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Deep Convolutional Matching based PIV

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Abstract

Deep convolutional matching is a new type of optical flow algorithm adopting the concept of pattern recognition of the deep learning based artificial intelligence. This matching approach enables dense correspondences between the reference and target images even in the presence of non-rigid deformations and/or repetitive textures. All these strengths of the algorithm seem to match the demands required by a higher order PIV image analysis and probably allow to get rid of the expensive calculation of deformation compensation additionally introduced in the standard cross correlation PIV. In such a perspective, the present study aims to implement this new matching algorithm in the displacement analysis of the 2D PIV and test the performance of the new algorithm by using synthetic as well as experimental particle images.

1 Introduction

In the PIV image analysis, the cross correlation method (Willert et al., 1991) is an unquestionably standard approach for calculating the frame to frame particle displacement. As is well known, this method samples a small interrogation window from the reference as well as from the target particle images at same positions and calculates the cross correlation spectra between the two interrogation windows according to the classical signal processing theory. The average displacement of particles between the two windows is obtained from the position at which the cross correlation spectrum is maximized but this averaging process inevitably leads to a certain loss of the local resolution in the measured particle displacement or the measured velocity. Another issue of the standard cross-correlation approach is the conceptual assumption that the particles in the interrogation window travel in parallel motion and their distribution pattern is not subject to any kind of rotation or deformation. As a matter of fact, this assumption does not hold in the case of highly turbulent flows. In order to resolve all these issued in the span of the cross correlation PIV, a more advanced image processing scheme based on a multi-pass multi-grid recursive algorithm with image deformation compensation strategy has to be introduced, which is computationally very expensive.

In the present study, a newly developed optical flow algorithm with the name of Deep Flow by Weinzaepfel et al. (2013) is introduced to cope with the local resolution and image deformation issues. The name of Deep Flow comes from the adoption of a deep learning process in the modern artificial intelligence system and mainly refers to the use of the convolutional neural network (CNN) and some other relating mathematical operations. This Deep Flow algorithm is implemented in the displacement analysis of the classical 2D PIV procedures and the performance is tested by using typical synthetic as well as experimental particle images in comparison with the standard cross-correlation PIV. One more additional objective of the study is the assessment of the HSV chromaticity presentation of PIV velocity maps in contrast with the more straightforward and commonly used vector plot presentation. As a matter of fact, the former type of velocity map presentation is only possible when the PIV algorithm is able to calculate a very dense distribution of velocity.

2 Deep Flow algorithm

The Deep Flow calculates optical flows in time sequence images by using a newly devised matching algorithm called Deep Matching. Through this matching algorithm, a dense pixel unit distribution of displacement (or velocity) can be obtained thanks to the recursive multi-resolution response maps calculated by a SIFT operator displace analysis combined with the dynamic programming strategy, followed by a series of deep learning algorithms including convolutional neural network filtering, maximum pooling, subsampling, and power-law conversion. The outline of the Deep Flow displacement analysis is provided in Figure 1.

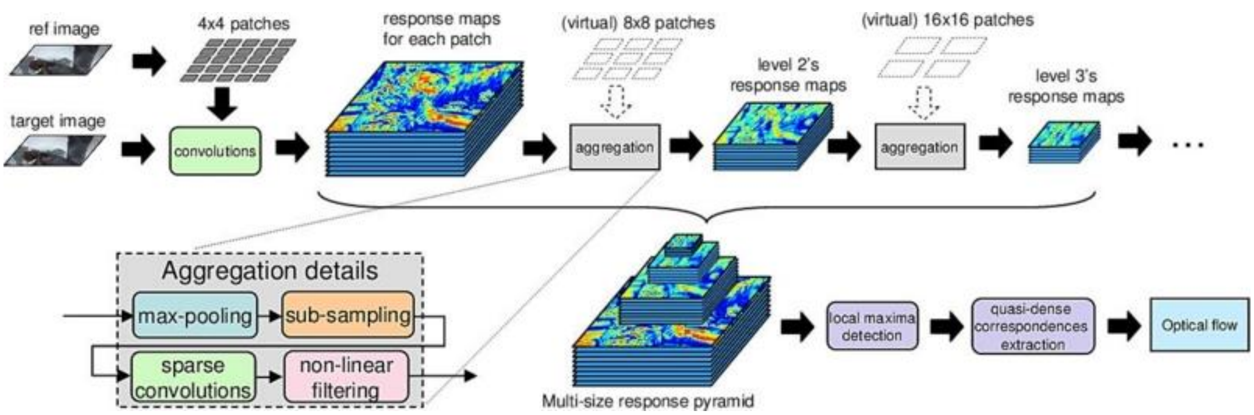


Fig. 1 Flow chart of Deep Flow algorithm (cited from Weinzaepfel et al., 2013)

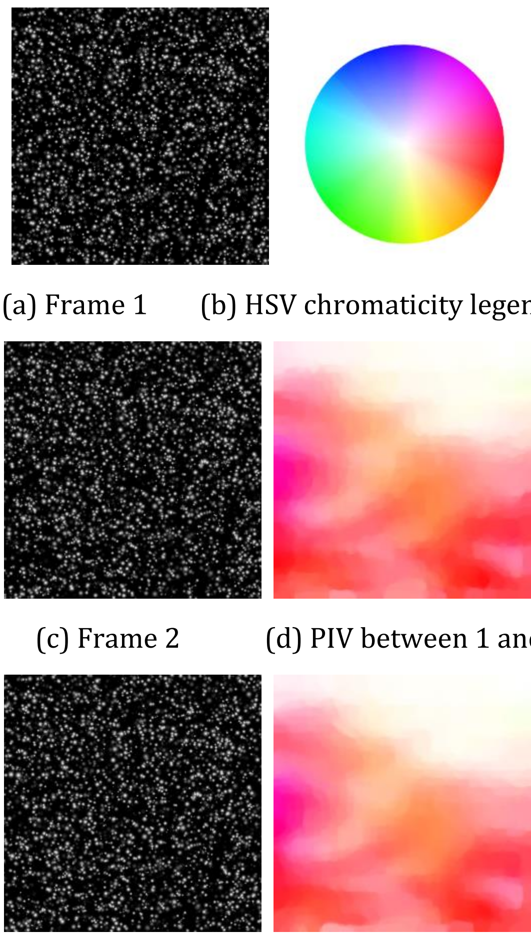
Deep Flow algorithm is now available online as one of the Contrib extension modules applicable to the OpenCV image processing library (see the first item in the References). OpenCV itself is a widely known open source library suitable for computer vision problems, which includes a wide variety of useful image processing codes such as effect filters, mathematical transforms, matrix operations, object tracking, etc… The library can be performed on various operating systems with multilingual platforms and, in the present study, the Microsoft Visual C++ version on the Windows operating system is used for implementing the Deep Flow module. In order to facilitate all the compile and build processes of the Deep Flow module in the OpenCV environment, a freeware application CMake is employed for the convenience of automatic procedures.

Since the default outputs of the Deep Flow analysis results are presented by HSV chromaticity velocity maps (in which the velocity orientation is indicated by color hue and the magnitude by chroma), the PIV results of the present study are firstly presented by this type of velocity maps. For the sake of comparison, some of the PIV results are also presented in a more conventional vector plot form. The HSV chromaticity maps are resolved up to a single pixel resolution, while the vector plot maps are at best up to a several pixel resolution because of the physical dimension of vector lines or arrows.

3 Experimental results

3-1 Deep Flow PIV results of the PIV standard images

In the first place, the Deep Flow algorithm is applied to a classical set of synthetic particle images, namely the PIV standard image (Okamoto et al., 2000). From a number of image sets of this synthetic particle image library, two sets #01 and #301 are selected for this first test of the novel PIV method. The results of the Deep Flow PIV are respectively shown in Figures 2 and 3. Note that Figure 2 (b) and Figure 3(b) are both a chromaticity diagram showing the velocity magnitude and direction, which should be referred to as a legend for the analyzed velocity distributions. The first set of PIV results in Figure 2 depicts nicely the globally horizontal but locally wavy jet flow with a strong velocity gradient in the upper middle of the captured images. Likewise, the second PIV results set in Figure 3 represents the globally vertical but locally wavy jet flow with a rather reduced velocity gradient in the curved vertical direction.

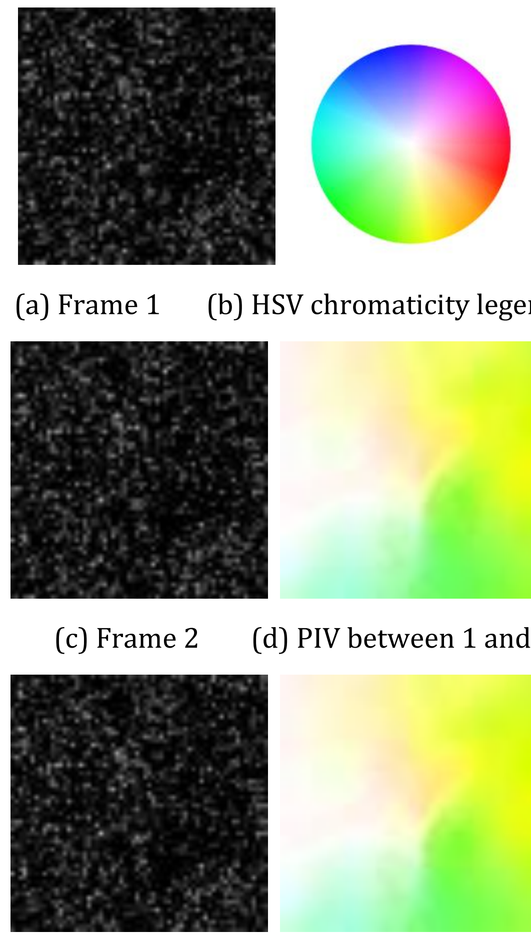


(a) Frame 1 (b) HSV chromaticity legend

(c) Frame 2 (d) PIV between 1 and 2

(e) Frame 3 (f) PIV between 2 and 3

Fig. 2 PIV results of PIV Standard Image #01



(a) Frame 1 (b) HSV chromaticity legend

(c) Frame 2 (d) PIV between 1 and 2

(e) Frame 3 (f) PIV between 2 and 3

Fig. 3 PIV results of PIV Standard Image #301

3-2 Deep Flow PIV results of experimental vortex flow in a circular cylinder wake

Figure 4 shows the time-series Deep Flow PIV results of a von Karman vortex wake of two tandem circular cylinders. Two cylinders are indicated by blue circles and the flow goes from left to right. As regards the velocity magnitude and direction, the same chromaticity diagram in Figures 2 and 3 can be applied to this set of PIV results. It is interesting to note that the concentric wave front shed from the downstream cylinder in response to the oncoming periodic vortex flow from the upstream cylinder are clearly observed in this type of velocity map presentation.

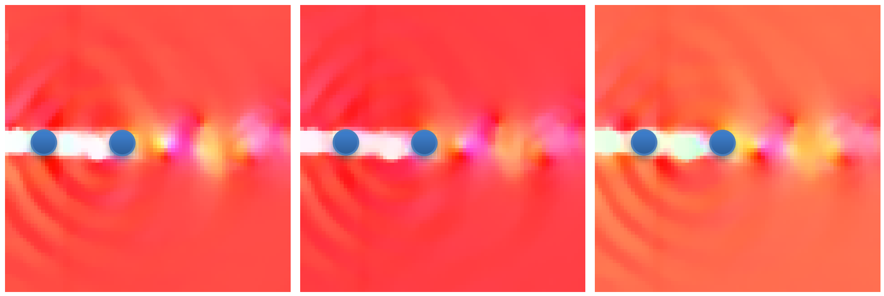


Fig. 4 Time series PIV results showing the wake of two tandem circular cylinders

3-3 Deep Flow PIV results of an experimental stirring flow in a rectangular water tank

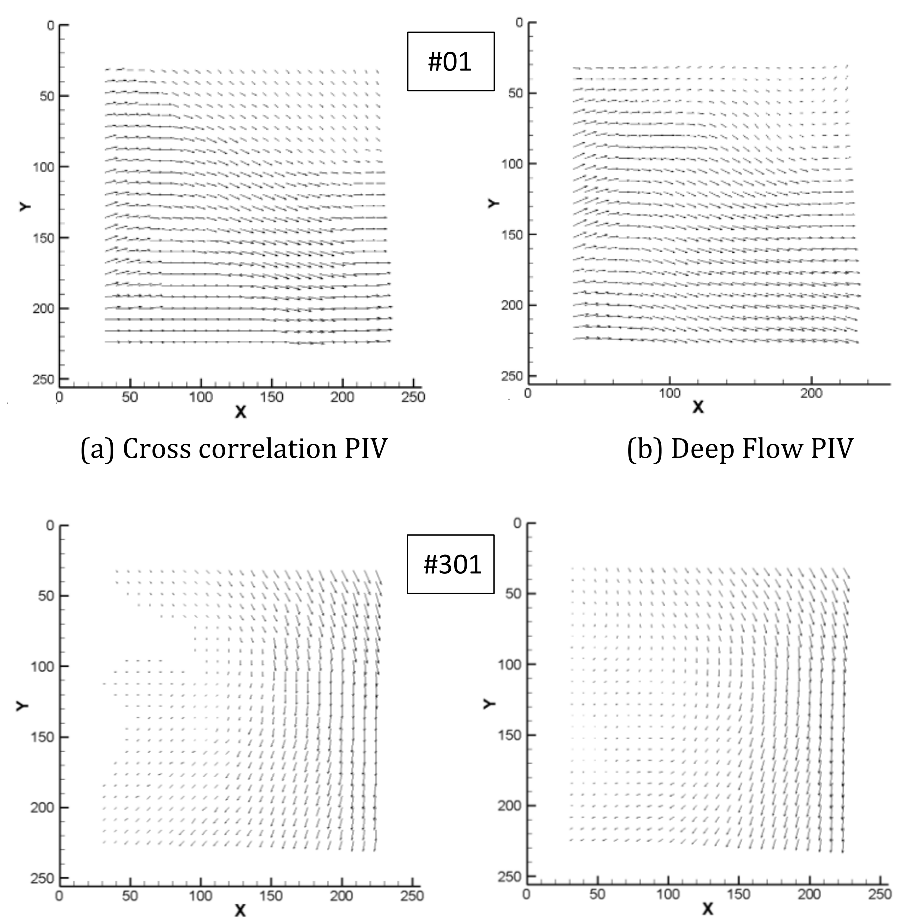
Figure 5 shows the time-series Deep Flow PIV results of a stirring flow in a rectangular water tank with 170×100×190 mm^3 capacity. The inclusion of a chromaticity diagram is omitted again because it is the same as in Figures 2 and 3. It is recognized from this set of PIV results that the stirring flow in this experiment forms globally an anti-clockwise swirling flow centered around the quasi-whitely mapped area in the center with a certain degree of turbulence in the peripheral part.

Fig. 5 Time series PIV results showing a stirring flow in a rectangular water tank

3-4 Deep Flow PIV versus standard cross correlation PIV

Figure 6 shows two sets of comparative results between the standard cross correlation PIV and the Deep Flow PIV, using the two synthetic image sets in Figures 2 and 3, namely the PIV standard images #01 and #301 respectively. The cross correlation PIV uses a basic single pass interrogation scheme with 32x32 pixel window size and 50% overlapping, while the Deep Flow PIV is a rather parameter free process if the maximum particle displacement does not exceed a certain limit. In these PIV results, the velocity maps are presented in the conventional vector plot form because if express by this type of velocity maps, the local velocity magnitude can be more precisely estimated for human eyes. Comparing the cross correlation PIV and the Deep Flow PIV results, both velocity maps are free of spurious vectors and qualitatively similar in terms of velocity magnitude especially, though the former results look a bit excessively local mean filtered in terms of velocity direction in some of the low speed regions. This effect is probably due to a larger set value of windows size (for suppressing spurious vectors) and will be improved by using a multi-pass multi-grid scheme.

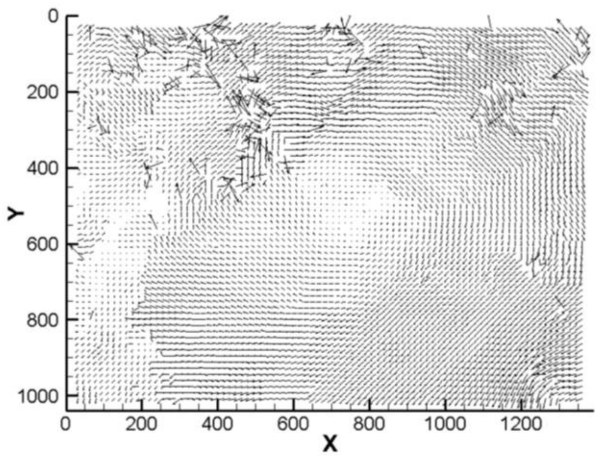
By contrast, Figure 7 shows another set of comparative results between the two PIV approaches, using the experimental PIV image set in Figure 5, namely the stirring flow in a rectangular water tank. Here, the cross correlation PIV uses a basic single pass interrogation scheme with 32x32 pixel window size without overlapping. Comparing the two types of PIV results, the cross correlation PIV is clearly prone to spurious vectors in strong shear flow regions, while the Deep Flow PIV is discernibly more robust against such a strong shear flow. In the cross correlation PIV, even if the presence of spurious vectors is not visibly clear as in the vertically spread large velocity gradient region in the left bottom part of the velocity map, the description of velocity variation in x direction in this region is much less detailed and refined if compared to the Deep Flow PIV. The spurious vectors in the cross correlation PIV result will be reduced by employing a larger windows size but with a cost of further local-mean filtering effect.



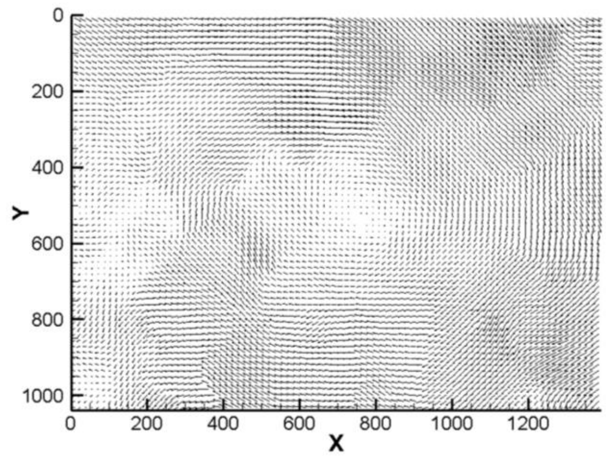
(a) Cross correlation PIV (b) Deep Flow PIV

(c) Cross correlation PIV (d) Deep Flow PIV

Fig. 6 Comparison of cross correlation and Deep Flow PIV results with the PIV standard images



(a) Cross correlation PIV

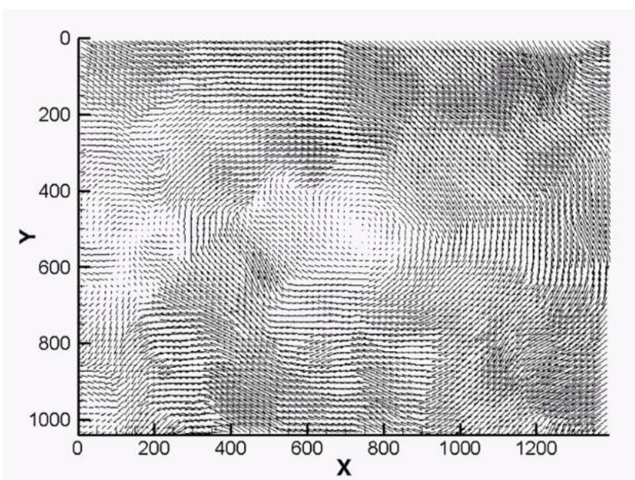


(b) Deep Flow PIV

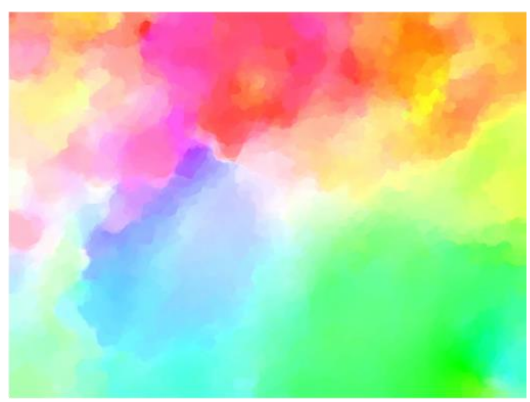
Fig. 7 Comparison of cross correlation and Deep Flow PIV results with the stirring flow in a rectangular water tank

3 5 Comparison of PIV results between the vector plot and HSV chromaticity presentations

Finally, Figure 8 shows a comparison of the PIV velocity map results between the vector plot and the HSV chromaticity presentations. The source velocity data are derived from the stirring water flow experiment in Figure 5 with the Deep Flow PIV algorithm. It is recognized in general that the vector plot presentation is more advantageous for the recognition of vortex flows as well as for the understanding of distribution of velocity magnitude, whereas the HSV chromaticity presentation is favorable for grasping the distribution of velocity direction and for detecting the periodic flow phenomena. One more advantage of the HSV chromaticity presentation is the enhanced resolution of local velocity up to a pixel scale of the recorded images.



(a) Vector map presentation



(b) HSV chromaticity presentation

Fig. 8 Comparison of PIV velocity map results between the vector plot and the HSV chromaticity presentations

4 Conclusion

Deep Flow algorithm was successfully implemented in the optical flow analysis process of the classical 2D PIV. The preliminary test results using some typical synthetic and experimental particle images showed that the Deep Flow PIV algorithm was able to perform dense correspondences of the sub-image patches between 2 time-sequential recorded images even in the presence of rotation and/or shear deformations. Nevertheless, the computation time of the Deep Flow PIV was more or less comparable with the standard cross correlation PIV without recursive multi-pass multi-grid interrogation or deformation compensation strategy. The quality of recovered velocity distribution was also highly estimated and no visible deterioration of sensitivity in spatial velocity variation was observed even in strongly shear flow regions. As regards the visual presentation of PIV velocity maps, the new concept HSV chromaticity presentation of velocity presentation revealed some important advantages for the understanding of flow behaviors, in particular in the sensing of local flow directions and in the detection of periodic flow phenomena.

Acknowledgments

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