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Nonlinear aircraft system identification using artificial neural networks enhanced by empirical mode decomposition

Seyed Amin Bagherzadeh *

Department of Mechanical Engineering, Najafabad Branch, Islamic Azad University, Najafabad, Iran

A R T I C L E I N F O

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A B S T R A C T

This paper aims to improve the performance of artificial neural networks used for the aircraft system identification by taking flight dynamic characteristics into consideration. In the proposed method, flight dynamic modes are recognized, isolated, and inputted individually to feed-forward neural networks. This method has several advantages such as being adaptive, involving all observable modes in the identification process, considering interactions between longitudinal and lateral-directional modes, and reducing noise effects. Simulated and real flight data of the HARV aircraft at high-angle of attack maneuvers are employed to train the neural networks and evaluate them. Results demonstrate improved accuracy and generality of the proposed method in comparison with the conventional ones.

1. Introduction

In order to gain tactical advantages, a high-performance aircraft such as an agile fighter should be able to perform controlled maneuvers throughout its flight envelope, especially at high angles of attack. In this regime, nonlinear and unsteady aerodynamics has drastic effects on the stability, controllability and maneuverability of the aircraft. Therefore, nonlinear aerodynamics should be considered in the design, development and flight of maneuverable aircraft.

From a detailed view, flow characteristics at high angles of attack are currently well-known. There is an enormous amount of information about small-scale flow behaviors (i.e., separation, vortex and boundary layer) in this regime, thanks to analytical, numerical and experimental aerodynamic approaches [1]. From a wider view, nevertheless, behaviors of a real aircraft in critical high angle of attack regimes such as the buffet, wing drop, wing rock, adverse yaw, departure, post-stall gyrations, incipient spin, deep stall and spin remain practically unknown yet. Modeling of these phenomena is inevitable for high-fidelity simulators and adaptive controllers. Aircraft complex behaviors in these regimes cannot be modeled according to conventional theories such as linear aerodynamic coefficients. Hence, nonlinear aerodynamic models are required in order to precisely predict actual behaviors of the aircraft at high angle of attack maneuvers throughout the flight envelope.

Aircraft system identification is an effective approach for the nonlinear aerodynamic modeling. This approach eliminates the need to employ assumptions, conventional theories and basic knowledge about the structure of the aerodynamic model. Therefore, it may provide more precise results than analytical, semi-empirical, numerical and experimental approaches. So far, several mathematical tools have been utilized for the aircraft system identification such as polynomials [2,3], kernel methods like support vector machines [4,5], splines [6,7], the multi-variable orthogonal model [8,9], the multipoint method [10] and Artificial Neural Networks (ANNs) [11–13].

Due to the capability to estimate a wide range of functions, the ANNs can provide effective non-parametric identification methods for nonlinear systems. Previous studies have indicated that feed-forward multilayer ANNs as general estimators can estimate any arbitrary function and its derivatives with any desired accuracy [14,15]. This feature called capacity has led the ANNs to be applied to system identification of dissimilar aircraft types such as airplanes [11–13], rotating wings [16,17], unmanned aerial vehicles [18] and missiles [19]. Furthermore, the ANNs have been employed to recognize and identify different flight phenomena such as aeroelastic [20], unstable [21,22] and nonlinear high angle of attack [23–27] behaviors of aircraft.

Despite the similar objective of the conducted studies, diverse ANNs have been employed for the aircraft system identification. For instance, both Feed-Forward Neural Networks [11–13] and Recurrent Neural Networks [23,24,28,29] have been widely used; however, the former is more common due to the flexibility in the parameter estimation. Also, different architectures have been

* Correspondence to: University Sq., Najafabad, Isfahan, Iran.
E-mail addresses: bagherzadeh@pmc.iaun.ac.ir, sabagherzadeh@gmail.com.

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Nomenclature

c	the IMF
x	the investigated signal
m	the signal trend
u	the upper signal envelope
l	the lower signal envelope
h	the proto-IMF
r	the remainder
t	time
α	angle of attack
β	side slip angle
M	Mach number
p, q, r	angular velocity components in body frame
$\delta_H, \delta_A, \delta_r$	stabilator, aileron and rudder commands
C_D, C_L, C_Y	force coefficients in the stability frame
C_l, C_m, C_n	moments coefficients in the body frame
$\bar{q}$	dynamic pressure
V	total velocity
b	aircraft wing span
$\bar{c}$	aircraft mean aerodynamic chord
δ_T	throttle command
h	altitude
$\boldsymbol{e}$	error vector
u, v, w	linear velocity components in body frame
g	gravity acceleration
ϕ, θ, ψ	Euler angels
m	aircraft mass
$\boldsymbol{x}$	state vector
$\boldsymbol{u}$	control vector
e	error
y	measured signal
d	desired output
o	real output
$\boldsymbol{J}$	Jacobian matrix
$\boldsymbol{w}$	weight vector
$\boldsymbol{I}$	the identity matrix
μ	the combination coefficient
Δ	difference
a_x, a_y, a_z	linear acceleration components in the body frame
T	thrust
W	aircraft weight
$I_{xx}, I_{yy}, I_{zz}, I_{xz}$	aircraft moments of inertia
$\bar{X}_{CG}$	the CG position
S	aircraft reference area
l_x, l_y, l_z	thrust arms to CG

Subscript

i, j	jth iteration for finding ith IMF
i	for ith IMF
$\beta, p, q, r, \dot{\alpha}$	due to $\beta, p, q, r, \dot{\alpha}$ respectively
x, y, z	components in body frame
1	at trim condition
L, R	left and right
m, p	for the mth output and the pth pattern

utilized; for example, the number of hidden layers varies from zero [18] to two [22,30–32] while the single-layer networks are widespread. Moreover, learning rules with different optimization algorithms are employed such as variations of the Kalman Filter [13,33], Gauss–Newton's algorithm [34], Levenberg–Marquardt algorithm [23,35–37] and scaled conjugate gradient algorithm [22,38]. Furthermore, there are various activation functions such as identity [17], sigmoid [12,19,24], radial basis function [13,16,39,40], hyperbolic tangent [22,28,30], logistic [35] and wavelet [33,41,42]. In addition, there are dissimilar numbers of neurons, learning and momentum rates, and connections between neurons in the conducted studies.

Despite numerous studies, the aircraft system identification via the ANNs faces some difficulties essentially caused by the nonlinearity at high angles of attack and angular rates. Therefore, new studies are undertaken in order to expand the fidelity range of the ANNs into nonlinear regions of the aircraft flight envelope [43–48]. A popular misconception is that changing the architecture or learning rule of the ANNs can resolves problems arose from the application of ANN to the aircraft system identification. Investigations, however, do not confirm this. It seems unlikely that variations on the architecture or learning rule of the ANNs will bring about a step forward unless new insights into the aircraft system identification are introduced. The current paper attempts to achieve new insights into the aircraft flight dynamics and to improve the aircraft system identification by considering them. The paper presents neither a new architecture for the ANNs nor a different learning rule; but it proposes to consider aircraft flight modes as inputs of the ANNs.

The remainder of the paper is organized as follows: Section 2 describes effects of flight dynamics on the aircraft system identification, and disadvantages caused by ignoring these effects. Section 3 explains the preprocessing required to be applied to flight data before the identification process, and introduces the empirical mode decomposition for this purpose. In Section 4, the simulation model including the aircraft model and aircraft equations of motion is presented. Section 5 proposes the improved ANN for the aircraft system identification, including the input data, output data, model architecture, and parameter estimation technique. In Section 6 comparative studies are conducted between the conventional and proposed ANNs for simulated and real flight data. Finally, Section 7 concludes the paper.

2. Effects of flight dynamics on the aircraft system identification

Experience has indicated that the aircraft flight is composed of various modes, and any aircraft flight parameter is a superposition of them. Containing dissimilar frequencies and amplitudes, these modes cause complex behaviors of aircraft. Therefore, the aircraft system identification is affected intensely by flight dynamics. The classical flight dynamic analysis is undistinguished in the estimation of flight modes. Under several assumptions such as flat earth, constant weight, rigid body, non-rotating components, shallow flight path angles, small perturbations, and decoupling of longitudinal and lateral-directional equations, the classical analysis describes aircraft motions as a linear time-invariant (LTI) model. Afterwards, second order linear differential equations with constant coefficients are converted to uncoupled longitudinal and lateral-directional transfer functions. Finally, flight modes are extracted by substitution stability and control derivatives into characteristic equations, and solving them. There are some fundamental problems in this process:

- The assumptions are not necessarily correct for all aircraft types.
- Based on the classical analysis, the longitudinal and lateral-directional modes are identical in the number and configuration of roots. However, studies have shown that there are

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