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A NEURAL-NETWORK-BASED SYNTHETIC BOUNDARY CONDITION FOR THE SIMULATION OF CHANNEL TURBULENCE

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Summary We describe a method combining Proper Orthogonal Decomposition (POD) and an artificial recurrent neural network to implement an inlet boundary condition for a turbulent channel flow. The boundary condition is reconstructed from POD modes, the amplitudes of which are predicted using a neural network (LSTM). We first assess the quality of the LSTM prediction in POD space. The reconstructed velocity is then used as an inlet boundary condition in a spatially developing channel. Statistics are compared with the reference and are found to be in relatively good agreement.

MOTIVATION

The generation of turbulent inlet boundary conditions is an important question for the simulation of flows around aerodynamic immersed bodies or a spatially developing boundary layer. Fully developed turbulent channel flow can be obtained using periodic boundary conditions, but in general turbulent flows such as boundary layers develop in the spatial direction and more effort is required to construct an inlet velocity condition.

Pamiès *et al.* [1] used a combination of structures to construct the inlet condition - synthetic eddy method. Proper Orthogonal Decomposition (POD) provides a natural reconstruction framework as the velocity field can be approximated as a linear combination of POD spatial modes, the amplitudes of which vary in time. The question of determining inlet boundary conditions thus boils down to predicting the temporal evolution of a relatively limited number of amplitudes. In this framework the issue is to predict the behavior of the amplitudes of the POD spatial modes. Druault *et al.* [2] combined linear stochastic estimation with POD to construct an inlet boundary condition for a spatially developing mixing layer. Perret *et al.* [3] used experimental data to construct a low-order model for the amplitudes of the POD modes and build an inlet condition for large-eddy-simulation (LES) of a mixing layer. In the present work, we predict POD amplitudes using a special type of neural network called a long-term short-term memory network (LSTM) [4]. We first describe the method and show how the network is able to predict the POD amplitudes of the velocity field in a turbulent channel flow. The method is then implemented to reconstruct the velocity field on a plane which is used as an inlet boundary condition for the numerical simulation of a turbulent channel flow. Turbulent statistics in the channel are then compared with those of a reference one.

RECONSTRUCTION METHOD

Description

We consider the numerical simulation of an incompressible turbulent channel flow characterized by a bulk velocity U and a half-height h . The Reynolds number based on channel half-height h and friction velocity u_τ is $Re_\tau = 194$, which corresponds to the reference channel. Application of Proper Orthogonal Decomposition to the velocity field yields

$$\underline{u}(\underline{x}, t) = \sum_n a_n(t) \underline{\phi}_n(\underline{x}) \quad (1)$$

The spatial eigenfunctions $\underline{\phi}_n$ are determined *a priori* from a reference simulation. We consider 300 snapshots separated by a time scale of $\delta t = h/\bar{U}$, which can be reorganized into a hierarchy of 300 modes.

Constructing an inlet condition at all times consists in predicting the amplitude of these modes. In order to this we use a LSTM. The network is trained on a subset of the snapshots and validated on the remaining subset. The goal of the LSTM is to predict the next values of the amplitudes at $t + \delta t$, given the values at t . It is a recursive procedure, so that the amplitudes can be predicted over a long period of time.

Once the predicted values obtained at regular intervals of δt , the amplitudes can be interpolated in the simulation at any instant within the range spanned by the prediction.

Results

In the results shown below, the LSTM was trained on 180 snapshots. The remaining 120 snapshots constitute the validation basis. The LSTM was iterated over $640-180=480$ snapshots - 120 of which can be compared with the reference and 360 of which correspond to entirely new times. We consider only the 100 most energetic POD modes, which capture about 85% of the energy.

We first compare the amplitude of the POD modes predicted with the LSTM to those the reference simulation.

Figure 1 represents respectively the energy content and frequency spectrum of the amplitudes (frequencies are expressed in wall units, denoted with a +). Overall the LSTM predicts relatively well the characteristics of the modes.

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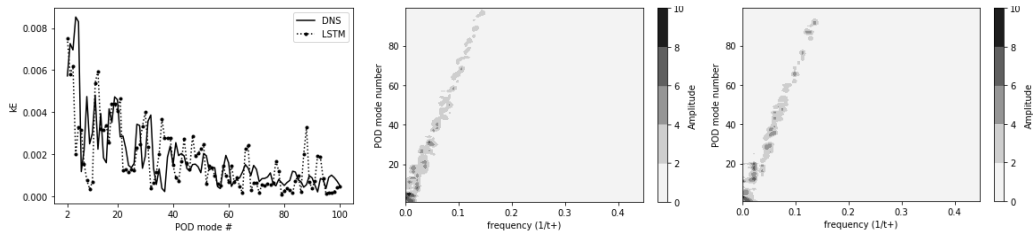


Figure 1: Left: Energy of the POD amplitudes as a function of POD mode number for the reference data and the prediction; Middle: Frequency spectrum of the reference POD amplitudes as a function of POD mode number; Right: Frequency spectrum of the predicted POD amplitudes.

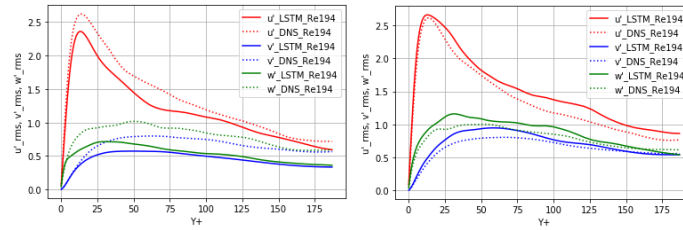


Figure 2: Turbulent intensities averaged over time and the spanwise direction at different streamwise locations as a function of the wall distance y (expressed in wall units $+$); top: channel inlet; bottom: channel outlet.

INLET BOUNDARY CONDITION

In this section we simulate a spatially developing turbulent channel using as an inlet condition the velocity field reconstructed using the POD eigenfunctions and the amplitudes predicted by the LSTM. A convective boundary condition is used at the outlet of the channel. The dimensions of the channel are $L_x = 2\pi$, $L - z = 4\pi$, $L_y = 1$ in respectively the streamwise (x), wall-normal (y) and spanwise (z) direction. The statistics are computed over 24 time units based on channel half-height and bulk velocity in cross-planes at the following streamwise locations: the inlet, the mid-channel $x = \pi$ and the outlet. They are compared with those of a reference simulation at the same Reynolds number with periodic boundary conditions in the streamwise direction.

Figure 2 shows the turbulent intensities (or normal components of the Reynolds stresses). The normal stresses components of the reconstructed velocity condition are slightly under-predicted, which corresponds to the fact that only 85% of the kinetic energy is captured in the reconstruction. However at the outlet of the channel, the stresses are in much better agreement with the reference.

CONCLUSIONS

A new method combining Proper Orthogonal Decomposition and neural approaches was developed in order to build an inlet condition for an turbulent channel flow. The boundary condition was reconstructed using POD modes determined *a priori*. The amplitudes of the POD modes were predicted using a LSTM network. The characteristics of the amplitudes were satisfactorily captured by the LSTM. The statistics of the channel with the synthetic inlet boundary condition were found to match relatively well those of a turbulent channel flow with standard periodic boundary conditions.

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