An assessment of the correlation-based particle identification (CPI) method in the framework of Dual-Plane Stereo-Astigmatism (DPSA)

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Abstract

A synthetic study is conducted to assess the performance of the correlation-based particle identification method (CPI). As a technique developed in the context of Dual-Plane Stereo-Astigmatism (DPSA), the CPI method allows the identification of particle image shapes by utilizing image cross-correlation. The performance assessment addresses the influence of noise, particle density, particle image size and particle image deformation. The study shows viable results for low to moderate particle densities. Generally, a stronger performance of the CPI method is observed for small particle image sizes and pronounced particle image deformations. However, in the absence of particle overlapping, such as in the case of small particle densities, bigger particle images show a stronger performance, since a finer numerical discretization of the particle image provides a more accurate computation of the image cross-correlation. A stronger incorporation of particle overlapping increases the rate of particle identification, however it diminishes the accuracy of particle localization and particle allocation.

Keywords: DPSA, CPI, astigmatism

1 Introduction

In the present work, the correlation-based particle identification (CPI) method, as introduced by Kling et al. 2019, is assessed by a synthetic study. The CPI method has been developed for the identification of particle image shapes within the framework of the Dual-Plane Stereo-Astigmatism (DPSA) approach (Kling et al. 2019). The DPSA method represents a quasi-volumetric velocimetry technique (2.5D3C), which utilizes dual-plane illumination and astigmatism-based depth codification for the classification of particle images. The concept of the DPSA approach relies on the joint recording of measurement planes and the subsequent allocation of particles based on the particle image classification.

In the work of Kling et al. (2019), the CPI technique and the iterative particle reconstruction method (IPR) (Wieneke 2013) has been employed for the identification of particles. The IPR method showed a strong performance of particle identification, even for dense particle fields. However, the method features a comparatively high computational expense, especially in terms of non-uniform particle images, which requires the use of adaptive particle image dimensions for image-matching. Moreover, due to its concept, the IPR method is particularly susceptible to intensity-based disruptions such as noise, reflections and background image.

Although the CPI method is limited to non-overlapping particles, the approach shows a significant potential, especially in terms of challenging conditions. Furthermore, the CPI method features a fast computation and a reasonable robustness with respect to particle image variation. The performance assessment of the present work is dedicated to outline the capability of the CPI technique. Furthermore, the investigation intents the derivation of general recommendations for the setup of the DPSA experiment. The study addresses the influence of noise, particle density, particle image size and particle image deformation.
In the following, both the methodology of DPSA and the principles of CPI are outlined briefly. A detailed description is provided by Kling et al. (2019).

2 Principles of DPSA

The DPSA technique is a multi-plane approach, which allows the characterization of the full velocity gradient tensor. The principle of the DPSA approach relies on the joint recording of measurement planes and the subsequent separation via image processing. For the separation of the measurement planes, the DPSA approach utilizes astigmatism-based depth codification. Depending on the particle image deformation, particles are allocated to the respective measurement planes. The separation allows the individual analysis of the particle displacement and the computation of the out-of-plane gradient. In Figure 1, the optical system of the DPSA approach is shown, which comprises a stereoscopic setup with the addition of dual-plane illumination and cylindrical lenses to introduce astigmatism.

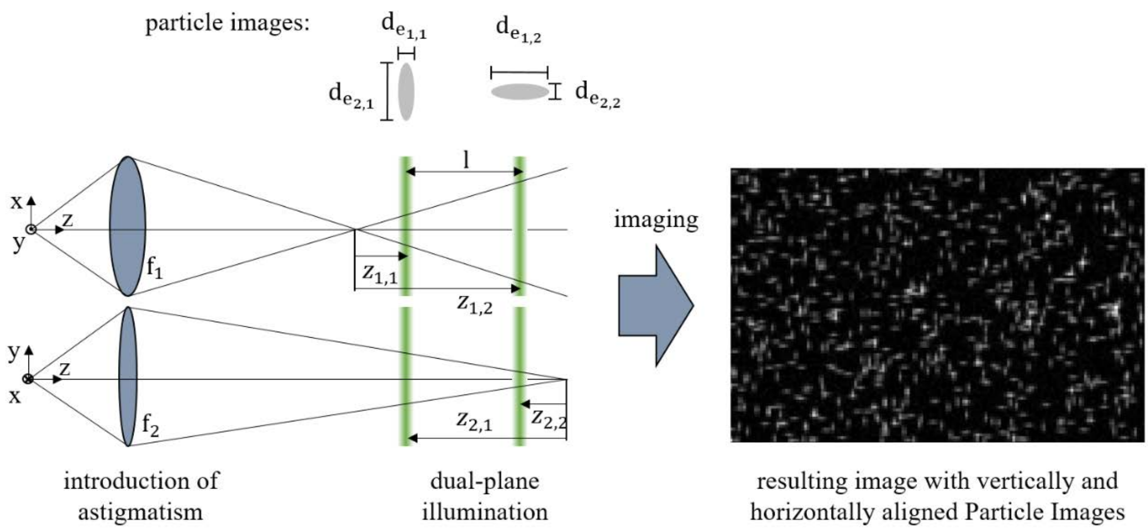

Figure 1: Optical system of a DPSA configuration (Kling et al. 2019). Illustration of the particle image dimensions in dependence of the focal lengths, the out-of-focus distances, the aperture and the optical magnifications. Exemplary image with horizontally and vertically aligned particle images.

Due to the incorporation of astigmatism, the optical system is spatially decoupled. In conjunction with the out-of-focus effect, the decoupling allows the separate manipulation of the particle image dimensions for both measurement planes and the specification of horizontally and vertically aligned particle images. For the specification of the desired particle image dimensions, the configuration of the optical system with respect to the experimental setup is essential. According to Olsen and Adrian (2000), the particle image dimensions are described by

$$d_{e_{i,j}} = \left(M_i^2 d_p^2 + 5.95(M_i + 1)^2 \lambda^2 f\#_i^2 + \frac{M_i f_i^2}{f\#_i^2} \frac{z_{i,j}^2}{f_i(M_i + 1) + M_i z_{i,j}^2} \right)^{\frac{1}{2}} \qquad \text{with } i,j = 1,2 \qquad (1)$$

where M_i are the optical magnifications, d_p is the particle diameter, λ is the wavelength of light, $f\#_i$ are the f-numbers, f_i are the focal lengths and $z_{i,j}$ are the distances between the object planes and the focal lines.

3 Correlation-based particle identification (CPI)

The CPI method features a modular structure consisting of multiple processing steps. As illustrated in Figure 2, the processing scheme comprises the identification of particles, the detection of particle overlapping and the characterization of particle image shapes. In the following, the methodology of the CPI technique is presented briefly. A detailed description is given by Kling et al. (2019).

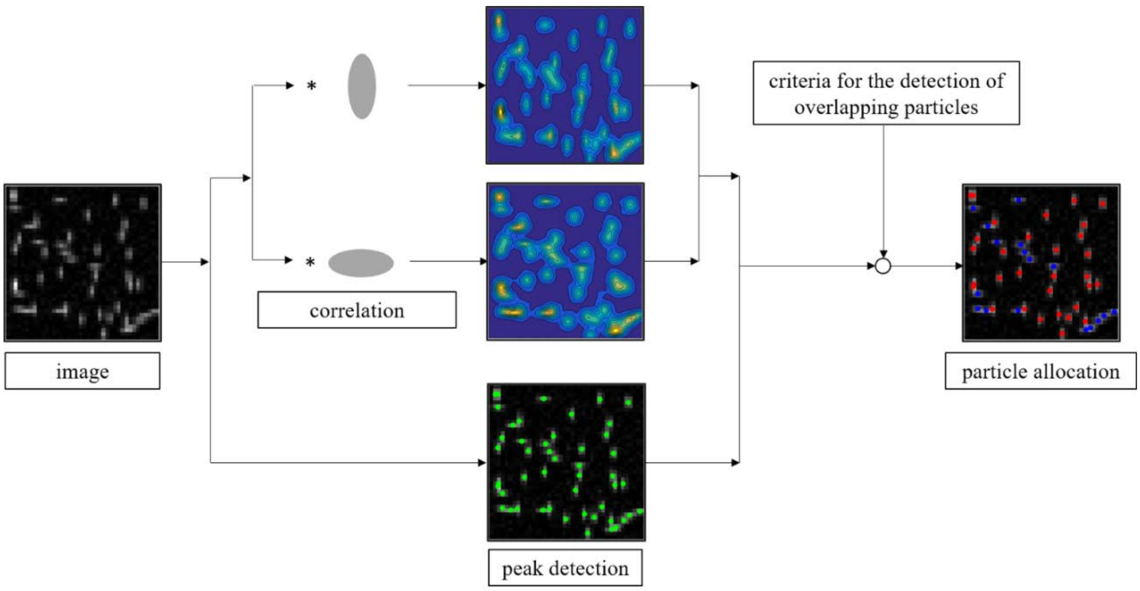

Figure 2: Processing scheme of the correlation-based particle identification method (CPI) according to Kling et al. (2019).

Particle detection
For the detection of particles, a peakfinder algorithm in conjunction with a Gaussian peak fit (Nobach and Honkanen 2005) is used. The principle of the peakfinder algorithm is based on the comparison of neighboring pixel values. A pixel is considered as a potential particle location if its value is greater than the adjacent pixel values. In order to reduce misdetection due to noise, a threshold is typically used.

Identification of the particle image shape
For the identification of particle image shapes, image cross-correlation with synthetic particle images is used. The synthetic particle images represent the estimated particle images of the individual measurement planes. The image cross-correlation quantifies the probability of particle image

matching. Based on the correlation, the particles are allocated to the corresponding measurement planes. In Figure 3, the correlation of a matching and a non-matching particle image pair is shown.

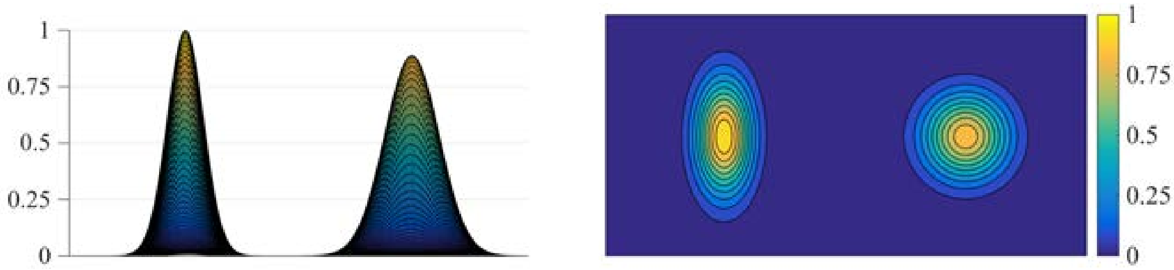

Figure 3: Side-by-side comparison of a matching and a non-matching image cross-correlation (Kling et al. 2019); particle image orientation: matching: vertically - vertically, non-matching: vertically – horizontally.

Criteria for the detection of overlapping particles

Since the CPI method is limited to non-overlapping particles, the detection of particle overlapping is essential. In Kling et al. (2019), three different criteria have been proposed. Firstly, a geometric criterion, which relies on the detection of potential particle image intersection, secondly, an intensity-based criterion, which utilizes particle image-matching for the quantification of the residual intensity and thirdly a correlation-based criterion, which compares actual and theoretical correlation ratios.

Since the intensity- and correlation-based criteria are sensitive to different factors, the geometric criterion is exclusively used for the detection of particle overlapping in the present work. The condition for particle overlapping is given by

$$\frac{\mathrm{I_{int}}}{\mathrm{I_p}} > \varepsilon_{\mathrm{geom}} \tag{2}$$

where $\mathrm{I_{int}}$ is the intensity within the domain of particle intersection and $\mathrm{I_p}$ is the particle intensity.

4 Performance assessment

For the assessment of the CPI method, synthetic images with different noise levels, particle densities, particle image sizes and particle image deformations are used. The definition of the particle locations is based on a random generator with uniform distribution. For particles of the same measurement plane, a minimum particle distance of 1.5 pixels is enforced to simulate homogeneous particle seeding. Hence, the occurrence of particle overlapping originates exclusively from the superposition of the measurement planes. Considering a sufficient number of particles for statistical significance, an image resolution of 500x500 pixels is used. The particle numbers range from 2.500 (0.01 ppp) to 25.000 particles (0.1 ppp). The simulation of noise is based on a normal distribution with the standard deviation $\sigma = \mathrm{I_n}/4$ where $\mathrm{I_n}$ represents the maximum intensity of noise. For the detection of particle overlapping, the threshold for the geometric criterion is set to $\varepsilon_{\mathrm{geom}} = 0.1$ and $\varepsilon_{\mathrm{geom}} = 0.2$. The computation of the image cross-correlation is conducted with a numerical discretization of 0.1 pixels. In Figure 4, the performance of the CPI method in terms of particle identification, particle allocation and particle localization is shown. A selection of analyzed particle fields are illustrated in Figure 5.

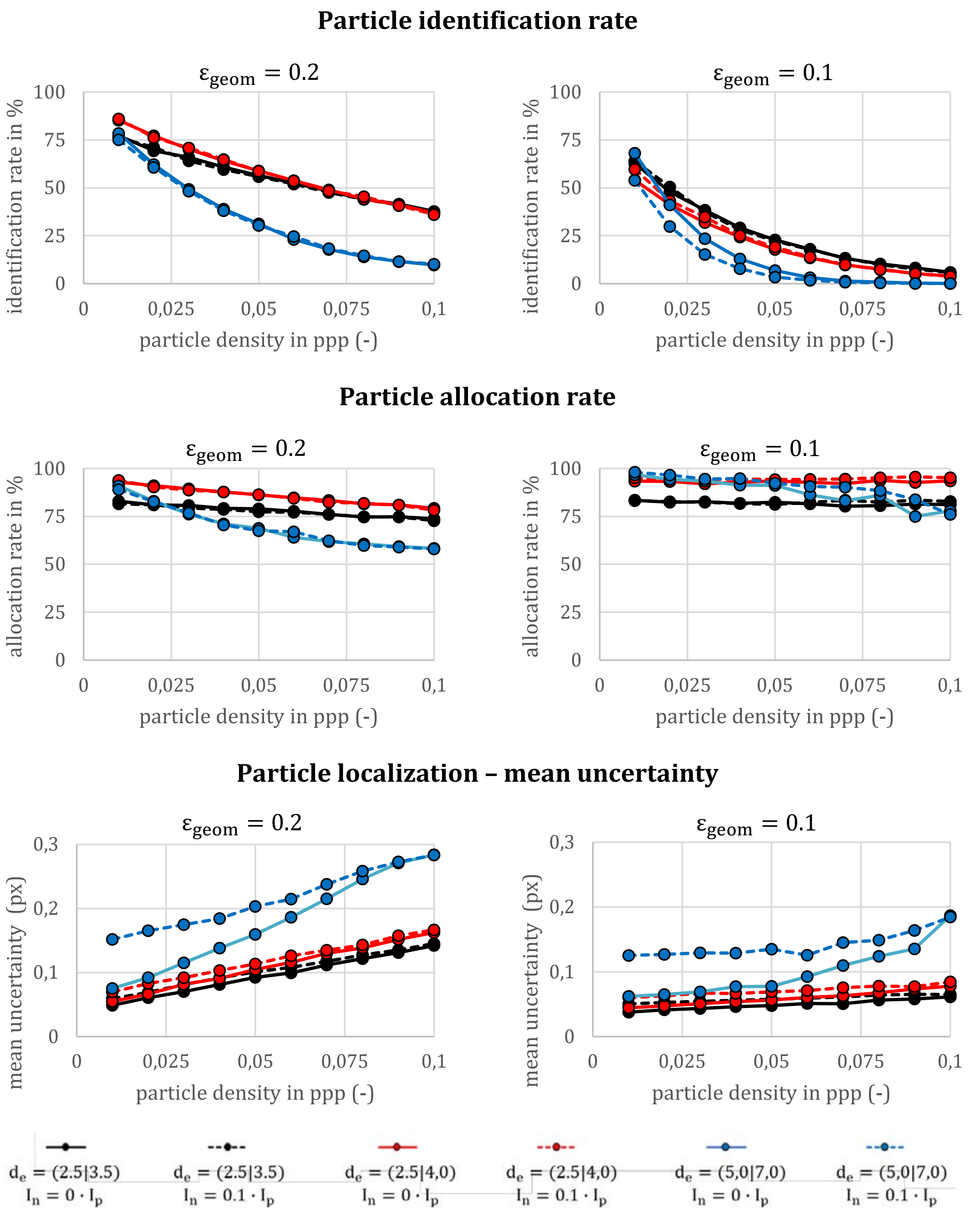

Figure 4: Performance assessment of the CPI method. Particle identification rate: correct particle localization (<0.5 px) and particle allocation, Particle allocation rate, Mean uncertainty of particle localization. Threshold: $\varepsilon_{geom} = 0.1$ and $\varepsilon_{geom} = 0.2$. Particle image dimensions: $\mathrm{d_e} = (2.5|3.5)$, $\mathrm{d_e} = (2.5|4.0)$ and $\mathrm{d_e} = (5.0|7.5)$. Noise: $\mathrm{I_n} = 0$ and $\mathrm{I_n} = 0.1 \cdot \mathrm{I_p}$.

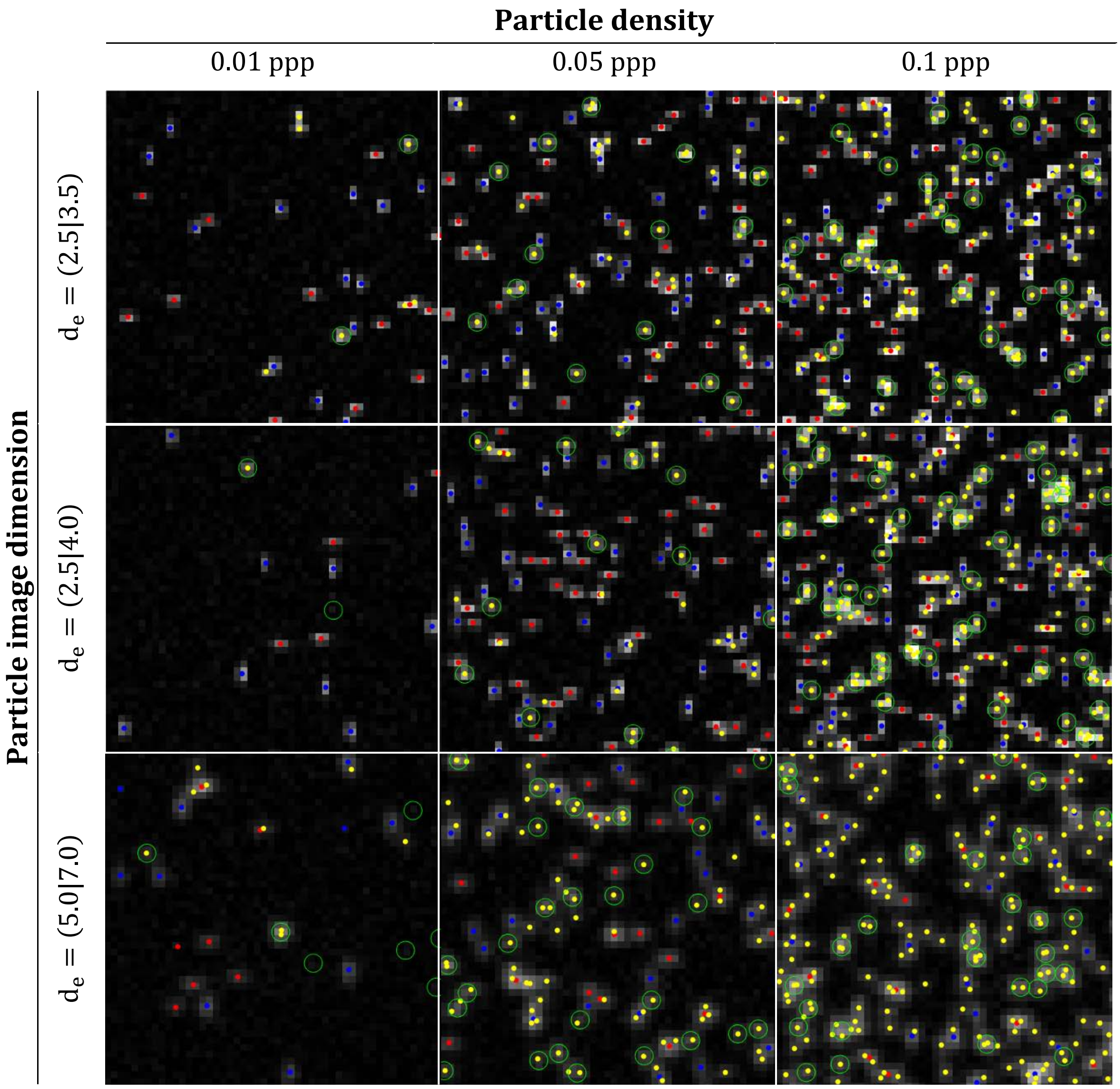

Figure 5: Particle fields for different particle densities and particle image dimensions. Threshold: $\varepsilon_{geom} = 0.1$. Noise: $I_n = 0.1 \cdot I_p$. red dot – horizontal aligned particle image, blue dot – vertical aligned particle image, yellow – undetected particle, green circle - miss detected. Image resolution 100x100 pixels.

5 Discussion

Generally, the accuracy of particle identification depends on the extent of particle overlapping and the rate of successful particle allocation. The probability of particle overlapping increases with higher particle densities, particle image deformations and particle image sizes. At low particle densities, the effect of particle overlapping gradually diminishes, while the accuracy of the particle image differentiation becomes increasingly prominent. The rate of particle allocation benefits from stronger particle image deformations and higher particle image sizes. The computation of the image cross-correlation benefits from a finer numerical discretization of the particle images. A pronounced effect of noise is observed particularly for higher particle image sizes. This is associated with an increased uncertainty of particle localization resulting from a reduced signal-to-noise ratio. The geometric criterion determines how much extent of particle overlapping is incorporated. A strong exclusion of particle overlapping results in low particle identification rates but a higher accuracy in particle localization and particle allocation. In contrast, an increasing incorporation of particle overlapping provides higher particle identification rates but lower accuracy in particle localization and particle allocation. The study suggests a setup of the geometric criterion in dependence of the measurement conditions, the objectives and the further processing. For example, PIV evaluation is generally more robust with respect to uncertainty of particle localization and miss allocation than PTV evaluation. A stronger incorporation of particle overlapping may provide a finer resolution for PIV evaluation if the beneficial effect is greater than the negative effect.

The study suggests the use of compact particle images and considerable particle image deformations. Especially in terms of low signal-to-noise ratios and non-uniform particle images, a pronounced particle image deformation enhances the accuracy of particle allocation. The overall performance of the CPI method indicates a limitation to low to moderate particle densities. A displacement analysis for higher particle densities becomes increasingly insufficient, especially for PTV analysis, since particles have to be identified in both time steps. Due to its statistical analysis, the PIV evaluation is more robust on the other hand.

6 Conclusions

The performance of the CPI method shows viable results for low to moderate particle densities. Since the technique is limited to non-overlapping particles, an application on dense particle fields is not feasible without further processing. To enhance the scope of application, the use of the multiple perspectives may be a conceivable strategy to reconstruct particles by mutual camera cross-checking. The approach addresses particle fields with a substantial ratio of non-overlapping particles. In terms of dense particle fields, the reconstruction of particles by means of image-matching and/or time-resolved particle tracking is required. To take advantage of the features of the CPI method, future works are dedicated to implement time-resolved particle tracking. Furthermore, since particle images are generally not uniform within the image plane, the development of an adaptive cross-correlation scheme is planned to enhance the robustness and hence, the applicability for challenging conditions. The present study suggests the use of compact particle images and sufficient particle image deformations to obtain a maximum performance of the CPI method.

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