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ROBUST OPTICAL FLOW ESTIMATION APPLIED TO PARTICLE IMAGE VELOCIMETRY IMAGES FOR HIGH RESOLUTION VELOCITY MEASUREMENTS

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Abstract

The article discusses application of Robust Optical Flow Estimation for increasing of Particle Image Velocimetry measurement resolution. Nowadays, one of the promising approaches for increasing the performance of the PIV systems is application of the Optical Flow Estimation for image analysis. Nevertheless, some of the OF implementations do not perform well in case of motion discontinues typically occurring in the PIV images. The purpose of this study is to validate the performance of the Robust Optical Flow Estimation. The tests were performed on simulated images of vortex flow and the results were compared with displacement fields calculated with the typical correlation PIV algorithm. The velocity for high and medium particle concentration was similar for Optical Flow and PIV-like analysis. Furthermore, the performance of the robust optical flow framework was tested with images corrupted with blurs and occlusions. The tests proved good performance of proposed analysis in case of non-Gaussian sources of measurement errors. The robust estimation framework performed well in the case of common image artefacts and proved to be a promising method for precise PIV flow measurements. The presented approach can be useful in development hybrid OF-PIV post processing software aimed for high-resolution measurements and provide a help in designing of experimental investigation of microscale fluid flow phenomena.

Keywords: *Particle Image Velocimetry, optical flow estimation, particle image density, image occlusions*

1. Introduction

Nowadays, high spatial resolution of velocity measurements is fundamental for investigation of complex flow phenomena in fluid dynamics research. For that, reason Particle Images Velocimetry (PIV) is commonly used in all research fields related to fluid flow measurements (for example in aerodynamic wind tunnel testing [1]). PIV is a non-intrusive instantaneous whole field velocity measurement technique. Typically, the experimental methodology consist of following steps: i) the investigated flow is seeded with tracer particles, ii) the flow is illuminated by laser light, iii) light reflected from illuminated particles is recorded by a CCD camera, iv) the recorded images are used to calculate the velocity field in the illuminated plane for 2D measurements or volume for 3D measurements. The velocity is determined by measuring the displacement of the particle pattern between consecutive frames in the small area of the image and the vector velocity field is reconstructed form a grid of all interrogation areas. Cross-correlation of particle pattern in a pair of corresponding interrogation windows is typically used to find the displacement [16]. The PIV method is constantly improved and used as a reliable tool for flow visualisation in fluid dynamic [20] with a great potential for application in general aviation [15] and nonitrusitive pressure measurement with use of time resolved 3D volumetric velocity measurements.

In order to gain better understanding of the spatial and temporal changes of complex flows, an enhanced effort is made to increase the spatial and temporal resolution of PIV measurements. The measurement frequency is raised with use of high-speed cameras and high repetition lasers [6]. The resolution of the vector velocity field is increased with use of high-resolution cameras [5] and improvements of the PIV image analysis [8]. In course of the development of the PIV algorithms, the accuracy of the particle displacement estimation was elevated to the sub-pixel level and the resolution of the velocity field was increased by multi scale iteration schemes and window overlapping [16].

Westerweel [21] proposed the analysis of PIV recordings with single-pixel resolution. The two-point ensemble correlation was proposed for investigation of small-scale flow phenomena in microfluidic research for stationary, periodic [2] and fully turbulent flows [12]. The single pixel approach was applied to near wall turbulence measurements and for Reynolds stress estimation using PIV measurements [13]. Nevertheless, further improvement of the classical PIV analysis is challenged by numerous limitations [16] that can be overcome by application of optical flow for PIV images analysis.

The computer vision community for determination of the visual motion developed the Optical Flow Estimation in a sequence of images. The optical flow analysis estimates the displacement field that transforms one image into next image. The methodology originally proposed by Horn & Schunck [11] is based on brightness constraint equation for the image intensity and additional smoothness assumptions required for optical flow problem solution. The method was intensively developed and variety of estimation methods was proposed including variation of the smoothness assumptions, texture decomposition, regularization, and image segmentation. A comprehensive review of optical flow estimation techniques can be found in [18]. Nevertheless, most of the optical estimation methods were designed and tested for estimation of motion of rigid objects. Since the brightness constraint does not have clearly defined physical meaning, application of the Optical Flow Estimation for determination of the fluid flow requires a careful examination. In recent years, an increased interest of the experimental fluid dynamics research community resulted in various adaptations of the Optical Flow Estimation for measurements of complex fluid flow. A review of variational approaches to image segmentation for flow visualization can be found in [9, 10]. In conclusion, application of Optical Flow Estimation seems to be promising tool for increasing the resolution of PIV measurements to level exceeding performance currently used cross-correlation analysis.

In the presented article, a robust estimation framework for optical flow estimation proposed by Black and Anandan [3, 4] was applied for PIV images analysis. In the course of the studies, performance of an optical flow estimation algorithm with Lorentzian and Charbonier penalty function [18] was tested. The tests proved good performance of proposed analysis in case of non--Gaussian sources of measurement errors.

2. Robust optical flow estimation

The optical flow estimation techniques are most often based on two constraints on image motion: data conservation and spatial coherence. The data conservation constraint states that the image intensity of a small region in one image remains constant over time [11]. The estimation of the image velocities u and v is typically performed be minimizing the sum of squared difference correlation

$$\boldsymbol{E_D(u,v)} = \sum_{(\boldsymbol{x},\boldsymbol{y})\in \boldsymbol{R}}[\boldsymbol{I(x,y,t)} - \boldsymbol{I(x+u\delta t, y+v\delta t, t+\delta t)}]^2, \tag{1}$$

where $I(x,y,t)$ is the image brightness, u and v are the horizontal and vertical image velocity at a point and δt is small and R is local neighbourhood where the image velocity is assumed to be constant [28]. Alternately, the data conservation constraint is expressed in gradient form or using a parametric function of the image coordinates for flow field modelling.

The choice of the region size R is known as generalized aperture problem (GAP) and it requires to balance the following issues: a) large region is needed to constrain the solution b) small region is necessary to satisfy the single motion assumption within the calculation region. Additionally, results of the computation of the flow estimates in the local region R can be influenced by small spatial intensity variations. Typically, these issues are overtaken by adding spatial coherence assumption to the data conservation constraint.

$$\boldsymbol{E(u,v) = E_D(u,v) + \lambda E_s(u,v)}, \tag{2}$$

where E_S is a regularizing term and λ controls the relative importance of the data conservation and spatial coherence terms. Nevertheless, estimation of the image velocity field is prone to errors caused by: i) multiple motions and indecently moving objects, ii) motion boundaries, iii) transparency, iv) shadows, v) reflections. The errors in the estimation result caused by listed motion discontinuities are not normally distributed and the typically used least-squares estimation does not perform well. In order to overcome this limitation a robust framework for optical flow estimation was proposed by the Black & Anandan [3]. In the proposed approach, the least square error norm was replaced with a robust ρ-function. In this case, correlation term (1) is reformulated as

$$\boldsymbol{E_D(u,v) = \sum_{(x,y)\in R} \rho(I(x,y,t) - I(x + u\delta t, y + v\delta t, t + \delta t), \sigma)}, \tag{3}$$

where σ is a scale parameter. The robust estimators, ρ, are functions that mineralize the influence of the outliners related to non-Gaussian measurement errors.

3. Synthetic PIV data

The data for tests was generated with synthetic PIV image generator [19]. The size of image was 800×800 px and the single particle image was 3 pixels with 0.5 pixel variation normally distributed. Three different sets of image pairs were generated with 1000, 10 000 to 100 000 particles per image resulting in following particle per pixel concentration (ppx): 0.001, 0.016 and 0.156. This allowed achieving low, medium, and high particles density, according to typically used qualification [16]. The trajectory of the particles followed Rankine vortex model. The Rankine model assumes that the velocity is always perpendicular to the radius of the vortex. The velocity rise linearly form 0 in the centre of the vortex up to a maximum value at specified distance *R* form the centre and decreases hyperbolically at the distance greater than *R*. For the generated images the radius *R* for single vortex was *R* = 100 px. A two-vortex system was modelled and the maximum displacement of particle between frames was 5 px. The two superimposed frames of a one set are shown in Fig. 1.

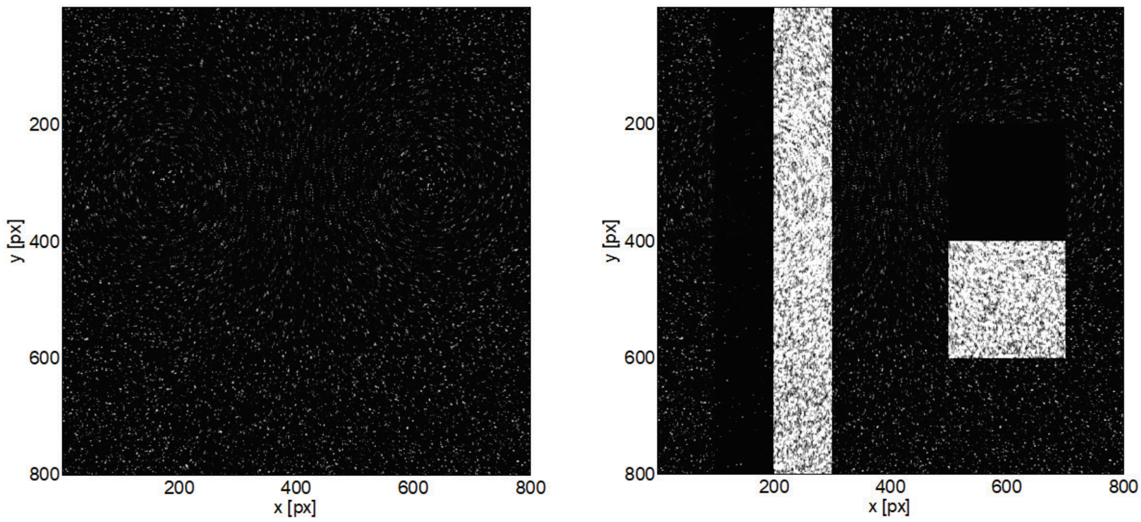

Fig. 1. a) Two frames superimposed for visualization of the particle movement. The number of particles is 10 000 per image, b) Pre-processed images, the following regions can be seen: lower particle concentration for x∈(0, 200), y∈(0, 800); low pass filtered region x∈(200, 400), y∈(0, 800) and x∈(500, 700), y∈(400, 600); all particles masked x∈(500, 700), y∈(200, 400)

In order to test the influence of image blurring occlusions on the robust optical flow PIV image analysis the images were pre-processed. The image with high particle image concentration (0.156 ppx) was divided in four regions: i) no changes to the particle distribution, ii) region filtered with low pass filter, iii) lower particle concentration (0.016 ppx), and iv) all particles masked. The distribution of the regions can be seen in Fig. 1b.

4. Results

Displacement field was determined from the particle images with PIV and Optical Flow analysis. In case of PIV, analysis a home build algorithm was used [17]. The algorithm used normalized cross correlation [14], window overlapping and Gaussian correlation peak approximation for subpixel accuracy [16]. The replacement of spurious and missing data was performed by applying a robust algorithm for automated post-processing of PIV data [7]. The vector displacements fields for high concentration of the particles are shown in Fig. 2. For the Optical Flow estimation the robust Lorentzian, ρ-function was used for the error norm [18]. The vector displacements fields determined with optical flow estimation for high concentration of the particles can be seen in Fig. 3.

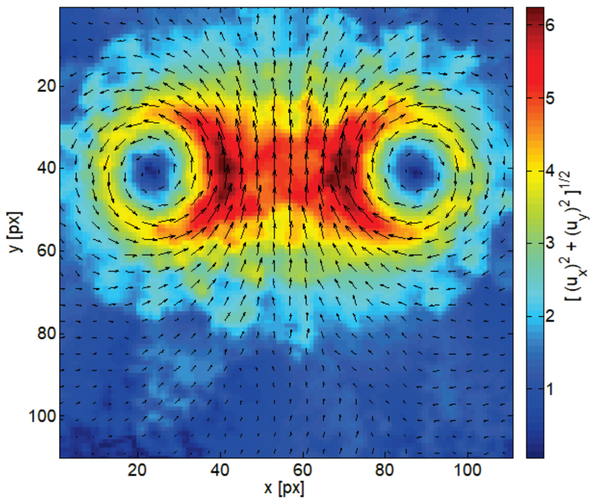

Fig. 2. Vector displacement field determined with PIV correlation algorithm

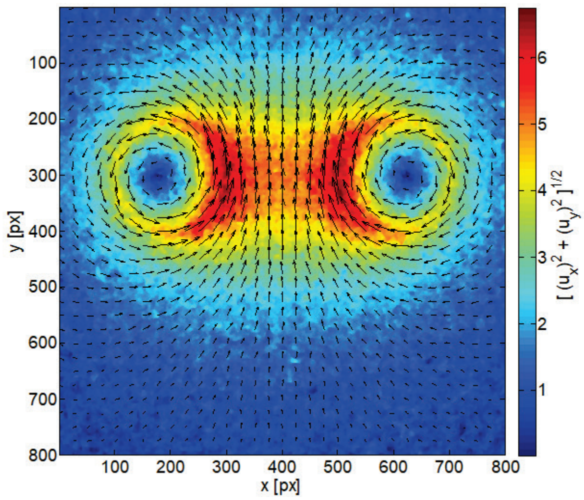

Fig. 3. Vector displacement field determined with robust optical flow algorithm

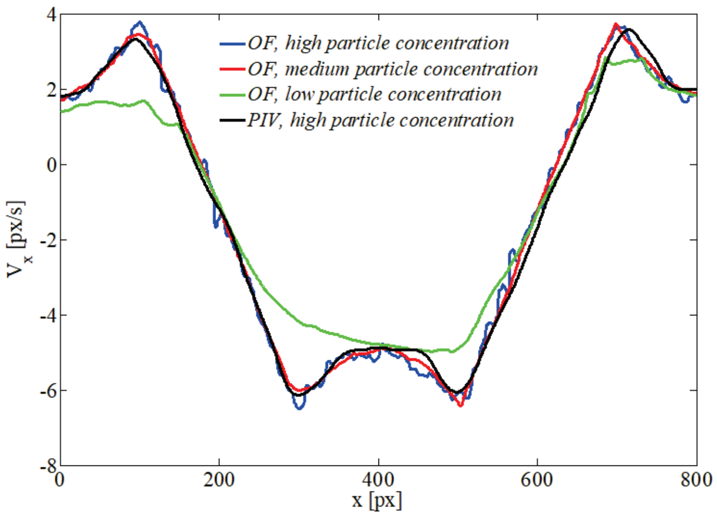

Fig. 4. Plot of a horizontal component of flow velocity for a line of following coordinates in the image plane $x \in (1, 800)$, $y = 300$

The horizontal component of the particle displacement for a cross section of the vortex pair system is plotted in Fig. 4. The values of the displacement determined by cross-correlation and Optical Flow algorithm are similar for high and medium particle image density. For low image density, the displacements are smaller.

In the test on masked data, two different error norms were tested: i) Lorentzian, and ii) Charbonier penalty function [18]. The result of the robust optical flow estimation applied to pre-processed images with Charbonier ρ-function is illustrated in Fig. 5. The influence of blurring and abrupt change of the particle concentration can be seen. In order to quantify the performance of the algorithms the horizontal and vertical component of the displacement are plotted in Fig. 6 and 7, respectively.

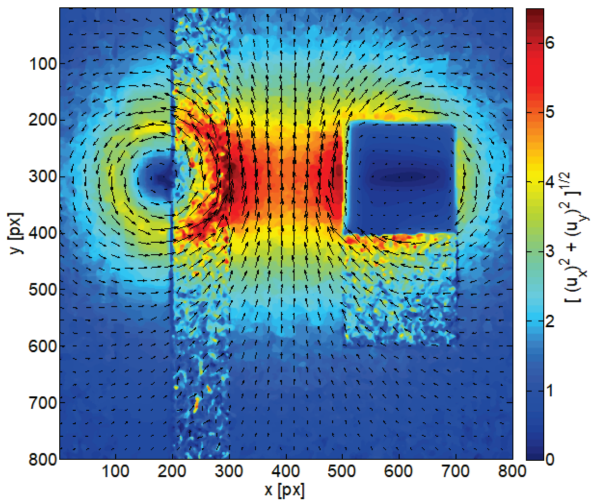

Fig. 5. Vector displacement field determined with robust optical flow algorithm with Charbonier ρ-function applied to corrupted PIV data

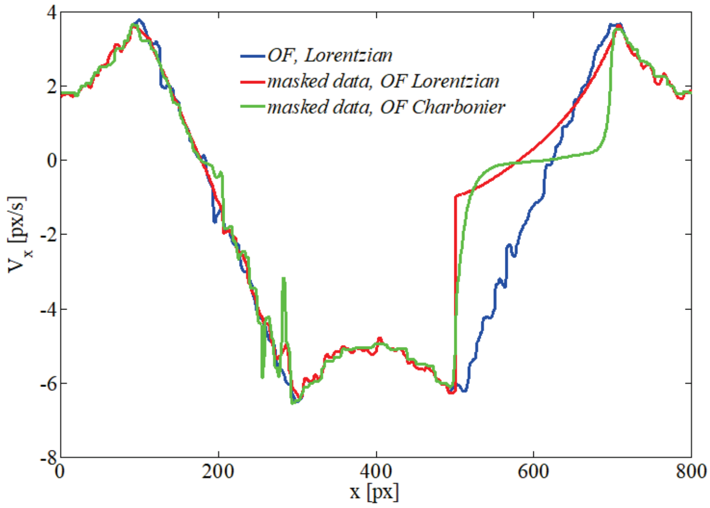

Fig. 6. Plot of a horizontal component of flow velocity V_x for a line of following coordinates $x \in (1, 800)$, $y = 300$ on the image plane

5. Summary

The optical flow estimation was originally proposed for determination of the motion of rigid bodies. Nevertheless, the optical flow estimation was successfully adapted for fluid flow velocity measurements using images of laser sheet illuminated particles [9, 22, 24]. In the presented article, a robust optical flow framework was applied for PIV images analysis. The test performed on

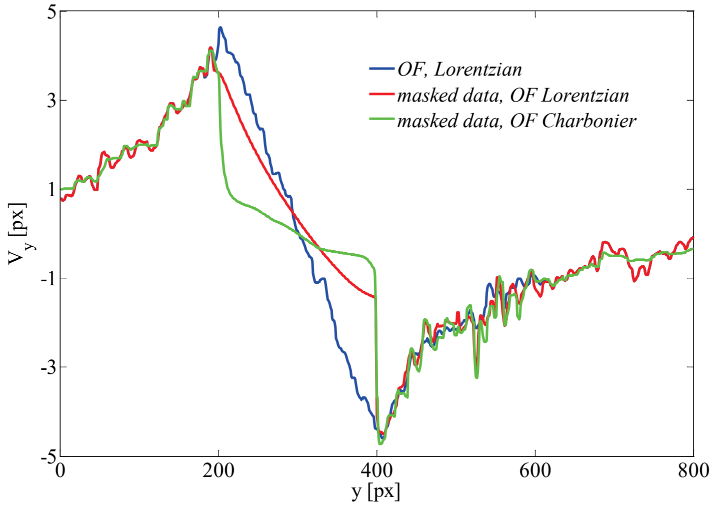

Fig. 7. Plot of a vertical component of flow velocity V_y for a line of following coordinates x = 600, y∈(1, 800) on the image plane

synthetic data proved qualitative and quantitative agreement between the results of optical flow estimation and classical PIV analysis for high and medium particle concentration. For low density of the particle image the values of flow velocity was underestimated. It is worthy to mention that for low consternation, the classical PIV algorithms also do not perform well and Particle Tracking Velocimetry (PTV) method is typically applied. The presented results should be taken under consideration in case of application of the modifications of the basic variational approach proposed by Horn and Schunck [11] to PIV images. Nevertheless, one should keep in mind that the number of vectors could not be greater than the number of particles on the image. Therefore, the increase of resolution in case of analysis can bring only about twice the increase in resolution comparing to maximum PIV-like analysis. The robust framework was proposed in order to handle Non-Gaussian measurement errors like changes in illumination and motion discontinuities. Similarly, the PIV images can be corrupted with low transparency regions and reflections. Therefore, in case of typical PIV particle images the proposed approach seems to be promising tool for robust high resolution velocity measurements. Further tests will be performed on PIV experimental images of boundary layer flow.

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