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Examining vortex-induced vibration through convolutional neural networks

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1. Introduction

Phenomena like flutter, vortex-induced vibration, or buffeting can manifest during fluid-structure interaction (FSI), potentially leading to structural failure. As a result, FSI problems have garnered significant attention in fields such as the nuclear industry, aeronautics, and turbomachinery. The computational demands of simulating practical FSI problems are substantial, with fluid flow simulations often constituting the most resource-intensive aspect. To significantly alleviate these computational demands, we propose using a neural network to predict fluid flow, replacing traditional computational fluid dynamics (CFD) solvers. Convolutional Neural Networks (CNNs) were initially developed for image pattern recognition [3]. Guo et al. [4] were pioneers in employing CNNs to predict steady fluid flow, demonstrating that their CNN could predict velocity fields four orders of magnitude faster than a CPU-based solver and two orders of magnitude faster than a GPU-accelerated lattice Boltzmann CFD solver while maintaining error levels below 3%. Building upon this, Hennigh [5] extended the concept to predict unsteady fluid flows. In these groundbreaking studies, CNNs were trained to predict flow fields with varying geometries but consistent flow parameters, such as Reynolds number and angle of attack. Subsequent research by Bhatnagar et al. [1] and Thuerey et al. [7] developed CNN models capable of predicting complete velocity and pressure fields around aerofoils of diverse shapes, considering parameterized Reynolds numbers and angles of attack. This paper aims to apply CNNs to fluid-structure interaction (FSI) problems. It is worth noting that most prior research utilizing neural networks for fluid flow prediction assumed stationary boundaries. However, for FSI applications, CNNs must predict flow fields with moving boundaries. To address this challenge, we have designed and trained a CNN specifically tailored to predict unsteady, incompressible fluid flow with moving boundaries.

2. Neural network architecture and training dataset

In order to forecast the behavior of unsteady, incompressible fluid flow around a mobile object, we employ a specialized convolutional encoder-decoder neural network known as U-Net, as introduced by Ronneberger et al. [6]. This architecture is visualized in Fig. 1. The neural network takes as input a three-dimensional array with dimensions of $128 \times 32 \times 8$. This array contains eight distinct values for each grid point, which encompass the following information: the x and y coordinates of the grid points at time instances t_n and t_{n+1}, the corresponding boundary indicator, fluid velocity components u and v, as well as the pressure p at time t_n. Including grid point coordinates is essential due to the non-Cartesian nature of the mesh. Since

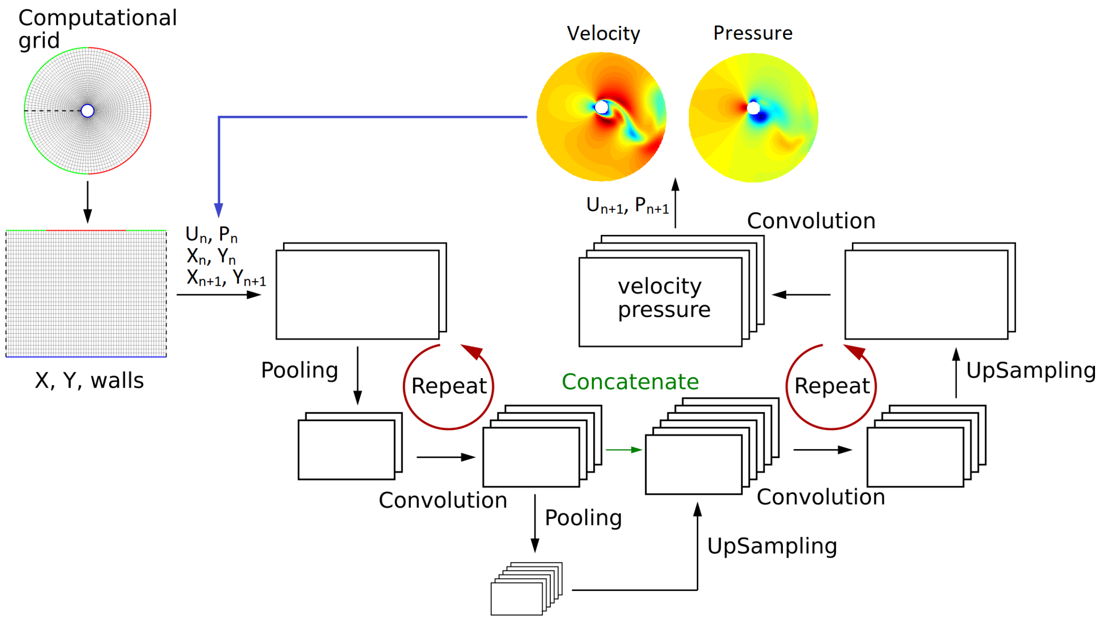

Fig. 1. Illustration of the network architecture

the mesh undergoes deformation, providing grid point positions at two distinct time steps is imperative. The boundary indicator is represented as a binary value equal to 1 if the grid point resides on the boundary of the blade profile and 0 if it is situated within the fluid domain. The network's output comprises pressure and velocity fields computed at the grid points for time t_{n+1}.

3. Structure model and fluid-structure interaction

We examine the interaction between laminar fluid flow and a solitary rigid body, which is elastically attached and can only move horizontally. Additionally, our simulation focuses solely on a 2D cross-sectional representation. The dynamics of this elastically-mounted body are encapsulated by the one-degree-of-freedom (1-DOF) linear mass-spring-damper model

$$\ddot{y} + 2\,\zeta\,\omega_n\,\dot{y} + \omega_n^2\,y = \frac{L}{m}.$$

In this context, where y represents horizontal displacement, we define several vital parameters: ζ as the damping ratio, ω_n as the undamped angular natural frequency (where $\omega_n = 2\pi f_n$ and f_n is the undamped natural frequency), m as the mass, and c and k as the damping and stiffness coefficients, respectively. Additionally, L represents the lift force. The relationship between the damped natural frequency and the undamped natural frequency is expressed as follows:

$$f_d = f_n\sqrt{1-\zeta^2}.$$

We discretize this equation using the BDF2 method, which is a 3-level implicit method.

To ensure the accurate interaction between the fluid flow and the solid structure, two conditions must be met at the fluid-solid interface: the equilibrium of forces and geometric consistency. Assuming that no external forces are acting on the body apart from aerodynamic forces, the equilibrium of forces can be expressed as follows:

$$L = \oint_\Gamma \left(\sigma_{xx}\,n_x + \sigma_{yx}\,n_y\right)\,\mathrm{d}S.$$

Here Γ is the boundary of the body, n is the unit outer normal to the boundary and σ is the aerodynamic stress tensor.

4. Numerical results

After conducting training sessions for a Convolutional Neural Network (CNN) using data from fluid flow around a cylinder subjected to prescribed harmonic motion with varying amplitudes and frequencies, we integrated the CNN with a structural solver. This integrated system was then employed for Fluid-Structure Interaction (FSI) simulations. The validation of the CNN-based FSI solver involved a thorough comparison of its outcomes with those of a Computational Fluid Dynamics (CFD)-based FSI solver. Notably, the CNN-based and CFD-based FSI solvers shared the exact structural solver and coupling algorithm; the primary difference lay in their respective fluid solvers. In our case, we utilized FlowPro [2] as the fluid solver, which also served as the source for generating the training dataset.

To validate the performance of the CNN-based FSI solver, we conducted multiple simulations with various natural frequencies and damping ratios for the structural component. The fluid parameters remained constant across all simulations. Specifically, we selected a Reynolds number of 100. We opted for damping ratios of 0.375 and 0.45. For each damping ratio value, we executed a series of simulations with different natural frequencies for the structure and subsequently visualized the resulting amplitudes and frequencies.

In Fig. 2, we compare amplitude characteristics obtained from the CNN-based and CFD-based FSI solvers for specific damping ratios. In essence, we depict the cylinder's amplitude response for various natural frequencies near the resonance frequency. Notably, we normalize the damped natural frequency f_d by the Strouhal frequency f_{St}, representing the vortex-shedding frequency for a stationary cylinder, and we normalize the amplitude A by the cylinder's diameter D. It is important to emphasize that f_{St} and D remain consistent throughout all simulations.

Fig. 3 illustrates the steady-state oscillation frequency f of the cylinder about the damped natural frequency f_d of the structure. Both axes are normalized by f_{St}. The horizontal black line signifies the Strouhal frequency f_{St}, which, due to normalization, equates to 1. The inclined black line corresponds to the natural frequency of the cylinder f_d, which, also due to normalization, aligns with the function $y = x$. The blue circles represent frequencies obtained from the CFD-based FSI solver, while the red squares represent frequencies obtained from the CNN-based FSI solver. For natural frequencies near the Strouhal frequency, i.e., when $f_d/f_{\mathrm{St}} \approx 1$, the vortex-shedding frequency deviates from its typical value and begins to follow the structure's

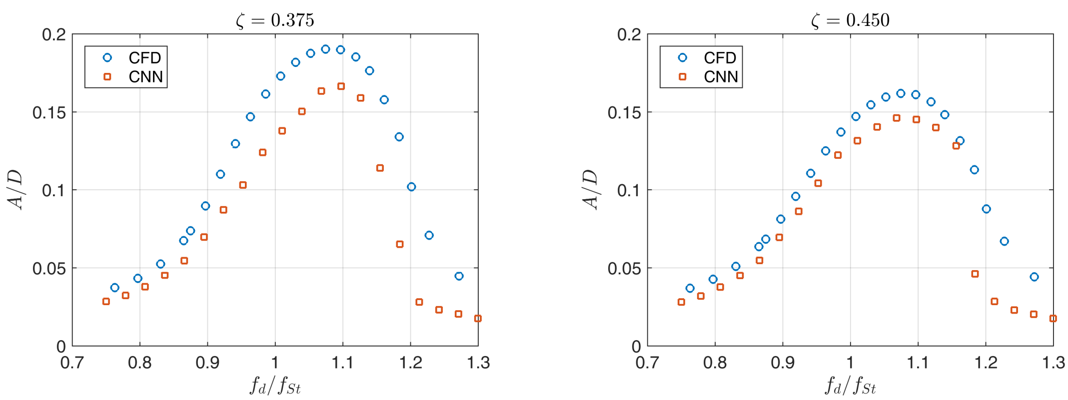

Fig. 2. Cylinder amplitudes A depending on the damped natural frequency f_d for various damping ratios ζ. The blue circles are the CFD-based results while the red squares are the CNN-based results

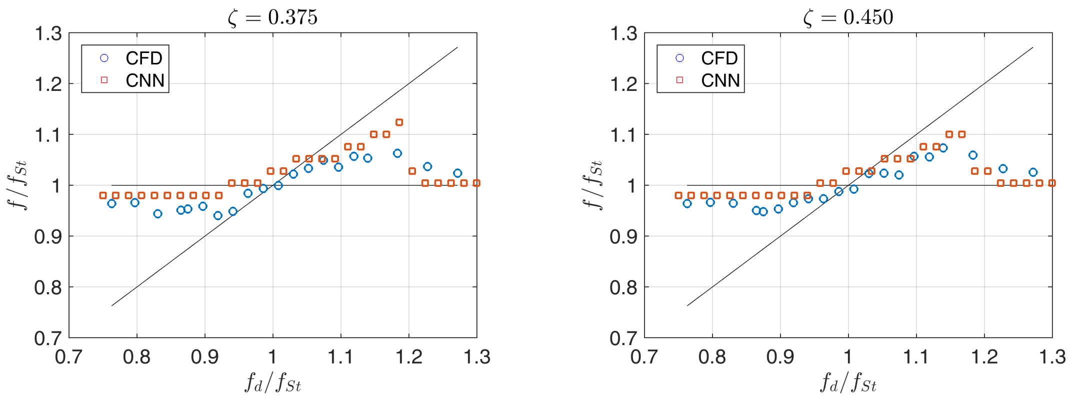

Fig. 3. Steady-state oscillation frequency f depending on the damped natural frequency f_d for various damping ratios ζ. The blue circles are the CFD-based results while the red square are the CNN-based results

natural frequency. This phenomenon indicates that within a specific region around resonance, the frequencies follow the inclined line instead of the horizontal line, commonly called "lock-in".

5. Conclusions

The findings demonstrate that the CNN-based Fluid-Structure Interaction (FSI) solver effectively captures the "lock-in" phenomenon in the vortex-induced vibration of a cylinder. Furthermore, the quantitative results closely align with those obtained from the CFD-based FSI solver. The CNN-based FSI solver also exhibits a remarkable speed advantage, two orders of magnitude faster than its CFD-based counterpart. This speedup is expected to be even more pronounced when applied to larger-scale problems.

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