

Main Results of the Second LPT Challenge

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Keywords: Lagrangian particle tracking, Particle tracking velocimetry, Flow reconstruction, Challenge

ABSTRACT

This work presents the main results of the second Lagrangian Particle Tracking (LPT) challenge, jointly organized by TU Delft, DLR, ONERA, and Penn State. We consider three test cases, namely two synthetic (a turbulent channel flow and the near-wall flow in the wake of cylindrical obstacles) and one experimental (Rayleigh-Bénard convection). Both time-resolved (for all test cases) and two-pulse (for the latter two test cases) image acquisitions are addressed. The effects of relevant parameters of the experimental setup are analysed, including the particle image density (ppp), the time separation between image recordings, the presence or absence of Mie scattering and the fraction of the total measurement volume imaged by all the cameras. The results are presented in terms of precision and recall of the particle reconstruction, as well as errors of the reconstructed particle positions, velocities and accelerations. The input data is freely available for download in the online portal (https://onera-flow-benchmarks.fr/en/Second_LPT_DA_Challenge), where the automatic evaluation of the submitted results is conducted.

1. Introduction

Digital three-dimensional (3D) Particle Tracking Velocimetry (PTV) dates back to the early 1990s (Nishino et al., 1989, Maas 1993, Malik, 1993). Its working principle relies on recording images of the tracer particles in the measurement domain from different (preferably at least three) views; intensity peaks are identified in the images, from which the lines of sight (LOS) are reprojected onto the measurement volume based on epipolar geometry, relying on an accurate camera calibration (e.g. based on a pinhole camera model, Raffel et al., 2018, or a polynomial mapping between image and world coordinates, Soloff et al., 1997). Refinement of the camera calibration using the tracer particles as markers has been shown to reduce the calibration errors well below one normalized back-projected pixel, denoted $1 \overline{px}$ (Volume Self-Calibration VSC, Wieneke, 2008, 2018). At each time instant, the 3D distribution of the tracer particles is obtained by intersecting the LOS from different cameras, within an allowed triangulation error, often selected as $1 \overline{px}$. In another family of PTV approaches, this initial triangulation is replaced by tomographic principles, with first guesses of particles positions and intensities found by discretizing the flow domain to a voxel grid, and identifying their intensities by projection onto the images (Cornic et al., 2020), these steps also requiring refined camera calibrations. A tracking approach is then applied to find the same particle along its corresponding trajectory, in

turn retrieving the particle velocity and, in case of multi-pulse or time-resolved measurements, its acceleration and even the jerk from its temporal derivatives. Because the particle velocity is not the only property that can be measured by the particle tracking approach, the latter has been renamed Lagrangian Particle Tracking (LPT, Schröder and Schanz, 2023).

Several methods have been developed to enhance 3D PTV particle image identification, positioning, tracking, and postprocessing (Dabiri & Pecora 2019). However, standard particle triangulation as well as tomographic-based approaches suffered from the formation of ghost particles and ambiguous match in the particle tracking stage, both of which increase exponentially with the tracer particle concentration, limiting the achievable image densities to between 0.005 and 0.02 particles per pixel (*ppp*; Oulette et al., 2006).

In a time-resolved context, the Shake-The-Box algorithm (STB, Schanz et al., 2016) makes use of advanced triangulation based on iterative particle reconstruction (IPR, Wieneke 2012, Jahn et al., 2021), in combination with the exploitation of the temporal and spatial coherence of the Lagrangian tracks, to achieve accurate particle tracking at image densities as high as 0.2 *ppp*, with an almost complete suppression of ghost particles, as also demonstrated in the main results of the first LPT challenge (Leclaire et al, 2021; Sciacchitano et al., 2021). Recent years have seen the emergence of other such advanced algorithmic chains, whether in the same context of LPT, or in the framework of shorter acquisition, either two-pulse (TP), or four-pulse (FP).

In this work, we expand on the results of the previous challenge (Leclaire et al, 2021; Sciacchitano et al., 2021) by considering three different test cases (two synthetic ones and an experimental one), where relevant experimental parameters are varied, namely: the time separation between recordings, the ratio between the intersection and the union of the volumes imaged by the cameras, the possibility to account for Mie scattering, and the tracer particle concentration. The input data can be downloaded freely from the online portal (https://onera-flow-benchmarks.fr/en/Second_LPT_DA_Challenge), where an automatic evaluation of the submitted results is conducted. Details on the online portal are reported in another contribution submitted to the Lisbon symposium (Leclaire et al., 2026).

2. Setup of the LPT challenge

2.1. Test cases description

Three test cases were considered, whose main parameters are summarized hereafter.

LPT Case 01: Turbulent Channel Flow

The first test case, provided by the group of Delft University of Technology in the Netherlands, consists of time-resolved (TR) synthetic particle image data of a turbulent flow in a square channel based on the DNS simulations from Pirozzoli et al. (2018). The simulated fluid is water (density $\rho = 1000 \text{ kg/m}^3$, kinematic viscosity $\nu = 10^{-6} \text{ m}^2/\text{s}$), the channel half-height is $h = 100 \text{ mm}$ and the bulk velocity is $u_b = 0.2 \text{ m/s}$, resulting in a bulk Reynolds number $Re_b = 40,000$ and a friction Reynolds number $Re_\tau = 1,000$.

An LPT experiment was simulated with four synthetic cameras positioned in a pyramidal configuration about 1 m above the channel, with cameras 1 and 3 along the streamwise direction and cameras 2 and 4 along the lateral direction; the viewing angles of the cameras were $\pm 30^\circ$, resulting in an overall tomographic aperture of 60° (see Figure 1).

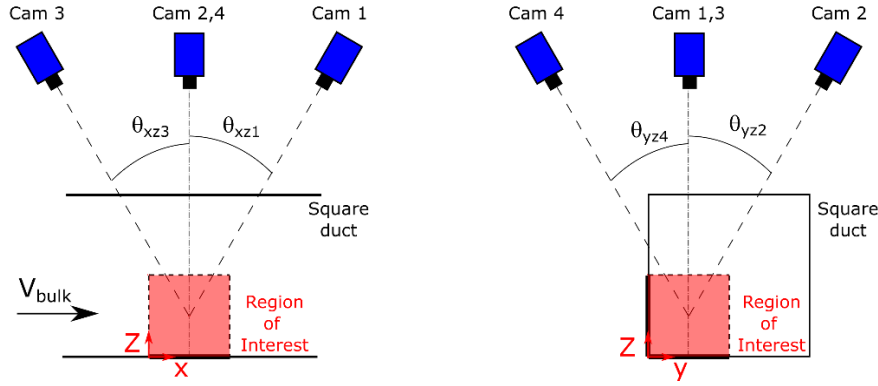


Figure 1. Position of the cameras, region of interest and frame of reference for LPT case 01.

The main parameters of the synthetic experiment are reported in Table 1. Notice that three different cases were considered, indicated as $\Delta t = 1, 2, 3$, corresponding to three different acquisition frequencies (169 Hz, 121 Hz and 94 Hz, respectively) and in turn different particle image displacements at the bulk velocity (approximately 10 px, 13 px and 18 px, respectively). A sequence of 100 images was provided to the participants for each situation.

Table 1. Main parameters of the LPT Case 01 synthetic experiment setup.

Parameter	Value
Number of cameras	4
Sensor size [px]	1024×1024
Pixel pitch [μm]	10
Focal length [mm]	105
$f\#$	22
Simulated particle diameter [μm]	50
Imaged volume [mm]	100×100×100
Number of particles	100,000
ppp	0.1
Size of back-projected pixel $\overline{p\bar{x}}$ [μm]	110.1
Acquisition frequency [Hz]	169, 121, 94
Illumination distribution	Uniform
Thermal noise [counts]	Mean: 50 Std: 20
Particle image intensity [counts]	Mean: 1700 Std: 200

LPT Case 02: Near-wall wake flow

The second test case, provided by the French Aerospace Laboratory ONERA, consists of two-pulse (TP) and time-resolved (TR) synthetic particle images of a near-wall flow downstream of cylindrical

obstacles. For both image acquisition modes, the inter-frame time separation was set to $40\ \mu\text{s}$. The datasets explore various seeding densities (ppp from 0.025 to 0.25), the presence or absence of Mie scattering, and the fraction of volume imaged by all cameras, controlled by the I/U ratio varied between 0.46 and 0.99, where I and U are the intersection and the union, respectively, of the volumes imaged by the cameras.

The physical situation corresponds to the wake of two cylindrical pillars (diameter $D = 10\ \text{mm}$, $H = 70\ \text{mm}$) placed in a turbulent boundary layer. The flow medium is air (density $\rho = 1.2\ \text{kg/m}^3$), and its free-stream velocity outside the boundary layer is equal to $10\ \text{m/s}$. At the streamwise position of the cylinders, the boundary layer is approximately $60\ \text{mm}$ thick, with a momentum thickness Reynolds number equal to $Re_\theta = 4,150$ and a bulk Reynolds number $Re_D = 6,670$. Numerical simulations were performed using Monotone Integrated LES with the ONERA HPC code FASTS (Dandois et al., 2018), wherein embedded propagation of virtual particles, hypothesized as fully passive tracers, was included. The main geometrical parameters of the synthetic experiment are illustrated in Figure 2.

The optical setup consisted of four virtual cameras viewing the measurement domain mainly from above (Z-direction), onto the X-Y plane. The cameras were located at the base of a square pyramid, at a height of around $0.45\ \text{m}$. The edges of this base were along the X and Y axes, with the edge size equal to $0.6\ \text{m}$. All cameras had a 2048×2048 sensor with $10\ \mu\text{m}$ pixel pitch, and were equipped with $f = 200\ \text{mm}$ lenses. In the TR case, the image sequences contained 50 frames for ppp values up to 0.16, and 100 images for the higher seeding concentration cases.

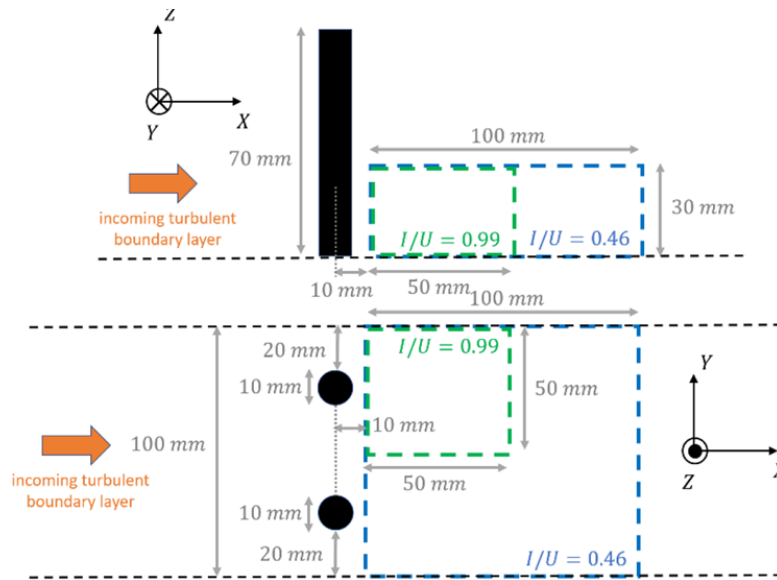


Figure 2. Main geometrical parameters of the LPT Case 02 synthetic experiment: side view (top) and top view (bottom).

LPT Case 03: Rayleigh-Bénard convection

LPT Case 03 is an experimental test case based on helium-filled soap bubbles (HFSB, Scarano et al., 2015) as flow tracers and pulsed LED illumination, whereby Rayleigh-Bénard Convection (RBC) is investigated using TP and TR sequences, at various seeding densities. The experiment, conducted at DLR Göttingen (see Figure 3, left), consisted of an electrically heated aluminium plate and a water-perfused cooling plate (Bosbach et al. 2021, Godbersen et al. 2021, Weiss et al. 2024). A total of six PCO edge 5.5 sCMOS cameras (2560×2160 pixels with a $6.5 \mu\text{m}$ pitch and an average magnification of 1.8942 px/mm) was installed and equipped with Zeiss Distagon 35 mm lenses, located at the height of the upper cooling plate and slightly tilted downwards to view the full cell. The flow was recorded at a repetition rate of 30 Hz for over 30 minutes. The images captured by all six cameras over 54,528 time-steps were used to reconstruct Lagrangian Particle Tracks using the DLR Shake-The-Box implementation (see Figure 3, right); these results were used as a Ground Truth for the evaluation of the participants' results. For the challenge data, only the four inner cameras of the in-line camera setup were selected, whereas the two outer cameras were omitted to severely aggravate the reconstruction problem (see Figure 3, middle). The number of images per *ppp* value supplied to the participants are summarized in Table 2.

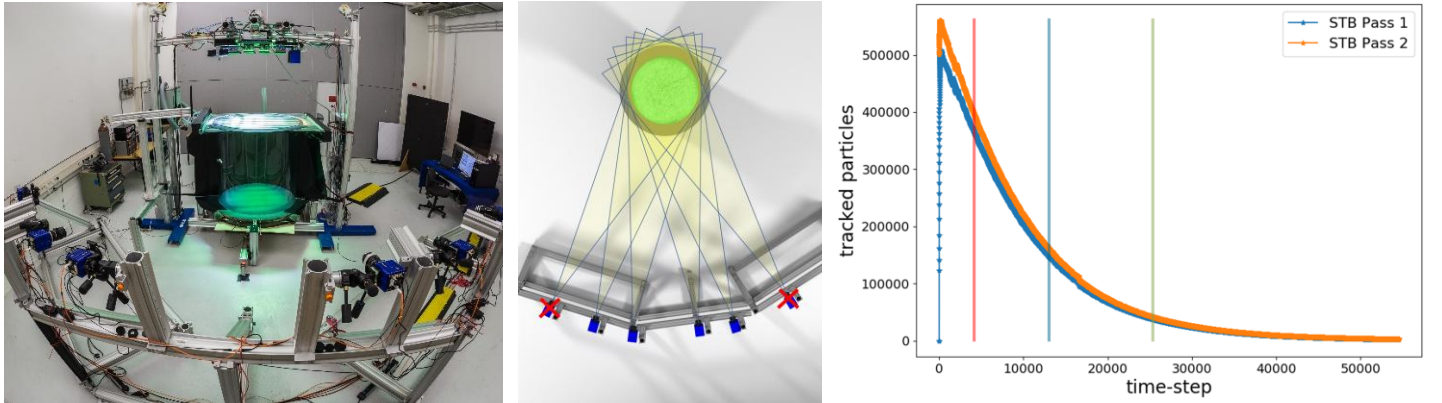


Figure 3. Photograph of the setup of the RBC experiment at DLR Göttingen (left); rendering of the camera configuration and fields-of-view; the full dataset comprises six cameras, from which the two outer ones (red crosses) are excluded for the challenge test cases (middle); tracking statistics for a two-pass STB evaluation serving as Ground Truth using the full six-camera dataset over 54,000 time-steps (right). As bubbles are bursting, particle image density is decaying over time. Cases for 0.01, 0.04 and 0.1 *ppp* are marked as green, blue and red vertical lines, respectively.

Table 2. Number of images per *ppp* value supplied to the participants for LPT Case 03.

Acquisition type	<i>ppp</i>	Number of images
TR	0.01, 0.04, 0.07	50
TR	0.1	100
TP	0.005, 0.015, 0.03, 0.045, 0.06, 0.075	2

2.2. Inputs and outputs of the challenge

From the online portal (https://onera-flow-benchmarks.fr/en/Second_LPT_DA_Challenge), the participants could download the input data, consisting of sequences of images stored in 16-bit tiff compressed format files, as well as the calibration data stored in ASCII files. In the latter files, each line contained the coordinates (X, Y, Z) of a point in the physical measurement domain together with its projections (x_i, y_i) onto the four cameras in pixel units, with i being the index of the camera number, ranging from 1 to 4. The pixel position $(0,0)$ corresponds to the centre of the pixel located at the top left corner of an image.

The following outputs were requested to the participants, at a specified time instant and stored in an ASCII file:

- *For both TR and TP cases*: Raw reconstructed particle positions (X, Y, Z) in mm, and estimated particle velocities (V_x, V_y, V_z) in m/s.
- *Only for TR cases*: Additionally, fitted reconstructed particle positions $(X_{fit}, Y_{fit}, Z_{fit})$ in mm, and estimated particle accelerations (A_x, A_y, A_z) in m/s^2 .

2.3. Definition of performance metrics

The capabilities of the LPT algorithms to accurately reconstruct the 3D distribution of the tracer particles were assessed via the *Precision* and *Recall* parameters, defined as follows:

$$Precision = \frac{\#TP}{\#TP + \#FP} \quad (1)$$

$$Recall = \frac{\#TP}{\#TP + \#FN} \quad (2)$$

Where the definitions of $\#TP$, $\#FN$, $\#FP$ are given in Table 3.

Table 3. Definitions of $\#TP$, $\#FN$, $\#FP$.

Parameter	Meaning	Definition
$\#TP$	Number of True Positives	Reconstructed particles for which a ground truth particle is found within a threshold distance ($1 \bar{p}x$)
$\#FN$	Number of False Negatives (or missed particles)	Ground truth particles with no reconstructed particle within a threshold distance ($1 \bar{p}x$)
$\#FP$	Number of False Positives (or ghost particles)	Reconstructed particles for which a ground truth particle is <u>not</u> found within a threshold distance ($1 \bar{p}x$)

The *Precision* quantifies the amount of ground truth particles reconstructed relative to the total number of reconstructed particles. Therefore, the value $Precision = 1$ is obtained in case of ghost-free particle reconstruction, independently of how many of the ground truth particles have been reconstructed. In contrast, the *Recall* represents the capability of the LPT algorithm to reconstruct the ground truth particles: hence, the value $Recall = 1$ is obtained if all the ground truth particles are reconstructed, independently of the number of ghost particles produced.

Additionally, the position, velocity and (for the TR cases) acceleration errors are computed as the root-mean-square (RMS) values of the differences between the True Positive particles and the Ground Truth particles.

2.4. Participants

The list of research groups who submitted their contributions to the different cases of the LPT challenge, together with the references to their algorithms, are summarized in Table 4.

Table 4. List of research groups that contributed to each LPT case, with references to their algorithms.

Test Case	Research Group	Algorithm	Reference
LPT Case 01	DLR Göttingen	Shake The Box	Schanz et al. (2016)
	LaVision GmbH	Shake The Box	Schanz et al. (2016)
	University of Naples	PaIRS-UniNa	Paolillo and Astarita (2024)
LPT Case 02 -TP	DLR Göttingen	Two-Pulse STB	Novara et al. (2023)
	LaVision GmbH	Two-Pulse STB	Novara et al. (2023)
	ONERA-CEA	ITE-PTV	Cornic et al. (2021)
	ONERA-CEA	VICCTOR	Le Bris et al. (2026)
LPT Case 02 -TR	DLR Göttingen	Shake The Box	Schanz et al. (2016)
	LaVision GmbH	Shake The Box	Schanz et al. (2016)
LPT Case 03 -TP	LaVision GmbH	Two-Pulse STB	Novara et al. (2023)
	ONERA-CEA	ITE-PTV	Cornic et al. (2021)
	ONERA-CEA	VICCTOR	Le Bris et al. (2026)
LPT Case 03 -TR	LaVision GmbH	Shake The Box	Schanz et al. (2016)
	University of Naples	PaIRS-UniNa	Paolillo and Astarita (2024)

The Shake-The-Box algorithm, employed by the DLR and LaVision groups, makes use of the Iterative Particle Reconstruction technique (IPR, Wieneke, 2012) to triangulate the three-dimensional particle positions from the two-dimensional intensity peaks in the images, followed by a 3D position and intensity optimization (“shaking”), and prediction of the particle positions at the next time instant (for the time-resolved case, Schanz et al., 2016). In the two-pulse variant (Novara et al., 2023), due to the lack of velocity information from time-resolved data, the Particle Space Correlation method is used to provide a predictor for the particle tracking.

The PaIRS algorithm from UniNa uses tomographic principles, and in particular voxel-based intensity reconstruction via the SMART algorithm (Atkinson and Soria, 2009) in combination with the Sequential Motion Tracking Enhancement approach (Lynch and Scarano, 2015), to reconstruct the 3D particle distribution in the first three time instants. After such start-up phase, the tomographic volumes are converted into sets of particles, each identified by position, diameter and intensity, used for the Lagrangian Particle Tracking via the IPR and STB approaches.

The joint research team between ONERA (the French Aerospace Lab) and CEA (French Alternative Energies and Atomic Energy Commission) submitted results by two algorithms. The Iterative Tomographic Enhanced Particle Tracking Velocimetry (ITE-PTV) algorithm is an evolution of the I-

DF-T-PTV algorithm developed by Cornic et al. (2020, 2021) for the 1st LPT Challenge (Sciacchitano et al., 2021). The approach employs the Multiplicative Line of Sight algorithm to reconstruct the 3D particle distribution on a voxel grid; a compressed sensing algorithm (COSAMP, Cornic et al., 2015) is used to select the most relevant peaks based on the expected number of particles. The particle tracking is performed via advection via a 3D Correlation field (Cheminet et al., 2014). The location and intensity of the particles is then refined based on a global L-BFGS optimization (Cornic et al., 2021). The VICCTOR algorithm first performs particle reconstruction from images using the Particle Volume Reconstruction (PVR) paradigm (Champagnat et al., 2014), modelling the image formation in a tomographic context. The particle tracking is then performed using the Flow Vector Field Consensus approach (Ma et al., 2014, Le Bris et al., 2025), a robust pairing algorithm with outlier removal, tailored to tackle high levels (up to 50%) of ghost particles. After matching, the same refinement step of the particle intensities and positions as in ITE-PTV, based on global optimization, is performed. Both ITE-PTV and VICCTOR perform these three steps (reconstruction, matching, refinement) within an iterative loop on residual images, to progressively reconstruct a maximum of particles.

3. Results

3.1. LPT Case 01

Figure 4-left shows the *Precision* results for the different Δt values: it is confirmed that, even at this high *ppp* value of 0.1, the LPT algorithms return ghost-free particle reconstructions, with *Precision* values mostly above 0.99. Among the different algorithms, minor differences are noticed: while the DLR implementation of STB and the PaIRS algorithm return a constant *Precision* above 0.998, for the LaVision implementation of STB (STB@DaVis) the *Precision* decreases slightly with increasing time separation, reaching a minimum of about 0.989 at the largest Δt .

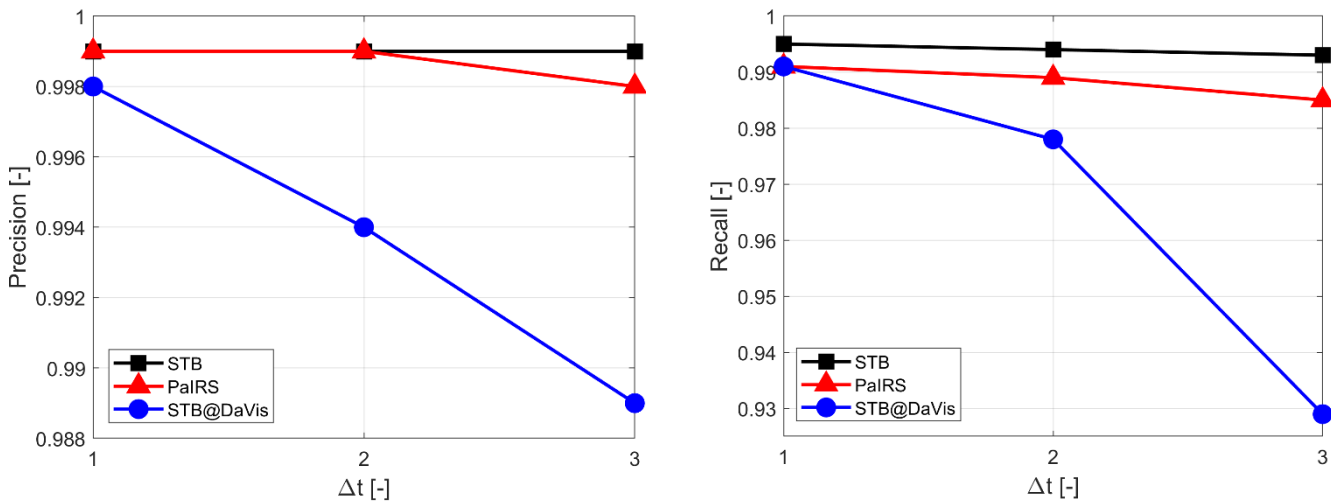


Figure 4. *Precision* (left) and *Recall* (right) for the three LPT algorithms as a function of Δt . Results for the LPT Case 01.

The *Recall* results, illustrated on the right of Figure 4, show that the DLR implementation of STB is capable of reconstructing correctly 99.5% of the true particles, independently of the time separation among recordings; slightly lower values (between 98.5% and 99%) are retrieved with the PaIRS algorithm. The LaVision implementation of STB returns similar *Recall* values at $\Delta t = 1$, but the *Recall* decreases down to 93% at the largest time separation.

The fitted position, velocity and acceleration RMS errors are summarized in Figure 5. Overall, the RMS errors of the fitted position are between 0.1 and 0.3 $\overline{px}$, with the minimum errors obtained for the DLR implementation of STB, and larger errors for the LaVision implementation, especially at the largest time separation. Similarly, the velocity RMS errors are between 1% and 3% of the bulk velocity, with similar differences among the algorithms as for the position errors. Surprisingly, the acceleration errors, shown on the right of Figure 5, exceed 100% of the reference acceleration V_∞^2/D for all the tested algorithms; the variations of the acceleration errors with the time separation are minor. Overall, this result indicates that, while the LPT algorithms capture correctly the particle positions and velocities, the accurate evaluation of the particle accelerations remains a challenge.

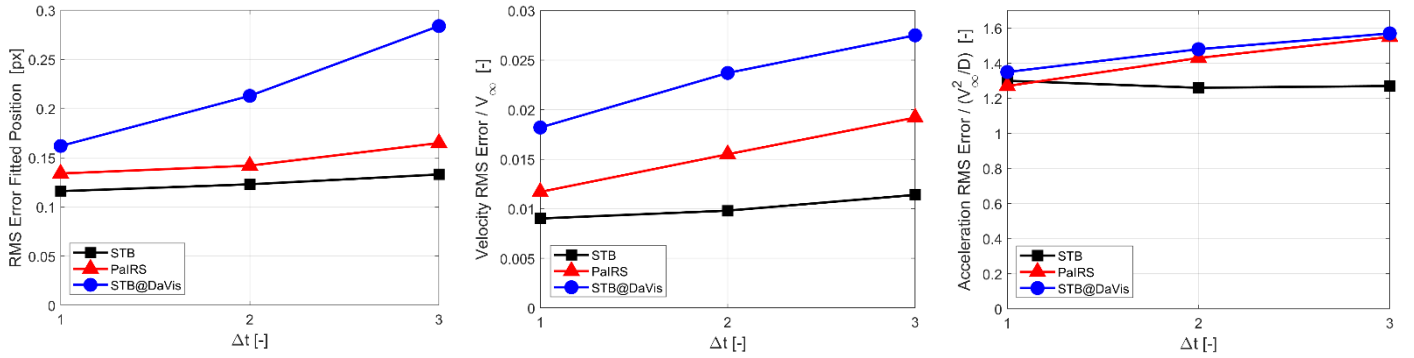


Figure 5. RMS errors of fitted position (left), velocity (middle) and acceleration (right) as a function of Δt . Results for the LPT Case 01.

3.2. LPT Case 02

3.2.1. LPT02 Two-pulse

The *Precision* and *Recall* of the reconstructed vectors, as well as the RMS error on the displacement of case LPT02, two-pulse configuration, are shown in Figure 6 as a function of ppp , for the case where the imaged volume is almost the same for all cameras ($I/U = 0.99$) and in absence of Mie scattering. The results illustrate that both the DLR and the LaVision implementations of TP-STB, as well as the VICCTOR algorithm, return a ghost-free particle reconstruction (*Precision* = 1, see Figure 6-left) at all ppp values; it should be mentioned, however, that only the DLR implementation of TP-STB processed the data at the highest ppp of 0.25, while the other algorithms were employed up to $ppp = 0.20$. The ITE-PTV algorithm exhibits a *Precision* close to 1 up to $ppp = 0.16$; however, at $ppp = 0.20$, the *Precision* drops significantly to 0.54, indicating that the algorithm struggles to perform accurate particle reconstruction at such high seeding concentration. Similar results are obtained for the *Recall* (Figure 6-middle), with values about 0.97 for all algorithms and all ppp values, except for ITE-PTV at

$ppp = 0.20$. The resulting errors on the displacement vector, illustrated in Figure 6-right, are typically about $0.1 \bar{p}\bar{x}$ and increase slightly with the ppp , with minor differences among the different algorithms; again, for ITE-PTV at the largest $ppp = 0.20$, the results are significantly less accurate, with displacement errors exceeding $0.5 \bar{p}\bar{x}$, which is associated with the larger uncertainty in the particle reconstruction.

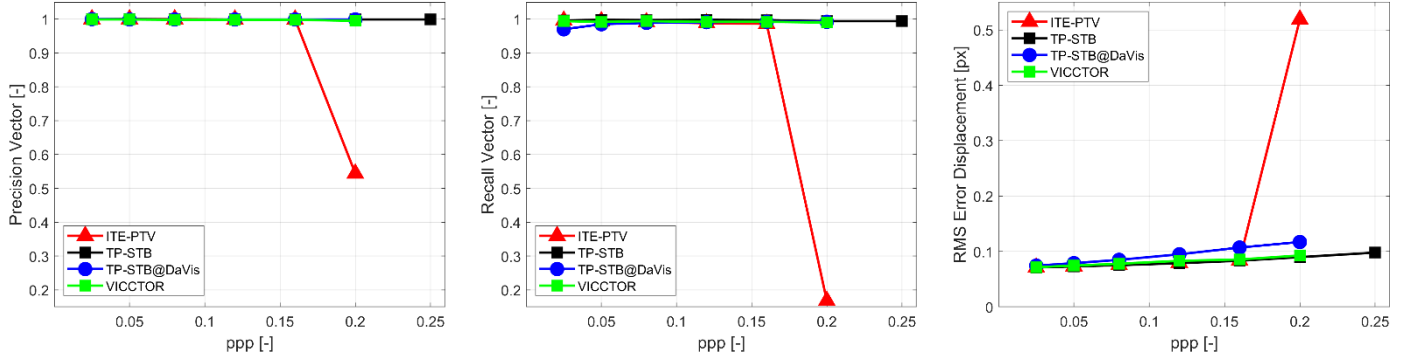


Figure 6. Precision (left), Recall (middle) and RMS of the displacement error (right) for the different LPT algorithms as a function of ppp . Results for the LPT Case 02 TP, with $I/U = 0.99$ and in absence of Mie scattering ($Mie = 0$).

Figure 7 analyses the effect of the ratio between the intersection I and the union U of the volumes imaged by the cameras, varied between 0.46 and 0.99. Note that error metrics are here built from particles located in the intersection volume. As expected, a reduction of the ratio I/U yields a reduction of the accuracy of the reconstructed particle distributions, with lower *Precision* (viz. higher number of ghost particles), lower *Recall* (viz. higher number of missed particles) and higher displacement errors, which may exceed $0.2 \bar{p}\bar{x}$ at $I/U = 0.46$, depending on the algorithm employed. It is worth noticing that the tomography-based algorithms, namely ITE-PTV and VICCTOR, exhibit values of *Precision*, *Recall* and displacement error that are in general lower than the LPT-based algorithms (the DLR and LaVision implementations of STB), especially at the lower I/U values: in other words, the tomography-based algorithms reconstruct less true particles, but yield more accurate displacement estimates. Also, it is noticed that the LaVision implementation of STB exhibits higher *Precision*, but lower *Recall*, than the DLR implementation: this means that the LaVision implementation produces less ghost particles, but also reconstructs less true particles, than the DLR implementation.

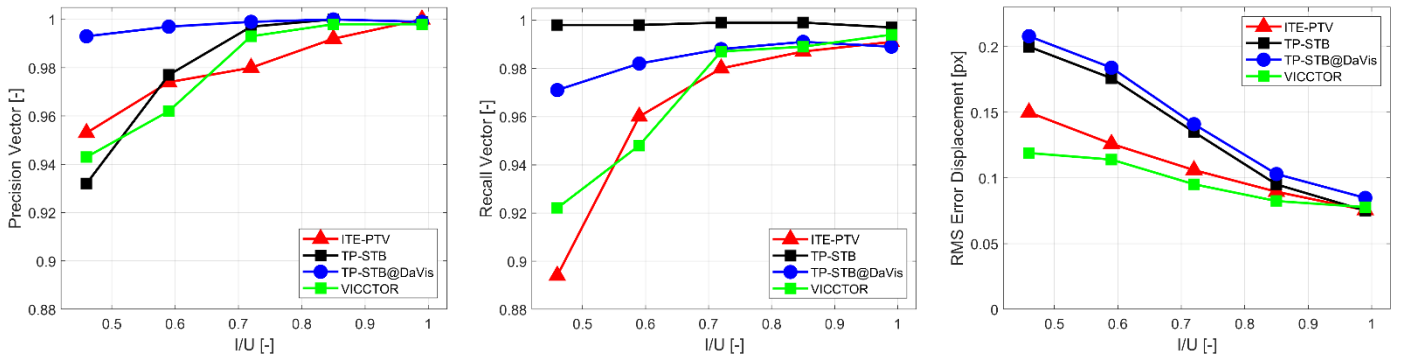


Figure 7. *Precision* (left), *Recall* (middle) and RMS of the displacement error (right) for the different LPT algorithms as a function of I/U . Results for the LPT Case 02 TP, with $ppp = 0.080$ and in absence of Mie scattering ($Mie = 0$).

The effect of Mie scattering, both for the highest and the lowest I/U values (continuous and dashed lines, respectively), is addressed in Figure 8. Overall, the presence of Mie scattering ($Mie = 1$) makes the particle reconstruction more challenging, decreasing *Precision* and *Recall* and increasing displacement errors. The effect is less pronounced at the highest I/U , especially for what concerns the *Precision*, whereas it becomes much more pronounced at $I/U = 0.46$. It is worth noticing that, while in absence of Mie scattering the displacement errors are mostly between 0.1 and 0.2 $\bar{p}\bar{x}$, in presence of Mie scattering they more than double, being in the range between 0.25 and 0.6 $\bar{p}\bar{x}$, indicating a significant increase in the uncertainty of the positions of the reconstructed particles.

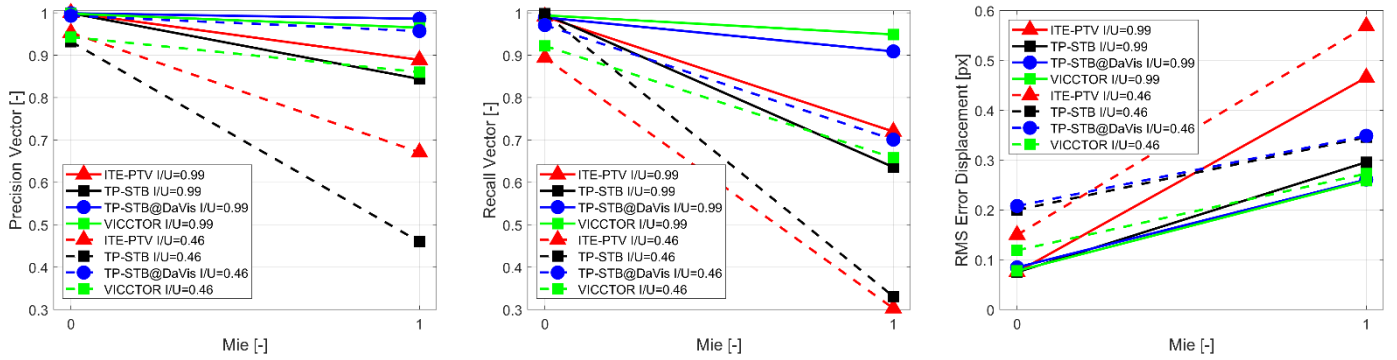
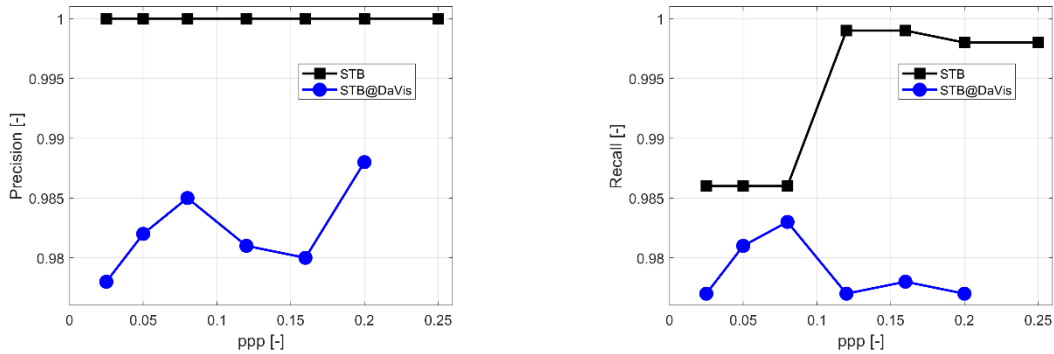


Figure 8. *Precision* (left column), *Recall* (central column) and RMS of the displacement error (right column) for the different LPT algorithms in absence ($Mie = 0$) and presence ($Mie = 1$) of Mie scattering. Results for the LPT Case 02 TP, with $ppp = 0.080$.

3.2.2. LPT02 Time-resolved

For the time-resolved case, the accuracy of the reconstructed particles shows little dependency on the seeding concentration (Figure 9; notice, however, that the LaVision implementation of STB was only used up to $ppp = 0.20$ and not at the highest seeding concentration of $ppp = 0.25$).



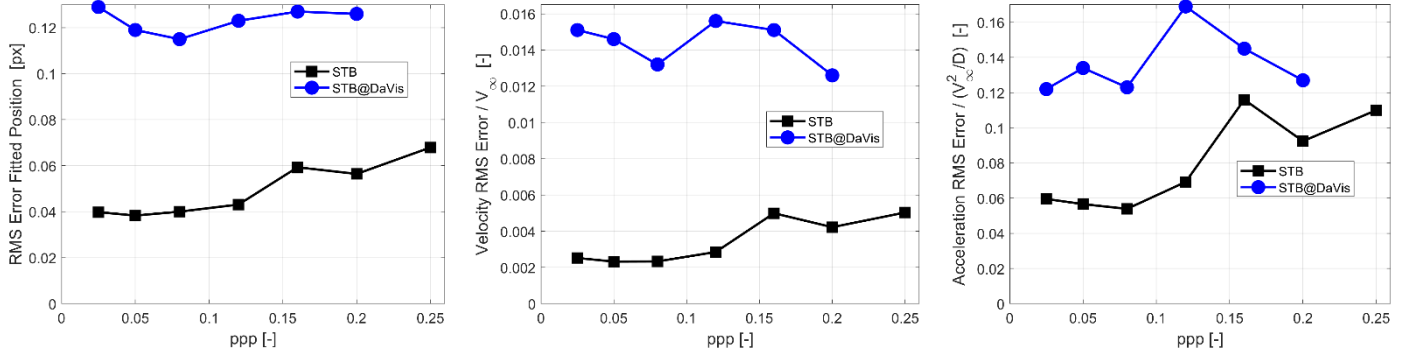
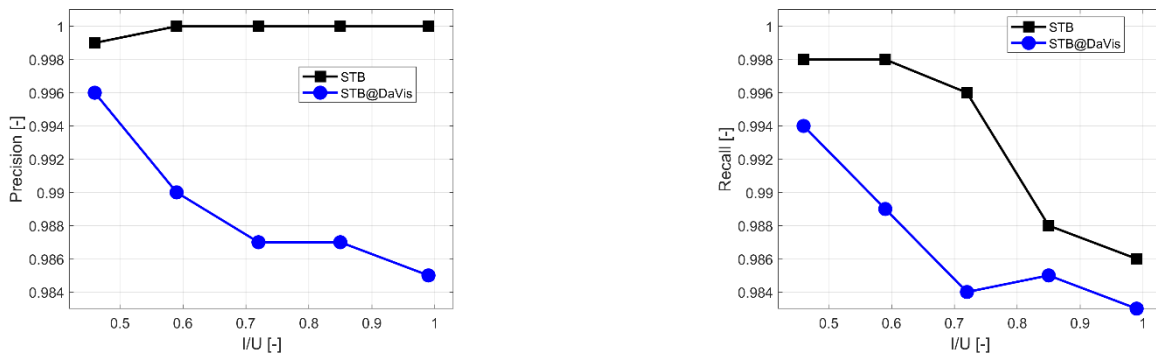


Figure 9. Results for LPT case 02 TR as a function of the ppp , for $I/U = 0.99$ and in absence of Mie scattering ($Mie = 0$). Top row: *Precision* (left) and *Recall* (right). Bottom row: RMS errors of the fitted position (left), of the velocity (middle) and of the acceleration (right).

For all ppp values and for both implementations of STB, the *Precision* and *Recall* are above 97%, with minor variations with ppp . The DLR implementation exhibits the lower errors on position, velocity and acceleration, which remain below $0.07 \bar{p}\bar{x}$, $0.6\% V_\infty$ and $12\% V_\infty^2/D$, respectively, at all ppp values; the LaVision implementation yields errors that are two to three times higher than the DLR implementation.

The effect of I/U is illustrated in Figure 10, where again error metrics pertain to particles within the intersection volume I : contrary to the two-pulse case, an increase of I/U does not necessarily yield an improvement of the results. For the DLR implementation of STB, the *Precision* remains above 0.99 for all I/U values, whereas for the LaVision implementation it drops slightly with increasing I/U . Also the *Recall* decreases with increasing I/U : this surprising result may be due to the fact that some parameters in the particle reconstruction and tracking have been optimized to improve the performance when the cameras do not images the same volume. The errors of position, velocity and acceleration show little dependence on I/U , indicating that the time-resolved algorithms are capable to perform accurate particle reconstruction even if the intersection of the volumes imaged by the cameras is only a fraction of the union of the volumes. As expected, the errors on the position are lower than those reported in the two-pulse case because temporal information of the time-resolved case allows suppressing the positional noise.



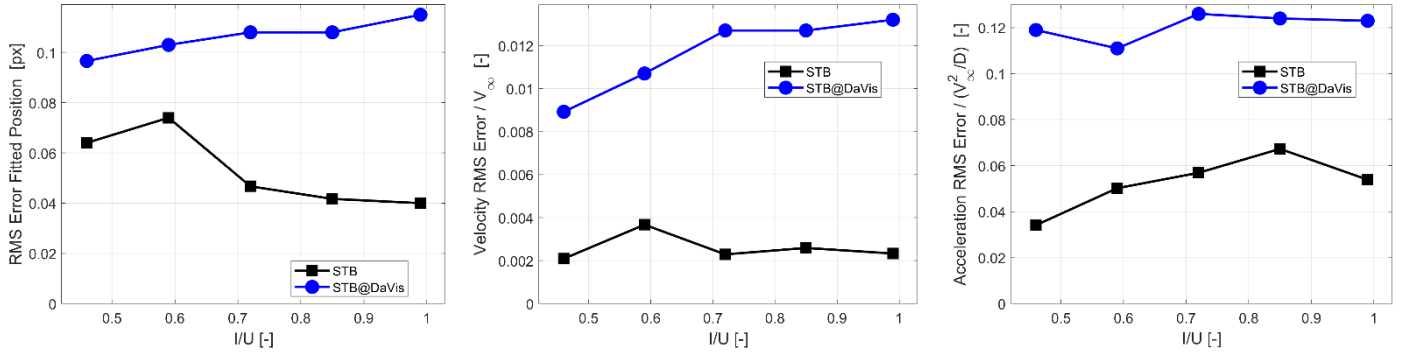


Figure 10. Results for LPT case 02 TR as a function of the I/U , for $ppp = 0.080$ and in absence of Mie scattering ($Mie = 0$). Top row: *Precision* (left) and *Recall* (right). Bottom row: RMS errors of the fitted position (left), of the velocity (middle) and of the acceleration (right).

The presence of Mie scattering does not affect the *Precision* (Figure 11 top-left), which remains above 98%, but reduces the *Recall*, especially at the lowest I/U (Figure 11 top-right), indicating that more true particles are missed due to the fact that they are visualised with different intensities from the different cameras. Additionally, the Mie scattering increases the displacement, velocity and acceleration errors (bottom row of Figure 11), rather independently of I/U : for example, the positional errors increase from the range 0.04-0.12 $\bar{p}\bar{x}$ in absence of Mie scattering to 0.14-0.20 $\bar{p}\bar{x}$ in presence of Mie scattering, indicating that this parameter contributes significantly to the positional uncertainty of the reconstructed particles.

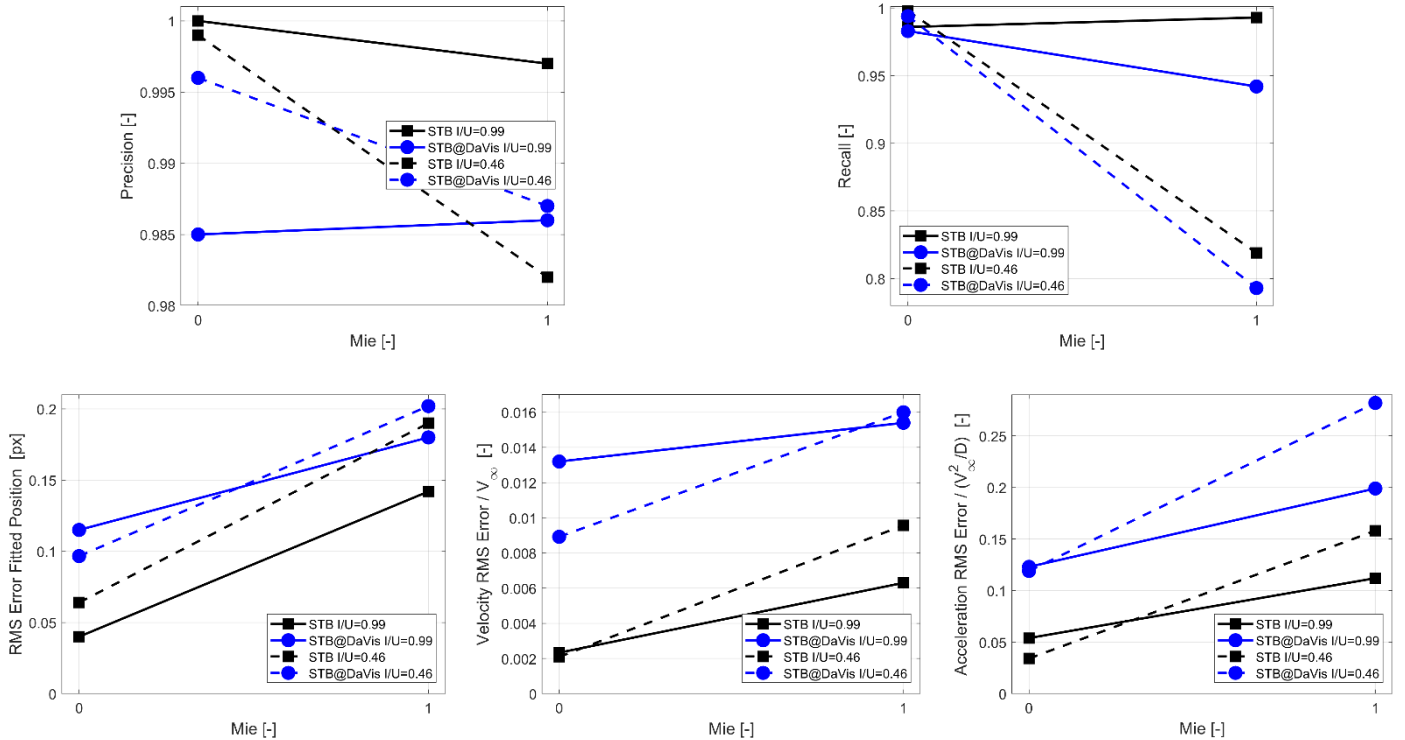


Figure 11. Results for LPT case 02 TR as a function of the absence ($Mie = 0$) or presence ($Mie = 1$) of Mie scattering, for $ppp = 0.080$. Top row: *Precision* (left) and *Recall* (right). Bottom row: RMS errors of the fitted position (left), of the velocity (middle) and of the acceleration (right).

3.3. LPT Case 03

It is reminded that LPT case 03 is an experimental test case; the non-idealized imaging conditions, such as background image noise and light reflections, non-uniform particle image size and presence of Mie scattering are expected to pose additional challenges to the LPT algorithms.

3.3.1. LPT03 Two-pulse

The *Precision*, *Recall* and *RMS* error of the displacement are shown in Figure 12 for the two-pulse case. While the *Precision* remains relatively constant with ppp and above 0.9 for the LaVision implementation of two-pulse STB, the results of ITE-PTV and VICCTOR are slightly lower, between 0.8 and 0.9, indicating a larger percentage of reconstructed ghost particles. For the ITE-PTV algorithm, a clear reduction of the *Precision* is noticed at ppp values exceeding 0.05. For the ITE-PTV and VICCTOR algorithms, the *Recall* is constant and above 0.9 for ppp lower than 0.02, while it decreases linearly for higher ppp values. For the LaVision implementation of TP-STB, instead, lower values of the *Recall* are retrieved at lower ppp , indicating that this algorithm reconstructs less true particles (but also less ghost particles, as seen from the higher *Precision*). Also this algorithm exhibits a linear decrease of the *Recall* for ppp values exceeding 0.03, although the steepness of the decrease is lower than for the other two algorithms.

The displacement errors, illustrated in Figure 12-right, show that even at the lowest ppp of 0.05, the errors are as large as $0.4 \bar{p}\bar{x}$ (ITE-PTV and LaVision implementation of TP-STB) and even $0.75 \bar{p}\bar{x}$ (VICCTOR), which are several times larger than the errors obtained in the synthetic test cases at higher seeding concentration. These higher values might be at least partly ascribed to the difficult calibration and self-calibration of the case, due to observation through a curved cylinder (Bosbach et al. 2022). In all cases, the error increases approximately linearly with the ppp , reaching values between $0.6 \bar{p}\bar{x}$ (LaVision TP-STB) and $0.8 \bar{p}\bar{x}$ (ITE-PTV) at $ppp = 0.08$. Interestingly, although based on different reconstruction principles (voxel-based tomographic PIV and particle-based iterative particle reconstruction, respectively), the ITE-PTV and TP-STB algorithms return very similar values of the displacement error at all the considered seeding concentrations.

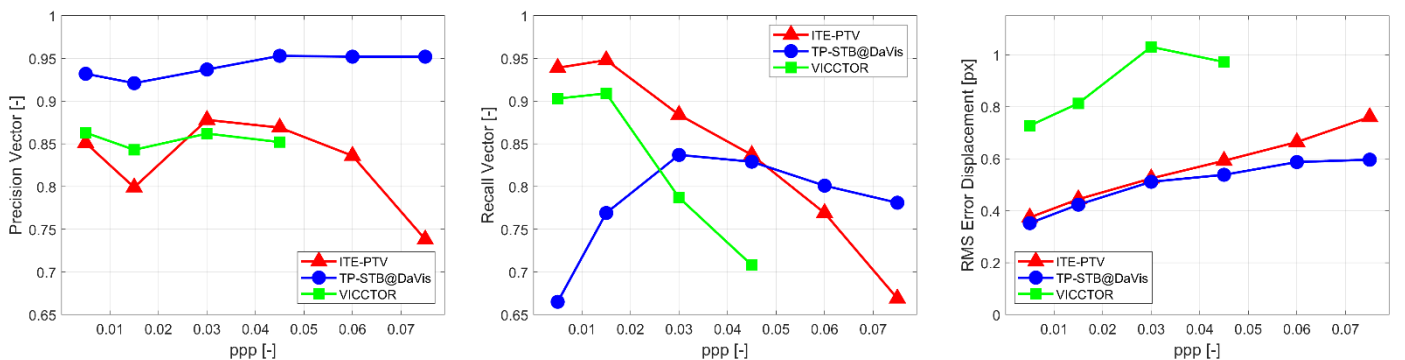


Figure 12. *Precision* (left), *Recall* (middle) and *RMS* of the displacement error (right) for the different LPT algorithms as a function of ppp . Results for the LPT Case 03 TP.

3.3.2. LPT03 Time-resolved

The *Precision* results of the time-resolved case, shown in Figure 13-left, are somehow unexpected: for both algorithms (PaiRS and the LaVision implementation of STB), the *Precision* increases with increasing *ppp*, indicating that a higher seeding concentration yields a reduction in the percentage of ghost particles. This results seems to both contradict theory (Discetti, 2013) and numerical assessments by Monte Carlos simulations (Scarano, 2013). The reason for this apparent contradiction is attributed to the fact that, in both algorithms, parameters (such as the number of forward and backward passes in the tracking) are adapted depending on the *ppp* value, resulting in a suppression of ghost particles at the highest seeding concentrations.

Instead, the *Recall*, reported in Figure 13-right, better agrees with expectations, showing a reduction (hence a decrease in the percentage of true particles reconstructed) with increasing seeding concentration. It is worth noticing that, even at the highest *ppp* of 0.1, *Recall* values between 0.7 and 0.75 are retrieved.

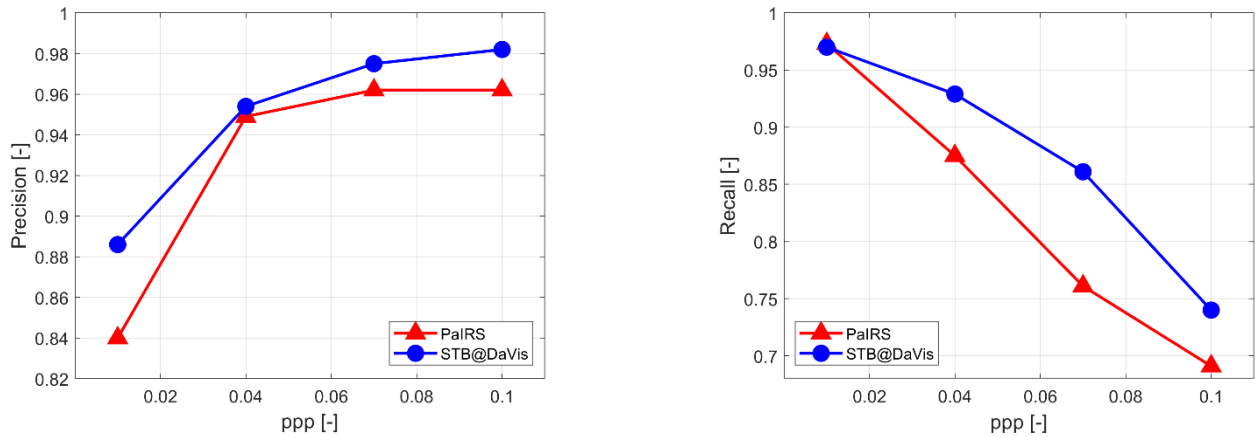


Figure 13. *Precision* (left) and *Recall* (right) for the different LPT algorithms as a function of *ppp*. Results for the LPT Case 03 TR.

The position, velocity and acceleration errors are illustrated in Figure 14. As in the two-pulse case for the displacement, the position errors are much larger than what reported for the synthetic test cases, with values ranging between $0.35 \bar{p}\bar{x}$ and $0.6 \bar{p}\bar{x}$, increasing slightly with the seeding concentration. The velocity errors (Figure 14-middle) are between 0.5% and 1.2% of the reference velocity (in this case, $V_\infty = 0.66 \text{ m/s}$ is the “free-fall” velocity, Bosbach et al., 2021), with relatively small differences between the two algorithms (within 0.5% of the reference velocity). Conversely, the acceleration errors exhibit much larger differences between the two algorithms: while the errors from the LaVision implementation of STB are between 0.1 and 0.2 of the reference acceleration, for the PaiRS algorithm the acceleration errors range from 0.3 to 0.9 of V_∞^2/D , indicating the even small differences in the accuracy of the particle reconstruction may result in large differences in the uncertainty of the acceleration.

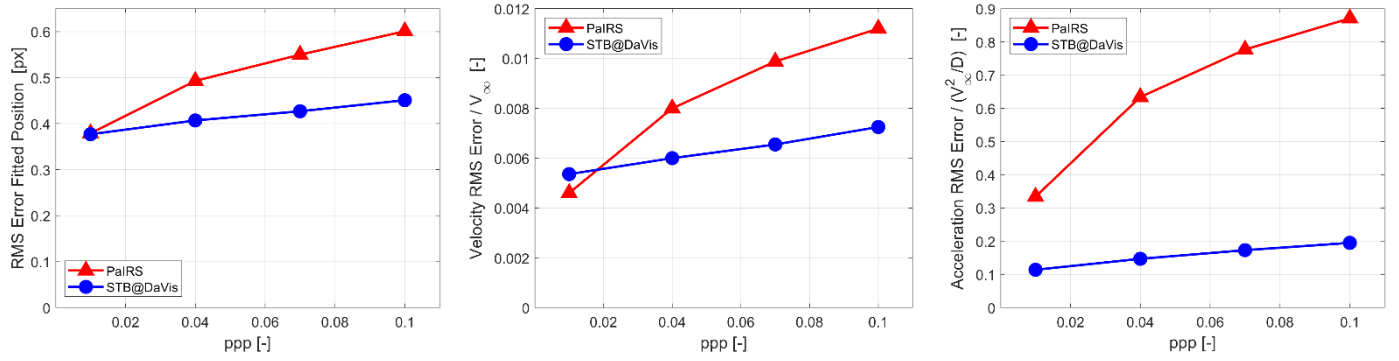


Figure 14. RMS errors of fitted position (left), velocity (middle) and acceleration (right) as a function of ppp . Results for the LPT Case 03 TR.

4. Conclusions

We present the main results of the second Lagrangian Particle Tracking (LPT) challenge, jointly organized by TU Delft, DLR, ONERA, and Penn State. In this challenge, three test cases were considered, namely a turbulent channel flow (synthetic), a near-wall wake flow (synthetic) and a Rayleigh-Bénard convection (experimental). The effects of relevant parameters of the experimental setup were addressed, including the particle image density (ppp), the time separation between image recordings, the presence or absence of Mie scattering and the fraction of the total measurement volume imaged by all the cameras.

The main results can be summarized as follows:

- *LPT Case 01*: all the submitted LPT algorithms (DLR and LaVision implementations of STB, and PaIRS from UniNa) are capable to correctly reconstruct over 99% of the ground-truth particles, with a negligible percentage of ghost particles (typically well below 1%). While position and velocity are retrieved with high accuracy (RMS errors of about $0.1 \bar{p}\bar{x}$ and $0.01 V_\infty$, respectively, for the best performing algorithm), the accurate evaluation of the acceleration remains a challenge, with RMS errors typically exceeding 100% of the reference acceleration.
- *LPT Case 02*:
 - *TP Configuration*: The sparsity-based ITE-PTV algorithm, using 3D correlation for matching, struggles at high seeding concentrations ($ppp \geq 0.2$), whereas the use of the Particle Volume Reconstruction and of the Flow Vector Field Consensus (VICCTOR) tracking algorithm enables high particle reconstruction accuracy also at those ppp values. For the other algorithms based on Iterative Particle Reconstruction, in absence of Mie scattering the *Precision* and *Recall* remain well above 0.90 at all ppp values. Decreasing the ratio between intersection and union of the volumes imaged by the cameras yields higher challenges to the particle reconstruction algorithms, decreasing *Precision* and *Recall* and increasing the displacement errors. The presence of Mie

scattering strongly decreases *Precision* and *Recall* and roughly doubles the displacement errors to the range between 0.25 and 0.6 $\overline{px}$

- *TR Configuration*: The errors of position, velocity and acceleration showed little dependency on I/U , indicating that the presence of temporal information enables to reduce the particle positional errors even at low I/U values. Conversely, as in the TP configuration, the presence of Mie scattering roughly doubles those errors.
- *LPT Case 03*: this being an experimental test case, lower value of *Precision* and *Recall*, and higher values of the displacement, velocity and acceleration errors are retrieved compared to the first two (synthetic) test cases, part of this lower performance being possibly due to the complex calibration. In particular, for the TP configuration, the displacement errors are between 0.6 and 0.8 $\overline{px}$ at $ppp = 0.08$. Interestingly, algorithms based on different principles (tomographic voxel-based reconstruction: ITE-PTV; particle-based reconstruction: LaVision implementation of TP-STB) returned very similar displacement errors. The use of the temporal information from the TR configuration reduces the positional errors to the range 0.35-0.6 $\overline{px}$; the velocity errors remained 0.4% and 1.2% of V_∞ , whereas the acceleration errors ranged within 10% and 90% of the reference acceleration.

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