EVENT-BASED LAGRANGIAN PARTICLE TRACKING FOR TURBULENT SHEAR FLOWS

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ABSTRACT

The application of event-based cameras in particle tracking velocimetry enabled cost- and energy efficient measurement setups with low latency and superior temporal resolution, naturally meeting the high demands of measuring turbulence and shear flow phenomena. However, handling the asynchronously recorded event-stream poses new challenges on data processing. In this work, we evaluate the performance of different processing strategies by using the modular framework for spatiotemporal event-based Lagrangian particle tracking (STELLA) recently developed. Besides deterministic algorithms, artificial neural networks tailored for object detection based on dense representations of the event-stream are used for particle detection. To reveal the versatile applicability of event-based particle tracking velocimetry to turbulent fluid flows, a synthetic as well as different experimental datasets are derived, spanning from the turbulent flow in the wake of a cylinder up to the shear flow in the turbulent boundary layer of a high-Reynolds pipe flow.

Introduction

Event-based particle tracking velocimetry (EBPTV) sparked a lot of interest in the scientific community, as it allows for cost- and energy-efficient experimental setups to measure Lagrangian particle tracks with superior temporal resolution. By combining a very low latency (< 100 µs) with a high dynamic velocity range ($> 3 \times 10^4$ pixel/s), EBPTV naturally matches the high demands to measure turbulence and shear flow phenomena without the need for expensive high-speed cameras, pulsed lasers and precise synchronization. At the heart of the technique, event-based cameras are utilized to capture pixelwise intensity changes as asynchronous events, which contrasts with conventional frame-based cameras. The obtained event-stream contains the position (x, y) within the pixel array, the timestamp (t) in microsecond resolution and the polarity (p) of the event, i.e. an increase or decrease in intensity. Since not the entire frame is read out, the event-stream inherently possesses a sparse nature in space and time, which reduces the acquired data rate significantly and enables real-time processing (Drazen *et al.* (2011); Rusch & Rösgen (2023)). In experimental fluid mechanics, EBPTV allows for low-cost constant illumination due to a high dynamic intensity range up to 130 dB, a large dynamic velocity range as slow and fast moving particles leave their own footprint in the event-stream, and to effectively remove motion blur effects up to a particle velocity of 10^6 pixel/s.

To process the event-stream, different processing pipelines are used, as illustrated in Fig. 1. In the upper pipeline, the recorded events are accumulated over a time interval Δt into so-called pseudo-frames, which can be processed by well-established image evaluation algorithms for particle tracking velocimetry (PTV) (Wang *et al.* (2020)) or particle image velocimetry (PIV) (Willert & Klinner (2022)). However, individual event timestamps are lost during the accumulation of events. In the middle pipeline of Fig 1, temporal correlations are considered by building event-tensors as input for recurrent neural networks (RNN) trained for object detection. Within each event-tensor, events are accumulated across a shorter time interval $\delta = \Delta t / n$ in n bins, which add up to a

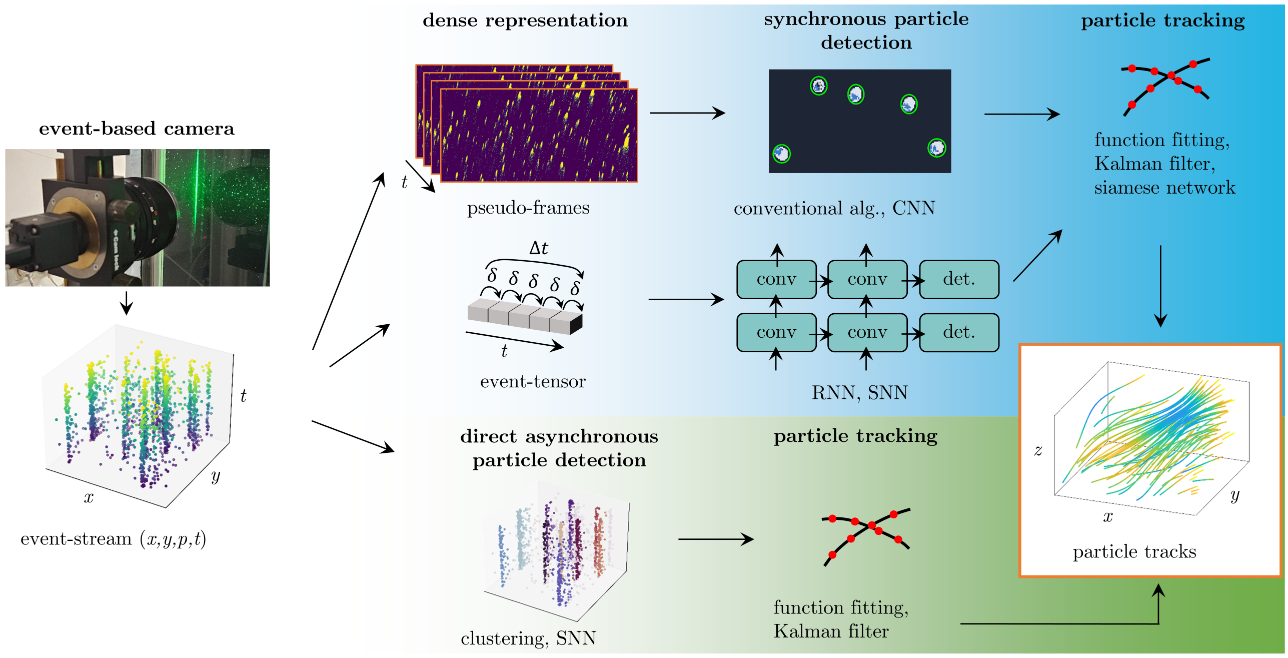

Figure 1. Established data processing pipelines for EBPTV, which either use dense representations (upper) by accumulating events into pseudo-frames or event-tensors, or direct processing of the event-stream (lower) received from an event-based camera (shown on the left).

longer time interval Δt. In the lower pipeline, the event-stream is processed directly by clustering events based on their spatiotemporal coherence (Rusch & Rösgen (2023)). In a subsequent step, particles can be tracked by using a Kalman filter or fitting individual path lines (Cierpka *et al.* (2013); Reed *et al.* (2025)). By directly processing the event-stream, the spatiotemporal sparsity and high temporal resolution of the events are utilized to achieve a high dynamic velocity range of detected particle tracks.

Spurred by the great success of artificial neural networks (ANN) in object detection, tailored ANN architectures promise significant benefits also for EBPTV using either of the described processing pipelines (Sachs *et al.* (2023)). In particular, a lower inference time and higher accuracy regarding the detected particle position, velocity and acceleration can be transferred from processing of frame-based images to pseudo-frames by using ANNs following the upper pipeline (Wang *et al.* (2024*b*)). Moreover, reliable object detection was demonstrated by processing event-tensors in RNNs in the middle pipeline, considering the temporal domain by, e.g., a Long Short-Term Memory (LSTM, Hochreiter & Schmidhuber (1997)) network as incorporated in the Recurrent Vision Transformer (RVT, Gehrig & Scaramuzza (2023)). For direct processing, Spiking Neural Networks (SNN) are conceivable to provide a reliable and computationally fast particle tracking (Wang *et al.* (2024*a*)). Especially when compiled on neuromorphic hardware, asynchronous processing of the event-stream becomes feasible while making use of the temporal and spatial sparsity of the events (Schuman *et al.* (2022)). However, current implementations for object detection fall behind well established ANNs mainly due to insufficient training strategies (Wang *et al.* (2024*b*)).

In this work, the advantages and disadvantages of the proposed processing pipelines as assisted by ANNs are revealed by using the modular framework STELLA (SpatioTemporal Event-based Lagrangian particLe trAcking, Sachs *et al.* (2026)). As demanding benchmarks, a synthetic dataset as well as velocity measurements in the wake of a cylinder, a turbulent flow around an hydrofoil, and a shear flow in the turbulent boundary layer of a pipe flow captured at the Centre of International Cooperation in Long Pipe Experiments (CICLoPE) will be presented. To encourage scientists within the turbulence and shear flow community to apply EBPTV, the modular framework as well as synthetic and experimental datasets will be made available: `https://github.com/sesa1504/STELLA`.

Methodology

Using STELLA, the recorded event-stream is evaluated by applying subsequent steps of preprocessing, detection, matching, and tracking. During preprocessing, negative events are filtered, and the event-stream is either passed on directly or accumulated into pseudo-frames or event-tensors. Subsequently, particles are detected by means of spatiotemporal clustering of events in direct processing of the event-stream, or image-based evaluation of pseudo-frames applying a circular averaging filter and segmentation using Otsu's threshold value (Otsu (1979)).

In comparison, the particle identification was further treated as an object detection task, handled by ANNs to detect particles based on pseudo-frames using the Mixture-of-Experts heat conduction-based detector (MvHeatDET, Wang *et al.* (2024*b*)) or event-tensors using the Recurrent Vision Transformer (RVT, Gehrig & Scaramuzza (2023)). Once the particles are identified, a matching step is applied to associate detections in the current time step to existing clusters based on spatiotemporal association or a nearest-neighbor algorithm. Finally, the particle position and velocity are derived by calculating particle tracks using a Kalman filter, spline fitting, or hybrid approaches combining both. As positive events are triggered only in the front end of the particle image where the intensity is rising, the particle position is typically detected with an offset towards the direction of motion. To enhance the ac-

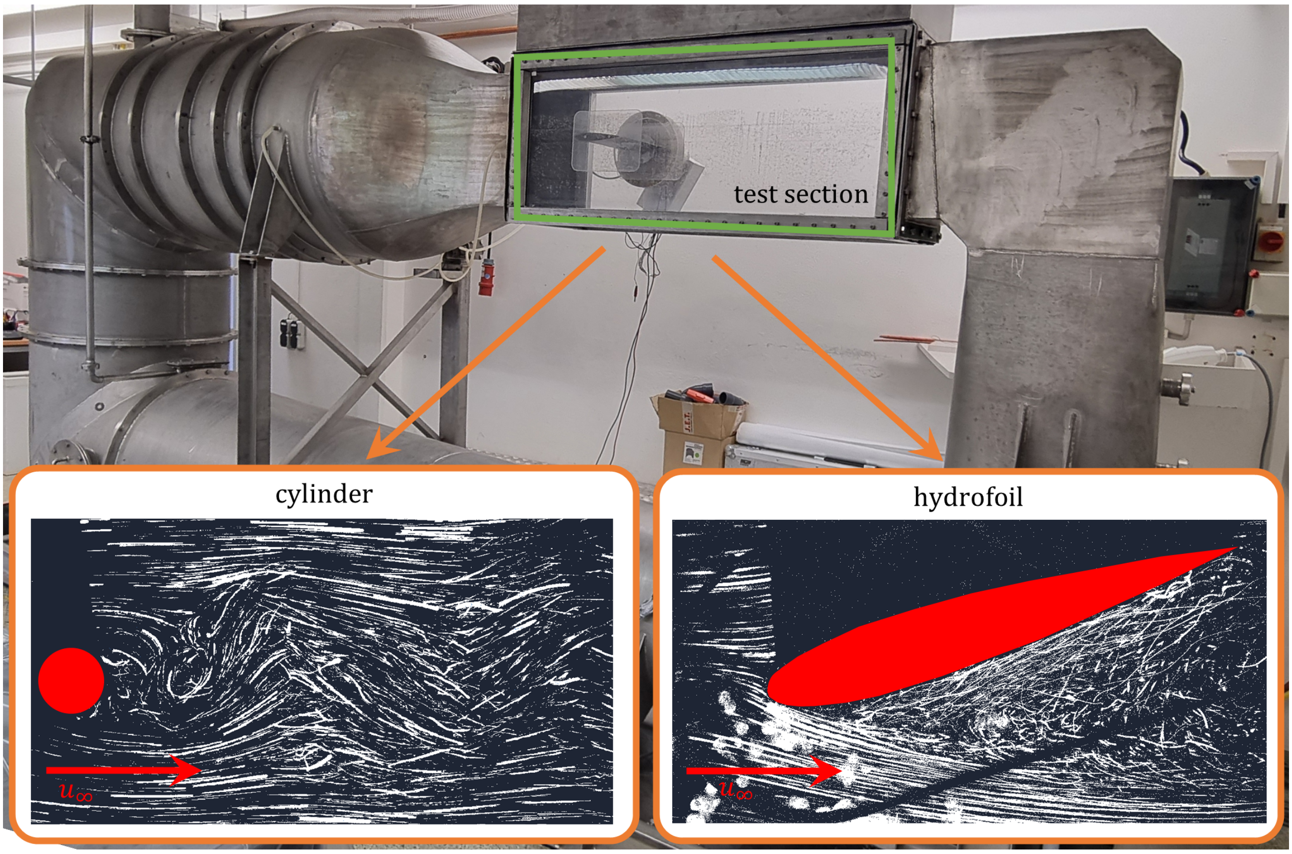

Figure 2. Water tunnel used to perform experiments on the flow around and in the wake of a cylinder and hydrofoil. The test section is highlighted in green. Exemplary recordings of an event-based camera are visualized by pseudo-frames in the bottom.

curacy of the framework, this offset is corrected based on the predicted velocity and spread of the events perpendicular to the direction of motion within each cluster.

To evaluate the performance of the EBPTV algorithms for turbulent fluid flows, both synthetic and experimental data sets are set up. In particular, synthetic data are generated by firstly using a developed synthetic image generator to create particle images with Gaussian intensity distribution in grayscale images. In between the images, the particles are shifted in position while perfectly following a divergence-free velocity field that is inspired by an Arnold-Beltrami-Childress flow (Fre & Sorin (2015)). However, to avoid particles leaving the computation domain rapidly in z-direction and to obtain elongated particle tracks, the velocity component in z-direction was scaled by a factor of 0.03. Based on the grayscale images, realistic event-streams with well-known ground truth are generated by using the event simulator ESIM (Rebecq *et al.* (2018)). To train the ANNs, the synthetic dataset is extended to $142 \times 2\,\mathrm{s}$ long sequences containing (300 ± 100) particles and variations in the velocity magnitude, particle size and spatial pattern of the velocity field. The data is split at a ratio of 70/10/20 for training/validation/testing.

Experimental datasets are captured in the wake of a cylinder and a hydrofoil mounted in a water tunnel as shown in Fig. 2. Exemplary pseudo-frames are depicted for both cases with Reynolds numbers $Re = u_\infty d_{\mathrm{cylinder}}/\nu$ up to 41.6×10^3, using the free-stream velocity u_∞, the diameter of the cylinder $d_{\mathrm{cylinder}} = 21\,\mathrm{mm}$ and the kinematic viscosity of water ν. The fluid flow was seeded with tracer particles (polyamide, $6\,\mu\mathrm{m}$, Evonik Industries AG) that were illuminated by a light sheet generated by using a DPSS cw-laser (Frankfurt Laser Company) and observed by an event-based camera (Prophesee EVK 4, 1280×720 pixel). Simultaneously, the particles were captured by a high-speed camera (Imager HS, 2016×2016 pixel, LaVision GmbH) for quantitative comparison. At the conference, further measurements conducted in the boundary layer of a high-Reynolds pipe flow at the Centre of International Cooperation in Long Pipe Experiments (CICLoPe) will be discussed.

Results

In Fig. 3, particle tracks detected in the wake of a cylinder at a Reynolds number of $Re \approx 41.6 \times 10^3$ are illustrated against a pseudo-frame of events accumulated during $\Delta t = 8\,\mathrm{ms}$. The event-stream was processed directly while only taking events with positive polarity into account. Furthermore, the particle tracks are color-coded by their streamwise velocity component u_x. In the analyzed fluid flow, particles are reliably tracked, while spanning four orders of magnitude in pixelwise velocity. Hence, proving the high dynamic velocity range achievable with EBPTV, which significantly challenges conventional particle tracking velocimetry based on a fixed timing scheme. As typically seen in a flow around a cylinder, highly turbulent vortices detach periodically from the rear of the cylinder, forming a vortex street with a frequency depending on the Reynolds number known as von Kármán vortex street. To analyze the frequency of vortex shedding based on the experimental data, the velocity component u_y measured within the pink frame is depicted in Fig. 4a as a function of time for $Re = 17.2 \times 10^3$. As vortices are detaching, u_y is fluctuating periodically. By fitting a periodic function to the measured velocity data, the mean frequency f of vortex shedding and the resulting Strouhal number $St = f d_{\mathrm{cylinder}}/u_\infty$ can be de-

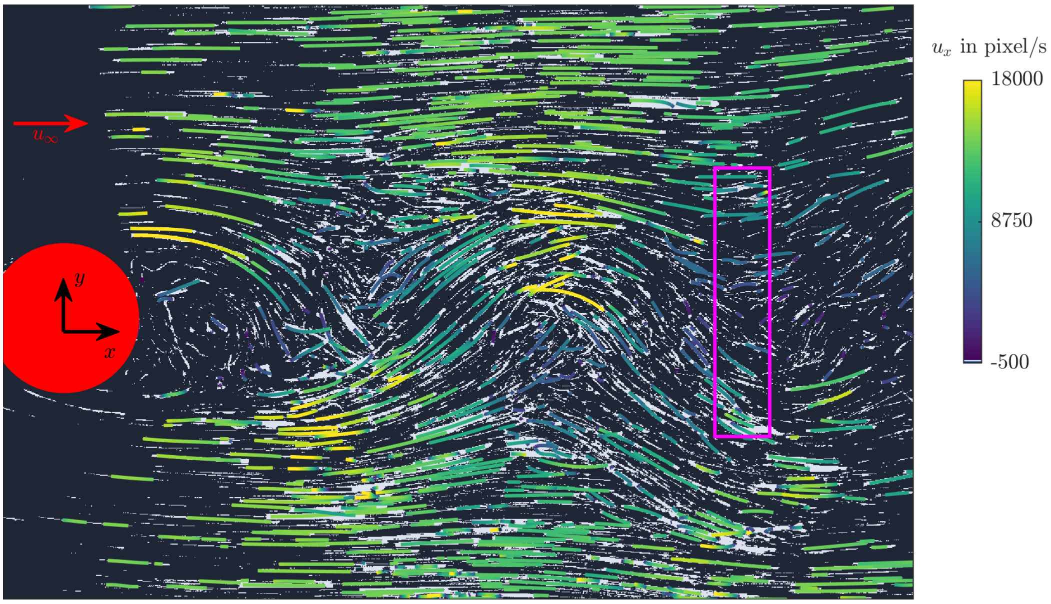

Figure 3. Particle tracks detected in the wake of a cylinder by directly processing the event-stream. A main flow was applied in positive x-direction. The streamwise velocity component u_x of the particles is color-coded in the Lagrangian tracks. In the background, a pseudo-frame containing events accumulated over 4 ms is shown.

termined roughly. The latter is depicted against the Reynolds number *Re* in Fig. 4b along with literature values illustrated by dashed lines (Lienhard (1966)). Within the measurement range, the derived Strouhal numbers scatter around a value of $St = 0.21$, averaging at values about 4.2 % higher than reported in literature. However, only marginal differences are found between EBPTV using either direct processing or pseudo-frames and conventional PTV results using a high-speed camera. Simultaneously, the feasible measurement range was extended up to $Re = 41.6 \times 10^3$ using the event-based camera as the event-stream was recorded continuously. In contrast, the measurement range was restricted to $Re = 20.6 \times 10^3$ using the high-speed camera as the signal-to-noise ratio significantly decreased with the applicable exposure time. Hence, EBPTV proved to achieve reliable and robust velocity data, suitable for flow diagnostics.

At the conference, an in-depth analysis on the accuracy of EBPTV will be discussed in relation to a known ground truth regarding the position and velocity of particle tracks. In particular, the mean absolute error is quantified to about 2 pixel in position and 3.5 % in velocity based on synthetic data when applying ANNs for particle detection. Furthermore, demanding benchmark scenarios were derived by measuring the fluid velocity field around a hydrofoil as well as in the thin boundary layer of a highly turbulent pipe flow. In this way, EBPTV is highlighted as a reliable and versatile measurement technique, applicable to a variety of turbulent fluid flows at low cost and low demand in data processing.

Conclusion and outlook

Event-based PTV combined with ANNs revealed as a promising tool for Lagrangian particle tracking in turbulence and shear flows. At the conference, the developed modular processing framework STELLA will be presented and discussed, which provides suitable access to the measurement technique, thus making it useful for the community of experimental fluid dynamics. The performance of the framework will be evaluated based on synthetic and experimental datasets of complex fluid flows with well-known ground truth, underlining the versatility of EBPTV. In this way, a fair comparison is provided between the different processing pipelines based on deterministic algorithms and ANNs. Moreover, the applicability of the algorithms, limitations regarding the processable particle image density, and detection accuracy will be analyzed based on experimental data.

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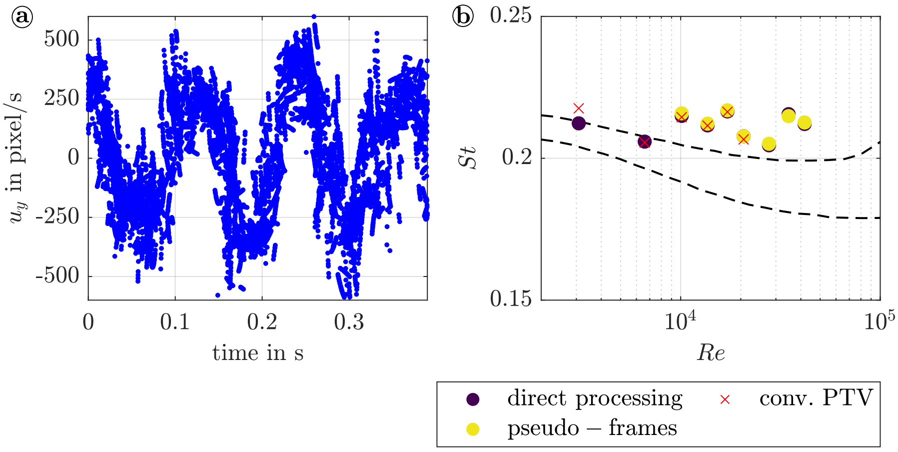

Figure 4. Vertical velocity component u_y measured within the pink frame in 3 as a function of time (a). Based on the periodic velocity fluctuations, the resulting Strouhal number St is calculated and depicted in (b) against the Reynolds number Re for different algorithms. Literature values are highlighted by dashed lines.

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