doi: 10.82124/CEAS-GNC-2026-104

EuroGNC CEAS Navigation Guidance Control Madrid, Spain May 5th-7th 2026 uc3m Universidad Carlos III de Madrid AIAA

Advancing flow diagnostics for sensing and control

Stefano Discetti Full Professor, Department of Aerospace Engineering, Universidad Carlos III de Madrid, Leganés, Spain. stefano.discetti@uc3m.es

ABSTRACT

Active control of turbulent flows is hindered by the resolution limits and latency of existing flow sensing technology. We address this issue via a data-driven framework focused on delivering enhanced flow descriptions from a combination of measurement techniques. The integration of sparse fast sensing with flow field measurements is outlined as an effective pathway towards a more complete flow description, which can be exploited for interpretation and control. Furthermore, recent advances in Event-based Imaging Velocimetry (EBIV) are now enabling low-latency flow field measurements, which can be directly exploited for active flow control applications. Examples of integration of EBIV in open-loop control optimization and closed-loop control of jet flows are illustrated.

Keywords: Flow diagnostics, Turbulence control, Flow measurements

1 Introduction

The performance of a wide variety of industrial devices depends heavily on our capability to control the fluid flow behaviour. Aerodynamic flow control, encompassing both passive and active strategies, serves several crucial functions: improving aerodynamic efficiency of aircraft, suppressing aeroacoustic signature, maximising energy generation from renewable sources and maintaining robust performances of devices interacting with fluids across a wide range of operating conditions. Achieving efficient active flow control is an overarching goal with one of the greatest transformative potentials in efficiency and sustainability [1, 2].

Active flow control hinges on the ability to sense and model fluid flows. Open-loop control strategies greatly benefit from the understanding of the flow behaviour (ideally in time-resolved, three-dimensional description) for the optimization of control laws. Closed-loop control, on the other hand, needs rapid state estimation to provide feedback. The sensing must be possibly non-intrusive and possess sufficient spatial and temporal resolution to capture the spectrum of coherent structures that play a role in momentum and energy transport in turbulent flows.

Experimental fluid dynamics tools are inherently constrained by trade-offs in their ability to provide a complete picture of a fluid flow. Techniques such as Particle Image Velocimetry (PIV) provide instantaneous, spatially-resolved planar or volumetric descriptions of the velocity fields, but often at the expense of poor time resolution due to hardware limitations. Furthermore, the dynamic range (i.e. the ratio between the largest and smallest measurable spatial/velocity scale) is often insufficient to fully resolve turbulent flows. On the other hand, pointwise techniques (such as hot-wire anemometry or pressure sensors) can provide data easily at high repetition rate, at the cost of being intrusive and providing only information at a few points. The sparse information from point sensors is thus often insufficient to describe the state of the flow. Furthermore, introducing flow measurements in the control loop requires efficient data handling and processing to minimise latency.

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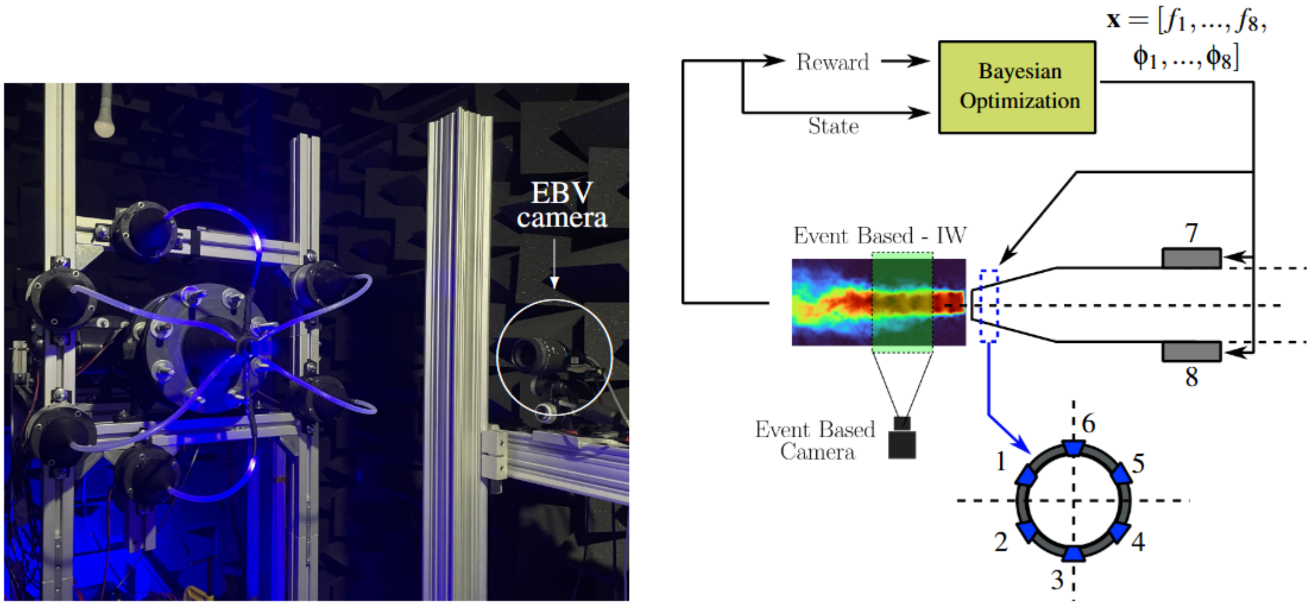

Fig. 1 Left: experimental setup of the jet facility equipped with actuators and an event-based camera. Right: EBIV-based control architecture for jet flow control experiments [11].

2 Combination of incomplete measurements as an opportunity for more informative flow sensing

A solution to circumvent some of the technological barriers of flow measurement techniques consists in blending sparse, diverse information sources and using data-driven methods to model the flow. This approach seeks to reconstruct spatio-temporal flow fields that are consistent with sparse measurements and the underlying physics, using as a training set simultaneous PIV and probe measurements. The problem is thus configured as a time-resolution enhancement of the PIV measurements, leveraging temporal information from probes. Full-state estimation from sparse and incomplete data, and integration of such data with the Navier-Stokes equation, can be used to obtain time-resolved pressure fields [3–5] from the velocity fields. Techniques based on linear (such as Extended Proper Orthogonal Decomposition [6]) and nonlinear estimators (e.g. Generative Adversarial Networks [7] or Physics-Informed Neural Networks [8]) have demonstrated being a promising avenue for this task.

3 New horizons for flow control with event cameras

Recently, Event-Based Imaging Velocimetry (EBIV) [9] has introduced new opportunities to include PIV measurements in the loop for flow control. EBIV is based on neuromorphic cameras, which provide an asynchronous stream of events of brightness changes. Compared to frame-based cameras, neuromorphic cameras provide a significantly lighter data stream, thus reducing overheads and paving the way to integration in control loops. EBIV offers quick extraction of latent coordinates for control [10], rapid evaluation in open-loop control optimization, and potential for direct integration in closed-loop control. An example of setup is illustrated in Fig. 1, in which EBIV is used for quick mixing rate quantification to optimize an open-loop control policy targeted on mixing enhancement using loudspeaker-driven actuators.

Acknowledgments

This project has received funding from the European Research Council (ERC) under the European Union's Horizon 2020 research and innovation programme (grant agreement No 949085, NEXTFLOW ERC StG). Views and opinions expressed are however those of the authors only and do not necessarily reflect those of the European Union or the European Research Council. Neither the European Union nor the granting authority can be held responsible for them.

Declaration of Use of Artificial Intelligence

AI was used to improve the clarity, grammar, and overall readability of the text. The author takes full responsibility for the content of this work.

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