control directives with a closed loop.

the robustness of the approach with respect to external disturbances and modeling errors.

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