Editors
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2nd 'CFD for PIV' Workshop

Proceedings

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Preface

It is a pleasure to write this preface for the proceedings of the 2^{nd} workshop on data assimilation and CFD processing techniques for particle image based measurement techniques (in short: the *CFD for PIV* workshop). We have seen great developments of both experimental and numerical techniques in the past years and are more excited than ever to see that forces are being joined for advanced data assimilation works.

Little more than a year ago we held the first workshop in Lisbon, Portugal, in order to bring together pioneering groups. The one-day schedule has now matured into a two-day workshop, but the ingredients remain the same: pioneering scientists in the field of data assimilation and CFD processing techniques for particle image based measurement techniques.

The proceedings in this book summarize the research presented at the workshop. Maybe more importantly however, these proceedings bundle key players within our field of research. It cannot be encouraged enough to take this book as an opportunity to embark in new collaborations. Contact details have been included of all first authors and as the field of data assimilation is inherently a field where fields are joined, we hope that this workshop and book will spark new ideas and works to be presented at a third workshop in the future!

Jan F. G. Schneiders
Andreas Schröder
November 2017, Delft

Contents

Keynote presentations

Data assimilation and dynamic observers for data-based flow field recovery

Peter Schmid, Imperial College, London

In many experiments only low-dimensional information about high-dimensional flow fields is attainable. To gain access to more information than what has been measured, computational techniques such as data assimilation and system identification have to be employed. We will discuss the general principles of data assimilation based on a data-driven variational formalism to recover flow field information from sparse measurements. In addition, dynamic observers will be used to extract the inherent flow dynamics from low-dimensional (but time-resolved) measurement signals. For both cases, issues such as three-dimensionality, measurement noise and regularity of the solution will be discussed, and possible generalizations and extensions will be proposed. Examples will used to illustrate both approaches.

Coupling experimental and computational fluid dynamics: Synopsis of approaches, issues and perspectives

Dominique Heitz, IRSTEA/INRIA, Rennes

Recently, the fluid mechanics community has been making increasing contributions to the field of dynamical flow reconstruction by coupling EFD with CFD. In my presentation I try to highlight significant achievements in this area with emphasis on data assimilation techniques. I discuss mathematical and physical modeling that have been used and are necessary when one intends to estimate the state of a dynamical flow based on plenty of or limited information.

Variational techniques

Variational 3D-PIV using Sparse Descriptors

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Abstract

In [1] we proposed a variational approach for 3D-PIV for incompressible fluids. We formalize, propose and evaluate different variants for both the data term and the regularizer. Best results were achieved with sum of squared differences (SSD) as data term and a novel regularization based on the Stationary Stokes Equations. This strictly enforces a divergence-free flow and additionally penalizes the squared gradient of the flow. Velocity estimation is performed on a regular grid, which can be of lower resolution than the inputting MART-reconstructed particle intensity volume. By using such a semi-dense formulation, we can reduce computation time and memory footprint without significant loss in accuracy (e.g. up to 4x lower resolution in each dimension, respectively 64x fewer variables). However, the discretization of the data term is still based on the high-resolution intensity voxel grid, whose size is chosen based on the image resolution. For bigger volumes, this leads to a large memory footprint, while the actual data, the particles, is sparse (i.e. for 0.1ppp and 350 depth slices we get approx. 0.0003 particles per voxel).

To overcome the coupling of the sparse particle data to the discretization of the volume, we propose a particle based data structure. In particular, we only need to store the particle location and intensity information but still can evaluate the data term at any position in the volume. Initial 3D particle reconstruction can be performed by MART and subsequent sub-voxel accurate peak detection or by direct particle based techniques like IPR. In practice, we chose the same regular grid to evaluate our novel data term based on the 3D sparse descriptor as for the flow estimation. The descriptor structure is defined by the descriptor radius and grid point layout, here different layouts are possible.
We propose a layer based structure, with grid points arranged on a sphere on each layer. For uniform distribution of grid points on a sphere, one can use an icosahedron structure or subdivisions of it. A particle within the radius of the descriptor is then splatted to its k nearest grid points (with a distance-based weight). An example of such a descriptor is shown in 2D in Fig.1. We further show visual results of a reconstructed flow field compared to the ground truth flow from DNS simulations in Fig.1. Performance is comparable to [1] while requiring less memory.

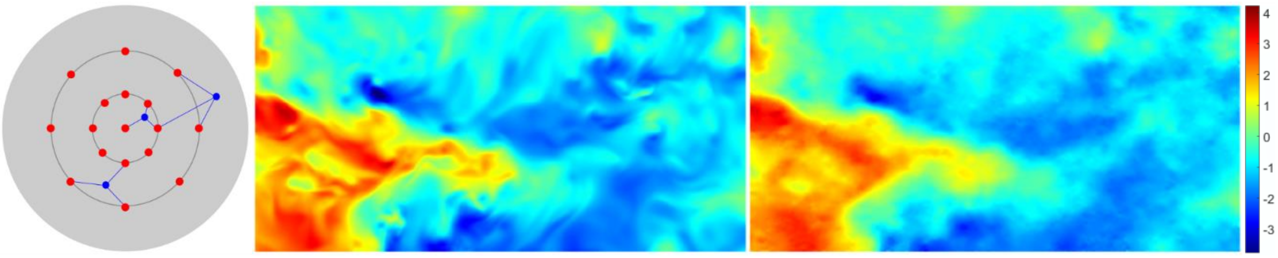

Fig. 1 Left: Schematic visualization of a 2D sparse descriptor with descriptor grid points (red) and particle locations (blue) whose intensities are splatted to the three nearest neighbors. Middle: xy-slice of the flow in X-direction for DNS simulated flow field (1024x512x352). Right: xy-slice of the reconstructed flow from approx. 0.1ppp.

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Ensemble-Variational methods in data assimilation

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Abstract

Ensemble-Variational (EnVar) methods have been drawn attention to the Data Assimilation community over the last decade. They open an alternative way between variational adjoint-based method and filtering probabilistic-based method. One major advantage of EnVar, compared to variational methods, is that the adjoint model can be avoided. Thus the EnVar is more portable and much easier to be deployed to the operational scenario in case of change of model because it is largely model-independent. Also, EnVar is proved to be an appropriate method able to tacking nonlinear non-Gaussian problems with considerable precision under reasonable computational cost. So we believe that this method constitutes a promising approach for flow measurement problems.

We are investigating the EnVar methods, for recovering the unknown state/parameter fields of non-trivial dynamic models by assimilating different types of image data of high resolution [1, 3]. We will show the performance and effectiveness of the EnVar method on Kinect captured depth-range data combined with shallow water model as well as synthetic SST image combined with the SQG model. More specifically we establish a stochastic dynamical formulation allowing explicitly taking into account of the subgrid effects resulted from scale discrepancy and we employ an augmented EnVar to identify those uncertainty parameters [2].

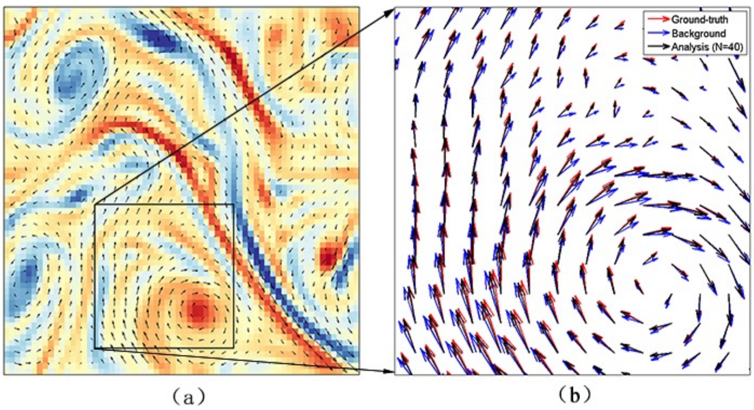

Fig. 1 Velocity vectors at initial time: (a) the ground-truth vorticity map; (b) the motion vectors of the ground-truth (red), the background (blue) and the analysis (black) in the zoomed area [3].

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Variational data assimilation of full particle trajectories for instantaneous flow reconstruction

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Abstract

In comparison to cross-correlation approaches, recent literature has shown that particle tracking measurements allow for increased measurement spatial resolution because of (i) avoiding spatial filtering introduced by cross-correlation and (ii) the possibility to obtain dense interpolations using governing equations. An example of the latter is the VIC+ technique (Schneiders and Scarano 2016), which introduced the use of the vorticity transport equation to couple instantaneous velocity and material derivative measurements. This doubles the measurement data ensemble that is available for interpolation of velocity to a grid and accordingly allows for sub-particle resolution, in contrary to normal particle tracking approaches that yield only data at particle positions.

When instead of only instantaneous data also velocity measurements over an extended number of exposures could be used for dense velocity interpolation, this could potentially lead to a further increase in spatial resolution. The concept of reconstruction the flow temporal evolution on a dense grid by making use of particle tracking measurements over an extended number of snapshots was investigated in two-dimensional test cases by Schneiders et al. (2016). In this work, the technique is extended to three-dimensional flows. The assessment of the technique in the case of simulated turbulent boundary layer measurements shows increased coherence of the vortical structures when a larger number of measurement time-instants is used for flow reconstruction. For illustration, figure 1-left shows the result using 2 consecutive particle tracking velocity measurements. Whereas the relatively large structure S1 is reconstructed, the smaller structure S2 is only recovered when an extended number of 10 consecutive velocity measurements is considered.

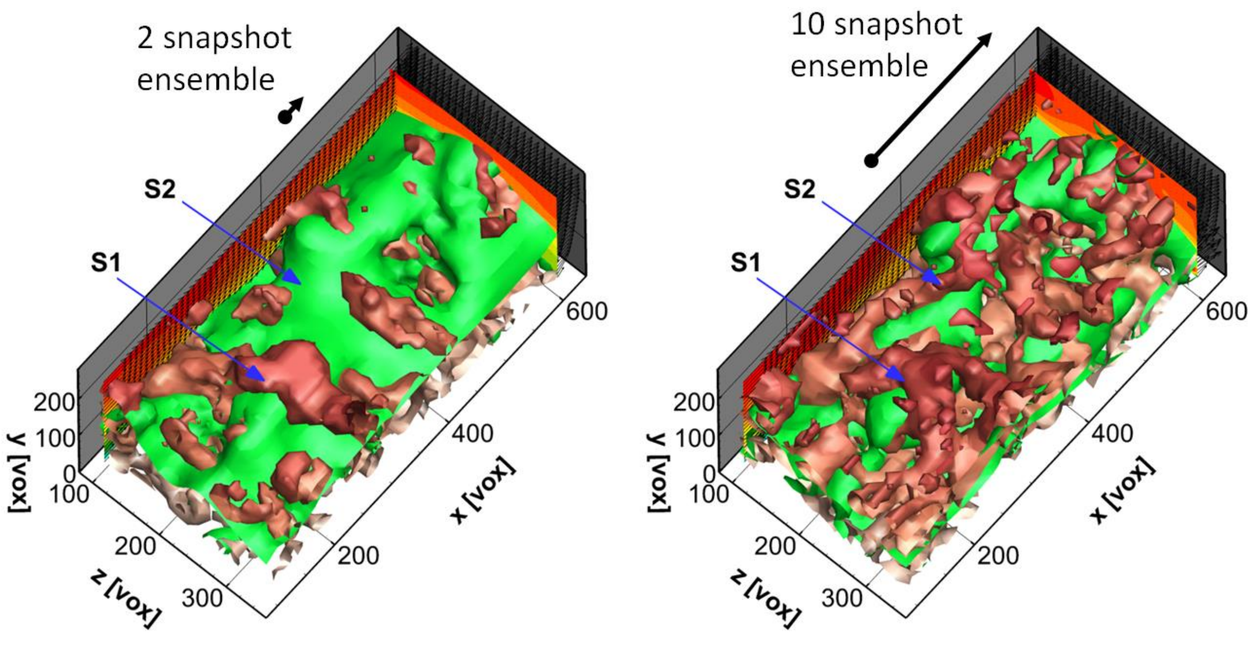

Fig. 1 Simulated turbulent boundary layer measurement visualized by isosurfaces of Q-Criterion (red) and u'/U = -0.15 (green). Reconstruction using 2 (left) and 10 (right) consecutive velocity measurements. The distance over which the flow is convected based on the free-stream velocity over the considered data ensemble is indicated by the black arrows.

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4D Turbulent Wake Reconstruction using Large Eddy Simulation based Variational Data Assimilation

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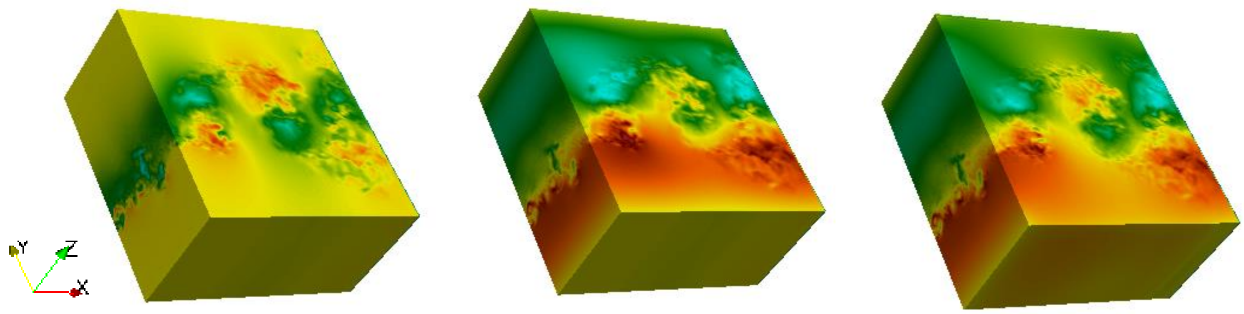
Abstract

Data Assimilation (DA) has been used as an effective tool for guiding simulations with observation data-sets for the better part of last few decades. However, DA has been mainly limited to applications within weather/meteorological studies with only recent excursions into conventional fluid dynamics. The limitations of computational fluid dynamics (CFD) due to complex or unknown boundary conditions and/or initial conditions can be alleviated using experimental observations through DA. Recent applications of such methodologies include [1] and [2] among many others. However, due to large computational power requirement, DA remains restricted to either 2D flows or to low Reynolds number (Re) 3D flows. A reduction in computational requirement is necessary to facilitate simulation of 3D higher Re flows. This can be achieved by using Large Eddy Simulation (LES) models within DA. This study proposes to perform Variational DA (VDA) with the adjoint of the Navier-Stokes equation using a LES model within DA to reduce computational cost.

An initial study of several sub-grid scale (SGS) models (see figure 1) have shown the newly developed Models under Location Uncertainty (MULC – StSp/StSm) to perform well for various turbulent flows [3]. In addition, these models can be shown to produce accurate results at just 0.46% the cost of performing a DNS making them ideal for performing DA with LES at reduced cost. In this work, the application of the MULC to VDA are analysed for the case of wake flow over a circular cylinder for a transitional Re of 3900. The 4DVar code (Incompact3d) of [2], who performed DNS based VDA for wake flow around a circular cylinder at Re 300, has been modified to include the SGS model. The adjoint is constructed using an auto-differentiation tool – tapenade [4]. Preliminary results are shown with synthetic data-sets and an optimal reconstruction is obtained using VDA with the MULC. Future studies include performing VDA using PIV data-sets as well as using DA to characterise the SGS model coefficient.



(a) Observation (b) Background (c)Assimilated

Figure 1. 3D vorticity contours at Re = 3900 for cylinder wake flow at the beginning (t = 0) of the assimilation window.

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A new hybrid optimization algorithm for variational data assimilation of unsteady wake flows

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Abstract
In typical variational data assimilation (DA) applications for unsteady flows the search space is large and multidimensional, while prior information about the control vector function is not available. Stochastic optimization algorithms like genetic algorithms (GA) perform global optimization but waste computational effort by doing a random search. On the other hand, deterministic algorithms like gradient descent converge rapidly but may get stuck in local minima of multimodal functions. Here, we present a new hybrid global optimization technique, where a gradient-based local search method is combined with a genetic algorithm to achieve faster convergence and better accuracy of final solution without getting trapped in local minima. The proposed methodology is applied to the reconstruction of unsteady bidimensional flows past a rotationally oscillating cylinder. More precisely, the possibility of reconstructing the rotational speed of the cylinder given observations of a reference flow was investigated via variational DA (Fig. 1).

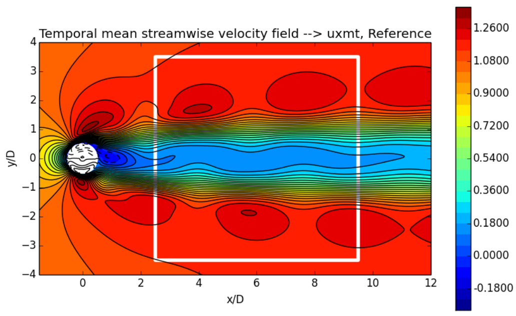

Fig. 1 Temporal mean streamwise velocity field for Reference flow, the observation domain is delineated in white lines.

In order to decrease memory and computational time requirements, we used an alternative formulation of the optimization procedure proposed by Tsoulos *et al.* (2008). This formulation avoids the execution of the local search process each time a local minimum is found progressively by the genetic operations step (Fig. 2-left). Accordingly, the genetic algorithm was first used to approximately locate a good global minimum. Then a gradient based local search was done with the best solution found by the genetic algorithm as its starting point (Fig. 2-right). Thus, the GA was used to go near the vicinity of a good global minima and the gradient descent scheme was used to find the global minimum accurately. This approach is advantageous because it allows for exploration of new regions of the search space while retaining the ability to improve good solutions already found. The stochastic approach utilizes the grammatical evolution (GE) procedure to create trial solutions, while the GA utilizes the operations of crossover and mutation to create the evolving generations.

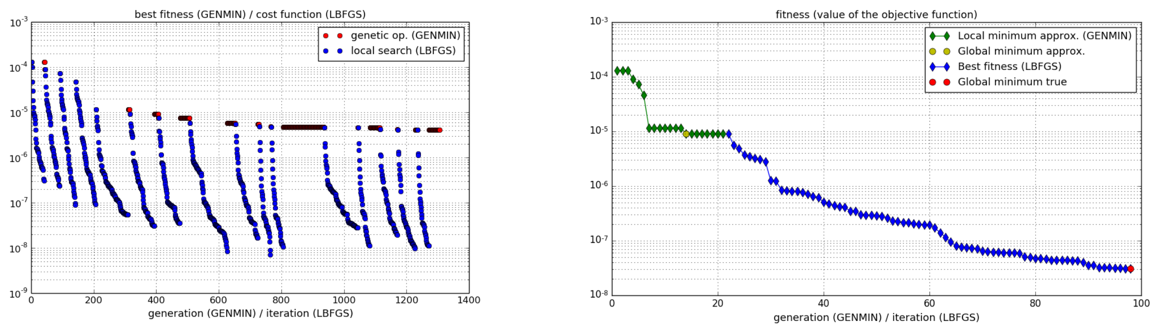

Fig. 2 Typical convergence histories for the Hybrid approach by Tsoulos et al. (2008) (left) and present formulation (right).

Contrary to Gronskis *et al.* (2013) where the cylinder was not modeled in the numerical experiments and the inflow was a control parameter, here we imposed the characteristic velocity at the boundaries of the computational domain. The control vector for the DA problem was thus formed by the solid boundary conditions for the cylinder, that meant its rotational speed at all times where no particular form was prescribed to the rotary movement of the body. We considered a configuration of reference flow in the lock-on regime given by Mons *et al.* (2017). Two categories of numerical experiments were identified. The first one corresponds to experiments where the first-guess flow was assumed to be known (as depicted in Mons *et al.*, 2017), while for the second set of numerical tests a first generation of flow solutions was created where each individual was initialized at random from a uniform distribution inside a feasible region subject to a continuity constraint (hybrid framework).

The present results suggest that in both hybrid and pure deterministic approaches the assimilated flows correctly fitted the observations of the velocity field, but the later context did not correctly identify the associated rotational speed. As shown in Fig. 3, the reconstructed rotational speed appeared globally closer to the reference one, compared to the solution obtained by running the DA problem using a pure local search based procedure.

This DA experiment thus confirmed that the addition of the stochastic process in the formulation may improve the reconstruction of quantities of interest such as the wall conditions in this high-dimensional problem, encouraging the application of the proposed methodology to more complex and realistic flows, like 3D turbulent flow reconstructions from sparse observations.

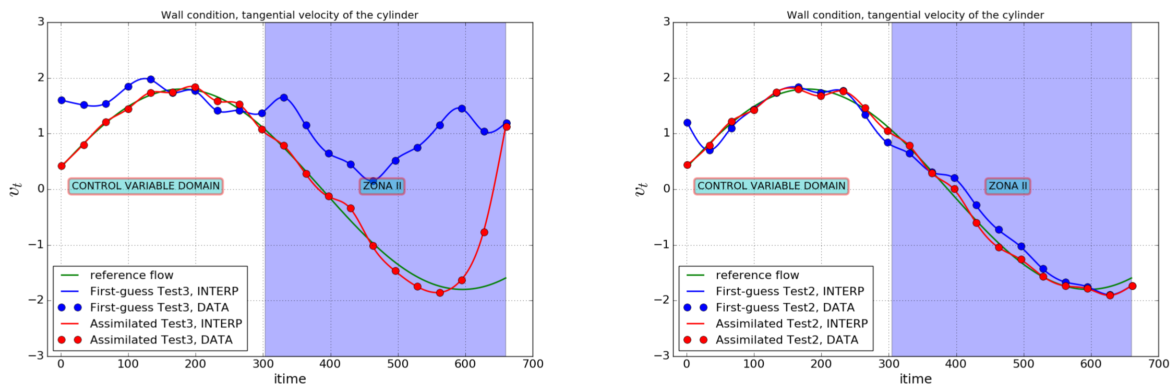

Fig. 3 Dimensionless rotational speed of the cylinder for reference (green), first-guess (blue) and assimilated (red) runs obtained by pure Deterministic (left) and Hybrid present approach (right).

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Flow Reconstruction Using FlowFit 2

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Abstract

With recent advances in particle tracking methods for 3D flow measurements such as the Shake-The-Box method the trajectories of hundreds of thousands simultaneously visible particles in the measurement volume can be estimated. Such a high sampling density of the flow field raises the question of how to estimate instantaneous velocity fields well given the scattered particle data. FlowFit is a method that takes scattered particle data (positions, velocities and accelerations for a point in time) as input and reconstructs a continuously defined velocity and pressure field under the assumption of an incompressible flow by minimizing a cost function. Enough degrees of freedom for the resulting fields will avoid any unwanted spatial smoothing effect and allow recovering details beyond the sampling limit by incorporating physically-based regularizations as part of the cost function. This talk will highlight some properties as well as implementation details of the method such as the choice of parameterization of the flow fields using B-splines, the cost function with grad-div stabilization and a multi-grid approach to speed up the reconstruction time.

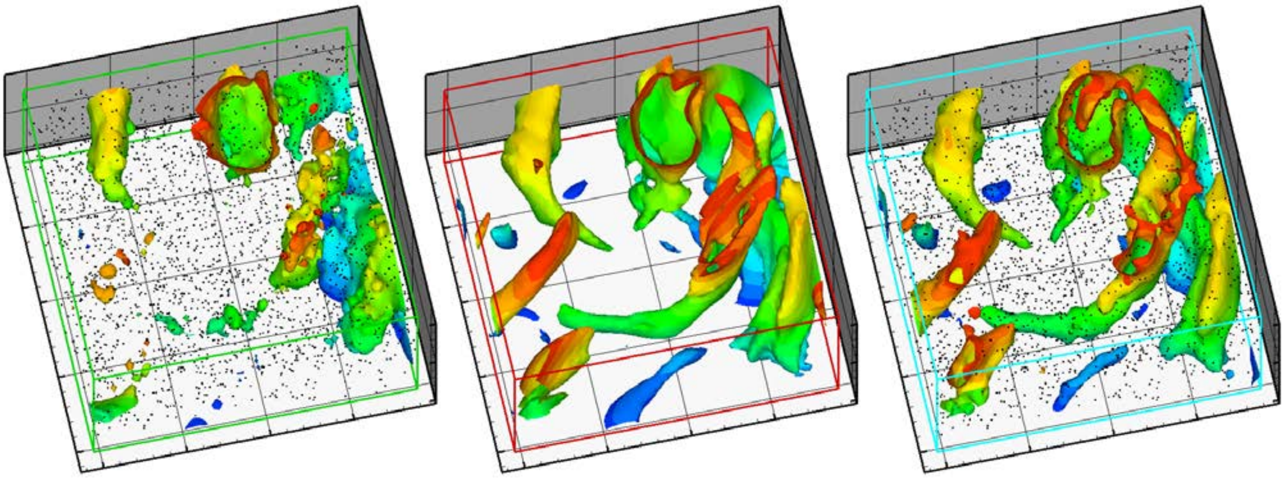

Fig. 1 Comparison between two reconstructed velocity fields (left and right) based on random samples of the ground truth (center) from a DNS. Vorticity isosurfaces are shown and colored depending on the depth (top is red, blue is bottom). This comparison shows the gain in details of the flow structures if physically-based regularizations are used. For the right reconstruction the cost function includes terms penalizing violations of mass conservation with the help of the Navier-Stokes momentum equation.

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Pressure from PIV and LPT

Pressure fields of an impinging jet from regularized interpolation of Lagrangian particle tracks

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Abstract

A recent comparison of a broad scope of techniques for pressure reconstruction (van Gent et al. 2017) demonstrates the high potential of Lagrangian particle tracking (LPT) techniques, where the material acceleration is obtained directly from individual particle trajectories. In this study, we apply the Shake-The-Box (STB) LPT technique (Schanz et al. 2016) to the tracking of helium-filled soap bubbles, illuminated by pulsed high-power LEDs in order to measure the flow of an impinging jet in a large volume. The presence of the wall allows for the installation of microphones for a validation of the pressure reconstruction.

An air jet impinges on a flat acrylic glass plate at an angle of θ = 90°. The flow is seeded with HFSBs with a diameter of 300 µm. The HFSBs are illuminated by pulsed LED arrays from above through the acrylic glass plate. The measurement volume, extending from the wall to the fan nozzle exit, is imaged by six high-speed cameras (4MP each), see Fig. 1(i). Three high-precision condenser microphones are mounted in the impinging plate at distances of 1D; 2D and 3D from the jet center. Lagrangian tracks are reconstructed with the Shake-The-Box (STB) method. Particle tracks with discrete positions are fit with a continuous function of cubic B-splines (Track-Fit, Gesemann et al. 2016). Pressure fields are reconstructed from velocity and acceleration data with the regularized interpolation scheme FlowFit (Gesemann et al. 2016). The interpolated fields are represented as a grid of cubic B-splines in steps of Δx = 3mm.

Fig. 1(iii) shows a central slice of the pressure reconstruction volume of 30 liters (400×500×150 mm^3) (see Fig. 1(ii)) at a jet velocity of U = 4 m/s, recorded at 1 kHz. In the shear layer (x/D = 0.5), strong pressure fluctuations develop due to large vortices. The vortices are advected upwards and impact on the wall leading to strong pressure fluctuations at the position of microphone 1 (black dot). Further outwards, following the flow in radial direction, the chain of alternating high and low pressure regions continues along the wall adjacent to microphone 2 and 3. The pressure fluctuations gained from the volumetric measurement and from the microphones show a high level of agreement (Correlation coefficient C = 0.88 for microphone 1, see Fig. 1(iiii). In-depth results will be presented, as well as details on measurement and evaluation techniques.

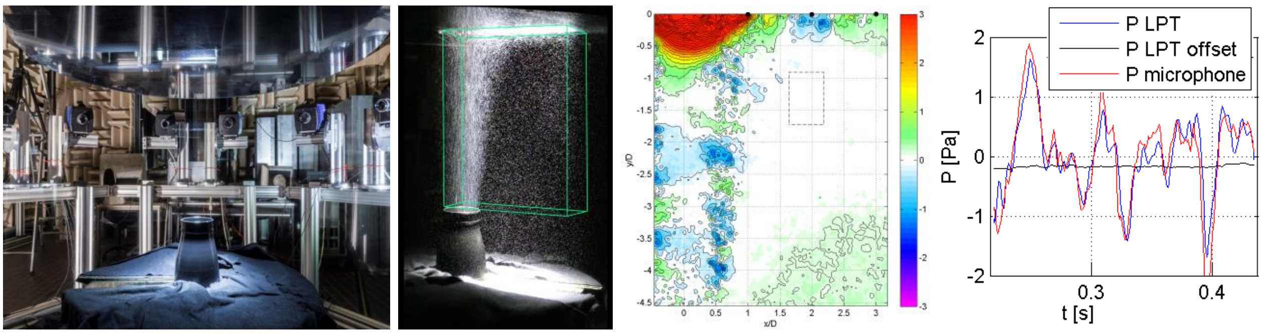

Fig. 1, from left to right: (i) Photograph of the experimental setup. (ii) Photograph of the jet, seeded by Helium filled soap bubbles, illuminated from above; green box indicates measurement volume.
(iii) Central slice of an instantaneous pressure field P(x) [Pa] with microphone positions (black dots).
(iiii) Direct comparison of pressure time series of microphone 1 and the reconstructed pressure from LPT.

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Insights into pseudo-tracking

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Abstract

Pseudo-tracking refers to the construction of imaginary particle paths from PIV velocity fields and the subsequent estimation of the particle acceleration. The thus obtained material acceleration fields may be used to obtain pressure fields. In view of the variety of existing and possible alternative ways to perform the method, it is not straightforward to select a suitable combination of (numerical) procedures and parameters for its implementation. To address this situation, the present study (detailed in van Gent et al 2017b,c) extends the theoretical framework for the approach with respect to error propagation and the spatio-temporal filtering associated with the procedure.

A combined theoretical and numerical assessment is performed that considers the relatively simple flow case of a two-dimensional Taylor vortex. Additional numerical and experimental assessments consider the more complex flow cases of a high-speed and a low-speed axisymmetric base flow, respectively. The numerical assessment uses the simulated experiment from van Gent (2017a). For the experimental assessment time-resolved tomographic PIV measurements and microphone measurements were obtained.

The findings of the investigations allow to formulate the following insights and practical recommendations:

1. The velocity errors along the imaginary particle track are primarily a function of local velocity measurement errors and spatial velocity gradients (see Fig. 1);
2. The particle path may best be calculated with second-order accurate numerical procedures, while ensuring that the CFL condition is met (see Fig. 1);
3. Least-square fitting of a first-order polynomial is a suitable method to obtain the material acceleration from the track velocity, being less sensitive to increasing track lengths than central differencing and performing similarly in terms of noise reduction and temporal filtering behaviour;
4. To achieve a peak-response below 0.7 (corresponding to -3dB reduction in the energy), the track length and spatial resolution should satisfy $(WS/\lambda_x)^2 + (\Delta T/\lambda_t)^2 < 0.2^2$ (see Fig. 2). Here, WS is the interrogation windows size, $2\Delta T$ is the temporal track length, and λ_t and $\lambda_x$represent the flow time and length scales, respectively.
5. Suitable track lengths with relatively low combinations of propagated velocity errors and truncation error may be selected on the basis of the variation in the r.m.s. of all material acceleration vectors in a single snapshot with track length (see Fig. 3), or on the basis of a spectral analysis. Interestingly, the experimental investigation showed that low-frequency flow dynamics is reproduced regardless of the track length.

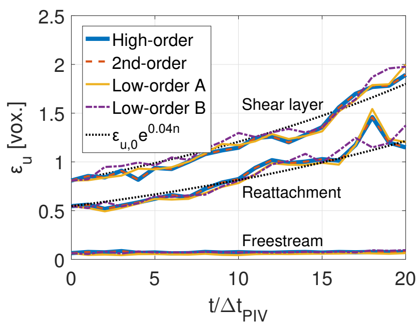

Fig. 1 R.m.s. velocity error along the track

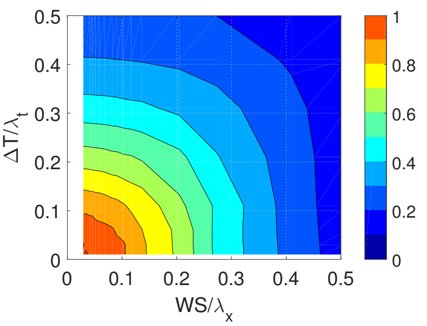

Fig. 2 Pressure peak response

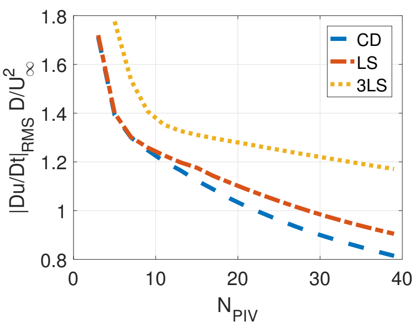

Fig. 3 R.m.s. of material accelerations versus track length

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Sensitivity analysis of two pressure reconstruction methods

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Abstract

We investigate the accuracy of two pressure reconstruction methods. The first method proposed by Jeon et al. (2017) is based on an iterative pseudo-Lagrangian approach [2] in order to obtain material acceleration from the velocity fields based on a second order polynomial trajectory. The integration domain is discretized into several subdomains in accordance with the local reliability. The pressure is then reconstructed sequentially from a minimization process of the difference between measured and reconstructed pressure gradients in a least-square sense [3]. A step of regularisation of the velocity field, based on the *Helmholtz* decomposition, is introduced to obtain a divergence-free velocity fields. The second method is a data driven PIV-CFD coupling in which the experimental results are assimilated within a simulated experiment. The uncertainty levels of both the simulation and the experiment are integrated in a stochastic framework to provide an improved estimate of the true flow.

The accuracy of the pressure reconstruction for both methods is evaluated on a numerical flow database. A flow around a rigid profile with a free tip is considered. From the numerical simulation data, PIV like data are extracted. Two types of error are modelled: a Gaussian noise is first introduced into the velocity field. Then, the effect of pixel-locking modelling is evaluated. The effect of the resolution on the pressure estimation is also discussed for both methods. An example of a noisy velocity fields (Gaussian noise) and the reconstructed pressure with the first method is provided in Figure 1.

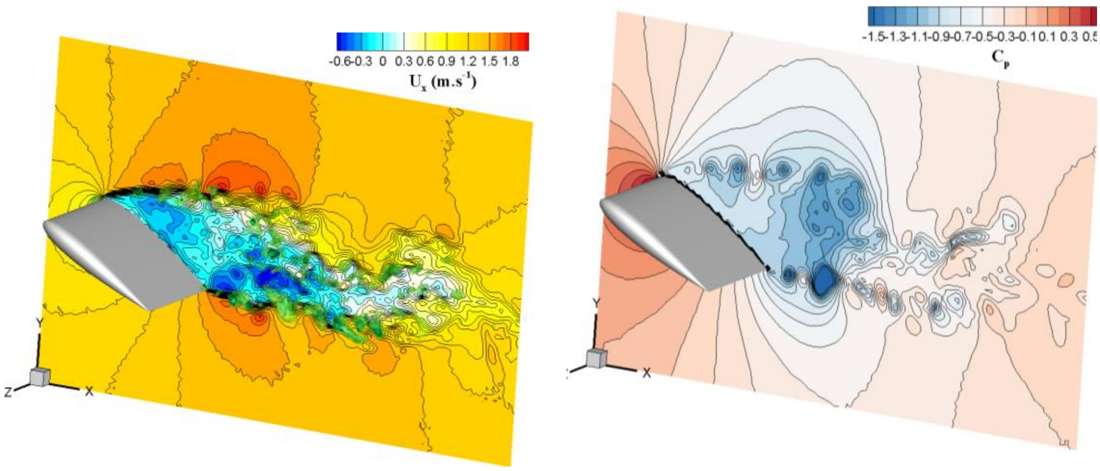

Fig. 1 (left) Noisy velocity field l (right) Reconstructed pressure by the method proposed by [1]

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Estimation of flow structure transport in TR-PIV data and its application to pressure field evaluation

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Abstract

Instantaneous vector fields which describe flow structure transport in TR-PIV data is estimated based on the well-known Taylor's hypothesis of "*frozen turbulence*" and the passive advection model [1]. The focus of this study is to grasp how small-scale flow structures passively travels over time, and thereby to seek its use for betterment of pressure fields. Note that the result from 4D pressure Poisson solver previously shown by the author [2] assumes zero flow structure transport.

Starting the advection model [1] which satisfies "perfect" frozen turbulence:

$$\mathbf{V}(\mathbf{x}+\mathbf{u}_c(\mathbf{x},\ t)\Delta t,\ t+\Delta t)=\mathbf{V}(\mathbf{x},\ t).$$

Where $\mathbf{x}$ is the position vector, $\mathbf{V}$ is the velocity field, $\mathbf{u}_c$ is the flow structure transport, Δh is the grid size and Δt is the temporal interval of TR-PIV data. Subtracting the above equation from its Taylor expansion leads:

$$\nabla\mathbf{V}(\mathbf{x},\ t)\cdot\mathbf{u}_c(\mathbf{x},\ t)=-\frac{\partial}{\partial t}\mathbf{V}(\mathbf{x},\ t)+\mathrm{O}(\Delta t)+\mathrm{O}(\Delta h).$$

As discussed by [3] and [4], the existence of valid $\mathbf{u}_c$ which satisfies the above equation is not guaranteed when a number of sampled data is not enough. By applying a proper spatiotemporal sampling kernel, $\mathbf{u}_c$ and a correlation coefficient between the spatial and the temporal derivatives, γ_c, can be estimated in a least-squares manner as:

$$\mathbf{u}_c(\mathbf{x},\ t)\approx-(\langle A\rangle^{\mathrm{T}}\langle A\rangle)^{-1}\langle A\rangle^{\mathrm{T}}\langle b\rangle \text{ and } \gamma_c(\mathbf{x})\approx\frac{|\langle A\rangle^{\mathrm{T}}\langle b\rangle|}{[tr(\langle A\rangle^{\mathrm{T}}\langle A\rangle)\langle b\rangle^{\mathrm{T}}\langle b\rangle]^{1/2}}\text{, where } A=\nabla\mathbf{V}(\mathbf{x},\ t) \text{ and } b=\frac{\partial}{\partial t}\mathbf{V}(\mathbf{x},\ t)$$

Here < > indicates the weighted spatiotemporal sampling, <*A*> is a 3*N*-by-3 matrix and <*b*> is a 3*N*-by-1 vector when *N* is a number of sampled points in spatiotemporal space. Note that these are equivalent to Eq. (2.4) and Eq. (2.5) in [3] when $\mathbf{u}_c(\mathbf{x}, t) = (u_c, 0, 0)$ and the sampling kernel is a single-point ensemble averaging kernel.

Figure 1 illustrates a preliminary result with a single iteration, the first-order Taylor expansion and the sampling kernel which consists of spatial Gaussian weighting ($\sigma = 4\Delta h$) and averaging over $\pm 2\Delta t$. Note that only small-scale structures are tracked due to a small sampling kernel in spatiotemporal space.

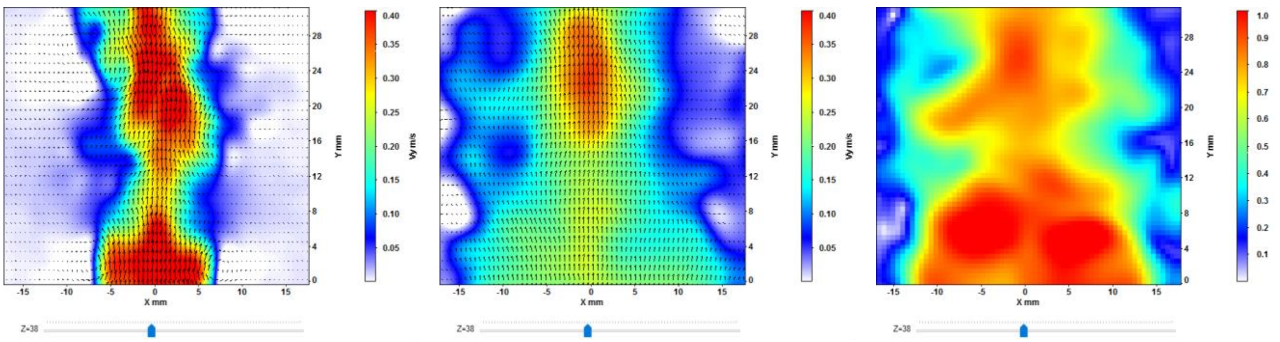

Fig. 1 (*from left to right*) instantaneous velocity field, flow structure transport estimate ($\mathbf{u}_c$) and correlation coefficient estimate (γ_c) from tomographic TR-PIV experiment for water jet from circular nozzle [5]

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Novel measurement techniques

3D Flow Measurement Using Rainbow PIV

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Abstract
Recent approaches regarding 3D fluid flow measurement are mainly focusing on Tomographic PIV [1], which utilizes multiples cameras observing a common region of interest, and then reconstruct light intensity distributions by means of optical tomography. Afterwards, the fluid velocity vector fields can be recovered by computing the spatial cross-correlation of the particle distributions at successive time steps. This approach suffers from a complicated setup (limited space, camera synchronization), erroneous calibration (approximated mapping function, misalignment of lines of sight) and limited depth-of-field.

In our recent research [2], we addressed on all of the above issues, proposing a 3D PIV system with a single camera, which requires a simple calibration step and achieves relatively large depth-of-field.

Our proposed PIV setup, termed as RainbowPIV (see Fig. 1 left), makes uses of a linear color filter to generate a set of wavelength varied light planes, such that the particles in the volume will be illuminated by a continuum of light planes, the depth of which will be encoded by color. Furthermore, a diffractive optical element (DOE) is custom designed to be attached in front of the camera lens, and it provides wavelength-selective focus to ensure all the light planes are in focus simultaneously. Therefore, in our setup, a single camera is capable to retrieve 3D particle locations by combining 2D spatial location and 1D color information.

The software part deals with the particle location reconstruction and fluid velocity estimation tasks. An inverse problem is formulated based on derived image formation model to recover particle locations. The corresponding optimization problem is constructed to tackle the ill-posed inverse problem since we compress full spectrum information into three color channels. After that, the 3D fluid velocity estimation is implemented by extending 3D Horn-Schunck optical flow model with divergence-free constraint as well as the image formation model. We will present our approaches on both synthetic data and practical fluid flows. One of the experimental results is shown in Fig. 1 right. It reveals that our system can robustly reconstruct the fluid flows at good accuracy.

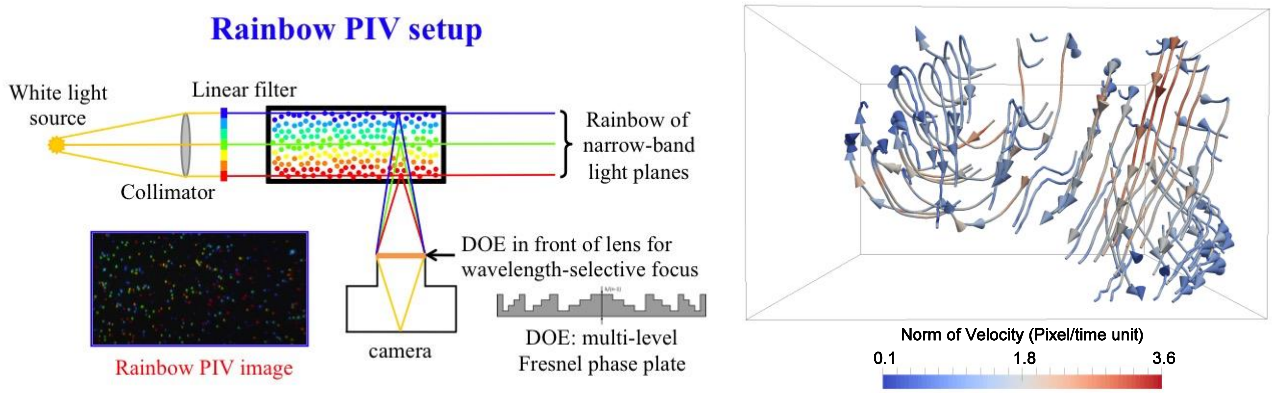

Fig. 1 Schematic diagram for RainbowPIV setup (left) and path line visualization for the dataset corresponding to a dropping experiment, specifically dripping a drop of water from the top of the volume (right).

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A LOCAL SPATIO-TEMPORAL APPROACH TO PLANE WAVE ULTRASOUND PARTICLE IMAGE VELOCIMETRY

ECATERINA BODNARIUC, STEFANIA PETRA, AND CHRISTOPH SCHNÖRR

ABSTRACT. Ultrasound enables noninvasive imaging in opaque media, in particular, the use of plane wave imaging improves the temporal resolution of the signal by recording sequential images at rates higher than 1000 fps. The high frame rates of plane wave ultrasound imaging lead to displacements that enable the application of *differential* motion estimation techniques [BPS15]. Motivated by the task of estimating the instantaneous velocity of blood flow using *plane wave ultrasound particle image velocimetry* (a. k. a. *Echo PIV*) [RJG13], we present a simple and efficient velocity field estimation approach based on a carefully designed filter bank [BPSV17].

The design of orientation- and motion-sensitivity local filters has a long tradition in image processing and computer vision. In this work, we adapt such techniques to the specific domain of Echo PIV. We propose a proper discretization of the half-space in the spatio-temporal Fourier domain (only relevant for real-valued signals) in terms of a collection of motion-sensitive filters whose spectral support form a partition of unity. This requirement rules out Gabor filters in favour of log-Normal filters that behave more conveniently in the spectral domain [MH08].

The basic assumption underlying our local motion estimation is that phase $\phi_i(x,t)$ of the response function $h_i(x,t) = (f * G_i)(x,t) = r_i(x,t)e^{\boldsymbol{i}\phi_i(x,t)}$ for a filter G_i, is approximately conserved under motion, and fulfils the equation

$$\frac{\mathrm{d}}{\mathrm{d}t}\psi_i = \langle \nabla\psi_i(x,t), (\dot{x},1)\rangle = \langle \nabla_x \psi_i(x,t), \dot{x}\rangle + \partial_t \psi_i(x,t) \approx 0, \quad \forall (x,t), \tag{0.1}$$

which results in estimating the local velocity $v = \dot{x}$ *for any fixed space-time point* (x,t) by minimizing the squared residual error of the latter equation

$$u(x,t) = \arg\min_v \sum_i \left(\langle \nabla_x \psi_i(x,t), v\rangle + \partial_t \psi_i(x,t)\right)^2. \tag{0.2}$$

We validate our local velocity estimation approach on simulated and *in-vitro* plane wave ultrasound PIV data, in scenarios with laminar as well as with turbulent pipe flow.

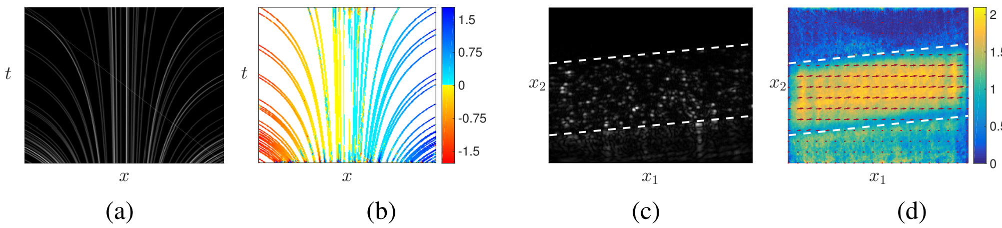

FIGURE 1. (a) One-dimensional synthetic video of diverging particles with (b) local flow estimation. (c) In vitro plane wave ultrasound image and (d) time-average local flow estimation.

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Advanced flow reconstruction

Spatial refinement of TR-PIV realizations using machine learning of high-resolution non-TR-PIV measurements

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Abstract

A machine learning strategy based on high-resolution non-TR-PIV measurements of the fluid flow is proposed to increase the resolution of time-resolved particle image velocimetry (TR-PIV) realizations; various high-resolution modes extracted from proper orthogonal decomposition (POD) were extensively used to construct the flow field. The TR-PIV instantaneous realization with relatively low spatial resolution is cross-projected onto the high-resolution POD modes to obtain the time-varying mode coefficients. Subsequently, the high-resolution time-resolved flow fields, which inherit the information of the superimposed multi-scale structures from the non-TR-PIV measurements, are reconstructed using the linear combination of the cross-projected mode coefficients and the corresponding high-resolution POD modes. Here, several different methods in determining the linear interpolation coefficient matrix were compared, including the geometrical weighted one, and the one determined from 'supervised learning' of the database. The comparison showed that the one corresponding to the machine learning works much better. Finally, application of the present method to TR-PIV data shows that the high-resolution time-resolved fields are successfully achieved with the temporal pattern similar to the original TR-PIV realizations, while much smaller structures are captured by the spatially refined flow.

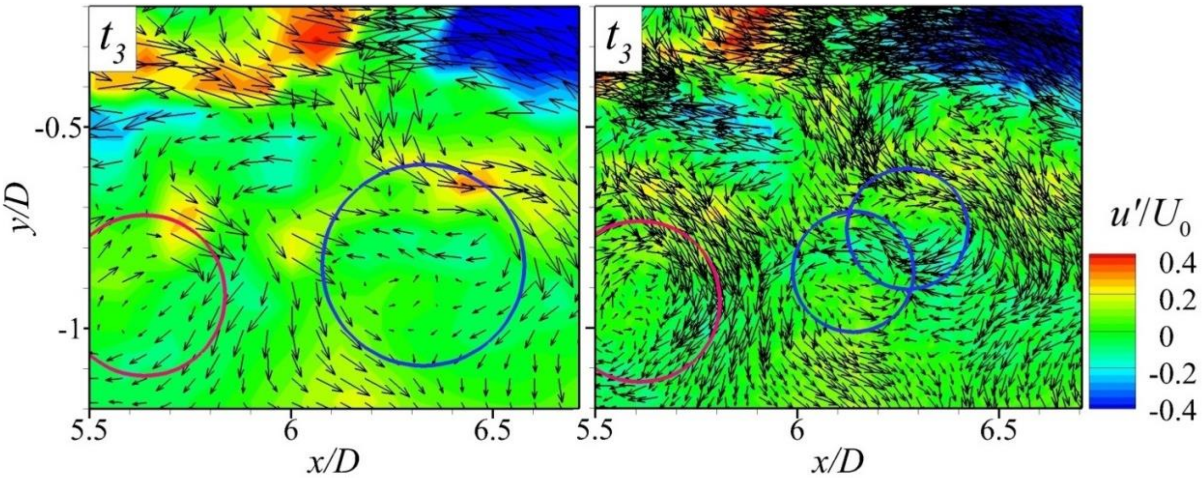

Fig. 1 Close-up view of the vortices in TR-PIV measurements (left) and spatially refined field (right).

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Estimation of time-resolved flow fields using simultaneous non-time resolved field measurements and time-resolved point measurements

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Abstract

A method to estimate time-resolved turbulent flow fields combining non-time-resolved field measurements with time-resolved point measurements is presented. The approach stands on a stochastic estimation based on the Proper Orthogonal Decomposition of the field measurements and of properly arranged time-resolved point measurements. The correlation between temporal modes of the field measurements and of the pointwise measurements at the same instants is evaluated; this correlation is then extended to time instants "out-of-sample" for the field measurements. This approach puts its ground on the Extended POD technique (Borée 2003) and extends the work by Hosseini et al. (2015) by proposing a truncation criterion which allows to remove the uncorrelated part of the signal from the reconstruction of the flow fields. In spectrally rich turbulent flows this truncation is shown to be fundamental due to the great wealth of scales that is involved, which weakens the correlation between the probes signal and the field measurements. The proposed threshold selection is general and poses its basis on the random distribution of the uncorrelated signal.

The method is validated with a synthetic and an experimental test case. A Direct Numerical Simulation database of a turbulent channel flow is selected since the proposed method is significantly challenged by spectrally rich fields. An example of dynamic estimation of the turbulent channel flow using 11 point probes on the right side of the domain is reported in Fig. 1. The experimental test case is the PIV measurement of the wake flow behind a high-angle-of attack airfoil at chord-based Reynolds number equal to 1800. In this application, a relatively small number of samples is used, and additionally the PIV snapshots are affected by significant noise. The quality of the dynamic estimation is found to be sensibly affected by the noise contamination of the data and by poor convergence of the POD modes, apart from the expected dependence on the probes location (i.e. on the correlation between probes events and flow features). The use of the determination coefficient directly between reconstructed data and in-sample data is proposed to assess the flow field quality; this would not normally be possible for non-truncated POD estimation or linear stochastic approaches, for which only out-of-sample data should be used.

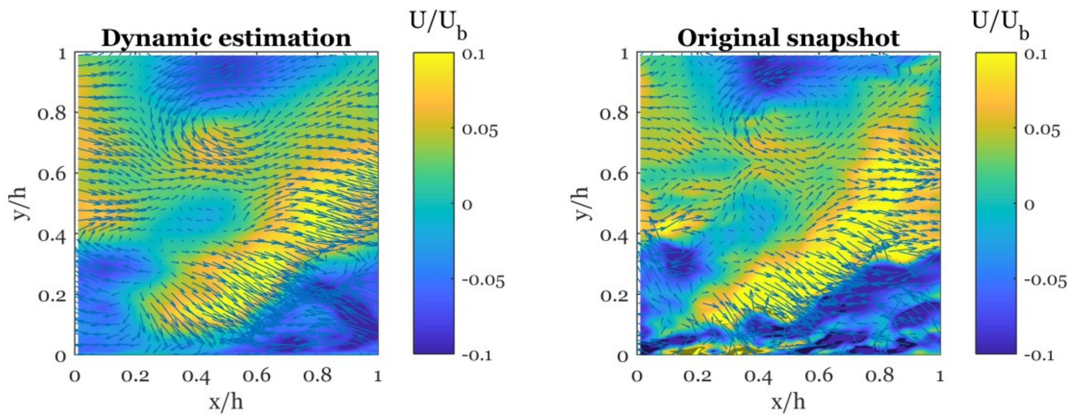

Fig. 1 Contour plot of fluctuating stream-wise velocity component with superimposed (down-sampled) vector arrows: comparison of the dynamic reconstruction (left) of the flow field against the exact flow field (right).

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Assimilation of surface pressure measurements into RANS simulations of a NACA0012 delta wing

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Abstract

One particularly intriguing method of data assimilation that has been developed in recent years is the state estimator method, or measurement-integrated simulation [3]. In this method, the Navier-Stokes equations are formulated for solution in an incompressible computational fluid dynamics simulation as such:

$$\rho\left(\frac{\partial \boldsymbol{u}}{\partial t}+(\boldsymbol{u}\cdot\boldsymbol{\nabla})\boldsymbol{u}\right)=-\boldsymbol{\nabla}p+\mu\nabla^2\boldsymbol{u}+\boldsymbol{f}; \qquad \boldsymbol{f}=-\boldsymbol{\phi}KA_C[(p-p_S)-(p^*-p_S^*)],$$

where $\boldsymbol{f}$ is an artificial body force field through which the experimental measurements are assimilated into the experiments, $\boldsymbol{\phi}$ determines the direction in which to apply the body force (in the case of surface pressure measurements, parallel to the surface and the free-stream flow), K is the feedback gain, A_C is the cross-sectional area of the cell, p^* is a measured static pressure, and p_S is a reference or stagnation pressure [2,3].

In this work, the state-estimator data assimilation technique is applied to steady RANS simulations of a NACA0012 delta wing, at angles of attack of 20 and 30 degrees. Pressure measurements are performed on the suction side of the wing, simultaneous with PIV measurements on three streamwise-transverse planes (see figure 1, left). By comparing PIV measurements, standard RANS simulations, and data-assimilated RANS simulations using three different configurations of pressure taps, this work investigates the degree of improvement in solution accuracy when pressure measurements are assimilated into steady RANS simulations. The relative degree of improvement in results provided by each pressure tap configuration is of particular interest, as this provides general design insight for optimal pressure tap positioning for data assimilation purposes. In addition, this work investigates the challenges inherent in extending a technique typically employed on coarse, uniform grids, to grids with spatial refinement, particularly at the wall, and resolutions on the order of what are typically required for practical engineering analyses.

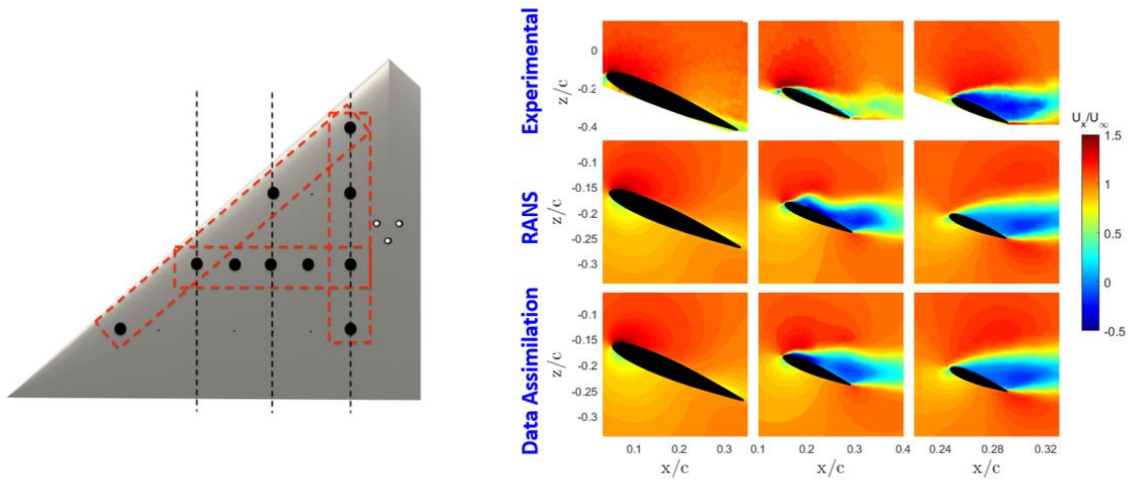

Fig. 1 (left) Schematic of suction side of the NACA0012 delta wing. Black dots indicate the position of pressure taps, black dashed lines indicate the location of PIV measurement planes, at y/c = 0.1, 0.3, 0.5 from the centerline of the wing, and red dashed lines box in groupings of pressure taps measured simultaneously. (right) Preliminary comparison of PIV measurements, RANS simulations, and data-assimilated RANS simulations of the time-averaged flow over the NACA0012 delta wing (columns from left to right are y/c = 0.1, 0.3, 0.5 from the center of the wing), indicating a disparity between the PIV and both the standard and data-assimilated RANS.

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Adjoint-based mean flow reconstruction of laminar separated bubbles based on PIV data

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Abstract

Laminar separated bubbles develop on airfoils when increasing the angle of attack and are linked to static stall, which limits the aerodynamic performance of aircraft. An adverse pressure gradient induces a separation of the laminar boundary layer; a shear layer then develops and strongly amplifies instabilities. A laminar-turbulent transition of the flow occurs and induces a reattachment of the mean shear layer. A turbulent boundary layer develops downstream this recirculation region.

Experimental or numerical investigations of laminar separated bubbles are challenging. In addition to providing only a pointwise information, measurements methods based on probes (e.g. hot-wires measurements) can present intrusiveness issues because of the interaction of the probe with the physical phenomena. On the other hand, less intrusive methods such as Particle Tracking Velocimetry (PTV) and Particle Image Velocimetry (PIV) are critical when measuring the flow close to the surface, mainly because of light reflections, lack of particles, and spatial filtering of the smallest scales, in the case of PIV. A purely numerical simulation approach based on the Reynolds-Averaged Navier-Stokes (RANS) approach is also complicated since the transition process is often not accurately taken into account by turbulence model. Modelling the transition process is still an open question in fluid dynamics and, hence, transition models are far to be a general reliable tools.

In this work, experimental techniques and numerical simulations cooperate to produce reliable measurements of the flow. An adjoint-based data-assimilation procedure is used to match experimental data and RANS simulations. Boundary conditions and turbulent viscosity -- i.e. the reconstructed variables -- are tailored to minimize a quadratic cost function based on the difference between RANS simulations and a mean flow field obtained by PIV. The gradient of the cost function with respect to turbulent viscosity and boundary condition is determined by solving a steady adjoint problem and it is used to obtain a descent direction in a minimization algorithm.

In this communication, we present validation and application of this procedure: the described technique is first tested in recovering a simulated recirculating bubble and, later, used to recover real PIV data from Simoni *et al.* (2017). Figure 1 reports a test case from the validation; synthetic PIV data are produced, while the simulation itself is used as ground truth. Starting from the laminar solution – i.e. with no previous information on the turbulent viscosity -- turbulent viscosity and boundary conditions are reconstructed via the presented algorithm and compared to the original simulation. The algorithm is shown able to effectively recover the reconstructed variables and the original flow, as it can be seen in fig. 1. Even when a reduced measurement set that does not include the recirculation region is used, the general shape and extension of the bubble are recovered.

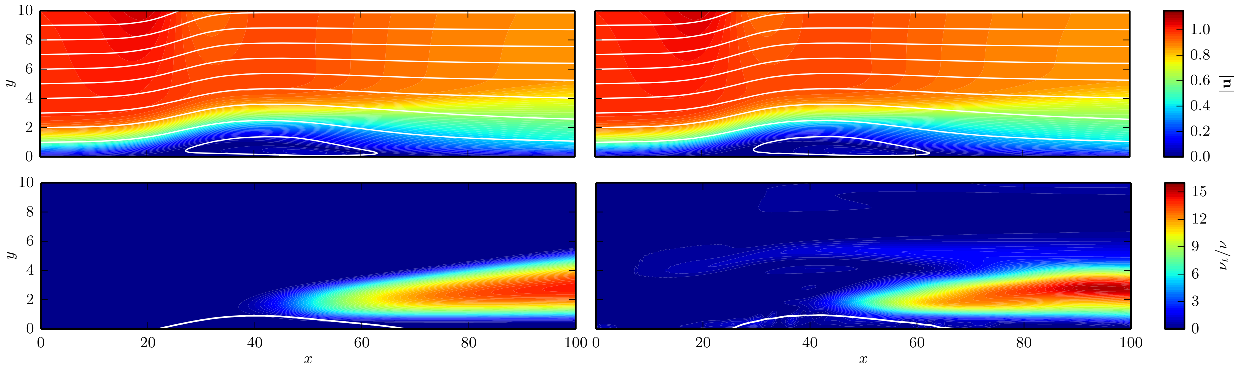

Fig. 1 RANS (left) and reconstructed (right) flow. Velocity (top) and turbulent viscosity (bottom) fields are reported. The reconstructed flow is based on discrete velocity measurements on a uniform rectangular grid with spacing 0.6 displacement thickness at the inflow; the first row of points from the wall is located outside the backflow region.

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Inverse problems in blood flows: recent progresses and current challenges

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Abstract

In this talk I will present recent advances and challenges in the field of mathematical modeling and data-based numerical analysis of blood flows. First, I will give motivations for the application of such models in the clinical context. Then, I will overview some results concerning inverse problems in blood flows based on medical imaging data, namely: (a) Parameter and state estimation in fluid-structure interaction problems [1,2,3], (b) pressure gradient estimation from full field velocity measurements [4]. Finally, I will present our ongoing research on robust velocity reconstruction from Magnetic Resonance Imaging.

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Delft, The Netherlands
13 - 14 December 2017
ISBN 978-94-6366-000-6