

High-Resolution, High Frequency, Real-Time Optical Flow Particle Image Velocimetry.

Juan Pimienta^{1,2,*}, Jean-Luc AIDER²

1: Photon Lines, 10 avenue des Touches, Pacé, 35740, France.

2: PMMH Laboratory, UMR7636 CNRS, ESPCI Paris, PSL Research University, Sorbonne Université, University Paris Diderot, 7-9 quai Saint Bernard, 75005 Paris, France.

*Corresponding author: ju-pimienta@photonlines.com

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ABSTRACT

Particle image velocimetry (PIV) is a non-intrusive method that allows for the estimation of velocity fields from particle displacement in a scene. We present in this work advances in Live-Optical Flow Particle Image Velocimetry (L-OF-PIV). We validate the precision of the displacement field estimation using an homogeneous isotropic turbulence (HIT) DNS (Direct Numerical Simulation) dataset. We also present advances in the computing performances of the Live measurements, achieving real-time velocity fields estimation at more than 2 kHz with 1 Mp images, up to 1.1 kHz with 4 Mp images, and up to 200 Hz with 21 Mp images. We provide experimental validation by monitoring the flow past a cylinder, at $Re_D \approx 6482$, for more than 4 hours at an acquisition frequency $f_{ac} = 100$ Hz. Moreover, velocity-derived quantities were extracted in real-time to explore phenomena that would be complicated or impossible to capture with conventional post-processing. Overall, we demonstrate that L-OF-PIV now enables complex fluid flow estimation with dense velocity fields (one vector per pixel) at high frequencies in both mono- and multi-GPU configurations, in real-time and over extended periods of time.

1. Introduction

Particle image velocimetry (PIV) is established as the standard non-intrusive technique to measure velocity fields in fluid mechanics. It consists of illuminating a section of a fluid flow that has been seeded with light reflective particles, to capture image pairs and estimate the displacement between successive images (Raffel et al., 2018). The standard algorithm to estimate the displacement fields relies on the computation of cross-correlations via fast Fourier transform (FFT). In the following, this approach will be referred to as CC-PIV. This method is constrained in its spatial resolution (based on Interrogation Windows) and post-processing (CC being relatively demanding on computational resources) for the most part. Optical Flow (OF) algorithms propose a different way to estimate displacement from successive images. Based on the assumption of image intensity constancy, OF methods are used to estimate displacement from images and are mostly used in

Machine Vision applications (Piga et al., 2021; Wang et al., 2011; Lim et al., 2017; Brebion et al., 2021).

Recently, the fluid mechanics community has increasingly adopted OF methods to treat PIV images, particularly with Machine Learning (ML) approaches or to improve spatial resolution of CC-PIV (Cai et al., 2019; Fischer et al., 2015; Yu et al., 2023; Teed & Deng, 2020; Hui & Loy, 2020; Lagemann et al., 2021). However, these methods still rely heavily on quality of training data and are not suitable for real-time estimation.

In the past, advances towards real-time velocity fields computation using Optical Flow had been achieved (Gautier & Aider, 2015b), particularly for flow control applications where the Live-OF-PIV was used as a visual sensor (Gautier et al., 2015; Gautier & Aider, 2013, 2015a; Varon et al., 2017). Yet very high frequencies of image treatment and high resolution were still unexplored territories.

In this work we present advances in Live-Optical Flow Particle Image Velocimetry (L-OF-PIV) based on a Lucas-Kanade OF algorithm that, with the advances in compute on graphics processing units (GPU), allows for estimation of velocity fields in real-time with high effective spatial resolution leading to dense velocity fields (1 vector per pixel). Here we present advances in the achieved real-time performances using a single GPU or two GPUs. We also demonstrate the quality of the results in terms of large and complex displacement gradients resolution, using synthetic particle images of a Homogeneous Isotropic Turbulence (HIT) Direct Numerical Simulation (DNS) dataset (Cardesa et al., 2017). We finally show an experimental validation case where velocity fields and their derivatives are computed in real-time for the flow around a cylinder at $Re_D \approx 6482$ in a hydrodynamic channel. We demonstrate that it becomes possible to obtain information usually inaccessible with standard methods, like long-time evolution of global quantities.

2. Experimental Setup

2.1. Hydrodynamic tunnel

Experiments were carried out in a hydrodynamic channel in which the flow is driven by gravity using a constant level water tank to ensure a constant pressure differential of $\Delta P = 0.3$ bar. The maximum free-stream velocity is $U_\infty = 22 \text{ cm.s}^{-1}$. The test section has a rectangular cross-section of width $W = 15$ cm and height $H = 7$ cm for a length $L = 80$ cm. A circular cylinder of diameter $D = 4$ cm, and same height as the test section, is placed at mid-length of the test section. For experimental validation, measurements were performed in a horizontal laser sheet at mid-height of the cylinder. Fig. 1 presents a 3D sketch of the model used for the measurements with the green shade plane depicting the measurement plane.

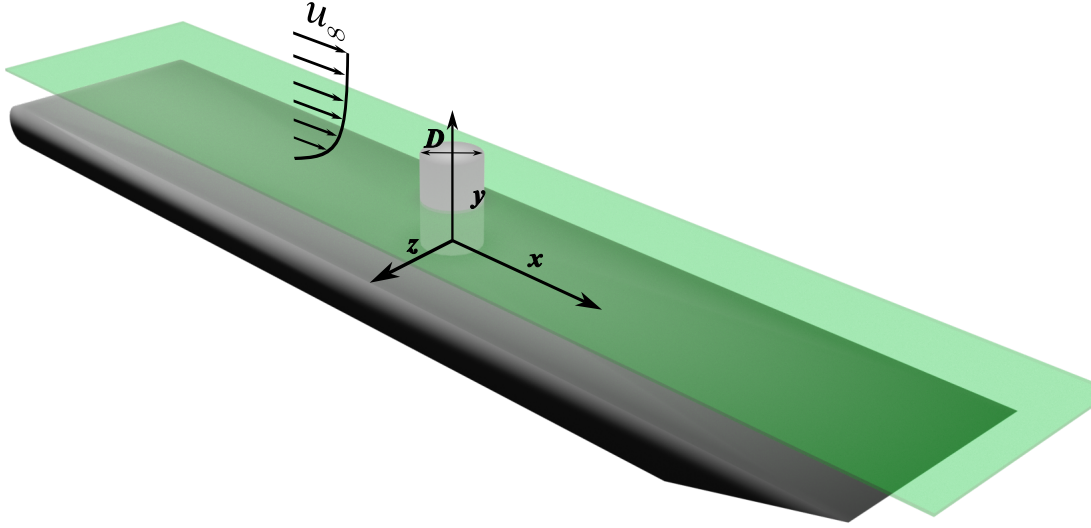


Figure 1. 3D sketch of the cylinder setup for the hydrodynamic channel. Green shade plane represents the laser plane where measurements were carried out.

2.2. Image acquisition system

To perform the PIV measurements, the water was seeded with light-reflecting neutrally buoyant polyamide microparticles $20\ \mu\text{m}$ in diameter. The flow was illuminated by a laser sheet generated by a laser beam (Coherent continuous Nd:YAG laser with a wavelength of 532 nm) passing through a Powell lens and operating at an output power of 2 W.

To record snapshot images of the flow, a Mikrotron 21CXP12 camera was used. It can record 21 Mpx images with an acquisition frequency of up to 240 Hz.

A dedicated and personalized computer was designed and built to optimize its performance for real-time acquisition. The system is based on an AMD Ryzen Threadripper PRO 9965WX processor with 24 cores operating at a frequency of 4.20 GHz and 64 GB of RAM. Two powerful latest generation Nvidia GPUs (Graphics Processing Unit) RTX5090 are supported on a custom open chassis that allows better access and easier connection/removal of the new GPUs.

3. Live-Optical Flow Velocimetry (L-OFV)

Motion estimation in OF assumes that the intensity brightness in a scene is constant, hence imposing the intensity brightness constraint equation, which linearized form is expressed as:

$$I_x u + I_y v + I_t = 0 \quad (1)$$

where I_x , I_y , and I_t are the spatial and temporal derivatives of the instantaneous intensity field $I(x, y, t)$, and $\mathbf{V}(x, y) = (u(x, y), v(x, y))^T$ is the inter-frame displacement field at each pixel.

Eq. 1 is not sufficient to resolve the OF problem, since the system is under-determined. Lucas & Kanade (1981) approach provides a local closure of the OF problem, by assuming that displacements in a small vicinity of a pixel are approximately constant. Displacements are then estimated via an iterative scheme that integrates the information around each pixel, while performing the calculations at each pixel.

A pyramidal image reduction scheme has been implemented to estimate large displacements, since original OF methods can only accurately solve small displacements (1 to 2 pixels).

As a pre-processing step, a normalization process of the images has been implemented, by means of a zero mean sum of squared differences within a kernel. This helps to deal with illumination inhomogeneities that would make the displacement estimation more difficult for the algorithm.

In general, the workflow is as follows: normalization step, pyramidal image reduction, displacement estimation iteratively, projection of the vectors to the next resolution level, new displacement estimation, so on until recovering a vector field of full image size, yielding one vector per pixel.

In the following, the results were obtained using *eyePIV*, a dedicated OF-PIV plugin that allows for velocity field measurements in real-time. *EyePIV* is the fruit of the long-lasting collaboration between the PMMH laboratory and Photon Lines SAS. More information on the development and OF-PIV optimization can be found in Giannopoulos (2021); Pimienta Alvernia (2024); Pimienta & Aider (2026a).

4. Homogeneous Isotropic Turbulence test case

In the following we use a HIT dataset from the Polytechnic University of Madrid to assess the OF-PIV's capability of dealing with a wide variety of scales in a complex flow (Cardesa et al., 2017). The dataset comprises instantaneous velocity fields in a cube on a 1024^3 grid at $Re_\lambda = 315$ with a maximum resolution $k\eta = 2$ (Fig. 2a). From each instantaneous 3D displacement field, the displacement components in the plane (u, v) were extracted in the median plane z of the data cube.

An in-house synthetic particle image generator was created to generate the image pairs of particles from the DNS displacement fields, since there is no publicly available generator that takes pre-existent displacement fields as input and generates the synthetic particle image pair as output. More details can be found in Pimienta & Aider (2026a).

Fig. 2 shows a comparison of the displacement magnitude of the DNS case (Fig. 2b) with OF-PIV (Fig. 2c) and a CC-PIV (Fig. 2d) algorithm (Thielicke & Sonntag, 2021) using three IW passes (64×64 , 32×32 , 16×16 px) with 50% overlap. Fig. 2c shows that OF-PIV produces a dense displacement field, visually very close to the DNS, where the CC-PIV shows a blurrier field in comparison.

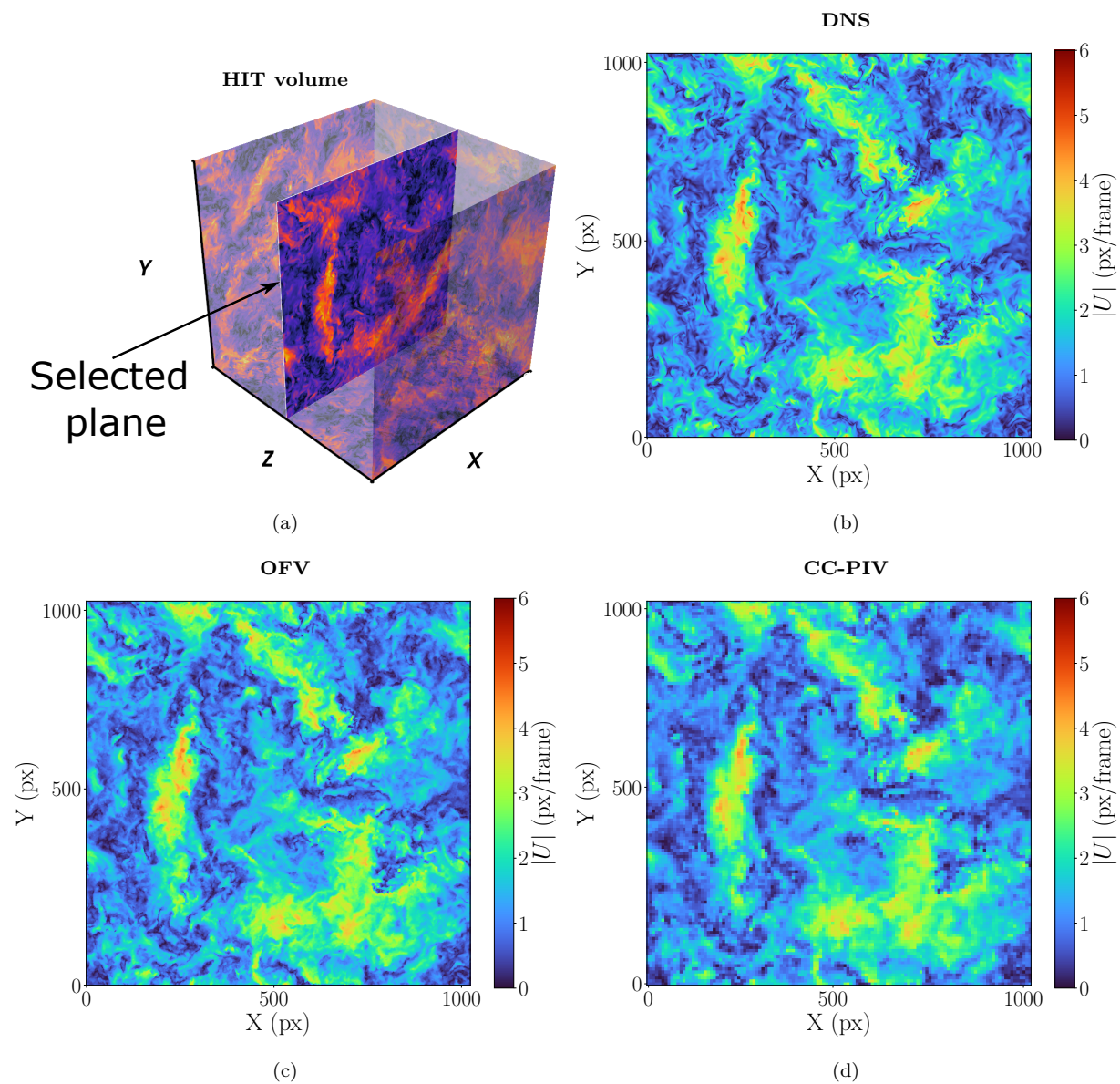


Figure 2. Snapshots of instantaneous displacement magnitude in the mid-section of the HIT dataset: **(a)** DNS ground truth, **(b)** OFV, **(c)** CC-PIV. From (Pimienta & Aider, 2026a). ©2026 American Physical Society.

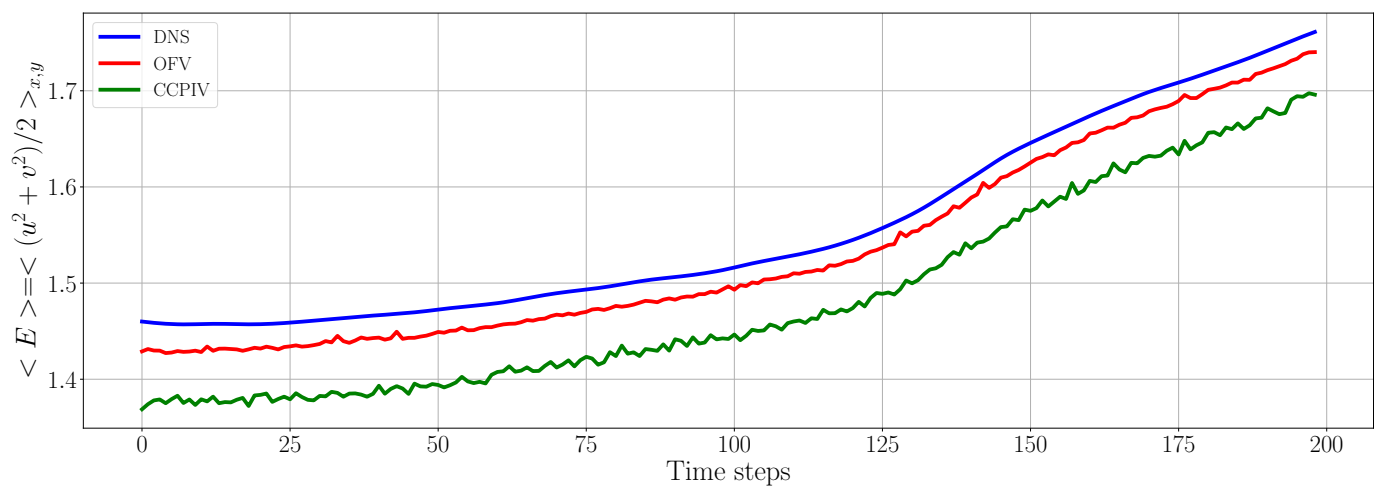


Figure 3. Spatially averaged kinetic energy over the 199 time steps. Comparison between the DNS, OF-PIV and CCPIV. From Pimienta & Aider (2026a). ©2026 American Physical Society.

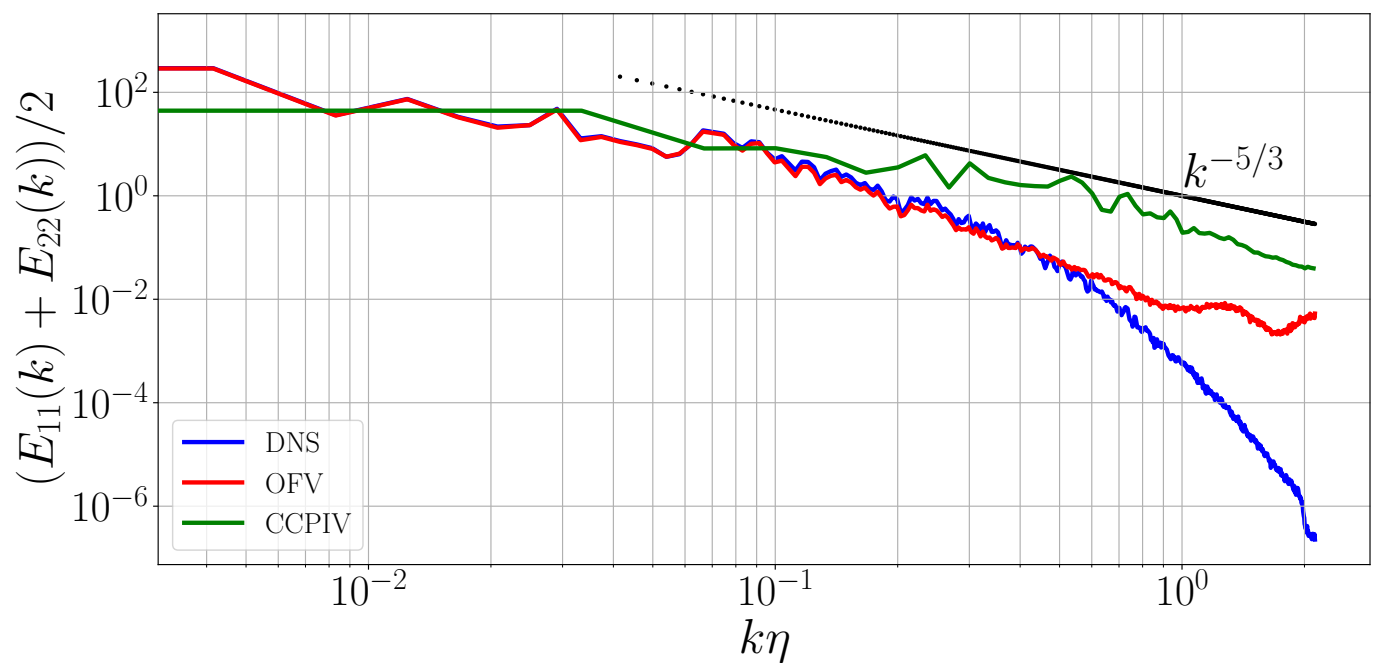


Figure 4. Spatial spectra of kinetic energy averaged over 199 time steps, computed along the mid-height profiles. From Pimienta & Aider (2026a). ©2026 American Physical Society.

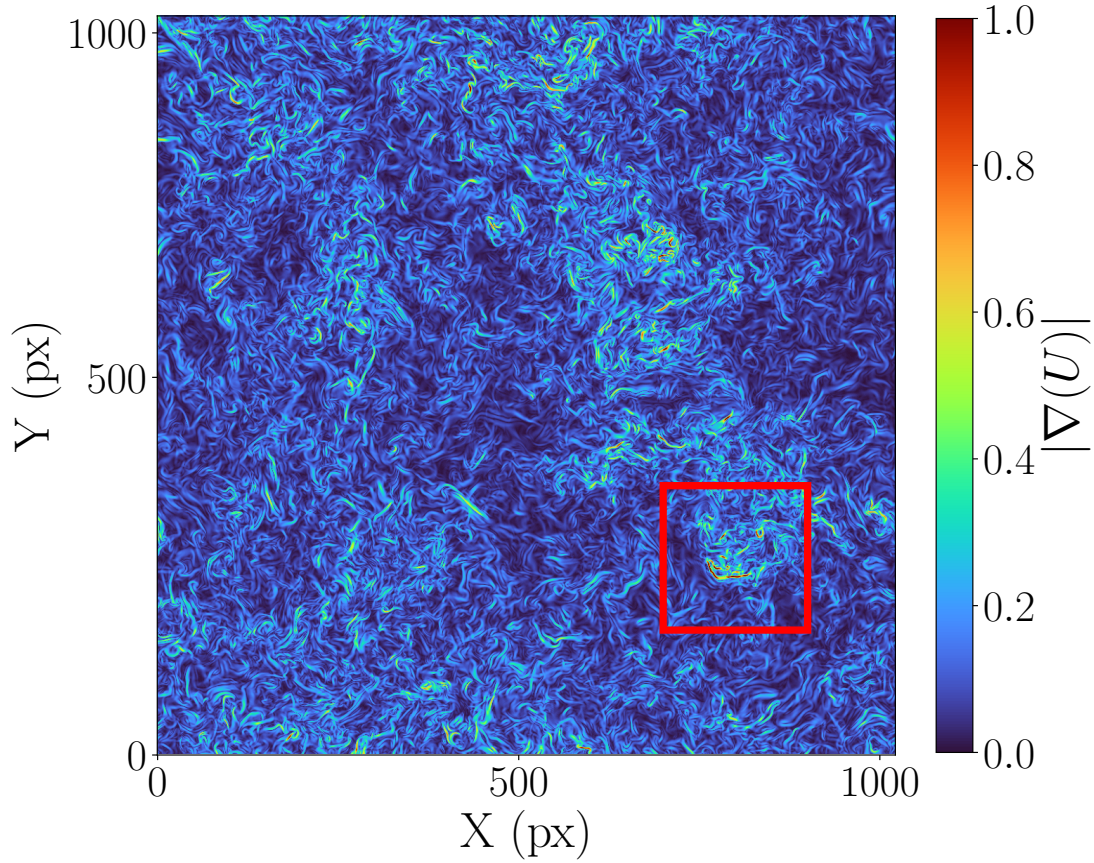


Figure 5. Structure detection map – DNS. From Pimienta & Aider (2026a). ©2026 American Physical Society.

Fig. 3 shows a comparison of the space averaged kinetic energy over 199 time-steps between the DNS results, OF-PIV and CC-PIV. Here it is clear that OF-PIV performs a better estimation in energy terms over all the field at each time step, since its estimation is closer to that of the DNS, in comparison to CC-PIV.

To inspect the small scale resolution capability, a time averaged spatial spectra comparison over the 199 analyzed time-steps is presented in Fig. 4. The spectra is computed from the instantaneous kinetic energy along a mid-height profile. OF-PIV follows closely DNS's spectrum in the inertial range and divergence starts $k\eta \approx 0.5$, with a cutoff close to $k\eta \approx 1$. Although OF-PIV does not reach the same resolution level as the DNS, clearly outperforms CC-PIV in such a complex case, which fails to track the DNS spectrum.

Following the insights provided by the spatial spectra in Fig. 4, a visual assessment is performed via a gradient-based structure map of the displacement magnitude $U(x, y) = \sqrt{u^2 + v^2}$ following a standard edge-detection computer-vision approach (Saif et al., 2016). The principle is simple: regions where $|\nabla U|$ is large mark sharp spatial variations, hinting at structures like shear layers or vortices, precisely the features that challenge CCPIV methods. The $|\nabla U|$ map is computed for a

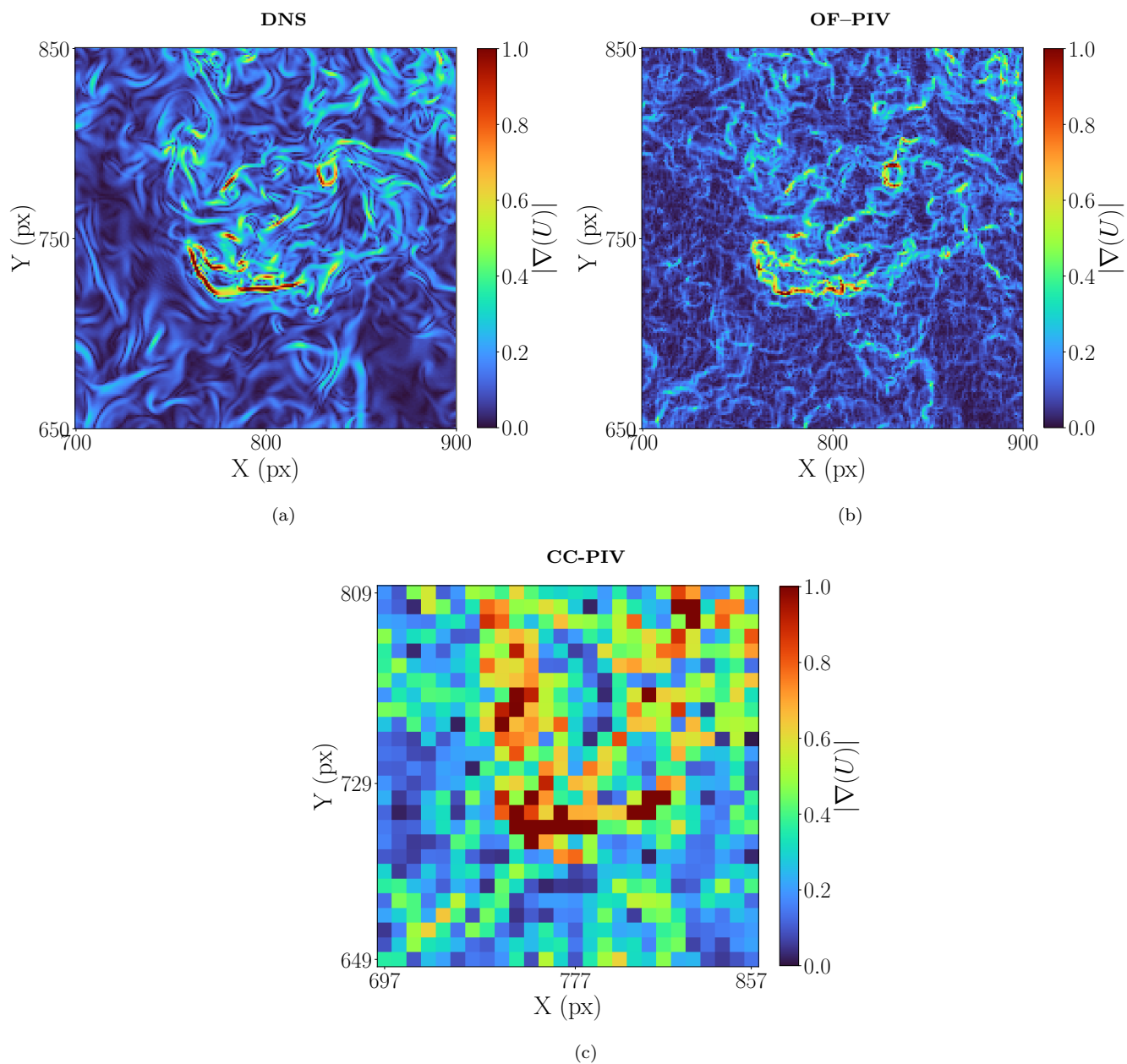


Figure 6. Structure detection. Zoom over a 200×200 px ROI. (a) DNS. (b) OF-PIV. (c) CC-PIV. From Pimienta & Aider (2026a). ©2026 American Physical Society.

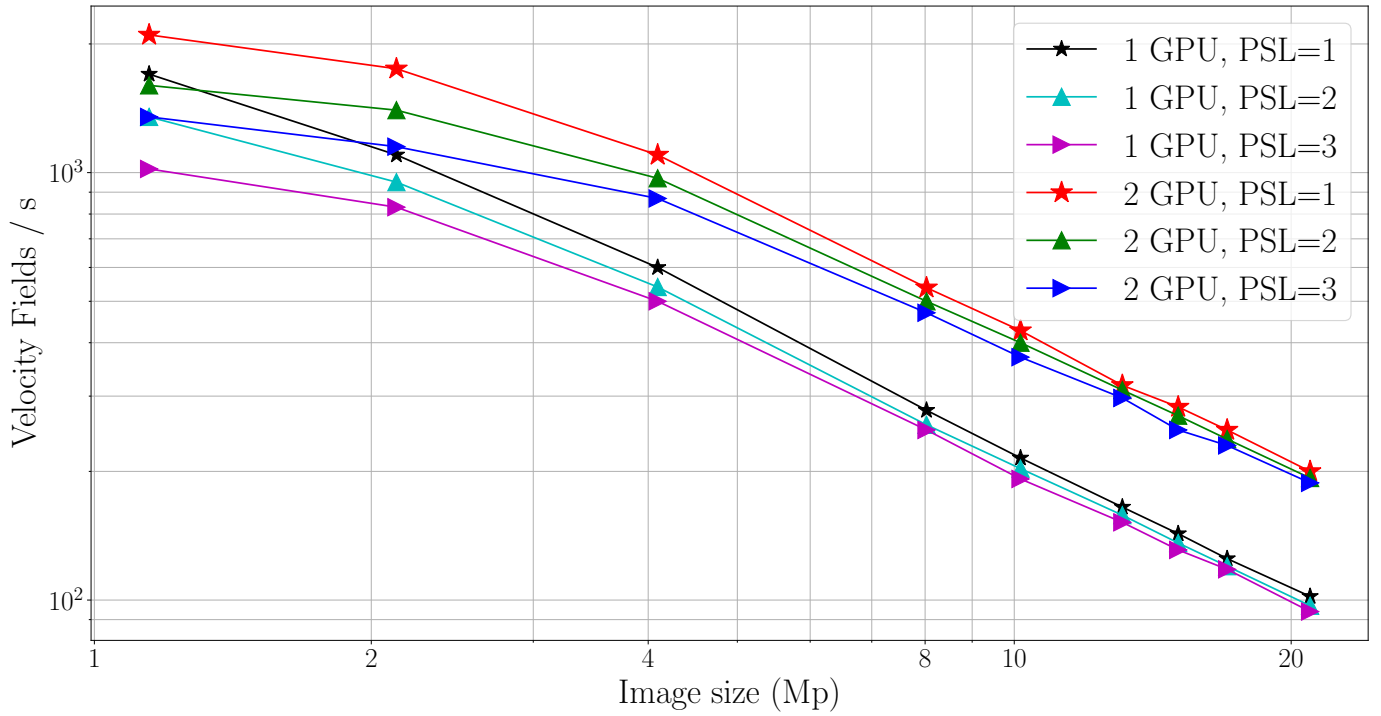


Figure 7. Live performance benchmark showing maximum performance in real-time for velocity field computation. Legend shows results discriminated between mono and multi-GPU, and PSL number.

snapshot using the discrete version of Eq. 2:

$$gU_x, gU_y = \nabla U(x, y), \quad |\nabla U(x, y)| = \sqrt{gU_x^2 + gU_y^2} \quad (2)$$

The results can then be compared between DNS, OF-PIV and CC-PIV. Fig. 5 shows the $|\nabla U|$ map from DNS, portraying an indeed highly complex fluid flow, rich in multiple scales of structures such as vortices and filaments. The red square in the map represents a region of interest (ROI) where the maps will be compared, since it shows challenging structures to reconstruct with high displacement gradient.

Fig. 6 presents a comparison between the DNS, OF-PIV and CC-PIV $|\nabla U|$ maps over the ROI depicted in Fig. 5. OF-PIV can recover small and intense structures up to a certain scale (as already suggested by the spectra in Fig. 4). It manages in general to capture complex fluid structures of the scene. In contrast, CC-PIV, with its limited spatial resolution, misses said small structures and under-performs in general in resolving fine structure detail.

5. Live OF-PIV Computing Performances

Live performance is measured by streaming images from the camera to the workstation and quantifying how many image pairs per second the system can process without losses. Fig. 7 presents the

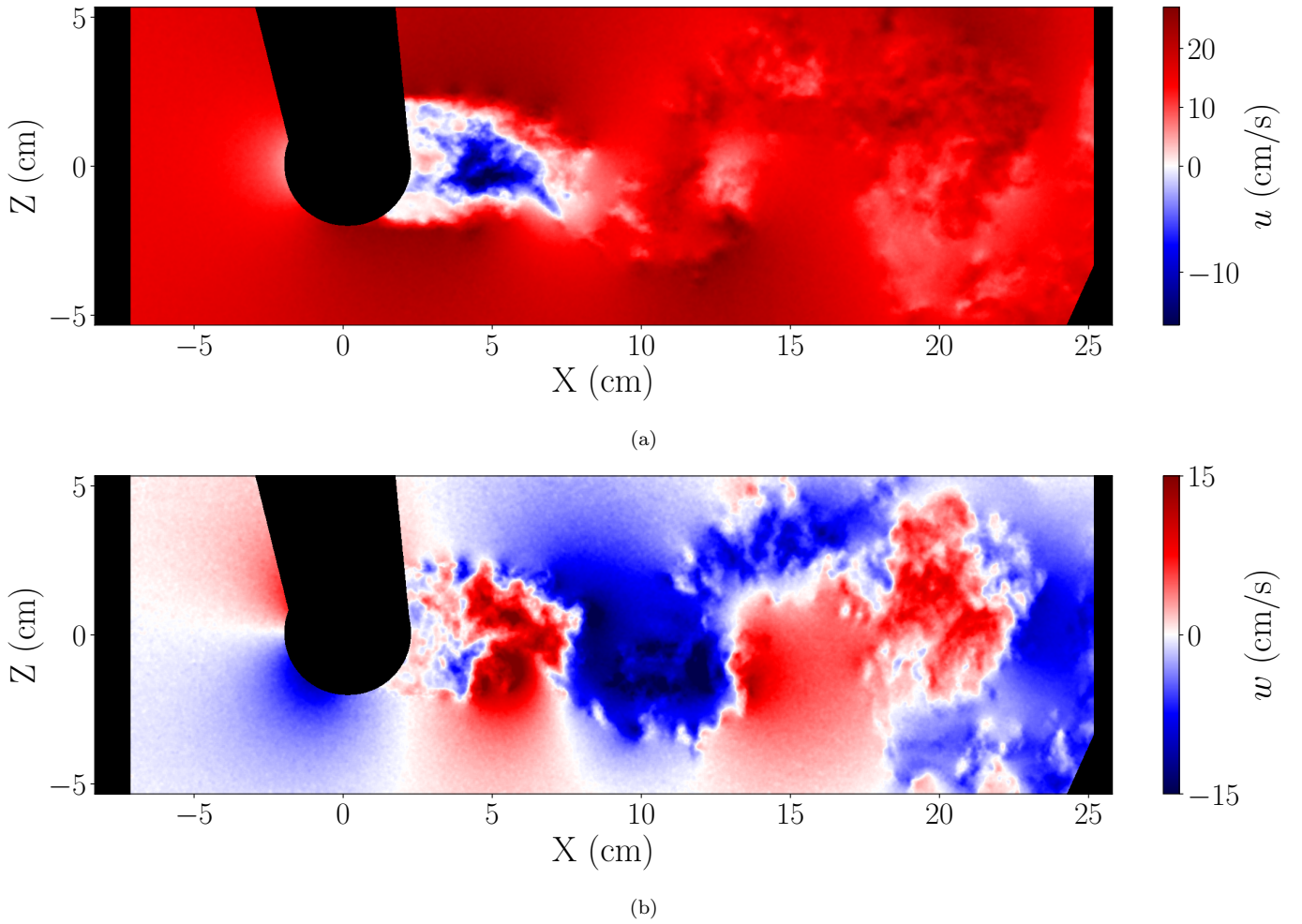


Figure 8. Instantaneous velocity fields of the wake flow past a Cylinder of diameter $D = 4$ cm at $Re_D \approx 6482$ measured in a horizontal plane at $y = H_c/2$. The black area corresponds to the masked regions (e.g. the cylinder and its shadow). (a) streamwise velocity component $u(x, z, t)$. (b) Cross-stream velocity component $w(x, z, t)$

maximum computational capabilities available with the given setup and fixed OF-PIV parameters as $NR = 2$ px, $KR = 10$ px, $PSL \in \{1, 2, 3\}$, and $IT = 3$. With a single GPU 1000 to 1600 velocity fields per second can be computed with 1 Mp images, depending of the PSL number which determines the maximum displacement that the algorithm can accurately resolve. With a 4 Mp sensor, velocity fields can be computed in real-time at 500 to 600 Hz. For larger image sizes the velocity fields can be computed at 200 Hz and 100 Hz for 10 Mpx and 21 Mp images respectively. It is Worth emphasizing that these high performances are achieved while yielding dense velocity fields with 1 meaningful vector per pixel.

In Fig. 7 we also present what is, to our knowledge, the first multi-GPU implementation for real-time velocity fields computation as well as the fastest computation time of PIV fields in real-time. Indeed, one can see that the frontier of 2 kHz is surpassed for 1 Mp snapshots and $PSL = 1$. For 4 Mp images, velocity fields can be computed at frequencies ranging between 870 to 1100 Hz. For

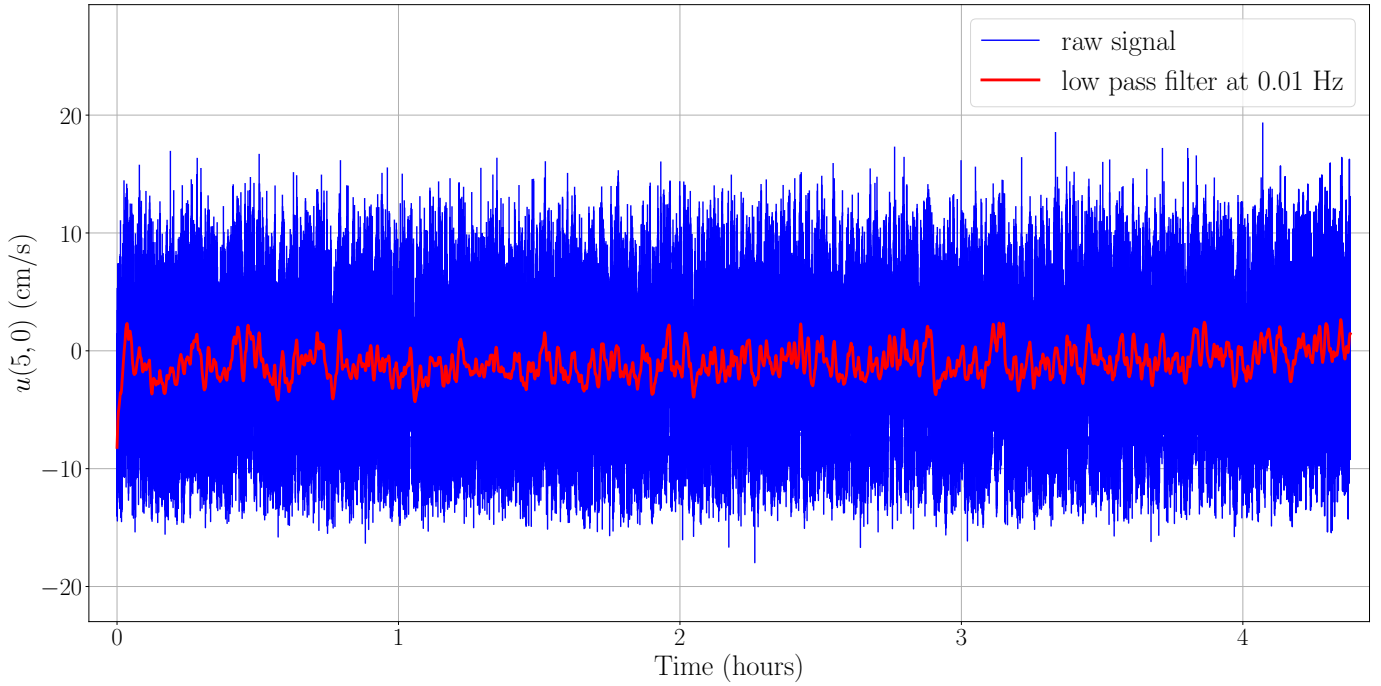


Figure 9. Time series of a streamwise velocity probe $u(t)$ located at $(x, z) = (5, 0)$ cm downstream of the cylinder.

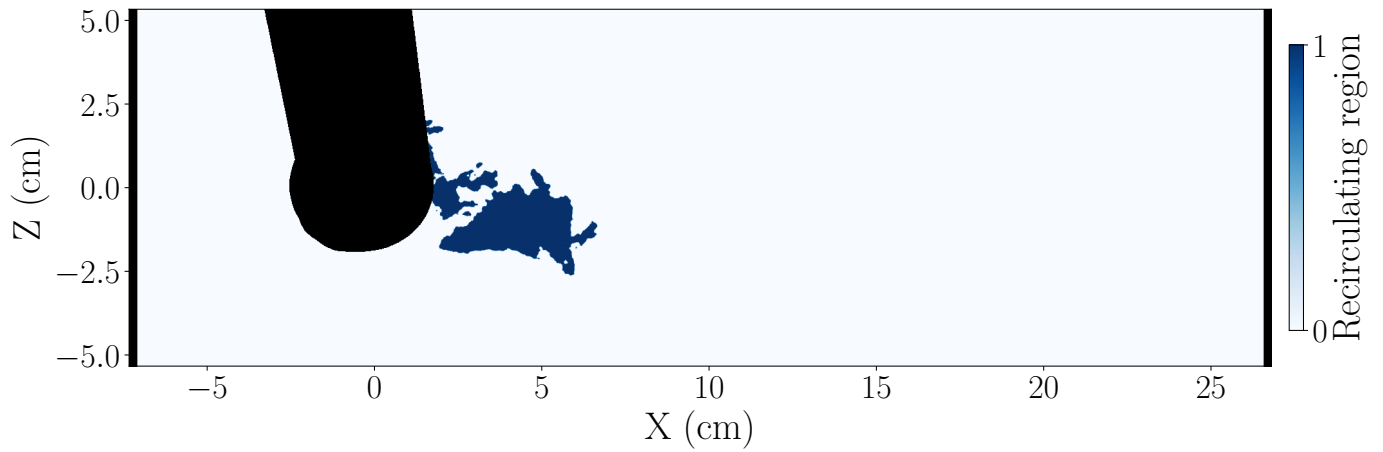
larger images, velocity fields can be computed at ~ 400 Hz for 10 Mp images and at ~ 200 Hz for 21 Mp images.

6. Experimental results

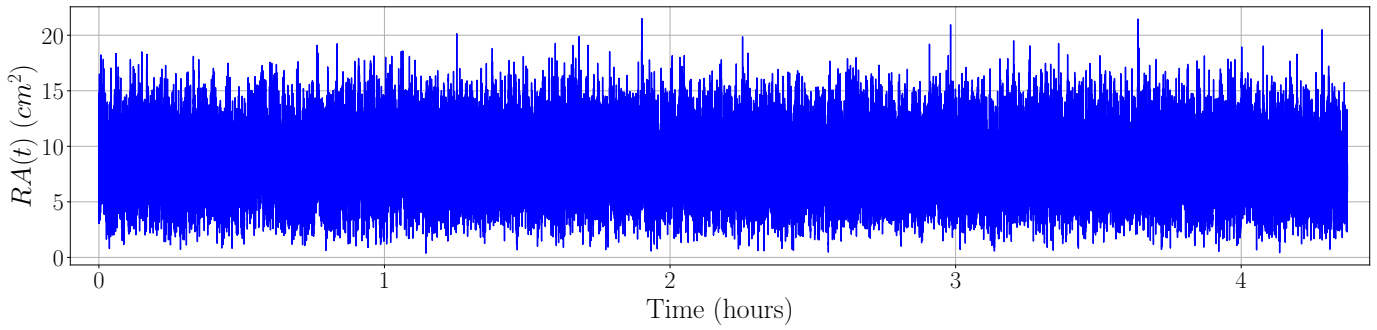
An experimental validation was carried out using the canonical wake flow past a circular cylinder of diameter $D = 4$ cm. The Reynolds number based on the cylinder diameter is $Re_D \approx 6482$. The L-OF-PIV measurements are carried out in a horizontal plane, as depicted in Fig. 1. Images were acquired using the Mikrotron camera described in Sec. 2.2 with an image size of 5120×1600 px and an exposure time of 1 ms. Image pairs were acquired at $f_{ac} = 100$ Hz with an inter-frame time $\delta t = 5$ ms. The pixel field of view was $\Delta x = \Delta z \approx 66.67 \mu\text{m}$, yielding a field of view of $X = 31.33$ cm by $Z = 10.67$ cm.

Both live measurements and image recordings were performed. Fig. 8 shows both instantaneous velocity components, calculated from the recorded images. Here OF-PIV's ability to produce dense velocity fields (1 vector per pixel) can be appreciated by the level of details in the velocity fields. It is noteworthy to emphasize that no smoothing has been applied to the computed velocity fields. From the streamwise velocity component $u(x, y)$ (Fig. 8a), the formation of shear layers on both sides of the cylinder can be observed, together with the recirculation region and the wake past the cylinder. From the spanwise velocity field $w(x, y)$ (Fig 8b), the spatial switch of direction in the wake is observed as expected in this flow, together with high level of details in the

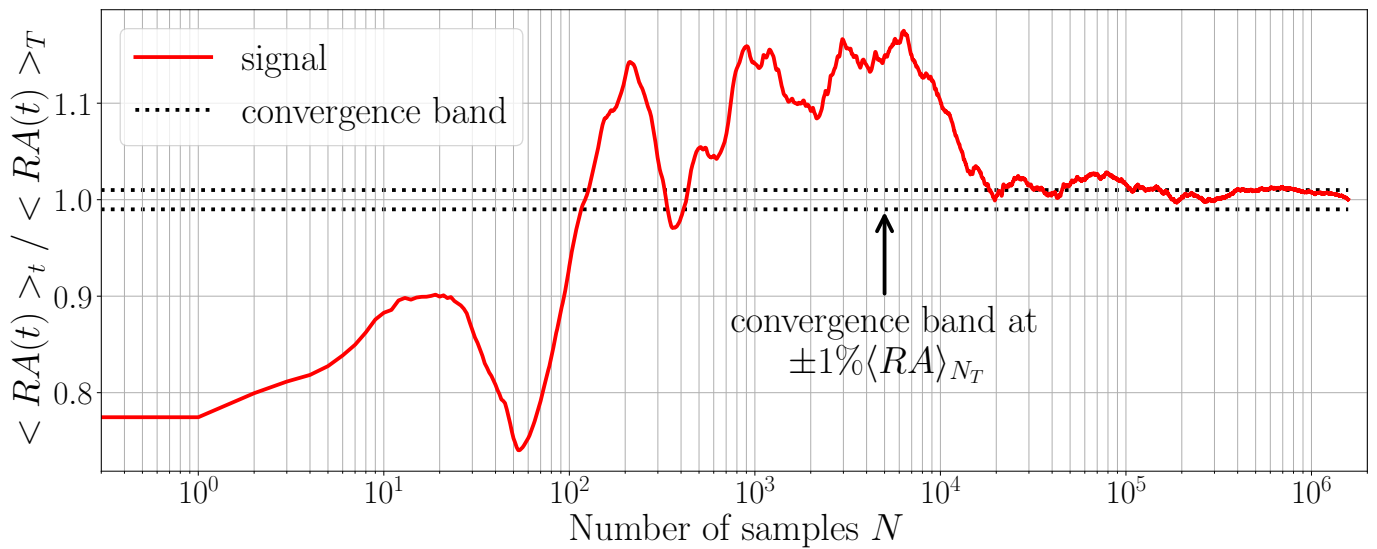
small structures, both close and far from the cylinder.



(a) From (Pimienta & Aider, 2026a). ©2026 American Physical Society.



(b) From (Pimienta & Aider, 2026a). ©2026 American Physical Society.



(c)

Figure 10. Recirculation area computations. (a) Recirculation region as displayed in the measurement field. (b) Recirculation area scalar over four hours of continuous monitoring. (c) Mean recirculation area value convergence in function of number of samples.

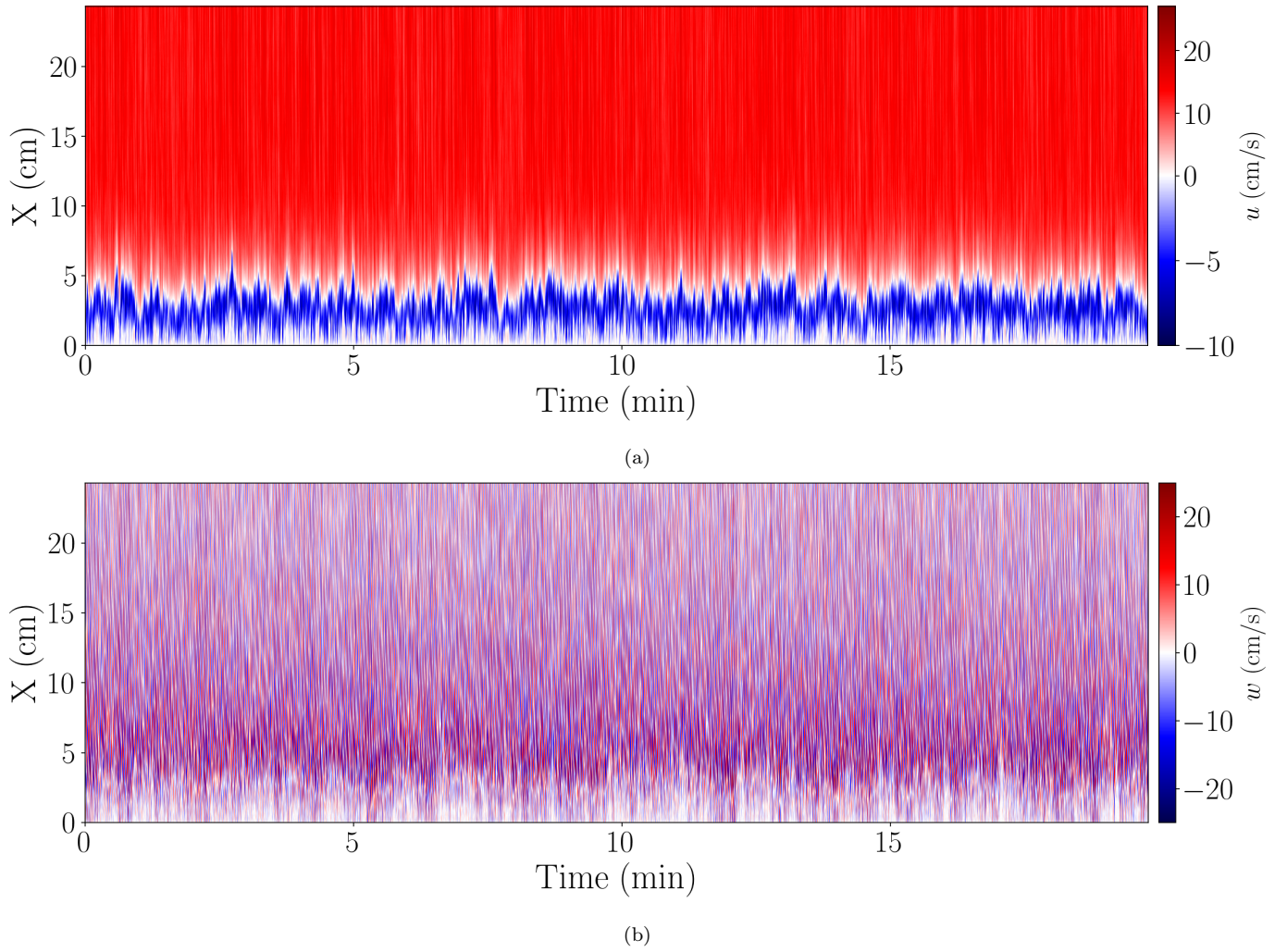


Figure 11. Space time diagrams from velocity profiles extracted at the symmetry line $z = 0$ over 20 min of monitoring at $f_{ac} = 55$ Hz. (a) u velocity component. (b) w velocity component.

Besides the high resolution that can be achieved with OF-PIV, one of the key advantages of the method is that it also allows the live computing of various data, either both local or global quantities, derived from the instantaneous velocity fields, whether they are extracted directly or computed from the velocity fields.

Fig. 9 shows the time series of a u component velocity probe placed at $(x, z) = (5, 0)$ cm from the cylinder for over 4 hours. This plot shows OF-PIV's ability to monitor continuously over extended periods of time determined quantities. In this particular case, it opens the door to explore very low frequencies in the flow, as portrayed by the signal filtered using a low pass filter at 0.01 Hz, which portrays frequencies lower than the threshold.

As mentioned, the capability of live data acquisition is not bound only to extract velocity data. We can track the temporal evolution of the recirculation region by using a scalar quantity that

represents the state of this region of the flow by computing its size from the velocity field. The recirculation area size is computed from the streamwise velocity component (u) by computing the amount of pixels in the image with a direction inverse to the free-stream.

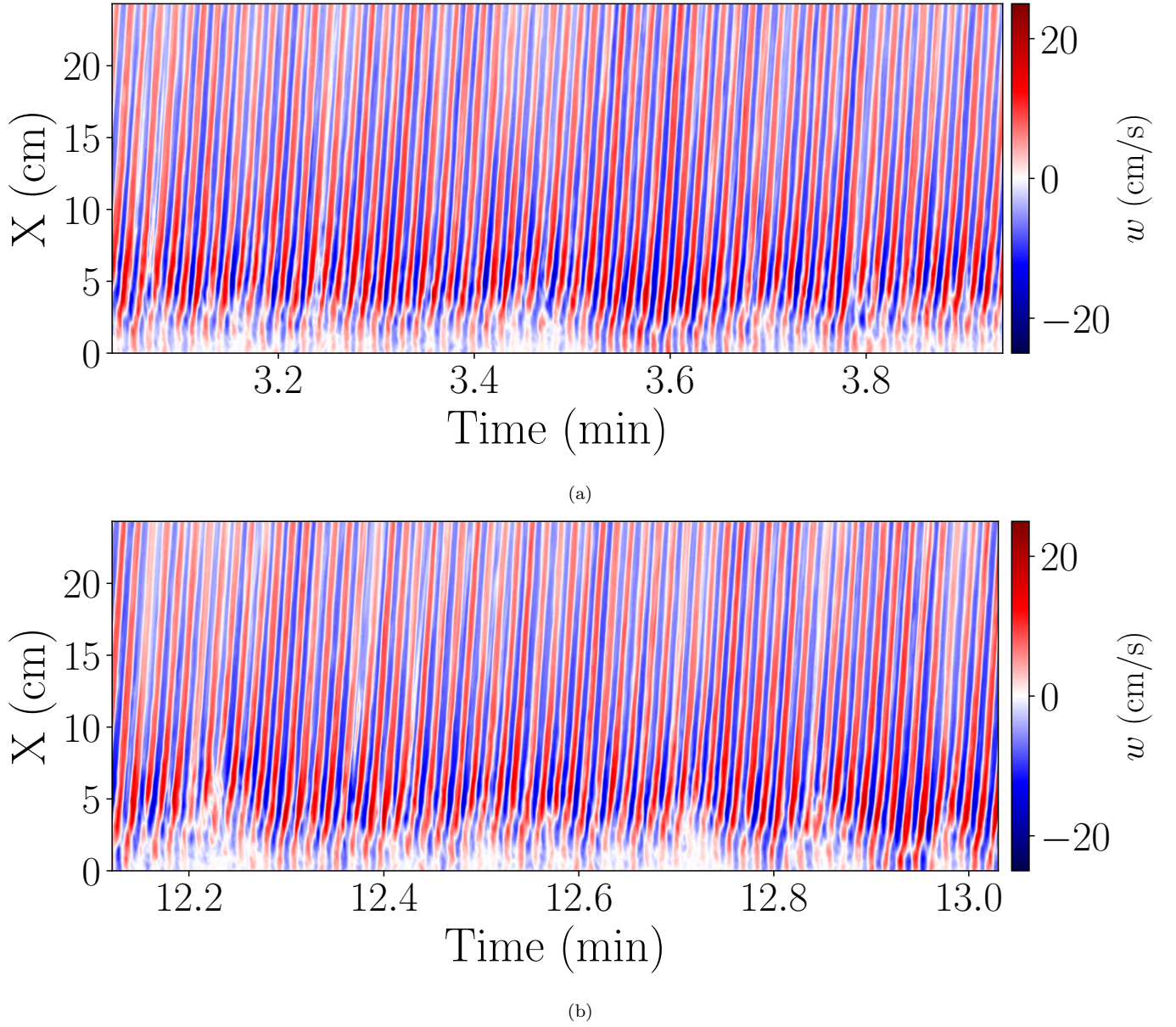


Figure 12. Zoom-in of the w velocity component space time diagram over different time windows. (a) From $t = 3$ to $t = 4$ min. (b) From $t = 12$ to $t = 13$ min.

Fig 10a shows a representation of the recirculation region at a given instant. From this binary field the instantaneous recirculation region $RA(t)$ can be computed as:

$$RA(t) = \sum_{i,j} H(-u_{i,j}(t)) \Delta x \Delta z, \quad (3)$$

where H is the Heaviside function, defined as $H(-u) = 1$ if $u < 0$, and 0 otherwise. With one vector per pixel and using a calibration of $\Delta x, \Delta z$, $RA(t)$ is expressed in cm^2 .

The resulting $RA(t)$ time series is shown in Fig. 10b for more than *four hours*. This very long monitoring process is also unique and made possible by Live OF-PIV. It allows to explore very low frequencies of any quantities in a fluid flow. For instance, long time-scale modulations can be observed. It can also be used to determine rigorous convergence criterion of the mean state. Fig. 10c shows the evolution of the time-averaged value, through a cumulative average plotted as a function of the number of samples taken into account. One can define a rigorous convergence criterion based on the variation of the average. For instance, one can consider that the mean is converged when the variations of the mean value are lower than $\pm 1\%$. In this case, more than 200 000 velocity fields would be needed to reach such a criterion, which is inaccessible with standard CC-PIV.

Velocity profiles extracted from the $z = 0$ line downstream of the cylinder have also been monitored. In particular, profiles from both velocity components have been extracted for a period of 20 minutes at an acquisition frequency $f_{ac} = 55 \text{ Hz}$, yielding to the recording of over 65 000 velocity profiles. Fig 11 presents space-time diagrams from the extracted velocity profiles for both components. For the u component (Fig. 11a) fluctuations of the recirculation region can be observed with different time-scales, hinting once more at the presence of low frequencies in the dynamics of the recirculation bubble. The w component (Fig. 11b) presents a high rate of oscillations in time and space from the dynamics in the Bénard–von Kármán vortex street. However, the dynamics in this regime are too fast to be appreciated in a single diagram. Fig. 12 presents two zoom-in versions of the $w(x, t)$ space time diagram over different time windows. Here it can be observed that, while the convection velocity remains pretty much constant over time (the slope of the diagonal bands in the space-time diagrams), there seems to be different dynamics that interact close to the cylinder wall, appreciated by changes in the slope and intensity of the color bands in both diagrams.

7. Conclusion

We presented a single GPU and multi-GPU implementation of Optical Flow Velocimetry, adapted to run PIV computations in real-time at high resolution and high frequency. We have shown that, with a single GPU, velocity fields can be computed from 1.6 kHz to 100 Hz depending on the image size. For the multi-GPU implementation, velocity fields computations in real-time can be achieved from 2.1 kHz to 200 Hz, depending on the image size. To our knowledge, these performances are currently unmatched.

A quality benchmark was also performed by means of synthetic particle images, using as displacement fields a Homogeneous Isotropic Turbulence DNS case to assess the quality and accuracy of OF-PIV's results under complex displacement case. Results are quite satisfactory, showing that

OF-PIV can accurately estimate displacements in complex conditions, and also follow closely the spatial energy spectrum of the DNS case thanks to its dense velocity field feature.

Lastly, an experimental validation using the flow past a cylinder at $Re_D \approx 6482$ has been presented. It demonstrates not only the quality of the results under real experimental conditions, but also the live data acquisition possibilities that the real-time computation enables. Data from the velocity fields, and quantities derived in real-time, were acquired for over four hours at relatively high frequency ($f_{ac} = 100$ Hz). The monitoring process for long time allowed for the extraction of data from longer runs, providing access to possible very low frequencies in the dynamics of the recirculation region and hints about the lack of convergence of the mean-state of this region. Also, the live data extraction allowed for the construction of space time diagrams over longer times than usual, being able to possibly visualize the change in the dynamics between the near and far wake regions and the difference between the time windows of observations.

This approach also allowed recently the monitoring of the flow downstream of a Backward-Facing Step to search for extreme and rare events (Pimienta & Aider, 2026b). Such experiments were impossible with standard experimental techniques. In general, we have shown that it is now possible to accurately monitor fluid flows for extended periods of time, providing rich information in both spatial and temporal terms due to the high resolution and high frequency L-OFPIV's capabilities. This can be expanded into applications such as flow control, rare event detection or very low-frequency measurements. Finally, it also should be noted that high computing performances are also obtained with a single GPU, leading to large energy savings and gain of time for post-processing.

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