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Adaptive PIV algorithm based on seeding density and velocity information

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ABSTRACT

An adaptive particle image velocimetry (PIV) processing algorithm to increase local spatial resolution and obtain accurate results is presented. Adaptive sampling criterion is based on seeding density and the analysis of velocity information. The proposed methodology places more measurement points in the region where high seeding density exists or flow parameters vary drastically. This methodology is effective in PIV image processing, especially in non-optimal PIV experimental conditions. The working principle of the adaptive processing method in this paper is to generate spring force on the bias of the deviation between the ideal and actual distances of measurement points. Under artificial force, the sampling points are moved to desirable places to satisfy sampling density function. Sampling density function is important in processing and ingeniously conceived based on the combination of vorticity and velocity gradients. The viability of the method is elaborated through synthetic and experimental tests. The synthetic test verifies the effectiveness of the adaptive processing on the basis of flow information. The bias and random error can be reduced by 7.3% and 4.0%, respectively. The result of the experimental test shows that the sampling points and the interrogation window size can be arranged according to the spatial distribution of seeding density and the actual flow features. Compared with iterative window deformation method, spatial resolution is locally enhanced, and the robustness and reliability of the result are increased, particularly in poor seeding regions.

1. Introduction

Particle image velocimetry (PIV) has become the universal measurement technique to obtain instantaneous velocity and its derivatives, study physical flow mechanism, and design the contour of vehicles. PIV images are analyzed by segmenting the images into small interrogation windows and using the correlation method based on fast Fourier transform to obtain the resulting velocity [1,2]. The most important parameters for the conventional PIV processing are the size of the interrogation windows, the window deformation strategy, and the overlap factor. The result is located in a discrete position, which depends on the PIV processing parameters set by the users (i.e., velocity information can be obtained only at a fixed instance with finite resolution). This strategy, which commonly uses a regular mesh grid in the processing method, is irrespective of the underlying signal [3]. Almost all the flow causes variations of local velocity and inhomogeneity of seeding density. Hence, the traditional PIV algorithm using the uniform interrogation window cannot satisfy the actual requirement completely.

PIV has undergone considerable progress on the analysis algorithm over more than a decade, and many researchers have made efforts to improve the performance of the processing algorithm. One of the typical improvements, the iterative strategy, has been implemented in the PIV algorithm. Both the accuracy of the measurement and spatial resolution have been improved [4]. This method has been commonly adopted because of its significantly augmented measurement capabilities and high spatial resolution. Moreover, extensive research has been conducted on the iterative image deformation method to improve the performance of the algorithm. Astarita [5,6] studied the influence of interpolation schemes in the image deformation method and provided useful suggestions on selecting the interpolation scheme. Schrijer [7] researched the stability of the iterative process and concluded that a well-designed spatial filter would improve process stability and increase the reliability of the velocity result. The iterative method improves the quality of the PIV result, but the spatial resolution remains limited because the uniform sampling method ignored the variations of seeding density and velocity dataset. Hence, two approaches can be applied to obtain high resolution in the processing algorithm: Particle Tracking velocimetry (PTV) and its

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developments, and the adaptive method for making PIV correlation on the basis of seeding density and velocity information.

The disadvantages of the traditional PIV processing method are caused by the adopted uniform spatial interrogation windows, which resolve velocity. Therefore, the actual situation of particle seeding cannot be considered. PTV has the potential to obtain a much higher spatial resolution because the velocity is based on the seeding particle although it uses a similar method to acquire the experimental images as PIV. However, PTV has inherent disadvantages, such as low particle density; by contrast, particle density is much higher in PIV. A reliable heuristic method called super PIV has been proposed to solve this problem [8–10]. The method has been successfully applied in actual experiments, thereby demonstrating that the method can increase spatial resolution. However, the performance of this method has been limited by the predictor algorithm, particle identification process, and its localization algorithm. Further development along this direction was made by Westerweel [11] by applying a single-pixel ensemble correlation and has been extended further by Billy et al. [12] and Kähler et al. [13]. Recently, the method was applied to compressible flows with high Mach numbers [14]. This innovative method has also increased the spatial resolution significantly for many microscopic applications when the flow is mostly (quasi-) stationary. Another approach is the adaptive method. Rohaly et al. [15] proposed a hierarchical processing scheme, which increased the correlation area gradually until the signal-to-noise ratio satisfied the requirement. This scheme is the basis of the adaptive method that considers seeding density only. A universal method is to apply the 2D Gaussian function on the basis of the velocity information to the interrogation area to reshape the window [16,17]. Becker [18] followed this idea but designed the Gaussian function on the basis of an error model function. The adaptive method is further implemented by resampling the measurement points on the basis of seeding density and velocity information [19–21]. Theunissen et al. [19,20] relocated measurement points by using the 2D PDF method, whereas Yu et al. [21] used artificial force to adjust the locations of the measurement points.

Adaptive PIV algorithm is a research topic that has been attracting considerable interest. The concept of adaptive processing method has been recently applied in the tomography PIV by Matteo Novara [22]. The reliability of the adaptive method was verified when more sampling points were dynamically redistributed to better resolve the region where more spatial resolution can be obtained or need to be processed. So an adaptive PIV processing algorithm to increase local spatial resolution and obtain accurate results is presented in this paper. The proposed method utilizes a different approach with high performance to implement the adaptive procedure. The concept of the implementation is based on the authors' previous work [21]. But the seeding density and velocity information are combined to construct the sampling density function rather than based only on the seeding density in the previous work. The sampling points change gradually under the influence of the artificial spring force until they satisfy the requirement of the local sampling density. Using the proposed sampling method, more details of the flow can be resolved. The first section of this paper describes the detail and the procedure of the adaptive method. The sampling density of the velocity is also introduced in detail. The performance, reliability, and robustness of the proposed method are verified through processing synthetic and experimental images. The advantages of the proposed adaptive sampling method are also presented.

2. Adaptive algorithm

2.1. Construction of adaptive sampling criterion

The adaptive algorithm described in this paper samples the measurement points and is designed as a self-contained subroutine. The method can be added to the existing PIV processing algorithm with minimal modification, which is convenient for users to utilize and make some improvements. The intrinsic processing algorithm can be implemented to obtain the final result once the positions of sampling points are obtained. High quality and resolution results can be obtained by concentrating sampling points on the positions where they are most needed at the expense of a reasonable computational cost. Hence, the two main components of the adaptive processing method are an optimal sampling criterion and a strategy to redistribute the points. From this perspective, the adaptive criteria should be designed carefully.

The adaptive processing method is described in this paper. It can relocate the sampling points by adapting to the flow features and the particle density. Thus, the sampling criterion must be organized through a special method. The sampling criterion cannot be organized clearly given that researchers do not always know a priori what constitutes the complex flow structures of the problem. The computational errors of the cross-correlation first come to mind because cross-correlation is the principal method to process the PIV images. However, computational errors remain unclear and cannot instruct the sampling procedure directly. The computational errors of cross-correlation tend to increase in regions where seeding density is low or velocity changes rapidly. Thus, seeding density must be the main criterion to instruct the sampling procedure. Yu et al. [21] chose seeding density as the first candidate in their work to implement the sampling procedure, which demonstrated the reliability and robustness of the proposed adaptive method based on spring force model. The details are given in our previous work [21]. Velocity and its derivatives are considered in the construction of the sampling criterion in this paper. Velocity must be adapted after the first sampling procedure based on the seeding density because velocity information remains unclear before sampling the points. The adaptive sampling procedure based on the seeding density is the first step. The sampling procedure based on the velocity information is the second step. The adaptive mesh is used in computational fluid dynamics (CFD) to finely resolve flow feature.

A choice of characteristic flow parameters can be detected in CFD, such as velocity, density, pressure, and temperature. Hence, the solution-based adaption method adopted in CFD is usually based on solution features, such as gradients, curvature, or specific features of the flow field (e.g., shock waves and expansion waves). The velocity and its derivatives should be the best candidates for the adaptation given that PIV algorithm obtains only the velocity results. Moreover, a combination of suitable parameters is necessary. Therefore, velocity gradients should be used to detect viscous regions and vorticity to detect shear layers. A new distribution of sampling points can be generated based on the solution obtained from the first step of seeding density-based sampling distribution. This distribution is more suitable for capturing flow features. Hence, the key point of the adaptation procedure is the construction of the sampling density specification function, which specifies the distances between sampling points through the experimental region. The distributions of sampling points can be generated by the influence of the spring force once the function has been established.

Prior knowledge of the adaptive mesh in CFD presents that the combination of the flow feature should be considered. Otherwise, the sampling criterion may cause the sampling points to become excessively concentrated or sparse. Hence, an optional sampling