Catching up with missing particles

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FLUID DYNAMICS: Catching up with the missing particles

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Standfirst: The implementation of particle tracking techniques with deep neural network approaches presents a promising way where classical tracking methods fail. Determining particle motion within complex flow structures with neural-network-enhanced-tracking methods however requires the development of high accuracy flow estimators with low computational cost.

Determining accurately flow fields near objects is crucial to problems ranging from fundamental physics to biology, and applications in engineering. A key approach in experimental fluid dynamics consists in learning quantitative information from collected data by constructing a vector field that describes the local displacements in the flow. With the drastic improvement in camera and data acquisition technologies, the ever-increasing volume of data presents new challenges for post-processing information, particularly in the development of motion estimation algorithms for three-dimensional particle tracking. These algorithms must not only handle an immense quantity of data but also adapt to widely varying conditions. As a result, there is a growing need for the development of novel, advanced algorithms, with machine learning techniques emerging as a particularly well-suited approach to tackle these problems. However, implementing machine learning tools to particle tracking velocimetry (PTV) datasets has remained challenging. The deep learning based approach presented by Liang et al. [1] uses a multifaceted series of deep neural networks called GotFlow3D to estimate particle displacements for PTV in three dimensions.

In applied physics and engineering, particle image velocimetry (PIV) and PTV are ubiquitous techniques to determine flow fields. While the first one informs on the velocity components at fixed positions in a flow field, the later provides the velocity variations along the trajectories of individual particles over time. Together, these measurement techniques provide complementary information about a given fluid flow. The development of deep neural networks, especially convolutional neural networks (CNN) techniques, has shown their potential to match or outperform state-of-the-art classical PIV algorithms [2, 3], their applicability to PTV measurements, however, remains less obvious. PTV datasets consists in lists of particle trajectories that are individually tracked, producing collected data that are not organized on a gridded structure and preventing the direct application of CNN-based approaches [4].

Typically, PTV analysis from experimental data is limited from particle loss during the particle linking step. Particle linkage can fail in regions of fast displacement when particles move farther than the PTV algorithm can track between two consecutive images. Increasing the tracking

characteristic length scale, allowing the PTV algorithm to search over larger distances, can lead to extremely large computational times and errors.

The authors introduce a novel deep learning based approach called Graph Optimal Transport ``GotFlow3D'' that can learn a three-dimensional flow field directly from two consecutive frames of particle images and be implemented as a-priori knowledge of the flow field into predictor-corrector schemes to assist an existing PTV algorithm (Fig. 1). In this approach, existing scene flow learning networks, commonly used for rigid body motion, are leveraged to circumvent the difficulties associated with unstructured point clouds datasets [5-8]. A graph neural network (GNN) is used to extract spatial geometric information from particles positions, the scene flow is then generalized to a complex non-rigid flow motion by using an optimal-transport guided recurrent neural network (RNN) framework.

GotFlow3D framework operation can be divided in three steps: first, geometric features are extracted from 3D particle coordinates in two consecutive frames using a series of GNNs (Fig. 1a), then the particles correspondence between the two frames is established using an optimal transport plan, finally the displacement field is iteratively updated using RNNs (Fig. 1b). More specifically, a static graph gathers spatial information about the individual particles and their k-nearest neighbours and is set prior to the training procedure in the first step, while another graph is determined from dynamic features during the flow learning process. This second dynamic graph corresponds to an extended network connecting particles with similar features across the entire domain. These two kinds of graphs are then fused into a static-dynamic GNN (SDGNN) that is employed to determine the optimal transport plan.

After training with a synthetic training dataset, GotFlow3D performance is evaluated with a series of testing datasets (Fig. 1c) and compared with other scene flow learning methods such as FlowNet3D [6], FLOT [7], PointPWC-Net [8] or PV-RAFT [9]. In all tested scenarios, GotFlow3D exhibits a better performance, especially in determining small-scale structures present in more complex flows. GotFlow3D appears to outperform other existing techniques in robustness and generalization when tested for artificially altered dataset, noisy particles positions, and low sampling rate.

The potential for improving PTV-based analysis is also evaluated by integrating GotFlow3D in the particle tracking process for classical PTV approaches (Fig. 1d). The presented method helps increase the spatial density of particle displacement fields by providing “a guess” to an existing PTV algorithm such that less particles are lost during the particle linking stage between two consecutive time frames. In both tested flows, velocity fields produced by GotFlow3D-enhanced PTV algorithms exhibit a higher density of vector fields, indicating a lower particle loss rate, specifically in regions with large displacements.

By recovering particle trajectories typically lost in conventional approaches, emerging PTV techniques augmented with deep neural networks such as GofFlow3D offer potential to advance tracking performance across diverse flow regimes of varying complexity. Irrespective of the particular neural architecture employed, these methods exhibit exceptional aptitude for

interpolation but more limited extrapolation capabilities. This underscores the need for judicious scrutiny when deploying these algorithms to predict flow fields significantly detached from the parameter space of training data. The next step will be to extend predictions far beyond the embedding space with careful evaluation of model limitations and uncertainty quantification to ensure robustness in more complex scenarios.

Figure 1. GotFlow3D working scheme. a) Geometric features extraction from 3D particles coordinates in two consecutive frames. b) Iterative updates of the displacement field. c) Flow learning evaluation. d) Integration for enhanced-PTV approach evaluation.

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