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Development of a rapid optical flow-based particle image velocimetry framework

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Abstract. This study aims to develop a particle image velocimetry (PIV) framework, intended for in-house use as a live telemetry tool during wind tunnel experiments, by implementing recently developed optical flow techniques to enable rapid flow field assessments of low-resolution PIV images without post-processing. The objective is to implement a data-driven optical flow algorithm that is capable of estimating velocity fields from image sequences in near real-time. The implementation consists of two parts: pre-processing and computation. Pre-processing includes data acquisition and image filtering, while the computation part involves applying a convolutional neural network-based PIV algorithm optimized through parallelization. Validation was performed on various flow cases, which includes Rankine vortex, channel flow, backstep flow, and turbulent mixing. Results show endpoint errors between 2% and 12%, with a processing speed of around 10Hz, which demonstrates its potential for live telemetry of flow structures during experiments. Future work includes object masking for moving boundaries, higher-resolution inputs, and integration with the experimental systems of METU Center for Wind Energy Research (RUZGEM) for on-site deployment.

1 Introduction

Particle image velocimetry (PIV) is one of the most widely used methods in the fluid mechanics research [7]. It is a non-intrusive technique in which neutrally buoyant tracer particles seeded in the flow follow its motion, which is captured using a thin, high-intensity laser sheet. A camera records two images of the particles within a very short time interval, on the order of microseconds. The fundamental principle of PIV lies in analyzing the displacement of these particles between successive images to calculate the instantaneous velocity field of the fluid flow. Standard PIV algorithms partition each image into small interrogation windows and compute the cross-correlation between corresponding windows in successive frames. The cross-correlation of two images (I_1, I_2) can be mathematically represented as:

$$R(m,n) = \frac{\sum_{i,j}[I_1(i,j) - \bar{I}_1][I_2(i+m, j+n) - \bar{I}_2]}{\sqrt{\sum_{i,j}[I_1(i,j) - \bar{I}_1]^2 \sum_{i,j}[I_2(i+m, j+n) - \bar{I}_2]^2}} \tag{1}$$

where R is the cross correlation map. The maximum value of this correlation indicates the most likely displacement of particles, which allows the calculation of velocity fields.

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Particle image velocimetry (PIV) is a highly effective method for calculating entire flow fields in a single iteration, offering non-intrusive and accurate measurements of fluid velocity. However, despite its widespread use and proven efficacy, PIV has certain limitations. It relies on complex algorithms, such as cross-correlation, which demand precise parameter tuning and adjustments to ensure accurate results. These challenges are particularly pronounced in scenarios involving high velocity gradients or strong vorticity, where traditional methods may yield low-resolution or inaccurate measurements. Additionally, the extensive post-processing requirements of PIV make it less suitable for applications requiring rapid or real-time analysis. This led researchers to look for alternatives to the traditional cross-correlation method. Researchers proposed the implementation of a computer vision algorithm created by Horn and Schunck [4] called optical flow to replace the cross-correlation method [8]. This method has been implemented by many, and offers potential. The more modern and optimized version of the optical flow PIV came nearly two decades later [5], where the use of machine and deep learning methods made the implementation a much feasible option.

Machine learning (i.e., modern data-driven optimization and applied regression) is a rapidly growing field of research that is having an important impact across many fields of science and engineering. Experimental fluid mechanics is one of the fields that is also being reformed using this newly emerging method [1]. The amount of data created during the experiments of fluid makes the application of the mentioned methods valuable.

In Lagemann et al. [5], the authors introduced RAFT-PIV, a convolutional neural network-based approach for PIV analysis that estimates high-spatial resolution displacement fields in images at the pixel level. RAFT-PIV is the modified version of the optical flow based CNN method proposed by Teed et al. [9], which operates as an end-to-end optical flow learner that refines displacement estimates using convolutional gated recurrent units (Conv-GRUs) and calculates a full correlation volume between pixel pairs. This approach improves the accuracy and robustness of optical flow, particularly in complex flows with strong gradients or high vorticity. The results of the research demonstrate that RAFT-PIV outperforms existing methods. More recently, researchers proposed the real-time on-site usage of RAFT-PIV [3]. By applying a version of the original RAFT-PIV algorithm called RAFT-StereoPIV to real-time measurements and wind tunnels, researchers gained high-resolution 3D flow field estimation on-site. Enabling PIV's potential with on-site real-time analysis is important for the design process of many engineering fields.

This study aims to develop a software framework for near real-time particle image velocimetry analysis using optical flow methods, intended for in-house use as a live telemetry tool during wind tunnel experiments.

2 Methodology

2.1 Proposed framework

The framework was designed around three engineering constraints: (i) the inference latency must allow for at least 10 Hz processing to enable live monitoring during wind tunnel experiments, (ii) the pre-processing pipeline must be modular so that filter parameters can be tuned to the specific imaging conditions of each experiment, and (iii) the computation stage must support deployment on the RUZGEM cluster while remaining lightweight enough to be developed and validated on standard consumer-grade GPUs.

The proposed framework to be implemented can be seen in Figure 1. The goal is to create

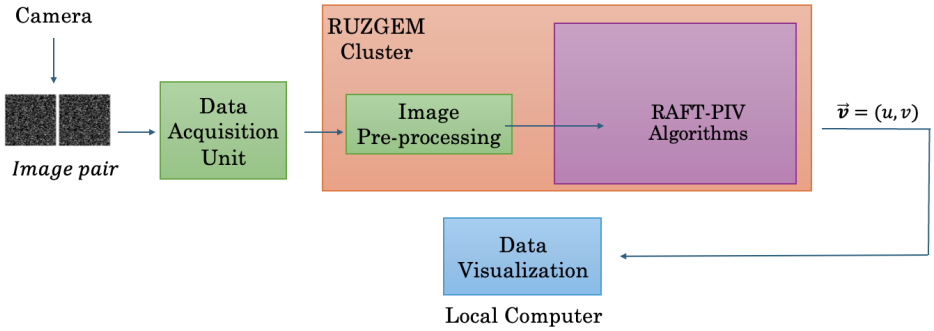


Figure 1: Proposed framework

a pipeline between the experimental set-up and the local visualization device comprised of a camera, a data acquisition unit, and a HPC cluster that is fitted with a parallel computing framework.

The framework operates as follows. Image pairs are captured by the experimental camera and transferred to the data acquisition unit, which forwards them to the RUZGEM cluster. On the cluster, the pre-processing module applies the filtering pipeline described in Section 2.3 to enhance tracer particle visibility, and the resulting filtered image pairs are passed to the RAFT-PIV inference module to produce dense displacement fields. The displacement output is then streamed to a local visualization workstation, where flow structures can be monitored by the operator in real time during the experiment.

2.2 Horn and Schunck optical flow

Optical flow was first developed in 1981 by Horn and Schunck [4] in the computer science field for machine vision. It describes how brightness patterns evolve over time due to relative motion. In optical flow, motion patterns of brightness are examined. Brightness (I) is defined as the intensity of a pixel of a gray scale image on a scale from 0 (black) to 255 (white) on an 8-bit image, and the brightness field of an image is given as $I(x, y, t)$. The primary assumption for the optical flow is that the displacement values δx, δy and the time step value δt are very small. This assumption allows us to take the intensity of a pixel as constant during the motion. The velocity field is given with

$$\vec{v} = (u, v) = \left(\frac{\delta x}{\delta t}, \frac{\delta y}{\delta t} \right) \tag{2}$$

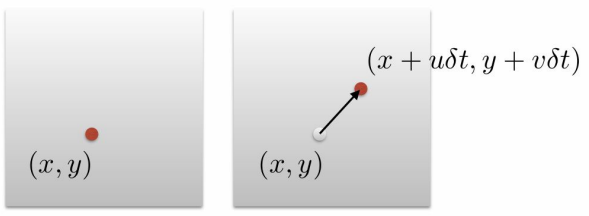


Figure 2: Change in the brightness across two consecutive images

Using this assumption, one might write the following equation

$$I(x + \delta x, y + \delta y, t + \delta t) \approx I(x, y, t) \tag{3}$$

Also, using the Taylor series expansion by neglecting the higher order terms,

$$I(x+\delta x, y+\delta y, t+\delta t) = I(x,y,t) + \frac{\partial I}{\partial x}dx + \frac{\partial I}{\partial y}dy + \frac{\partial I}{\partial t}dt \tag{4}$$

Combining these two equations, dividing by δt and representing the partial derivatives as subscripts, one obtains:

$$I_x u + I_y v + I_t = 0 \tag{5}$$

This equation is called the constraint equation. Between two consecutive images, the partial derivatives of I can be found using methods such as finite difference, thus in this equation, there are only two unknowns, which are the components of the velocity field u and v. Since there is only one equation and two unknowns, the problem is indeterminate. This phenomena is called the aperture problem. To obtain a solution for this system, one must obtain a solvable system first. There have been many different solutions to this problem in the literature. To overcome the aperture problem and obtain a solvable system, our proposed framework employs RAFT (Recurrent All-Pairs Field Transforms), which is a convolutional neural network-based method that learns to estimate dense, physically plausible velocity fields from consecutive PIV images.

The RAFT method is a deep learning-based approach for estimating optical flow. It has three stages: feature extraction, calculation of a full correlation volume between all pixel pairs, and iterative updates using convolutional gated recurrent units (Conv-GRUs). These steps allow RAFT to predict flow at a pixel level and refine estimates iteratively. By leveraging the full correlation volume, RAFT mitigates the aperture problem and enables accurate motion estimation across the entire image [9]. This computation architecture is used with various parallelization methods for faster results. The convolutional neural network is trained with synthetic and publicly found PIV data.

2.3 Image pre-processing

The pre-processing of PIV images is an important step of the framework, since the quality of the input images plays a major role in determining the accuracy of PIV analysis. In PIV, any noise or artifacts in the images can distort the displacement field calculations, leading to less reliable results. For this framework, the pre-processing stage includes a key task: noise filtering. The goal is to increase the visibility of the tracer particles as much as possible. There are four key filters involved in the image pre-processing stage: mean intensity subtraction, a highpass filter, contrast limited adaptive histogram equalization (CLAHE), and intensity thresholding.

2.3.1 Mean intensity subtraction In this approach, we take n consecutive PIV images and compute the average intensity for each pixel in the images. The idea is to subtract the average intensity of the n frames to focus on the changes due to particle motion. This helps eliminate any consistent background noise or variations in lighting that might occur between frames. Also, a running average approach is used to account for the new members of the dataset, meaning at each new image, the average is calculated again.

2.3.2 Highpass filter After subtracting the mean intensity, the next step is to apply a highpass filter. This filter is used to enhance image clarity by removing low-frequency components, such as gradual changes in brightness or background noise, while preserving the fine details of the tracer particles. A highpass filter works by subtracting a lowpass filtered version of the image from the original image. Mathematically, it can be represented as:

$$I_{highpass} = I_{original} - I_{lowpass} \tag{6}$$

The lowpass filtered image is typically obtained using a smoothing operation, such as a Gaussian blur. This operation ensures that only the high-frequency details remain in the image. By doing so, we enhance the features that are most relevant for PIV analysis while suppressing unwanted background variations. The kernel used in this case is the simple $3x3$ Gaussian kernel. The cutoff frequency for the filters was determined empirically.

2.3.3 CLAHE (Contrast Limited Adaptive Histogram Equalization) CLAHE (contrast limited adaptive histogram equalization) enhances PIV images by locally adjusting the contrast in small regions, which makes particles more distinguishable. This improvement helps in accurately tracking particle movements without excessively amplifying noise.

2.3.4 Intensity thresholding Once the contrast is enhanced, the intensity thresholding is applied to focus only on the pixels that are most relevant. This filter helps remove any remaining low-intensity noise by setting a threshold value, meaning the pixels below this value are ignored, and only the brighter, more meaningful features are kept. The threshold value can be set empirically depending on the experimental environment.

$$I' = \begin{cases} I(x,y) & \text{if } I(x,y) > T \\ 0 & \text{if } I(x,y) < T \end{cases} \tag{7}$$

Applying these filters together ensures that the image is not only clean but also well-prepared for accurate PIV analysis.

After finding the displacement fields, one may multiply these fields by a magnification factor and divide by the appropriate timestep to find the velocity field required.

In order to understand whether the results of the Δx and Δy calculations are viable or not, one has to use a measure of error. In optical flow, the most common measurement of error is average endpoint error (AEE). It can either be calculated for the velocities or the displacements. Equation 8, which describes the AEE using pixel displacements is used in this study. N is the total number of points on the grid, the **pred** is the predicted value, and **gt** is the ground truth value. The exact flow field for some datasets have been provided.

$$AEE = \frac{1}{N}\sum_{i=1}^{N}\sqrt{(\Delta x^i_{pred} - \Delta x^i_{gt})^2 + (\Delta y^i_{pred} - \Delta y^i_{gt})^2} \tag{8}$$

The average endpoint error gives a scalar value that is comprehensive of the total error in the flow field. The normalized version of AEE with respect to the maximum displacements are used in this study.

3 Results and discussion

3.1 Test cases

In order to validate the accuracy of the framework, four different synthetic and publicly available flow cases (Rankine vortex, fully developed channel flow, backstep flow, and turbulent flow) were taken from the datasets of Mendes et al. [6] and Cai et al. [2]. The images in these datasets are provided at 256×256 or 512×512 pixel resolution. The following flow fields were obtained for these cases.

3.2 Comparison and computational time

Validation experiments were performed on a single consumer grade GPU, demonstrating that the framework can be developed and tested on accessible hardware before deployment on the dedicated RUZGEM cluster shown in Figure 1.

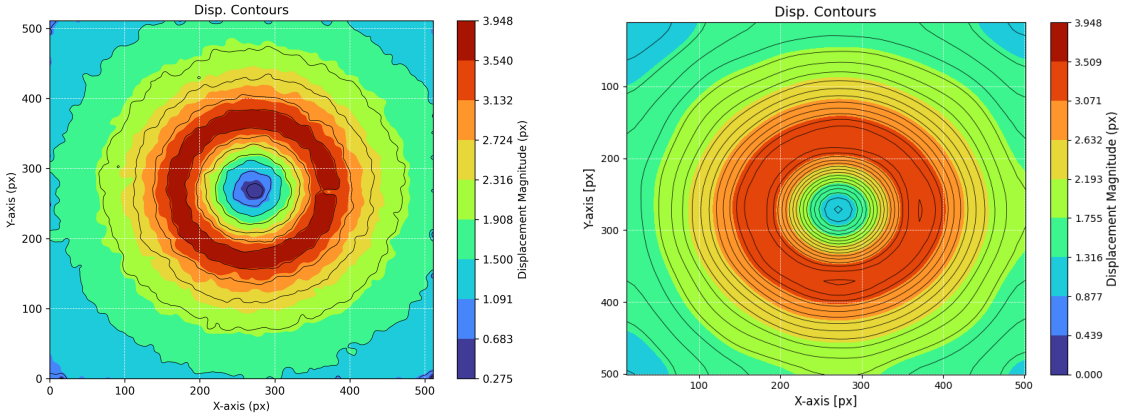


Figure 3: Rankine vortex: framework output (left) and ground truth (right).

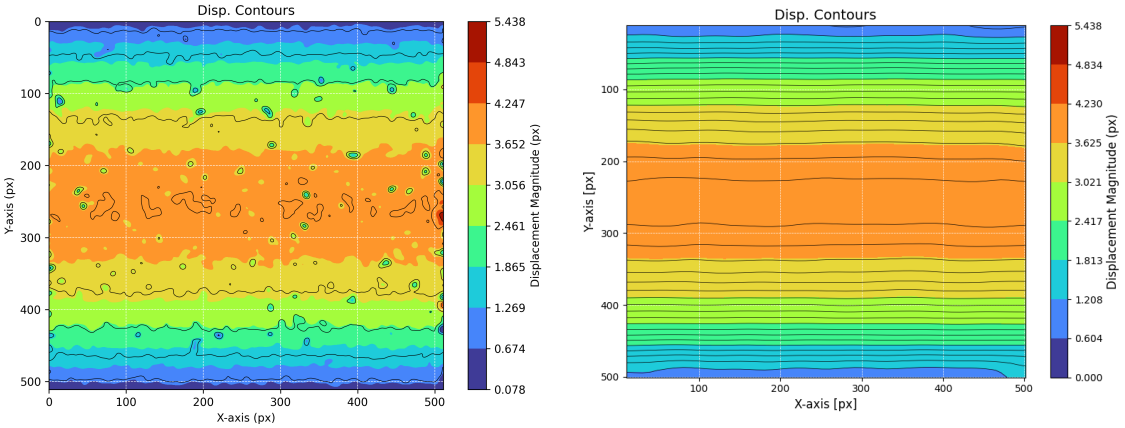


Figure 4: Channel flow: framework output (left) and ground truth (right).

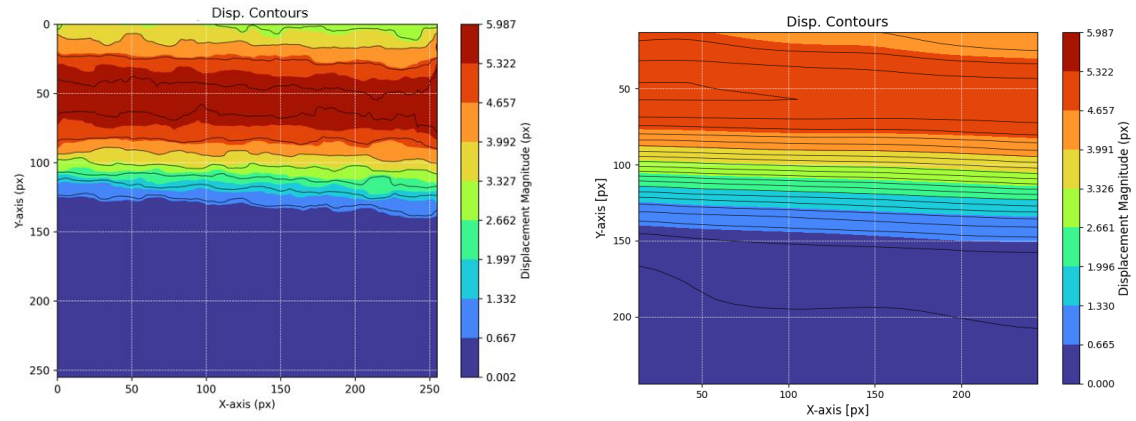


Figure 5: Backstep flow: framework output (left) and ground truth (right).

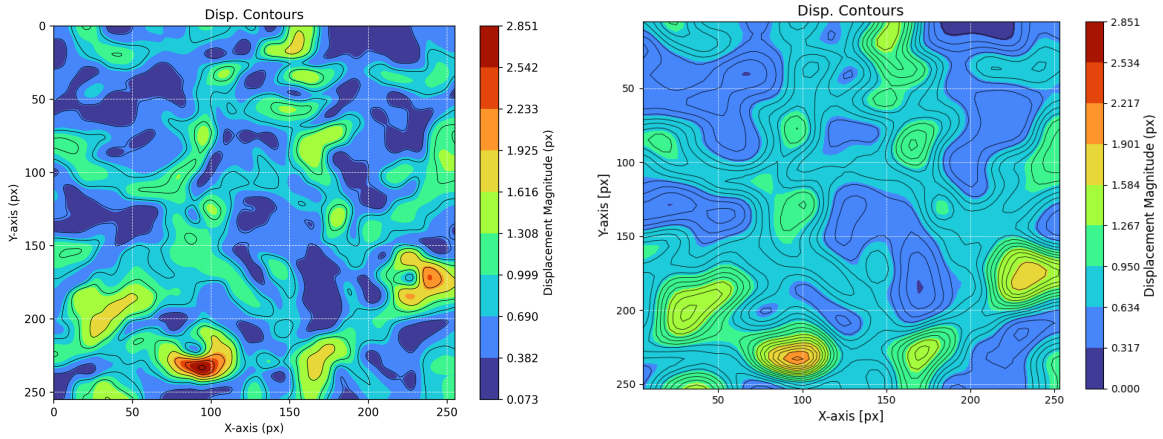


Figure 6: Turbulent mixing flow: framework output (left) and ground truth (right).

3.2.1 Comparison of errors Table 1 reveals that the type of flow significantly influences the error rates of our PIV analysis tool. Flows with strong rotational elements, such as the Rankine vortex and turbulent mixing, exhibit higher errors of approximately 5.5% and 12%, respectively. In contrast, more uniform flows like channel flow and backstep flow show lower errors, around 4.5% and 2.3%. This suggests that rotational characteristics and the presence of outliers in the flow contribute to increased inaccuracies in the PIV measurements. Overall, the complexity and rotational nature of the flow type play a crucial role in determining the accuracy of our analysis tool.

Table 1: Analysis of errors

Flow	**Image Size (px•px)**	**AEE w.r.t the max disp. %**
Rankine vortex	512x512	5.49
Channel flow	512x512	4.450
Backstep flow	256x256	2.254
Turbulent mixing	256x256	12.06

3.2.2 Computational time Due to the initialization phase of the PIV analysis tool being much longer than analyzing a single image, understanding the computational performance of the tool would not be feasible by only observing the calculations between a single pair of image. The 2D turbulent mixing data consists of 1000 $.tif$ files. When analyzed, the total computational time, which consists of initialization, calculation of the displacement fields and outputting in various formats, is around 84 seconds on average. A 1000 image dataset consists of 999 image pairs to be computed, which leaves us a computational time per pair of:

$$t_{pair} = \frac{t_{total}}{N_{pair}} = 0.084 \; sec \tag{9}$$

or around 10 Hz of processing speed.

4 Conclusions

The results presented in Table 1 demonstrate a clear relationship between the type of flow and the error rates observed in our PIV analysis tool. Flows exhibiting strong rotational characteristics, such as the Rankine vortex and turbulent mixing, have higher error percentages of 5.49% and 12.06%, respectively. This trend aligns with our initial hypothesis that rotational dynamics introduce complexities that lower the accuracy of optical flow-based measurements. In contrast, more streamlined and uniform flows like channel flow and backstep flow exhibit lower error rates of 4.450% and 2.254%, respectively. These flows possess smoother velocity profiles with fewer abrupt changes, allowing the PIV tool to maintain higher precision in tracking particle displacements.

Moreover, the computational time analysis reveals that our PIV framework is capable of processing large datasets efficiently, with an average computational speed of 10 Hz on a consumer-grade GPU. This performance is promising for using the model to provide live telemetry of flow structures during experiments. Future work will focus on object masking for moving boundaries, integration with higher-resolution camera systems, deployment on the RUZGEM cluster for production use, and validation against experimental measurements obtained during wind tunnel campaigns.

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