

# Event-based imaging for Lagrangian particle tracking using continuous illumination

S. Brückner<sup>1,\*</sup>, M. Barnes<sup>2</sup>, M. Hilfer<sup>1</sup>, D. E. Rival<sup>1,2</sup>

1: Institute of Fluid Mechanics, TU Braunschweig, Germany

2: Department of Mechanical Engineering, Queen's University, Canada

\*Corresponding author: [sylvia.brueckner@tu-braunschweig.de](mailto:sylvia.brueckner@tu-braunschweig.de)

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## ABSTRACT

The objective of the current study is to quantitatively assess the position error obtained from event-based data by comparing with frame-based data as ground truth. To this end, a turbulent flow is seeded with air-filled soap bubbles imaged simultaneously by an event-based and a frame-based sensor. For the event-based data, a fit-based approach using Savitzky–Golay filtering is implemented. The distribution of the local error is characterized, and a mean position error of  $\bar{e} = 0.31$  px, a standard deviation of  $\sigma = 0.19$  px, and a  $RMSE = 0.36$  px are reported, suggesting that sub-pixel position information can be recovered from event-based data through fit-based particle track reconstructions. Furthermore, velocity, acceleration, and radius-of-curvature statistics are derived to demonstrate the potential of event-based methods for reconstructing Lagrangian statistics.

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## 1. Introduction

Event-based imaging fundamentally differs from conventional frame-based techniques. Unlike frame-based cameras, event cameras respond independently and asynchronously to brightness changes at each pixel (Gallego et al., 2020; Chakravarthi et al., 2024), producing a data stream of spatial coordinates, timestamp, and contrast change polarity. Event cameras provide high temporal resolution, dynamic range, and robustness to illumination changes, while generating considerably less data than frame-based cameras (Gallego et al., 2020; Sun et al., 2021; Zhu et al., 2023; Barrios-Avilés et al., 2018). However, the different nature of event-based data necessitates more processing methods (Gallego et al., 2020). As events encode binary information corresponding to brightness changes (Gallego et al., 2020), the two-dimensional (2D) Gaussian particle-intensity distribution cannot be resolved in pseudo-images reconstructed from event-based data, leading to peak-locking effects and residual displacement errors of up to 0.5 pixels (Maya et al., 2025; Franceschelli et al., 2025). In contrast, frame-based methods can estimate particle positions with a resolution of  $\sim 0.1$  pixels (Raffel et al., 2018). Event cameras, however, provide event detection

and timestamp generation with microsecond resolution (Gallego et al., 2020).

This current study addresses the two following questions: (i) (as in Fig. 1) How is the event-based air-filled soap bubble (AFSB) position error distributed relative to the frame-based reference?

(ii) How can Lagrangian statistics be obtained from event-based data? To address question (i), an image-based processing approach is applied to the event data, with the frame-based reconstructions serving as reference. The present study focuses on event-based Lagrangian methods, where centimeter-sized AFSBs are used as tracers. AFSB motion is captured by tracking the two dominant glare points, and depth information is retrieved using the glare-point particle tracking (GPPT) technique. Further details on the method can be found in Hou et al. (2021); Kaiser & Rival (2023); Leister & Rival (2025).

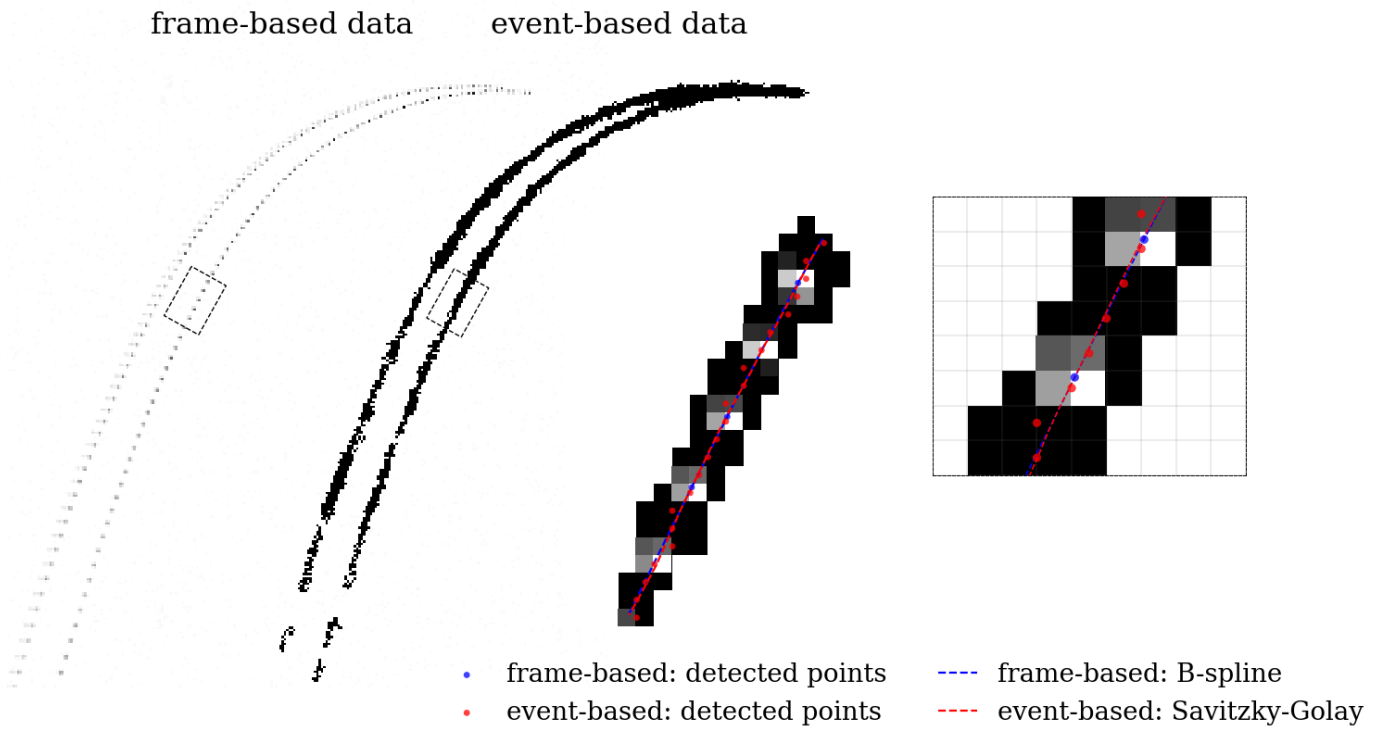


**Figure 1.** As the event-based sensor only records intensity changes at the pixel level, peak locking effects and a resulting displacement error of up to 0.5 px (pixel) occur (note that the event-based detected points lie at pixel centers or on pixel boundaries). However, event detection and timestamp generation can be performed with microsecond resolution. For visualization purposes, the grayscale intensities of the frame-based AFSB track on the left are inverted.

This paper is organized as follows. In Sect. 2 the measurement setup and the post-processing procedures are described. In Sect. 3 the position-error results and the event-based Lagrangian statistics are presented and discussed. In Sect. 4 conclusions are presented, with particular emphasis on the achievable event-based AFSB centerline-position accuracy.

## 2. Experimental methods

This section outlines the methods used for addressing the research questions in Sect. 1, including the experimental setup in Sect. 2.1 and the post-processing procedures in Sect. 2.2.

### 2.1. Setup

A non-uniform flow is generated by a flow simulator with a cross-section of  $2 \times 2$  m, consisting of 36 fans arranged in a  $6 \times 6$  grid and operated at identical speeds. This configuration produces a freestream velocity of  $U_\infty \approx 6 \text{ m s}^{-1}$ , measured at a distance  $d = 2$  m from the propeller plane, and corresponding to a Reynolds number of  $U_\infty D_B / \nu \sim 12\,000$ , with the AFSB diameter  $D_B$  and the kinematic viscosity of air  $\nu = 1.47 \times 10^{-5} \text{ m}^2 \text{ s}^{-1}$ . The flow is seeded with centimeter-sized AFSBs of diameter  $D_B \approx 30$  mm produced at a rate of  $\sim 25$  AFSBs/s, with the AFSB generator aligned vertically with the camera setup and the LED. The test section is illuminated laterally by an LED operated in steady mode.

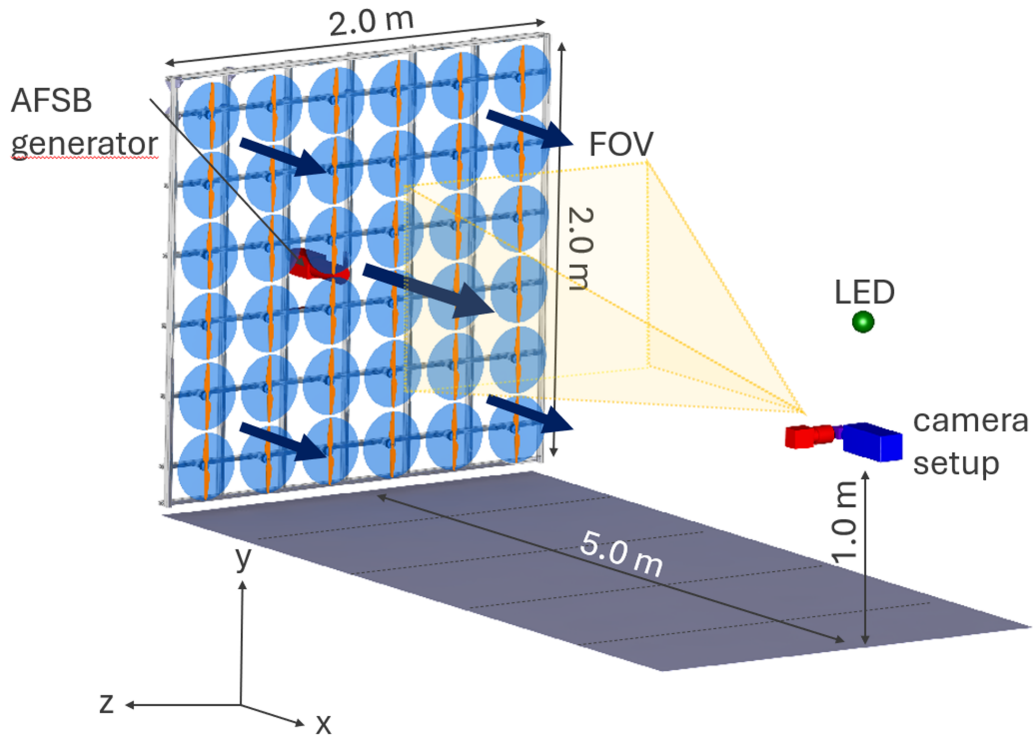


**Figure 2.** The experimental setup consists of the flow simulator, the AFSB generator, the camera setup, and the LED. The AFSB generator, positioned upstream of the flow simulator, is vertically aligned with the LED (positioned laterally of the test section) and the camera setup (positioned downstream of the measurement region). The latter includes the event-based camera (red), the frame-based camera (blue) and the beam splitter. The flow is seeded with AFSBs and has a freestream velocity of  $U_\infty \approx 6 \text{ m s}^{-1}$ .

Imaging is performed downstream of the measurement region using two synchronized cameras: an event camera (uEye IDS UE-39B0XCP-E, Prophesee) with an 8.5 mm focal-length lens (Edmund Optics), set to an aperture of  $f/11$ , and a high-speed camera (Phantom V711, Vision Research) with a 35 mm focal-length lens (Nikon), set to an aperture of  $f/5.6$ . Both cameras are operated at an image size of  $1280 \times 720$  pixels, and the same field of view (FOV) is imaged using a beam-splitter cube (LDOPTIC). Frame-based image acquisition is externally triggered at 400 Hz, with the exposure time set to  $1/5000$  s.

## 2.2. Post-processing procedure

### 2.2.1. Position accuracy

An image-based approach is used to extract the event-based AFSB centerline position error. The images reconstructed from frame-based and event-based data are generated using an integration window of 500 ms, and only events corresponding to an increase in intensity are used for generating the event-based images. The frame-based camera images are monochromatic and recorded with a 12-bit depth. For reduction of background information, a pixel-wise 10th intensity percentile is computed over a subset of frames and subtracted from each frame. The resulting frame-based images are thresholded at 185 intensity counts to obtain binary masks, which are used together with the corresponding intensity images. Frame-based subpixel particle positions are determined by fitting a 2D Gaussian model to a  $5 \times 5$  pixel window centered on each detected peak, while the corresponding binary masks are used for candidate-region restriction. For the event-based data, particles are detected row-wise, followed by gap handling and small-object removal. In particular, the event-based positions are determined from the mean x-position of detected event regions on a row-wise basis. The event-based particle positions are smoothed using a Savitzky-Golay filter with a polynomial order of 3 and a window length of 23, followed by linear interpolation to obtain interpolated particle tracks. Frame-based tracks are reconstructed using cubic smoothing B-splines. The tracks are evaluated at common y-positions, and the AFSB centerline is computed as the row-wise midpoint between both tracks. Fig. 3 shows the detected particle positions, the reconstructed left and right particle tracks, and the AFSB centerline for both frame-based and event-based data.

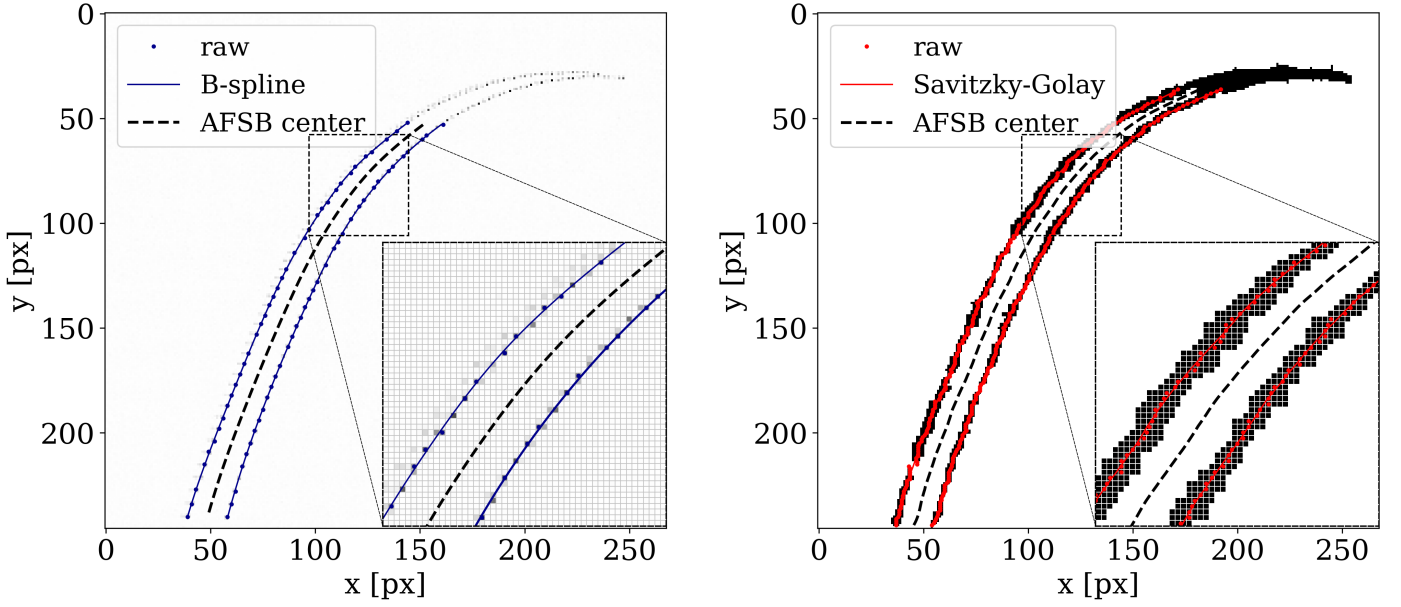


**Figure 3.** For extracting the event-data position error, the position difference of the event-based and frame-based AFSB centerlines (dashed black lines) is calculated. Two different approaches are used for track reconstruction. **Left:** Frame-based method for track reconstruction (blue) with Gaussian-based subpixel estimation and cubic B-splines. **Right:** Event-based method for track reconstruction (red). Particle positions are calculated using the row-wise mean x-positions of detected event regions, and Savitzky-Golay smoothing is applied. In both cases, the reconstructed AFSB centerline is calculated from the respective tracks as the row-wise midpoint between both tracks. For visualization purposes, the grayscale intensities of the frame-based tracks are inverted.

To compute the position error between event-based and frame-based centerlines, the AFSB centerlines were densely sampled. For each event-based centerline point, the nearest frame-based centerline point was identified using a nearest-neighbor search, with the local error  $e_i$  defined as the Euclidean distance between both points:

$$e_i = \sqrt{(x_i^{EVB} - x_{j(i)}^{FRB})^2 + (y_i^{EVB} - y_{j(i)}^{FRB})^2}, \quad (1)$$

with the horizontal and vertical coordinates  $x$  and  $y$ . The index  $i$  denotes the event-based AFSB centerline sample point, and  $j(i)$  denotes the nearest frame-based centerline sample point. The superscripts  $EVB$  and  $FRB$  denote the event-based and frame-based AFSB centerlines, respectively. The root mean square error (RMSE) was computed over all  $e_i$  from all evaluated tracks as a single error measure:

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N e_i^2}, \quad (2)$$

where  $N$  is the total number of centerline sample points included in the evaluation.

Fig. 4 shows examples of accepted tracks used for the statistical analysis. These examples illustrate spatially continuous and predominantly straight structures of varying length. The larger apparent width of the event-based tracks supports track continuity and improves robustness of the row-wise midpoint estimation.



**Figure 4.** Examples of event-based tracks considered in the position-error analysis, characterized by predominantly straight and spatially continuous structures.

### 2.2.2. Derivation of Lagrangian statistics

First, the event-based 2D tracks corresponding to the same AFSB are paired based on spatial and temporal proximity. For each pair, only the time interval over which both 2D tracks coexist is retained. Subsequently, the timestamps are grouped into temporal bins of width  $172\ \mu\text{s}$ , and the median timestamp of each bin is used as the common evaluation time. The temporal bin width of  $172\ \mu\text{s}$  corresponds to the median time interval between consecutive events across all reconstructed tracks. The smoothed positions, obtained by Savitzky-Golay filtering, are evaluated at the median timestamps, providing synchronized 2D positions for the two tracks without imposing a fully equidistant temporal grid. Depth information is extracted from the 2D positions using the GPPT technique, described by Hou et al. (2021), Kaiser & Rival (2023), and Leister & Rival (2025). The reconstructed 3D tracks are subsequently used to compute velocity, acceleration, and radius of curvature. As the event-based reconstruction does not impose a strictly equidistant temporal grid, velocities and accelerations are estimated using a local polynomial fit in physical time, with a second-order polynomial fitted to position samples within a local time window centered at each evaluation time. The first and second derivatives provide the instantaneous velocity and acceleration components.

### 3. Results and discussion

In this section, results are presented and discussed. First, the event-based AFSB centerline-position error relative to the frame-based reference position is shown. Then, event-based Lagrangian particle statistics obtained from the turbulent flow are presented.

Fig. 5 shows the distribution of the local error  $e$  for  $n = 250$  particle tracks, with the centerlines sampled at  $\sim 1$  pixel arc-length intervals. The distribution is characterized by a mean error of  $\bar{e} = 0.31$  px, a median error of  $\tilde{e} = 0.28$  px, a standard deviation of  $\sigma = 0.19$  px, and a  $RMSE = 0.36$  px.

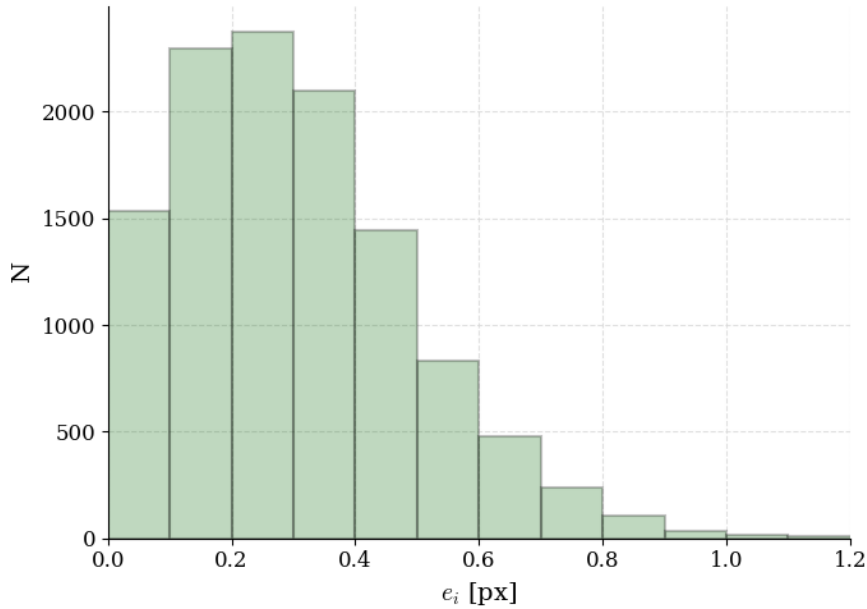


**Figure 5.** The distribution of the position error  $e$  for  $n = 250$  tracks is characterized by a mean error of  $\bar{e} = 0.31$  px, a median error of  $\tilde{e} = 0.28$  px, a standard deviation of  $\sigma = 0.19$  px, and a  $RMSE = 0.36$  px. The analysis includes predominantly spatially continuous and straight tracks. The bin width is set to 0.1 pixel and the centerlines are sampled at  $\sim 1$  pixel arc-length intervals. The distribution suggests that sub-pixel-accurate position information can be recovered from event-based data by using a fit-based track reconstruction approach.

The error distribution is concentrated below 0.5 pixels, which is consistent with the inherent residual particle displacement error of up to 0.5 pixels resulting from peak locking effects (Maya et al., 2025). While sub-pixel localization is established in frame-based particle imaging, its direct use in event-based methods is less straightforward, as described in Sect 1. However, Fig. 5 suggests that sub-pixel position information can be recovered from event-based data through a fit-based particle track reconstruction from multiple event-data samples. Thus, the sub-pixel estimate originates from the fitted representation of the event-based track. Since the present implementation relies on a row-wise reconstruction of the event-based tracks, it is currently best suited to weakly curved tracks. Flows involving small radii of curvature, track crossings, or rapid changes in particle direction may challenge this method and should be addressed in future work.

### 3.1. Reconstruction of event-based Lagrangian statistics from a turbulent flow

Using event-based imaging, AFSBs in a flow with a freestream velocity of  $U_\infty \approx 6 \text{ m s}^{-1}$ , measured at a distance  $d = 2 \text{ m}$  from the propeller plane, are recorded over a period of 30 min, and velocity, acceleration, and radius-of-curvature statistics are derived using the method described in Sect. 2.2.2. Fig. 6 shows the derived velocity, acceleration, and radius-of-curvature distributions for  $n = 2405$  tracks and  $N = 113\,389$  data points, with bin widths of 50 and 150 for velocity and radius of curvature, and acceleration statistics, respectively. The observed anisotropy of the velocity distributions in panel (a) is consistent with a dominant flow component  $v_x$  in the x-direction, while the  $v_y$  and  $v_z$  components remain comparatively smaller. The slight shift of the  $v_z$  distribution toward negative values is consistent with the AFSBs not being neutrally buoyant. The radius of curvature is calculated as:

$$R = \frac{|\vec{v}|^3}{|\vec{v} \times \dot{\vec{v}}|}, \quad (3)$$

with velocity  $\vec{v}$  and acceleration  $\dot{\vec{v}}$ . The probability distribution of the normalized acceleration components is shown in panel (b). The black line corresponds to the parametrization of La Porta et al. (2001):

$$P(a) = C \exp\left(\frac{-a^2}{((1 + |\frac{a\beta}{\sigma}|^\gamma)\sigma^2)}\right), \quad (4)$$

with constants  $\beta = 0.539$ ,  $\gamma = 1.588$ , and  $\sigma = 0.508$ . Extracting these quantities from event-based data highlights the potential of event-based methods for investigating a broad range of fluid flows.

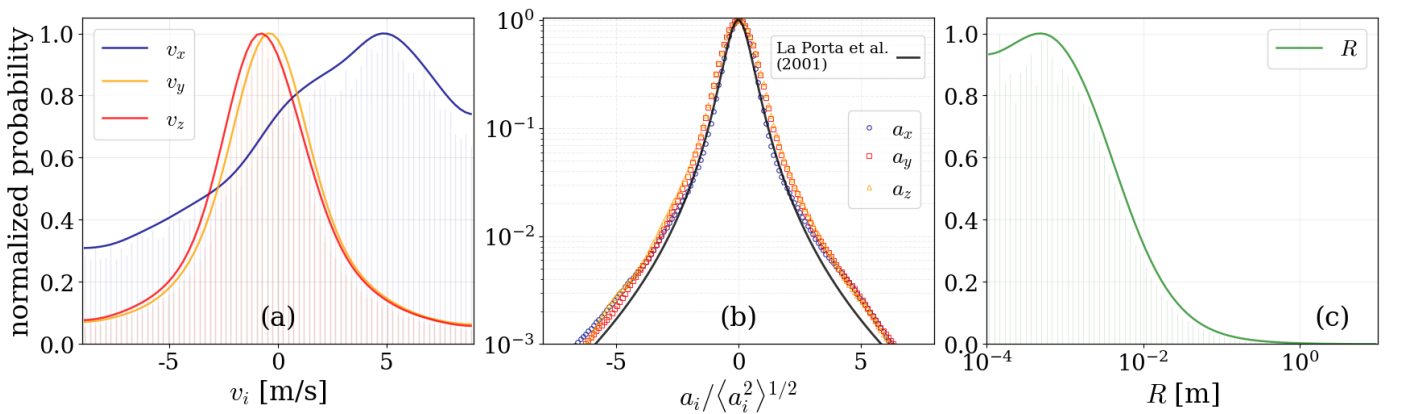


**Figure 6.** The obtained event-based Lagrangian statistics include velocity components (a), acceleration components (b), and radius of curvature (c).  $n = 2405$  tracks and  $N = 113\,389$  data points are evaluated. The bin width is set to 50 for (a) and (c), and to 150 for (b). Savitzky–Golay smoothing was applied to the image positions (effective smoothing window of  $\sim 1 \text{ ms}$ ) and to the image glare-point distance (effective smoothing window of  $\sim 3 \text{ ms}$ ). The distributions in panels (a) and (c) are normalized by their respective maxima. The black line in (b) corresponds to the parametrization of La Porta et al. (2001) for nearly homogeneous turbulence.

#### 4. Conclusions

To address the two research questions formulated in Sect. 1, two processing strategies were applied to the event-based AFSB data. For research question (i), an image-based approach was used to quantify the event-based AFSB centerline-position error relative to synchronized frame-based reference data. Event-based images were reconstructed from events corresponding to an increase in intensity and processed to obtain AFSB centerlines, whereby Savitzky-Golay smoothing was applied on the event-based particle positions. The frame-based tracks were reconstructed using Gaussian-based subpixel localization and B-spline smoothing. The local error was then computed as the Euclidean distance between densely sampled event-based and frame-based AFSB centerlines. For research question (ii), a non-image-based approach was applied directly to the event data: First, event-based AFSB tracks were reconstructed from the detected glare points. Subsequently, tracks corresponding to the same AFSB were paired based on spatial and temporal proximity. From each 2D track pair, the glare-point distance was computed and mapped to physical depth using the GPPT technique. The resulting AFSB tracks were then used to derive velocity, acceleration, and radius-of-curvature statistics.

The image-based position-error analysis shows that subpixel AFSB centerline information can be recovered from event-based data. For  $n = 250$  evaluated tracks, the local error distribution is characterized by a mean error of  $\bar{e} = 0.31$  px, a standard deviation of  $\sigma = 0.19$  px, and an  $RMSE = 0.36$  px. The error distribution is predominantly concentrated below 0.5 px, which is consistent with the expected particle displacement error of up to 0.5 pixels resulting from peak-locking effects. The non-image-based reconstruction further shows that event-based data can be used to obtain Lagrangian statistics, in this case from a turbulent flow with a freestream velocity of  $U_\infty \approx 6 \text{ m s}^{-1}$ .

The findings indicate that event-based (AFSB) measurements can provide both subpixel-resolved centerline-position estimates as well as Lagrangian statistics. The image-based comparison establishes the achievable position accuracy with respect to a frame-based reference, while the non-image-based processing demonstrates the potential of event data for direct track-based flow analysis. The present implementation is particularly suited to spatially continuous and weakly curved tracks, whereas strong curvature, track crossings, or rapid changes in particle direction may require different reconstruction strategies. Overall, the study shows that event-based imaging is a promising tool for Lagrangian flow measurements, especially in applications where high temporal resolution and reduced data rates are advantageous.

## Nomenclature

|                 |                                                                           |
|-----------------|---------------------------------------------------------------------------|
| $d$             | distance from the propeller plane [m]                                     |
| $D_B$           | AFSB diameter [mm]                                                        |
| $e$             | local position error between event-based and frame-based AFSB centerlines |
| $\bar{e}$       | mean position error                                                       |
| $\tilde{e}$     | median position error                                                     |
| $n$             | number of tracks                                                          |
| $\dot{\vec{v}}$ | acceleration                                                              |
| $\vec{v}$       | velocity                                                                  |
| $U_\infty$      | freestream velocity [ $\text{m s}^{-1}$ ]                                 |
| $\nu$           | kinematic viscosity of air [ $\text{m}^2 \text{s}^{-1}$ ]                 |
| $\sigma$        | standard deviation                                                        |
| AFSB            | air-filled soap bubble                                                    |
| EVB             | event-based                                                               |
| FOV             | field of view                                                             |
| FRB             | frame-based                                                               |
| GPPT            | glare-point particle tracking                                             |
| N               | number of data points                                                     |
| px              | pixel [px]                                                                |
| RMSE            | root mean square error                                                    |

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