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From wall measurements to three-dimensional turbulent-flow fields via GANs

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In this work, we aim to estimate the three-dimensional turbulent flow in a channel using wall measurements of pressure and shear stress with 3D generative adversarial neural networks (GANs). The research extends previous work of the coauthors on wall-parallel plane estimation based on two-dimensional 2D GANs. We demonstrate that, with a moderate increase in the number of training parameters, the entire reconstruction is achieved with only slightly lower accuracy than that of the 2D GANs. This approach will pave the way towards more efficient flow estimation from wall sensors.

INTRODUCTION

The estimation of turbulent flow fields from wall-embedded sensors is a key aspect for the implementation of boundary-layer flow control. In this framework, linear methods have proven to be able to obtain accurate flow reconstructions up to the logarithmic region of channel flows [1]. Furthermore, deep neural networks [2] [3] [4] have proven to increase significantly the accuracy of these estimations, enabling an improved modelling of the non-linear relation between wall and flow data.

In Ref. [4], two-dimensional (2D) wall-parallel instantaneous velocity fields were reconstructed from wall-pressure and wall-shear-stress measurements of a turbulent open channel flow at a friction-based Reynolds number equal to 200. The approach was based on generative adversarial networks (GANs), which can cope with non-linearities, and it was proved to work effectively in establishing the relation between the wall measurements and the velocity fields.

In the present work, we move from the previous 2D flow-field reconstruction to a three-dimensional (3D) scenario, i.e. the GANs are trained to perform a full 3D reconstruction of the flow field. This allows reducing the training to a single network, instead of having different networks for each wall distance. As an additional advantage, a 3D description of the flow is readily achieved, instead of relying on plane segmentation.

METHODOLOGY

The GAN consists of two networks: a generator and a discriminator. The generator takes as input the wall measurements of spanwise and streamwise shear stress and pressure, producing the corresponding field as output. Its training process is complemented with that of the discriminator, whose goal is to detect whether a field is original or produced by the generator. The generator is trained to obtain realistic fields so that it confuses the discriminator, with both networks competing against each other during training.

The main novelty with respect to Ref. [4] is the use of 3D convolutional layers. In the generator, these layers are combined through multiple residual blocks, which contribute to the stability and convergence of the training process.

The data set used for this work was obtained from a direct numerical simulation (DNS) of a turbulent open-channel flow at friction based Reynolds number equal to 200. The dimensions of the domain are πh in the streamwise direction (x), $2h$ in the wall-normal direction (y) and $\pi/2h$ in the spanwise direction (z). The domain has 64, 128 and 64 points respectively, equispaced along x and z. The region of interest for this work includes the whole domain in the streamwise and spanwise directions, and half the domain in the wall-normal direction, *i.e.* from a wall to the mid-plane.

RESULTS

The network has been proven to successfully predict the flow field with an error level comparable to that reported in the 2D analysis. This result is very significant, because with similar computational resources, it can predict at once many wall-parallel layers, which conform the 3D volume of interest. In particular, the generator of the network implemented in the 2D setup [4] has about 1 million of trainable parameteres, while in this work it has 9 million and it predicts 64 wall-normal planes.

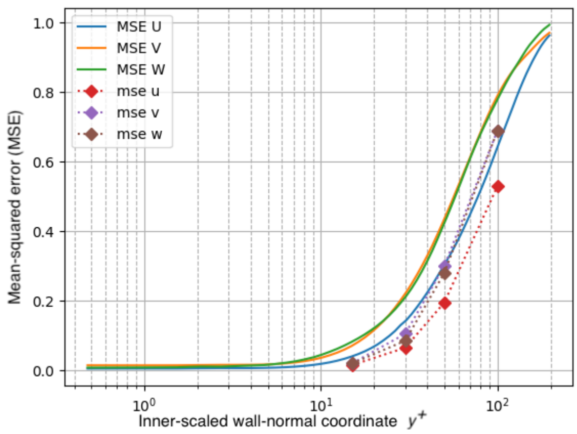

FIG. 1. MSE of the prediction of the three components of the velocity fluctuations as a function of the inner-scaled wall-normal coordinate y^+. The solid lines refers to the 3D prediction presented in this work, and the dotted lines were collected from the Ref. [4], with predictions at $y^+ = [15, 30, 60, 100]$.

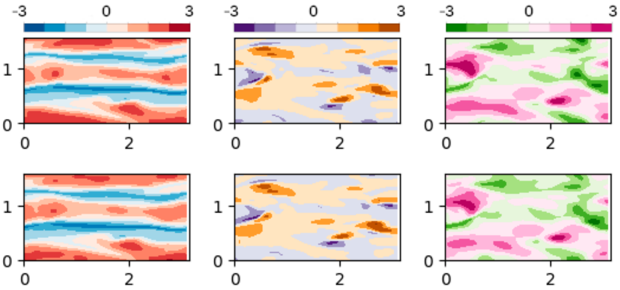

FIG. 2. (Top) Reference and (bottom) predicted instantaneous fields of (left) u, (middle) v and (right) w, for $y^+ = 10$.

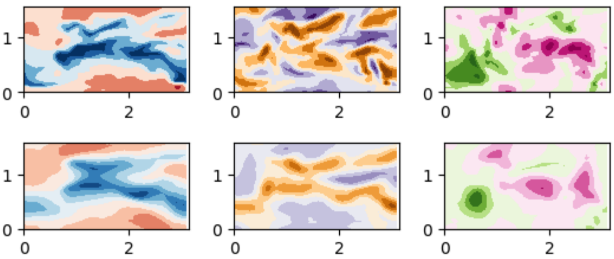

FIG. 3. (Top) Reference and (bottom) predicted instantaneous fields of (left) u, (middle) v and (right) w, for $y^+ = 70$.

Figure 1 reports the normalized mean-squared error (MSE) of the prediction along the wall-normal direction, showing that the results obtained in this work have a slightly lower accuracy than those from Ref. [4]. The turbulent features are predicted with high accuracy in the viscous layer, and then become progressively worse through the buffer and logarithmic layers.

Figures 2 and 3 show a comparison of sample predicted instantaneous velocity fields from wall measurements with respect to the target fields. The network performance is much better in the vicinity of the wall, with structures of different sizes being present in the prediction. In particular, the streamwise streaks are very well recovered. As one moves farther from the wall, the MSE of the prediction increases, mainly due to attenuation of the intensity of the structures and the filtering of the smaller scales. This is expected, since the sizes of the patterns observed in the wall data and the distance to the wall determine the size of the structures that could be detected at some point from wall measurements, in line with the attached-eddy hypothesis.

One of the advantages of this 3D flow prediction with respect to the 2D setup is that it allows to obtain a direct 3D visualization of the turbulent structures present in the flow. Fig. 4 (top) shows a representation of the vortical structures predicted from a sample of wall measurements. Note that the structures in the near-wall region are very accurately predicted.

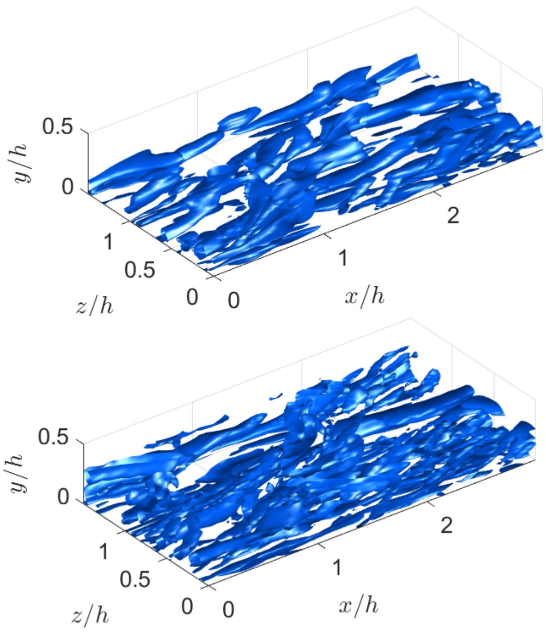

FIG. 4. Representation of turbulent structures with *Q-criterion* for the predicted flow with GANs (top) and from the original DNS dataset (bottom).

CONCLUSIONS

We demonstrated that GANs with 3D convolutional layers can efficiently predict the 3D turbulent channel flow, with levels of accuracy similar to those of 2D GANs, at a comparable computational cost. The method lacks ability to reconstruct small-scale features far from the wall, although this limitation is shared with linear methods and was also reported in the 2D analysis [4]. Hence this limitation can be ascribed to a physical limitation of the small-scale structures having a limited imprint on the wall rather than to the reconstruction algorithm and its implementation.

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[1] Encinar M. P. and Jiménez J. (2019) "Logarithmic-layer turbulence: A view from the wall". *Physical Review Fluids*, vol. 4, no. 11, pp. 114603.
[2] Güemes A. *et al.* (2019) "Sensing the turbulent large-scale motions with their wall signature". *Physics of Fluids*, vol. 31, no. 12, pp. 125112.
[3] Guastoni L. *et al.* (2021) "Convolutional-network models to predict wall-bounded turbulence from wall quantities". *Journal of Fluid Mechanics*, 928
[4] Güemes A. *et al.* (2021) "From coarse wall measurements to turbulent velocity fields through deep learning". *Physics of Fluids*, vol. 33, no. 7, pp. 075121.