Neural network identification of aircraft nonlinear aerodynamic characteristics

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Abstract. The simulation problem for the controlled aircraft motion is considered in the case of imperfect knowledge of the modeling object and its operating conditions. The work aims to develop a class of modular semi-empirical dynamic models that combine the capabilities of theoretical and neural network modeling. We consider the use of semi-empirical neural network models for solving the problem of identifying aerodynamic characteristics of an aircraft. We also discuss the formation problem for a representative set of data characterizing the behavior of a simulated dynamic system, which is one of the critical tasks in the synthesis of ANN-models. The effectiveness of the proposed approach is demonstrated using a simulation example of the aircraft angular motion and identifying the corresponding coefficients of aerodynamic forces and moments.

1. Introduction

We proposed in [1-3] a semi-empirical approach to ANN-modeling of nonlinear controlled dynamical systems. This approach is based on combining theoretical knowledge about the object of modeling and experimental data on its behavior. The result is a model of the gray box type, which can be configured by machine learning methods. In the problems of modeling the motion of aircraft, the traditional theoretical model, widely used in the solution of various applied tasks, is a system of ordinary differential equations (ODE). This model, in combination with the corresponding experimental data, can be used to form a semi-empirical neural network model of aircraft motion. The source theoretical model of the aircraft motion model [4] contains, as constituent elements, expressions for the dimensionless coefficients of aerodynamic forces and moments. One of the variants of the classical problem of system identification [5-8] is related to them, namely, the problem of identifying aerodynamic characteristics of aircraft [9-15], which consists in restoring the relationships for the nondimensional coefficients of forces and moments from the available experimental data on the behavior of the aircraft. In the problem considered below, as the source theoretical model, we use a system of ordinary differential equations describing the total angular motion of the aircraft. The semi-empirical neural network model formed on this basis includes five black-box ANN-modules, describing the coefficients of the lift and lateral forces, the pitch, yaw, and roll moment coefficients, each of which depends nonlinearly on several parameters of the aircraft motion. These five relationships need to be found (recovered) basing on available experimental data for the observed variables of the dynamic system, i.e., we have to solve the problem of identifying the aircraft aerodynamic characteristics. We confirm the effectiveness of the proposed approach using the corresponding simulation results.
2. Comparison of the proposed and traditional approaches to the identification of aerodynamic characteristics of an aircraft

The proposed approach to the identification of aerodynamic characteristics of an aircraft differs substantially from the traditionally accepted way to solving problems of this class. Namely, with the traditional approach [9-15], as a rule, we use a linearized model of the disturbed motion of an aircraft. In this case, the relationships for the aerodynamic forces and moments, acting on the aircraft, are represented in the form of expanding them into a Taylor series, leaving only first-order terms in them (in rare cases also second-order terms). Then the solution of the identification problem is reduced to obtaining from the experimental data the relations describing the coefficients of the Taylor expansion. The values of these factors are determined, first of all, by the value of the partial derivatives of the dimensionless coefficients of the aerodynamic forces and moments by the various parameters of the aircraft motion ($C_{Lx}$, $C_{me}$, $C_{Iy}$, $C_{mz}$ etc.).

In contrast, the semi-empirical approach realizes the derivation of the relationships for the coefficients of the forces $C_p$, $C_l$, $C_n$ and the moments $C_r$, $C_e$, $C_m$ as holistic nonlinear dependencies from the corresponding arguments, without using their Taylor expansions. Thus, the proposed approach evaluates the functions themselves, and not the coefficients of their Taylor expansions. We implement each of these dependencies as a separate ANN-module, built into the semi-empirical model of the aircraft motion.

Sometimes the derivatives $C_{Lx}$, $C_{me}$, $C_{Iy}$, $C_{mz}$ etc. are necessary for solving some problems, for example, for analysis of the stability and controllability characteristics of an aircraft. In this case, it is easy to find them using the appropriate ANN-modules obtained in the formation of the semi-empirical ANN-model of the aircraft motion.

3. Semi-empirical ANN-model of aircraft three-axis angular motion

To estimate the efficiency of the proposed approach, let us consider the problem of simulating the aircraft three-axis rotational motion. We describe it by a typical set of equations for aircraft flight dynamics [4]. This set consists of fourteen differential equations, which we do not present here because of it being too complicated. The state variables of the dynamic system are the roll angular rate $p$, the pitch angular rate $q$ and the yaw angular rate $r$ (degree/second); the roll angle $\Phi$, the yaw angle $\Psi$ and the pitch angle $\Theta$ (degree); the angle of attack $\alpha$, the angle of sideslip $\beta$, the angle of the all-moving tailplane deflection $\delta$, the angle of the rudder deflection $\delta$, the angle of the aileron deflection $\delta$ (degree); the angular rates of the all-moving tailplane, the rudder and the aileron deflections $\dot{\delta}$, $\dot{\delta}$, $\dot{\delta}$ (degree/second), respectively. The control inputs are the quantities $\delta_{aw}$, $\delta_{aw}$, $\delta_{aw}$ that are command driving signals supplied to the all-moving tailplane, the rudder and the aileron (degrees), respectively.

The given theoretical model contains six unknown nonlinear functions of several variables. These functions describe the dependences on the state variables for the coefficients of the axial $C_l(\alpha, \beta, \delta, q)$, the transverse $C_t(\alpha, \beta, \delta, \delta, p, r)$ and the normal $C_n(\alpha, \beta, \delta, q)$ aerodynamic forces, respectively. They also define aerodynamic moments $C_m(\alpha, \beta, \delta, \delta, \delta, p, r), C_{me}(\alpha, \beta, \delta, q)$ and $C_{me}(\alpha, \beta, \delta, \delta, \delta, p, r)$ of the roll, the pitch and the yaw, respectively. To implement these functions we include in the developing model six neural network modules in the form of the sigmoid feedforward neural networks with one hidden layer. The hidden layers include 1, 5, 3, 5, 10 and 5 neurons for the modules $C_l$, $C_t$, $C_n$, $C_m$ and $C_{me}$, respectively.

Note, since in the model there are no controls acting on the acceleration/braking along the longitudinal axis of the aircraft, it is not possible to obtain the training set for the neural network module representing the drag coefficient $C_d$. This is the reason why we form the neural network module for $C_d$ independently basing on the data from [20]. We embed it into the generated semi-empirical model. Then we “freeze” this module, that is, we disable variations of its adjustable parameters.
4. Generation of representative training set

When synthesizing the neural network models one of the critically important problems is the formation of a representative data set characterizing the behavior of the simulated dynamic system. Unfortunately, this problem has no simple solution, but it is crucial for obtaining an efficient and reliable model of the dynamic system.

In paper [3] we showed that for the class of problems we consider, the most effective way is to use the polyharmonic (multisine) actuating signal. According to this approach we form for each of \( m \) aircraft controls the input actions as the sum of harmonic signals each of which has its own phase shift \( \phi_k \). The input signal \( u_j(t) \) corresponding to the \( j \)-th control surface has the form:

\[
 u_j(t) = \sum_{k=1}^{M} A_k \cos \left( \frac{2\pi k t}{T} + \phi_k \right), \quad j = 1, \ldots, m, \quad I_j \subset K, \quad K = \{1, 2, \ldots, M\},
\]

\[
 u_j^*(t) = \tilde{u}_j(t) + u_j(t),
\]

where \( M \) is the total number of harmonically connected frequencies, \( T \) is the interval of time during which the test actuating signal acts upon the dynamic system; \( A_k \) is the \( k \)-th amplitude of the sinusoidal component; \( u_j^*(t) \) is the complete controlling action for the \( j \)-th control surface; \( \tilde{u}_j(t) \) is the controlling action for the \( j \)-th control surface realizing the test maneuver.

When generating the training set as well as when testing the obtained semi-empirical neural network model the controlling actions affected the aircraft over all three channels simultaneously and at that the signals \( \delta_{e}^{ai}, \delta_{r}^{ai}, \delta_{u}^{ai} \) were formed as the polyharmonic ones when obtaining the training set and as random ones when testing the trained model.

5. Computer simulations

In our computer simulations using the theoretical model, the interval of time was \( t \in [0, 20] \) seconds when obtaining data for the ANN-model learning, and it was \( t \in [0, 40] \) seconds when testing the obtained neural network model. In both cases simulations were performed with the time step of \( \Delta t = 0.02 \) sec for the partially observable state vector \( y(t) = [\alpha(t); \beta(t); p(t); q(t); r(t)]^T \). The additive white noise with the standard deviations \( \sigma_\alpha = \sigma_\beta = 0.02 \) degree and \( \sigma_p = 0.1 \) degree/sec, \( \sigma_q = \sigma_r = 0.05 \) degree/sec affected the system output \( y(t) \). If the neural network model reproduces the original system perfectly well, the noise affecting the system output defines the error of simulation completely. Consequently, comparison of the error of simulation with the standard deviation of the noise allows us to assess how well our simulations were. The standard deviation of the noise can be regarded as the target error of the simulations.

The learning was carried out basing on the sample (training set) \( \{y_i\}, i = 1, \ldots, N \), obtained for the source theoretical model with the aid of the Matlab system using the Levenberg–Marquardt algorithm and the root-mean-square error (RMSE) criterion. We calculated the Jacobian matrix according to the RTRL (Real-Time Recurrent Learning) algorithm [16-19].

From Figure 1 we see that the errors for all the observable state variables are sufficiently small. Moreover, these errors do not increase with time, and this is the evidence of good generalization ability of the obtained neural network model. It must be emphasized that to ensure a great variety of the modeled system states as well as to ensure the largest possible variety of the differences between states at the adjacent instants of time, when testing the model we simulated very active work of the aircraft controls. An additional complicating factor was in providing the subsequent input disturbance affected the aircraft before the transition processes from one, or several preceding disturbances were finished.
Figure 1. Estimation of generalizing properties for the neural network model after completing of the 1000-step of the learning process: \( E_\alpha, E_\beta, E_p, E_q, E_r \) are the measures of inaccuracy of the corresponding observed data; the horizontal lines show the values of the controls corresponding to the test maneuver (the absolute altitude is 300 m, the airspeed is 148 m/sec)
We are also interested in the accuracy of solution when identifying the aerodynamic characteristics. We can estimate it comparing the values generated by the relevant neural network modules with experimental data [20]. The values of the root mean-square errors (RMSE) of the reconstruction of each function provided by the corresponding neural network modules are \( \text{RMSE}_{c_1} = 5.4257 \times 10^{-4} \), \( \text{RMSE}_{c_2} = 9.2759 \times 10^{-4} \), \( \text{RMSE}_{c_3} = 2.1496 \times 10^{-5} \), \( \text{RMSE}_{c_4} = 1.4952 \times 10^{-4} \), \( \text{RMSE}_{c_5} = 1.3873 \times 10^{-5} \).

At that, the error level does not change significantly with time. We did not find the variations of the error that can influence negatively the adequacy of our semi-empirical neural network model.

6. Conclusion

The obtained results show that the methods of neural network modeling combined with knowledge and experience from the relevant subject area, as well as a representative training set, are a powerful tool for solving complicated problems for controlled dynamical systems of various classes. They also allow efficiently solving the problem of identifying aerodynamic characteristics of an aircraft.

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References

[1] Egorchev M V, Kozlov D S, Tumentsev Yu V and Chernyshev A V 2013 J Computer and Inform Technology No 9 pp 3–10 (In Russian)
[2] Egorchev M V, Kozlov D S and Tumentsev Yu V 2014 ICAS Paper 2014-0530 pp 1–8
[3] Egorchev M V and Tumentsev Yu V 2015 Optical Memory and Neural Networks (Information Optics) 24 (3) pp 210–17
[4] Bochkariov A F et al 1985 Aeromechanics of airplane: Flight dynamics 2nd Ed. (Moscow: Mashinostroyeniye) (In Russian)
[5] Nelles O 2001 Nonlinear system identification: From classical approaches to neural networks and fuzzy models (Berlin: Springer)
[6] Sjöberg J et al 1995 Automatica 31 (12) pp 1691–1724
[7] Rubio J J and Yu W 2007 Neurocomputing 70 (13-15) pp 2460–6
[8] Singh M et al 2007 IETE J of Research 53 (1) pp 45–50
[9] Jategaonkar R V 2006 Flight vehicle system identification: A time domain methodology (Reston, VA: AIAA, Inc.)
[10] Klein V and Morelli E A 2006 Aircraft system identification: Theory and practice (Reston, VA: AIAA, Inc.)
[11] Hamel P G and Jategaonkar R V 1996 J of Aircraft 33 (1) pp 9–28
[12] Jategaonkar R V, Fischenberg D and von Gruenhagen W 2004 J of Aircraft 41 (4) pp 681–91
[13] Klein V 1989 Progress in Aerospace Sciences 26 (1) pp 1–77
[14] Morelli E A 2003 13th IFAC Conf. on System Identification, Paper REG-360 pp 1–7
[15] Juditsky A et al 1995 Automatica 31 (12) pp 1725–50
[16] Haykin S 2006 Neural networks: A comprehensive foundation: 2nd Ed (Amsterdam: Prentice Hall)
[17] Hagan M T, Demuth H B, Beale M H and De Jesus O 2014 Neural network design, 2nd Ed (Longview, TX: PSW Publishing Co)
[18] Dreyfus G 2005 Neural networks: Methodology and applications (Berlin: Springer)
[19] Mandic D P and Chambers J A 2001 Recurrent neural networks for prediction: Learning algorithms, architectures and stability (New York: John Wiley & Sons)
[20] Nguyen L T et al 1979 NASA TP-1538 pp 1–223