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Editorial

Special Issue on Machine learning and data assimilation techniques for fluid flow measurements

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Fast-paced advances in the fields of machine learning and data assimilation are triggering the flourishing of a new generation of measurement strategies in a vast variety of applications, including fluid flow measurements. Techniques often used in data post-processing are progressively being pushed upstream in the measurement chain to improve the quality of the processed data. Advanced image processing techniques, data mining and compressed sensing strategies to overcome the inherent limits of measurement techniques are just few examples of the novel research pathways opened in the field of fluid flow measurements. Additionally, the advent of three-dimensional (3D) and time-resolved flow measurements has opened new avenues to augment the spatial and temporal resolutions and minimize the measurement uncertainty by enforcing the compliance between the measured data and the governing equations of fluid motion. This Special Issue features 11 contributions covering relevant aspects of the most recent advances in machine learning and data assimilation techniques applied to flow field measurements, with particular emphasis on particle image velocimetry (PIV).

The Special Issue contains two contributions aiming at reviewing and assessing the state of the art in machine learning and manifold learning techniques in experiments. Discetti and Liu [1] offer a perspective on the current status and tendencies in machine learning techniques in flow field measurements. The perspective focuses mainly on pre-processing, data treatment and conditioning in post-processing for PIV measurements. Possible routes for research in the next years are depicted, tailored to the current limitations in terms of robustness, generalizability and uncertainty quantification. In his review paper, Mendez [2] spans a range of dimensionality-reduction tools, covering linear and nonlinear techniques. The work is a journey guiding the reader through nonlinear techniques such as kernel principal component analysis, locally linear embedding and isometric mapping, and their application for tasks of great interest in flow field measurements such as filtering, identification of oscillatory patterns, and data compression.

Several contributions of this Special Issue have focused on the use of deep learning to process PIV images, focusing on feature identification [3, 4] and direct extraction of flow fields [5, 6]. Tsalicoglou and Rösgen [3] investigate the use convolutional neural networks (CNNs) to identify, segment and classify streaks in 3D particle streak velocimetry (PSV) and tufts for flow visualization. The proposed architectures show good robustness also for high seeding densities, thus paving the way to high-resolution 3D PSV. Dreisbach *et al* [4] address the problem of the generalization capability to experiments of neural networks trained on synthetic images for particle image detection in defocusing PIV. In particular, they demonstrate improved performance when synthetic images are enriched with image features from the experimental recordings using an unsupervised

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image-to-image translation. Two works of the Special Issue exploit machine learning for direct flow prediction from images. Lagemann *et al* [5] investigate the performances of a neural network architecture for optical flow estimation (the recurrent all-pairs field transforms) under varying image and lighting conditions, using both synthetic and experimental data. The algorithm shows good robustness against common error sources and peak locking, as well as high spatial resolution. Manickathan *et al* [6] propose training CNNs with synthetic data generated from random displacement fields. This procedure reduces the burden of generating large datasets from simulations, and allows feeding the training with sufficient data to avoid overfitting at a reasonable computational cost. Their results show that this kinematic training improves significantly the accuracy of the CNN.

The contribution by Sharifi Ghazijahani *et al* [7] leverages machine-learning for data post-processing. The authors use an echo state network to predict temporal coefficients from proper orthogonal decomposition in the wake of a cylinder at Reynolds number equal to 100 and 1000. Their results show that the time horizon for an accurate reconstruction decreases with increasing Reynolds number.

In this Special Issue, data assimilation approaches that combine numerical models and flow measurements by PIV, particle tracking velocimetry (PTV) or Lagrangian particle tracking (LPT) are shown to be a powerful tool to enrich the measured flow fields, e.g. by suppressing the measurement noise, increasing the spatial resolution beyond the Nyquist limit or providing access to flow properties not measured directly. Hasanuzzaman *et al* [8] introduce a physics-informed neural network model aimed at reducing the noise of stereoscopic PIV velocity measurements. The approach provides accurate predictions of the flow statistics by solving the Reynolds-averaged Navier-Stokes (RANS) equations for incompressible turbulent flows without any *a-priori* turbulence model, and employing the measured mean velocity and Reynolds stresses at the domain frontier as boundary conditions. Mons *et al* [9] present a variational data assimilation procedure to infer 3D flow velocity, Eulerian acceleration and pressure fields from sparse single-instant velocity measurements, as those obtained by two-pulse PTV. The approach is based on the solution of the unsteady Navier–Stokes equations, whereby the Eulerian acceleration is treated as a forcing term, which is adjusted to minimize the discrepancy between the reconstructed and the measured velocities. Cakir *et al* [10] extend the use of the vortex-in-cell (VIC) framework to increase the spatial resolution of sparse LPT data in presence of solid objects within the measurement domain. The authors assess the performances of two methods, namely the arbitrary Lagrangian–Eulerian VIC+ and the immersed-boundary approach: the results showed the increased accuracy of these approaches in reconstructing the flow properties in proximity and on the surface of solid objects. In the work by Sperotto *et al* [11], the authors propose a meshless approach based on radial basis functions regression to compute pressure fields from PIV or PTV data. The method hinges upon the solution of two constrained least-square problems, the first one to generate an analytical representation of the velocity field and the second one to perform a meshless integration of the Poisson equation for pressure. The regressions allow accounting for physical knowledge on the problem under investigation, in the form of boundary conditions (e.g. no-slip condition at solid walls) and compliance with the governing equations of fluid motion (conservation of mass and momentum).

We sincerely hope that the readers of Measurement Science and Technology will find this Special Issue as a compass for orientation in the recent developments of machine learning and data assimilation for fluid flow measurements.

Data availability statement

No new data were created or analyzed in this study.

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