Kernelized LPT and Lagrangian PIV

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Abstract

Shake-the-Box (STB) method (Schanz er al. 2016) has become the *de facto* standard Lagrangian Particle Tracking (LPT) approach that reconstructs the 3D particle tracks from time-resolved particle-seeded stereoscopic images. To our knowledge, the STB is the only available LPT method on the market that works on highly concentrated particle images (beyond 0.1 particle per pixel (ppp)). Many developments on the STB method have been published ever since. Some developments concentrated on extending the power of STB to other types of data. For example, Novara et al. (2016, 2019) proposed the multi-pulse STB to deal with high-speed flow applications where the time-resolved data is not available. Tan et al. (2020) introduced the pruning algorithm to remove ghost particles and applied the STB method to blurred particle images. Others are more application-specific concerning a particular sub-module of the whole LPT workflow, such as the calibration procedure (Schröder et al., 2020). But very few works exist to improve the core tracking ability of STB. STB's core tracking scheme features a prediction phase that forecasts a particle's position for the current frame given its history and a correction phase that finds its optimal location around its predicted position by minimizing the gap between the records and the projected image residual. We argue that the optimization scheme in STB, initially proposed in Wieneke (2012), can be less effective or even fail with the sparse temporal data or with data extracted from complex flows. The consequences are either one track is terminated prematurely, or one particle is identified on the wrong track. The main reason is that STB's optimization scheme requires the cost function to be relatively smooth locally to perform well. This high level of smoothness can not be guaranteed when the predictor failed to provide a good starting point for data with large-time separation or local complicated flow structure. In this work, we propose a tracking scheme rooted in the function learning/approximation paradigm. For particle *p,* we intend to learn a nonlinear function $\mathbf{f}$ that maps the image set Π_p, containing the small square local patch I_p extracted from the recorded image for all cameras, to X_p, the particle's 3D coordinate. The function $\mathbf{f}$ can be learned by minimizing an empirical risk loss built on sample pairs (Π_p, X_p). The sample image set is obtained using the camera model and the optical transfer function. Under this formulation, the resulting algorithm can be solved efficiently using gradient-based algorithm therefore much more robust. This solution can be expressed efficiently using the kernel function $k(\bullet,\bullet)$. The kernel measures the similarities between the two sample images and controls the goodness of the solution. One is encouraged to choose a valid and pertinent kernel function that mostly represents the characteristic of data. Our approach is based on kernel methods and is thus called Kernalizaed LPT (KLPT). KLPT is evaluated against both synthetic and real experiments. The synthetic data is generated based on a Large Eddy Simulation data simulating the turbulent cylinder wake-flow at Re3900 (Parnaudeau et al. 2018). Figure 1 shows the mean error of detected particles of KLPT and compared to 2 different implementations of STB (one from an in-house code, one from the commercial software Davis10.4). Our KLPT produces satisfactory results for data with medium to high ppp levels and large time separation. We also apply KLPT and STB (Davis 10) to data depicting an impinging jet at Re2500. Figure 2 visualizes a subset of the tracks reconstructed by STB (left) and KLPT (right). We observe that, compared to STB, KLPT can capture longer tracks and allows more detailed flow reconstruction at highly turbulent regions. We conclude that our KLPT scheme always is more robust compared to STB and more accurate for densely seeded particle flow fields.

Another line of work concerning STB is to retrieve the volumetric data (typically velocity) on Eulerian grids from the Lagrangian data generated by STB. Representative methods include FlowFit (Gesemann et al. 2016) and VIC+ (Schneiders et al. 2016)/VIC# (Jeon et al. 2018). Their main idea is to leverage the volumetric velocity field between the particle-based data and an Eulerian dynamical model's solution. We argue that if only the Eulerian flow variables are needed, it is naturally more accurate to base our knowledge on raw images instead of passing through the redundant LPT procedure. On the other hand, the TomoPIV method estimates the volumetric velocity field by first reconstructing the 3D voxel intensity volume from 2D stereoscopic images, then inferring the 3D velocity vectors using volume

correlation techniques. Our proposed method Lagrangian PIV (LAPIV, Yang et al. 2019), differs from the above two approaches. Our primary motivation is to *directly* infer the volumetric velocity fields from raw image data without any intermediate procedure. To this end, we adopt the above kernel formulation under KLPT, taking account of a transport model that links the particles' 3D coordinate X at frame *k* to the Eulerian velocity field at frame *k-1*. By doing so, we are able to obtain the unknown flow velocity field. Our formulation allows estimating the velocity vector through tracking a group of particles, contrary to single-particle tracking done in KLPT. Naturally, LAPIV can handle particle image data of very high ppp levels (beyond 0.12) at which any single-particle tracking scheme failed to converge. Inspired by the successful practice in optical flow estimation, we implemented a coarse-to-fine estimation scheme combined with the median filtering of the estimated velocity field. The added trick is able to handle large displacement and can significantly boost the performance of our proposed approach. LAPIV can deal with both time-resolved and two-pulse data. Although labeled as a PIV approach, LAPIV can also produce accurate particle positions. This feature is particularly relevant for very high ppp data. The results will be shown during the workshop.

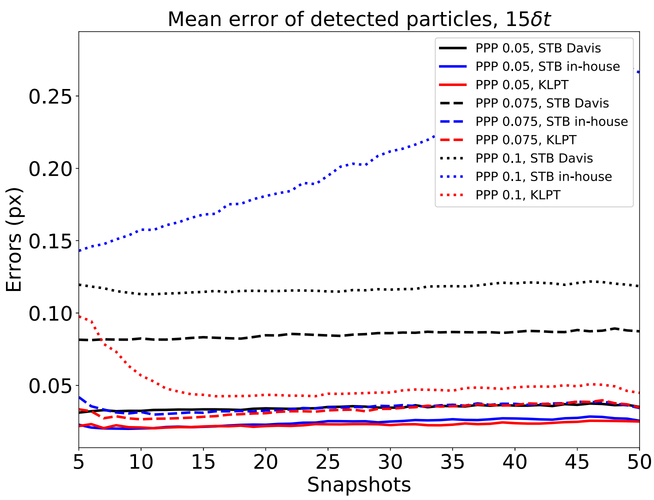

Fig. 1 Synthetic test result on mean error of detected particles.

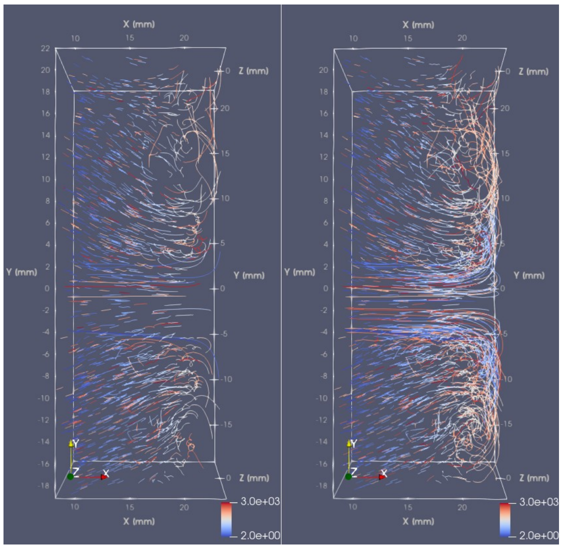

Fig. 2. The particle tracks of the first 3000 reconstructed particles visualized at the 50th snapshot: left, STB in Davis, right, KLPT.

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