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Event-Based Flow Sensing: From Coherent Structures to Neuromorphic Sensors

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ABSTRACT

Recent advances in data-driven modeling, neuromorphic engineering, and bio-inspired sensing can reshape how we perceive and control turbulent flows. To sample turbulent flows, we need to generate vast amounts of data that are well-resolved in both space and time. This might lead to complex multi-input multi-output optimization problems for flow control. Moreover, traditional sensing approaches rely on continuous or periodic-sampled acquisition, leading to signal properties in accordance with the Nyquist–Shannon sampling theorem.

Reduced-order modeling allows for a representation of the flow fields as a combination of a limited number of coherent structures. Event-based sensing, where information is acquired only when significant changes occur, offers a radically different paradigm for sensing. Last but not least, neuromorphic sensors in biological systems release spikes based on the convolution of a signal with specific filters tailored to detect specific events.

In this presentation we will explore the physical, computational, and biological foundations of event-based flow sensing, illustrating how turbulence physics, reduced-order modeling, and neuromorphic hardware can converge toward the next generation of intelligent flow control systems.

Keywords: Flow Control, Reduced-order modelling, Event-based sensing

1 Motivation and Background

The impact of turbulence on the performance of countless engineering devices motivates the need for developing control strategies and equipping engineering devices with flow control systems. Active closed-loop control is one of the grand challenges and opportunities of modern fluid dynamics [1]. However, the high-dimensional and multi-scale nature of turbulent flows [2] make real-time estimation and feedback control extremely demanding. Resolving turbulent flows requires high spatial and temporal resolution data leading to the need of collecting high-dimensional snapshot data at high repetition rate.

2 Coherent Structures and Bio-Inspired Paradigms: Opportunities

Despite their chaotic nature, turbulent flows are characterized by recurrent flow patterns, typically referred to as coherent structures. The beauty of these patterns fascinated empirical observers since at least the time of Leonardo da Vinci [3]. The existence of coherent structures, according to Ref. [4] *triggers the "hope" that at least part of the dynamics [of the flow] can be described in terms of a relatively small number of elementary objects that, at least for some time, depend predominantly on a "few" similar objects and on themselves, with only minor contributions from an "unstructured" background.*

Reduced-order modeling is a tool to represent complex features in smaller dimensional spaces. For turbulent flows, such low-dimensional representations can be deemed to represent the turbulent coherent structures. Classical modal decomposition methods, such as POD [5], identify coherent structures that capture most of the flow energy or dominant dynamic behavior. These modes form the foundation for low-dimensional representations and models, as, e.g., Galerkin models [6]. Recent nonlinear techniques such as Isomap [7] or autoencoder-based latent spaces [8] allow compact modeling of non-stationary, nonlinear flow dynamics. Following the Whitney embedding theorem [9], such models could guide optimal sensor placement and data reduction, highlighting what and where to measure.

Many natural flyers and swimmers sense and control complex flow environments using sparse, distributed sensors. Insects rely on campaniform sensilla—strain-sensitive mechanoreceptors distributed over their wings to detect deformation and unsteady aerodynamic loads [10]. These sensors operate asynchronously, firing neural spikes only when a strain signal, convoluted with a certain filter, returns an activation value, thereby encoding aerodynamic events efficiently [11]. Event-based sensing, originally developed for neuromorphic vision applications [12], addresses the periodic sampling limitation by measuring only changes in the measured signal. This represents a paradigm shift and is also referred to as Lebesgue sampling [13]. In vision applications, the sampling is not focused on the type of event to be observed; each pixel or sensor operates independently, generating discrete events upon threshold crossings. Each pixel or sensor element produces an event, a spike in time, whenever the local signal crosses a relative threshold. The resulting asynchronous signal stream is highly sparse although temporally precise.

3 Outlook and Research Vision

The application of Lebesgue sampling to conventional flow sensing methods, such as hot-wire anemometry, pressure transducers, or particle image velocimetry (PIV), can significantly mitigate data redundancy, enabling real-time feedback applications with less stringent latency and bandwidth constraints. The implementation of a bio-inspired paradigm on the selection of filters for Lebesgue sampling might lead to an optimized sampling of specific flow-events related to coherent structures. These technologies together will enable a sparse, asynchronous data stream with sub-millisecond latency and significantly reduced data and computational power usage. Finally, the direct sensing of *flow events* could directly trigger actuation commands, closing the feedback loop with very low latency.

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Declaration of Use of Artificial Intelligence

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