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Multi-kernel neural networks for nonlinear unsteady aerodynamic reduced-order modeling

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A R T I C L E I N F O

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This paper proposes the multi-kernel neural networks and applies them to model the nonlinear unsteady aerodynamics at constant or varying flow conditions. Different from standard radial basis function (RBF) networks with a single Gaussian hidden kernel, the multi-kernel neural networks improve the accuracy and generalization capability through linearly combining the Gaussian and wavelet basis functions as the hidden basis functions. In order to capture the complex nonlinear characteristics under noisy or multiple flow conditions, a novel asymmetric wavelet kernel is also introduced. The training of network parameters is achieved by incorporating proper orthogonal decomposition and particle swarm optimization algorithm, where the former process is adopted to decide the representative hidden centers and the latter technique is introduced to calculate the remaining parameters, including the widths of each multi-kernel and the linear weighting values. The proposed aerodynamic reduced-order models based on symmetric or asymmetric multi-kernel neural networks are tested by three groups of cases. Firstly, a routine reduced-order modeling task of predicting the aerodynamic loads at a constant Mach number is performed. Then the measurement noise is added to test the models under noise conditions. Finally, these models are utilized to identify the aerodynamic loads across a range of transonic Mach numbers. Results indicate that the proposed multi-kernel neural networks outperform the single-kernel RBF neural networks in modeling noise-free and noisy aerodynamics at a constant Mach number, as well as predicting the aerodynamic loads with varying Mach numbers.

1. Introduction

In recent years, computational fluid dynamics (CFD) has been the most reliable tool to perform high-fidelity numerical simulations of the full-order aerodynamic systems. However, the large computational efforts in CFD-based analysis always make it inconvenient in some engineering applications with respect to aerodynamic or aeroelastic analysis. This limitation catalyzes the development of aerodynamic reduced-order models (ROMs) [1–4] based on CFD technique. An obvious advantage of aerodynamic ROMs is that they can predict the linear and nonlinear aerodynamic phenomenon accurately within a fraction of time compared with that of CFD-based analysis. By means of different computational methods, various ROMs can be constructed through learning the mappings from training samples extracted from the full-order CFD system. The well-established ROMs achieve not only fast aerodynamic predictions but fluid–structure interaction analysis [5,6], flight dynamics [7], limit-cycle oscillation (LCO) simulations [8], optimization [9] and control designs [10–12].

Among current reduced-order modeling practices, system identification approaches occupy an important position, since identifying the input–output relationship is of great interest in some studies like aeroelasticity or flight dynamics, which can be directly achieved by these identification-based methods. For an effective aerodynamic reduced-order modeling, the dynamics of aerodynamic systems are described by the input–output relationship between structural displacement and aerodynamic coefficients. In the transonic flow regime, when the structure moves at a small amplitude, the flow variables and shock wave motion exhibit a linear fashion, which can be modeled by dynamic linear ROMs, such as the autoregressive with exogenous input (ARX) model [13]. The aerodynamic nonlinearity arises due to larger shock wave motions resulted from the increasing structural amplitudes [14]. Under this circumstance, the dynamically nonlinear models must be adopted. Neural networks [15–19], Kriging model [20,21], support vector machine [22], high-order Volterra series [23,24] and block-oriented

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Wiener models [25,26] have all been utilized for modeling nonlinear aerodynamics, as well as performing nonlinear aeroelastic simulations. It is worth noting that the use of neural networks is extensive in current aerodynamic ROM studies, because neural networks have the properties and capabilities of inherent nonlinearity, adaptivity and fault tolerance [27].

Neural networks are massively parallel distributed processors composed of processing units that acquire the knowledge from a learning process [27], which have been applied to a wide range of areas including nonlinear system identification [28–30], time-series prediction [31–33], system control [34,35], optimization design [36,37] and classification [38,39]. Therefore, they provide a powerful tool for modeling nonlinear aerodynamic systems. Marques and Anderson [15] applied a multi-layer temporal neural network implementing a generic algorithm to identify the nonlinear unsteady transonic aerodynamic responses at fixed or a range of Mach numbers. Suresh et al. [16] utilized a recurrent neural network to predict the lift coefficient through experimental data. Huang et al. [25] proposed a Wiener-type cascade aerodynamic ROM containing a linear state-space model followed by a nonlinear neural network for modeling the nonlinear aerodynamics of an aeroelastic system. Moreover, a recurrent neural network aerodynamic model is developed by Mannarino and Mantegazza [17], which gave reasonable descriptions of transonic nonlinear LCO phenomena induced by aerodynamic nonlinearity. The recurrent neural network allowing output delay can also be extended to model the unsteady pitch moment coefficient from the experimental data of an aircraft model with a canard [18]. Recently, Winter and Breitsamter [19] applied a recurrent neuro-fuzzy aerodynamic ROM trained by a local linear model tree algorithm to accomplish flutter analysis across varying freestream conditions. These reduced-order modeling practices indicate the potential for reducing the computational effort in aerodynamic and aeroelastic analysis by means of neural networks, but only a few of them consider modeling the aerodynamic systems at different flow parameters.

Furthermore, a typical neural network modeling approach, which is based on radial basis function (RBF) networks [40], has also been widely used to reduce the order of unsteady aerodynamic simulations. RBF neural networks have advantages of a simple network structure, good generalization capability [41] and universal approximation [27], thus allowing many applications such as accurate system identification [42,43] and effective control design [44,45]. In 2012, Zhang et al. [46] proposed an aerodynamic ROM on the basis of a recursive RBF (RRBF) network to predict the LCO behaviors of two benchmark airfoils in transonic flow. Although the developed RRBF network produces accurate temporal predictions on unsteady aeroelastic outputs, the ROM has a limited robustness to different structural parameters since the training signal is calculated from the coupled responses at specific aeroelastic parameters. Therefore, Kou and Zhang [47] and Zhang et al. [48] made some improvements on the network training process in order to obtain a well-trained ROM accounting for random structural motions with various structural characteristics. Ghoreyshi et al. [49] exploited the ability of RRBF network in modeling unsteady aerodynamics at low-speed flight conditions and constructed a computational effective aerodynamic ROM by a hierarchy of low-fidelity and high-fidelity aerodynamic simulations. Winter and Breitsamter [50] tested the recurrent RBF network model on describing the nonlinear aerodynamic effects of a supercritical airfoil. Lindhorst et al. [51] adopted RBF networks to construct a nonlinear mapping between the input and output coefficients with a low order reduced by proper orthogonal decomposition (POD) technique. Recently, Kou and Zhang [52] proposed a layered modeling approach combining linear ARX model and nonlinear RRBF neural network model to mimic both linear and nonlinear aerodynamic loads accurately. However, in order to extend these ROMs to more complex flow-induced effects like varying flow conditions or existing measurement noise, it is often desirable to develop more effective and accurate learning methods for generalization capability enhancement of current RBF networks.

Generalization refers to the neural network's capability of producing reasonable outputs for inputs not encountered during training [27]. To enhance the efficiency and the generalization capability of RBF neural networks, a variety of training approaches are developed. These methods overcome the difficulties in determining the optimal number [53–55] and centers [56,57] of hidden neurons, calculating the weights between the hidden and output layer [58–60], and extend the network with multi-scale basis functions [61]. Moreover, using asymmetric basis functions [62–65] or global optimization algorithms [66–68] also provides an integrated training process to decide all the network parameters. Although these studies contribute to enhancing the network generalization capability, they are all limited to a single hidden kernel and are not flexible to identify any type of dynamic systems. For example, when a three-dimensional wing model is considered, Lindhorst et al. [69] adopted an RBF network with inverse quadric basis functions rather than the Gaussian basis functions used for a two-dimensional configuration in their previous study [51]. To overcome this limitation, developing more robust RBF networks with multiple kernels is desirable, which has indicated better learning and generalization ability than traditional single-kernel models [70,71]. Fu et al. [72] proposed sparse RBF networks with multi-kernels combining both Gaussian and wavelet functions, which outperformed the single-kernel RBF neural network in modeling high-dimensional dynamic datasets. Fernández-Navarro et al. [73] investigated the mixed use of different shapes of Gaussian RBF based on different generalized Gaussian distributions for classification problems and found that the proposed generalized RBF models were better than RBF networks with a single type of kernel. Subsequently, Khan et al. [74] employed an adaptive RBF kernel using Euclidean and cosine distances, and exploited the reciprocating properties of the two kernels. This manual fusion of kernels showed the outperformance on three problems of estimation. These successes in combining different hidden kernels indicate a promising improvement on current aerodynamic ROMs based on RBF networks.

In this paper, two efficient aerodynamic ROMs based on RBF networks with multiple hidden kernels are developed. These ROMs include a multi-kernel function by combining neural network kernels linearly, and the combined symmetric and asymmetric basis functions are both utilized. It should be emphasized that for asymmetric kernels, the name “radial basis function” is problematic because the asymmetric basis function is not radial. Therefore, the proposed models are named as symmetric or asymmetric multi-kernel neural networks. The proposed ROMs are trained to identify the dynamic relationship between the structural motions and the aerodynamic loads of an airfoil in transonic flow.

The main contribution of this work lies in the development of multi-kernel neural networks for aerodynamic applications. Besides, an original asymmetric multi-kernel function is proposed to enhance the performance of neural networks based on symmetric basis functions. This paper is organized as follows. Sec. 2 is the introduction of the RRBF network used for modeling unsteady aerodynamics. The proposed multi-kernel neural networks are described in Sec. 3. In Sec. 4, three aerodynamic test cases, including constant, noisy and parameter-varying flow conditions, are presented to validate the effectiveness of the proposed reduced-order modeling approaches. The conclusion is shown in Sec. 5.

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