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Nonlinear aerodynamic reduced order modeling by discrete time recurrent neural networks

Andrea Mannarino, Paolo Mantegazza

Dept. of Aerospace Science and Technology, Politecnico di Milano, Via La Masa 34, 20156 Milano, Italy

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ABSTRACT

Nowadays, viable estimations of transonic aerodynamic loads can be obtained through the tools of computational fluid dynamics. Nonetheless, even with the increasing available computer power, the cost of solving the related non-linear, large order models still impedes their widespread use in conceptual/preliminary aircraft design phases, whereas the related nonlinearities might critically affect design decisions. Therefore, it is of utmost importance to develop methods capable of providing adequately precise reduced order models, compressing large order aerodynamic systems within a highly reduced number of states. This work tackles such a problem through a discrete time recursive neural network formulation, identifying compact models through a training based on input–output data obtained from high-fidelity simulations of the aerodynamic problem alone. The soundness of such an approach is verified by first evaluating the aerodynamic loads resulting from the harmonic motion of an airfoil in transonic regime and then checking aeroelastic limit cycle oscillations inferred from such a reduced neural system against high fidelity response analyses.

1. Introduction

Nowadays, a viable estimation of transonic aerodynamic loads acting on flying airplanes is often provided by computational fluid dynamics (CFD) codes, so allowing to adequately tackle aircraft stability and response analyses, for both flight mechanics [1,2] and aeroelastic [3,4] applications. However, such simulations are still computationally expensive, being characterized by a large number of unknowns and often limited to the most significant validation cases [3,5,6].

In order to introduce the typical nonlinear effects encountered in transonic flows, researchers have focused some of their efforts toward the development of reduced order models (ROMs). These compact system representations are designed to maintain an accuracy as close as possible to that of their parent high-fidelity aerodynamic analyses. An extensive overview of these methods can be found in [6] and references therein. The techniques mainly employed in the literature for the generation of reduced order models can be roughly subdivided in three main branches.

The first is the group of subspace projection techniques, such as the proper orthogonal decomposition [7,8], and, in a generalized sense, the harmonic balance method [9]. These approaches project the high fidelity model into a subspace spanned by a very efficient basis, which is able to represent any solution of interest through a small number of states. With proper orthogonal decomposition-based techniques, the related numerical bases are computed mostly through the singular value decomposition of a snapshot matrix, whose columns are time samples of very accurate responses to well chosen forcing terms [10]. The harmonic balance method on the other hand considers directly a truncated Fourier series as reduced order basis, limiting its application to periodic solutions [11,12].

The second branch is related to the adoption of generalized interpolation methods, e.g. radial basis function or Kriging interpolators [13,14]. Such methods employ a high-fidelity system for pointwise evaluations of its response, while a high order interpolation is applied for computing the response at any intermediate points of interest. Therefore, this ROM works as a general nonlinear input–output mapping, permitting to represent the dynamic system analytically. Even if it is a robust technique, its application seems limited to the evaluation of nonlinear aeroelastic systems stability, as demonstrated in the cited references.

The third group is represented by identification techniques based on input–output data pairs. The Volterra series method [6], i.e. the generalization of the impulse response to nonlinear systems, belongs to this group. Another approach, the one followed in this work, is characterized by the adoption of neural networks.

E-mail address: andrea.mannarino@polimi.it (A. Mannarino).

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Nomenclature

b	airfoil/wing semi-chord
c	airfoil chord
C_L, C_M	coefficients of lift and moment
$\mathbf{e}$	network output error
h, θ	plunge and pitch degree of freedoms
$k = \frac{\omega c}{V_\infty}$	reduced frequency
m	airfoil/wing mass
$r_\theta^2 = \frac{J_\theta}{mb^2}$	nondimensional airfoil/wing moment of inertia
$\mathbf{u}$	network input
$V^* = \frac{V_\infty}{\omega_\theta b \sqrt{\mu}}$	reduced velocity
$\mathbf{W}^a$, $\mathbf{W}^b$, $\mathbf{W}^c$	network synaptic weights
$x_\theta = \frac{S_\theta}{mb}$	nondimensional airfoil/wing static unbalance
$\mathbf{x}$	network state
$\mathbf{y}$	network output
$\mathbf{\Lambda}$	network Jacobian matrix
$\mu = \frac{m}{\pi \rho_\infty b^2}$	fluid-mass ratio
ρ_∞	fluid density
$\tau_s = \omega_\theta t$	structural adimensional time
$s = \frac{V_\infty t}{b}$	aerodynamic adimensional time
$\Phi(v)$	network activation function
ω_h, ω_θ	uncoupled plunging and pitching circular frequencies
CFD	Computational fluid dynamics
DTRNN	Discrete time recurrent neural network
LCO	Limit cycle oscillation
ROM	Reduced order model

Recently, discrete time recurrent neural networks have been employed in the order reduction of relatively simple aeroelastic systems [15–17]. In particular, the first two references employ a neural system with radial basis functions as computational units, within a framework that can be interpreted as a system identification based on a nonlinear autoregression with exogeneous input [18]. Reference [17] instead employs a support vector machine in the identification of unsteady aerodynamic loads. This technique has shown promising results in various machine learning applications and seems to have found its way also in problems where compact system representations are required.

Particular emphasis will be given in the present work to the determination of limit cycle oscillation (LCO) solutions of nonlinear aeroelastic systems.

In the context of the related theory, an LCO is a dynamic bifurcation. The reader can find a vast supporting literature on the analysis of all the different bifurcation types, regarding generic nonlinear systems [19,20] and aeroelastic applications [5,21]. A few details pertaining to the aeroelastic case are considered here.

Within the framework of fluid–structure interaction, LCOs may be driven by aerodynamic nonlinearities, and the related behavior can be associated to the formation of large vortical flow structures, as in the case of low speed, high angle of attack flow regimes [22,23], or to complex shock motions in transonic flows, even when using Euler flow models [5,24,25]. In this last case, which is of main interest in this work, a nonlinear aerodynamic model would allow the simulation of this phenomenon.

Such a moving shock wave may undergo very large displacements, eventually disappearing and reappearing during an LCO period [5,9]. Because of the fact that a shock wave introduces a discontinuity in the flow field, this kind of behavior can be assumed as dynamically nonlinear [24].

Also structural nonlinearities can lead to LCOs, whether the flow is transonic or not, as presented in [23,26,27], but the study of this kind of phenomena is not of interest here.

Aeroelastic limit cycles are usually determined in numerical experiments by time marching integrations [5,6]. Such methods seem to be used mainly to validate the stability changes predicted by Hopf bifurcation analyses with varying dynamic pressure, leading to stable/unstable responses or LCOs. Here instead, the system bifurcation point will be identified through free responses calculations, checking a posteriori if the system is asymptotically stable around the origin or if its behavior converges toward an LCO.

In this work a discrete time recurrent neural network (DTRNN) in state-space form [28] is used to identify nonlinear aerodynamic responses and compute aeroelastic limit cycle oscillations. Such formulation permits to consider the state and the input of the network only one step behind the current state, without keeping the old values of the input (and output in the case of references [15–17]) of several previous time steps in memory.

The present effort has multiple goals: present a novel, neural network-based ROM technique in the discrete time domain, analyze the performance of this methodology in Euler-based aerodynamic loads identification, perform nonlinear aeroelastic simulations comparing the results with the related high fidelity outcomes and determine the ROM sensitivity to parameter changes.

The work is organized as follows. In Section 2.1 the CFD solver employed is presented and all its main features are detailed. In Section 2.2 an introduction to neural networks terminology and to its recurrent framework for dynamic systems modeling is provided. Section 2.3 details the training algorithm used to optimize the network parameters in order to predict any response of interest. Section 3 presents in detail the results obtained for two standard test cases: an airfoil oscillating in pitch and a two degree-of-freedom typical section undergoing limit cycle oscillations due to large shock wave motion. Finally, in Section 4 the most interesting findings of this work are resumed.

2. Numerical methodology

2.1. Aerodynamic solver

For a high fidelity modeling of the aerodynamic problem, the in-house solver AeroFoam developed at Politecnico di Milano [29] is chosen. This application is supported by OpenFOAM libraries for the management of the mesh data, the computation of the numerical solution and the pre/post-processing phases. It is a Reynolds-Averaged Navier Stokes (RANS) density-based solver for aero-servo-elastic applications, written exploiting the Arbitrary-Lagrangian-Eulerian formulation for moving grids. It is a finite volume, cell-centered solver, that can treat both structured and unstructured grids. In the present computations, the Euler flow model is chosen, therefore the effects of viscosity and thermal conductivity will be neglected.

AeroFoam is the first density-based RANS solver implemented within the framework of OpenFOAM, realized to overcome the limits of built-in pressure-based solvers in the transonic regime, e.g. sonicFoam, because their non-conservative formulation does not permit to solve accurately transonic and supersonic regimes.

Regarding the present inviscid application, the convective fluxes are discretized by the classical Roe's approximated Riemann solver, which is a first order, monotone scheme, blended by the centered approximation provided by the Lax–Wendroff scheme, resulting in a second order, high-resolution scheme. The spatial discretization is completed by the entropy fix of Harten and Hyman and the flux limiter by van Leer [30].