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Semi-empirical Neural Network Based Approach to Modelling and Simulation of Controlled Dynamical Systems

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Abstract

A modelling and simulation approach is discussed for nonlinear controlled dynamical systems under multiple and diverse uncertainties. The main goal is to demonstrate capabilities for semi-empirical neural network based models combining theoretical domain-specific knowledge with training tools of artificial neural network field. Training of the dynamical neural network model for multi-step ahead prediction is performed in a sequential fashion. Computational experiments are carried out to confirm efficiency of the proposed approach.

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Keywords: nonlinear dynamical system, semi-empirical model, neural network, sequential learning

1 Introduction

A modelling and simulation problem for multidimensional, highly nonlinear and nonstationary controlled dynamical system such as maneuverable aircraft is considered. Traditional approach to mathematical modelling and computer simulation of dynamical systems relies upon differential equations. However, dynamical system models based on differential equations lack adaptivity, which motivates the search for alternatives. One possibility would be to develop dynamical system models based on artificial neural networks (ANN). This would allow for model adaptivity, but at the same time it would significantly restrict level of complexity for the plant and thus prohibit application to most of the practical problems. The reason is that traditional ANN approach considers plant as a "black box" [17], which leads to significant increase of model dimensionality and, as a consequence, to increase of training dataset size up to values, unattainable in real world problems. Basic idea of suggested approach is to introduce available theoretical knowledge for the plant into the purely empirical model in order to decrease both model dimensionality and required training set size. Such semi-empirical ("gray box") models [5, 3, 15] possess the required adaptivity feature and utilize both theoretical knowledge for the plant and experimental data of its behavior. Models of this class attain high accuracy and performance, as evidenced by computational experiments.

Learning recurrent neural networks to perform multistep prediction is a difficult optimization problem. In the following sections, we present sequential learning algorithm designed to

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circumvent some of the difficulties and illustrate efficiency of the proposed approach by results of computer simulations.

2 Semi-empirical neural network based model development

Development process for semi-empirical neural network based model of dynamical system consists of the following stages:

1. development of continuous-time theoretical model for the considered dynamical system as well as acquisition of experimental data about behavior of the system;
2. accuracy assessment for theoretical model of dynamical system using collected data;
3. conversion of original continuous-time model into a discrete-time model [18];
4. generation of ANN-representation for discrete-time model [4, 12];
5. learning of ANN-model [13];
6. structural adjustment of ANN-model to fit modelling accuracy requirements.

To estimate efficiency of proposed approach, let us consider a problem of modelling and simulation of aircraft three-axis rotational motion. Traditional continuous-time theoretical model for aircraft flight dynamics consists of 14 ordinary differential equations [2], omitted here for the sake of brevity. State variables of corresponding dynamical system include: roll angular rate p, pitch angular rate q and yaw angular rate r (degree/second); roll angle ϕ, yaw angle ψ and pitch angle θ (degree); angle of attack α, angle of sideslip β; angle of all-moving tailplane deflection δ_e, angle of rudder deflection δ_r, angle of aileron deflection δ_a (degree); angular rates of all-moving tailplane, rudder and aileron deflections $\dot{\delta}_e$, $\dot{\delta}_r$, $\dot{\delta}_a$ (degree/second), respectively. Control inputs include command signals supplied to all-moving tailplane, rudder and aileron δ_e^{act}, δ_r^{act}, δ_a^{act} (degrees), respectively. This theoretical model contains 6 unknown nonlinear functions of several variables that correspond to aerodynamic coefficients of axial $C_x(\alpha, \beta, \delta_e, q)$, transverse $C_y(\alpha, \beta, \delta_r, \delta_a, p, r)$ and normal $C_z(\alpha, \beta, \delta_e, q)$ aerodynamic forces, as well as roll $C_l(\alpha, \beta, \delta_e, \delta_r, \delta_a, p, r)$, pitch $C_m(\alpha, \beta, \delta_e, q)$ and yaw $C_n(\alpha, \beta, \delta_e, \delta_r, \delta_a, p, r)$ aerodynamic moments. These unknown functions are replaced by 6 feedforward neural network modules with one hidden layer. Hidden layers include 1, 5, 3, 5, 10 and 5 neurons with sigmoid activation functions for modules C_x, C_y, C_z, C_l, C_m and C_n, respectively. Output layer neurons are linear functions. This semi-empirical neural network based model has quite complex structure, thus we consider a restricted case of longitudinal rotational motion for illustration purposes: structure of this simplified model based on Euler difference scheme is given in Fig. 1a. Colored arrows on illustration correspond to inter-neuron connections with varying ("learnable") weights. Colored nodes represent neurons that have at least one such connection as its input. For comparison, structure of the completely empirical NARX model (Nonlinear AutoRegressive neural network with eXogenous inputs) is given in Fig. 1b.

3 Sequential learning algorithm and simulation results

Learning of long input sequences with recurrent ANNs is difficult due to the existence of spurious valleys on the error surface [9], effects of exponential decrease or increase of the gradient norm [16], possible unbounded growth of network outputs. Thus, gradient optimization methods fail to find satisfactory solution except for rare occurrences when initial values for network parameters are very close to such solution. Now we might consider a problem of finding such