EXPERIMENTAL APPLICATION OF A DYNAMIC OBSERVER TO CAPTURE AND PREDICT THE DYNAMICS OF A FLAT-PLATE BOUNDARY LAYER

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<u>Abstract</u> The recent approach, proposed by Guzman-Inigo et al. [5], using System Identification to derive a Reduced Order Model from snapshots of a flow is applied to a transitional boundary layer growing over a flat-plate. It is shown that such an approach can indeed be applied to experimental PIV snapshots. Using a proper learning dataset and a proper local sensor, it is shown that the evolution of boundary layer can be properly estimated from the time evolution of the local probe and with no more than ten POD modes for the Reduced Order Model. The influence of the various parameters on the efficiency of the system identification technique is discussed.

INTRODUCTION

One of the approach to closed-loop flow control is to try to reduce the high degree of freedom of a full fluid system to a lower order model which could be handle by a controller. The usual approach, mainly applied to simple flow configurations and to numerical simulations, consists in a flow decomposition using Proper Orthogonal Decomposition (POD) followed by a Galerkin projection of the equations onto the reduced basis [1, 2]. To extract a Reduced Order Model (ROM) from experimental data is a more challenging task, especially for noise amplifier flows. Recently a more "experiment friendly" approach has been proposed using system identification [6, 5].

Experiments have been carried out in a low-velocity hydrodynamic channel. The boundary layer grows over a dedicated flat plate with a smooth profiled leading-edge (Fig. 1). The Reynolds number of the flow based on the boundary layer displacement thickness δ^* is $Re^*_{\delta} = 400$ corresponding to a shape factor H = 1.6. The boundary layer is forced by a spanwise slotted jet located at $x_{forcing} = 10$ cm downstream the leading edge. The forcing consists in random variations of the amplitude and actuation time of the jet velocity $u_{forcing}$. The maximum amplitude of the forcing is low to remain in the linear regime. The instantaneous snapshots of the velocity field are obtained using the Real-Time PIV (Particle Image Velocimetry) setup detailed in Gautier & Aider [4] and used as inputs (visual sensor) for closed-flow control experiments [3]. Only the fluctuating velocity field is considered.



Figure 1. Sketch of the experimental setup and definition of the PIV window and local sensor s.

RESULTS

Among the snapshots recorded at a frequency of 35 frames per second, the first 1500 have been used as learning data set to identify the ten modes containing most of the energy (> 80%) and defining the POD basis. A sensor *s* measures the instantaneous vertical component of the velocity field averaged in the small area shown in Fig. 1. It is used as a local probe (similar to the wall sensor used in Guzman-Inigo et al. [5]) to monitor the flucuations of the flow field (Fig. 2 (a)). The model is defined through the data sensor and the POD coefficients as inputs during the learning step. Then the next snapshots are computed taking into account only the data sensor. The Fig. 2(c) shows the resulting estimated snapshot

obtained by the system identification which is in good agreement with the real snapshot (Fig. 2 (a)). The reconstruction of the structures is sensitive not only to the sensor location and nature but also to the POD modes since the less modes are used, the more filtered the velocity field is. For example the most energetic coefficient is plotted in Fig. 2 (d). Other comparisons are explored, such as the total TKE measured in the PIV window. The system identification can be used in a closed-loop flow control experiment.



Figure 2. Vertical components of the experimental velocity field (a) and computed velocity field (c). Data sensor (b). Experimental and computed first POD coefficient (d).

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