ASSESSMENT OF IMPROVED VOLUMETRIC PARTICLE TRACKING VELOCIMETRY

B. JOSHI[1,c], K. OHMI[2], K. NOSE[2]

[1] Dept. of Information Systems Engineering, Graduate School of Osaka Sangyo University, Osaka 574-8530, Japan
[2] Dept. of Information Systems Engineering, Osaka Sangyo University, Osaka 574-8530, Japan

[c] Corresponding author; Email: joshi_basanta@hotmail.com

KEYWORDS:
Main subjects: Flow visualization
Fluid: Hydrodynamics
Visualization method(s): Tomography
Other keywords: Volumetric reconstruction, Camera calibration, 3D particle tracking velocimetry, 3D PTV, MART reconstruction

ABSTRACT: The particle image based flow measurement has been accepted as a powerful diagonal tool in the experimental fluid mechanics. In particular, in recent years, the tomography based full 3D measurement methods are attracting more attention in that type of flow measurement. The objective of the present work is to incorporate this tomography based volumetric reconstruction technique in the particle tracking velocimetry and thereby performing full 3D flow mapping and measurement. The camera calibration required for tomographic reconstruction is carried out by the Soloff model [14]. The tomographic reconstruction of particle seeded flow is performed by a basic or accelerated MART algorithm using an iterative update scheme of voxel intensity. Then, a dynamic threshold binarization scheme is applied to the reconstructed voxel intensity distribution to extract the particles centroids, followed by a new validation scheme to remove the ghost particles generated as the by-product of the reconstruction. The reconstruction accuracy is further boosted by another filtering scheme. The performance of the developed volumetric reconstruction method is checked by using synthetic particle flow images with varied particle density.

INTRODUCTION. In many fluid mechanics applications, there is a special interest for non-contact time-resolved fully 3C3D (3 components of velocity in 3D space) measurement techniques. Most methods are based on seeding particles, which visualize the motion of flow and can be recorded by an imaging system. Among others, the particle image velocimetry (PIV) is a well established technique for the determination of fluid velocities [1]. By contrast, the particle tracking velocimetry (PTV) is another established method to determine the 2D or 3D trajectories of a large number of seeded particles in the flow. The latter approach is based on the detection of discrete particles in the images, the establishment of multi-image correspondence of same particles in the images sequence and the determination of particle trajectories by tracing the movement of same particles. In the case of 3D-PTV [2], there is one more corresponding step of same particles between the detection of discrete particles and the establishment of correspondence of particles, that is the spatial correspondences step in which the particles viewed by two (or more) stereoscopic cameras with different viewing angles are correctly paired and the 3D coordinates of the particles are calculated based on the triangulation. To calculate the 3D particle coordinates with accuracy and with high recovery ratio, a strict camera calibration model and a suitable numerical scheme for determining the calibration parameters are necessary. Furthermore, with an increasing number density of particles the maximum number of particles successfully traced from one frame to another is reduced because of the ambiguities met in the processes of particle detection and multi-image correspondence establishment [3].

In the present work, a new method is introduced which should work rather insensitively to the seeding density in contrast to other established 3D particle tracking approaches. The method is based on the tomographic reconstruction of the instantaneous volumetric distribution of particle field intensity calculated from simultaneously recorded multiple 2D projection images of the seeded particles, as in the case of the cross correlation based 3D tomographic PIV [4]. More specifically, the tomographic reconstruction is performed by iterative voxel intensity update techniques (MART) which is highly computationally intensive and memory inefficient. There are a couple of new ideas introduced to circumvent the use of memory intensive weighting matrices for 3D particle reconstruction. Mass et al. [5] used a method based on multiple projective transformations of each camera view into the object space that use the transformation parameters derived from the camera orientation. Atkinson and Soria [6] limited the use of weighting matrices in regions with particles by using the principle of multiplicative line-of-sight (MLOS). However, the cost intensive iterative process still exists. Using telecentric lenses and the combination of the epipolar geometry and the tomographic reconstruction scheme used by Soria and Atkinson [6], Kitzhofer et al. [7] introduced a new simplified algorithm which avoids the iterative update process and eliminates the cost intensive weighting matrix. In the present work, the tomographic reconstruction is basically performed by a standard MART algorithm but in the process of the voxel intensity update, the calculation is not done for all camera pixels as in the case of the MLOS based update. One more issue of every tomographic particle reconstruction method is the generation of ghost particles. The number of ghost particles depends on the number of cameras at different viewing directions. Methods to reduce the intensity and influence of these ghost particles have been introduced using the information contained in subsequent (future) exposures of a particle intensity field [8]-[9]. The present authors have also proposed a MART based tomographic reconstruction scheme with post-processing steps for reducing ghost particles [10].

The objective of the present work is the implementation of the tomographic reconstruction of a particle constellation from a limited number (three) of camera views with a high spatial resolution and proper suppression of ghost particles. The intensity variation in the image pixels are reconstructed into a 3D observation space divided into fine 3D voxel grid structure with a resolution adapted to the camera resolution and the particles are detected as voxel clusters with gray value information. The present authors have introduced a special algorithm to suppress the effect of ghost particles and enhance the reconstruction process. The product of the image intensity for a particular voxel and volume of the all the detected particles are chosen as the criteria for the segregating real and ghost particles. The real presence of a particle is confirmed if the product of the intensity in the spatial image sequence and the volume exceeds some threshold value.

TOMOGRAPHIC RECONSTRUCTION. The calculation of the pixel intensity is done from the voxel intensity distribution of the 3D illuminated volume. The recorded intensity P_i on each pixel i of the camera can be expressed as the sum of a weighting matrix W_{ij} storing the contribution of each voxel j to a pixel i multiplied by the voxel intensity I_j along the line-of-sight as in Eq. 1.

$$P_i \approx \sum_j W_{ij} I_j \tag{1}$$

The weighting matrices are determined by using the line of sight of camera, a voxel in object space, a pixel in the image plane. In the real experimental scenario, there is a limited number of synchronized camera views and the CCD arrays records the projections of a common laser illuminated particle seeded in the fluid volume. So, the problem is reversed and the reconstruction of 3D particle constellation using the intensity variations on image planes is necessary. This results in an underdetermined system of linear equations such that an iterative correction of the voxel intensity is required, which must be performed until the variables of the equation converges within a defined error limit. The MART reconstruction involves multiplicative correction to voxel intensity I_j at iteration k based on the projected pixel intensity P_i of the camera as given by Eq. 3. The intensity of each voxel is corrected to match the intensity of one single pixel at a time.

$$I_j^{k+1} = I_j^k \left(\frac{P_i}{\sum_j W_{ij} I_j^k} \right)^{\mu W_{ij}} \tag{2}$$

where μ is a relaxation parameter.

When the intensity of each pixel from one camera image is projected to the object space along the line of sight, those voxels which falls on the line of sight gets the gray value equivalent to the contribution of each voxel j to each pixel i. This contribution factor is expressed by the weighting matrix W_{ij}, which depends on the camera orientation and the measurement volume configuration. Therefore, the camera calibration parameters are first estimated by using the non-linear model of Soloff [14]. Once the camera calibration parameters are determined, a mapping curve relating each center of pixel to the voxels along the line of sight is calculated such that it intersects at specific points on XY plane in the voxel space. In the present work, the Euclidian distance between the intersection point and the voxel center is calculated and the weight of that voxel is given as a Gaussian function of the distance as shown in Fig. 1 and Eq. 3.

$$W_{ij} = \exp(-k * D) \tag{3}$$

Obviously, not all the voxels of the grid fall on any line of sight. Therefore, the space complexity in the calculation can be reduced as there are only limited voxels in the line of sight of a pixel, say 5 voxels, in each z plane. In the next step, every pixel of camera image is again projected to the voxel domain by applying the iterative correction scheme in Eq. 2. The same process is repeated for all the camera views. Then, the whole process is again and again repeated until a certain quality of reconstruction is attained. As a result, the voxel space contains multiplicatively accumulated image intensity information of the instantaneous particle constellation. Only voxels at valid particle positions will show high values theoretically but there is presence of the ghost particle in the real reconstruction.

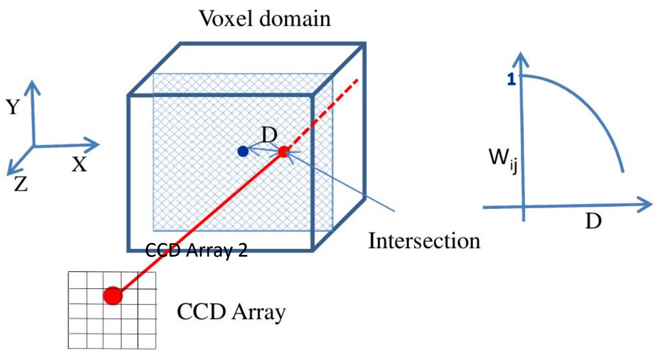

Fig. 1 Estimation of weighting matrices.

PARTICLE IDENTIFICATION. A by-product of every tomographic particle reconstruction method is the generation of ghost particles. The number of ghost particles depends on the number of cameras at different viewing directions. In the case of the tomographic PIV, several methods to reduce the intensity and influence of the ghost particles using the information contained in the subsequent exposures of a particle intensity field during the reconstruction process have been introduced [8]-[9] but they are only applicable when followed by the cross correlation image pattern tracking. The aim of the PTV is the reconstruction of individual particle paths, thus it is highly necessary to detect and delete ghost particles. For this purpose, some efforts have been made in the current work to enhance the reconstructed volume and thereby extract the real particles from the reconstructed voxel space. At first, the global threshold binarization on the basis of a fixed threshold intensity level is conducted which not only removes some of the ghost particles but also the low intensity real particles. So, a more versatile dynamic threshold binarization [11] is finally adopted to detect particle constellations and followed by the 22-neighbors labeling scheme and the particle centroid calculation process. Each particle centroid in the voxel space can be projected into the camera image planes and the corresponding pixel in each image space can be identified by using epipolar geometry. If a particle in a voxel space is visible from all the cameras, then it can be seen in all those camera views when back projected from the voxel space to the pixel plane. But the ghost particles cannot be properly back projected in all the camera views. This principle is considered as a major criterion for the filtering of ghost particles.

RESULT AND DISCUSSION. For the verification of the proposed methodology, the present authors have chosen the 3D PIV Standard Images data available from the Visualization Society of Japan [12]. These data are composed of various time-series sets of synthetic particle images generated from direct numerical simulation (DNS) results of a 3D impinging jet in a square cavity. Most of the 3D images are generated for three camera views. One advantage of this type of standard images is that the particle image data come with the exact particle coordinates data, so that one can compare any particle tracking results with the correct (theoretical) data. From these 3D standand image data, two image series (numbered as 352 and 351) were choosen for the present tests as they come from the same flow volume with the same viewing angle but with different particle density. The images size is 256x256 pixel and the three cameras are fixed at 30°, 0° and -30° with respect to the normal axis to the view plane. The first frames of the standard image #352 are shown in Fig. 1.

The calibration images and the accompanying data to the calibration images available in the image dataset #352 were used to determine the camera calibration parameters and generate the mapping function. Based on this mapping function, the weighting matrices of the voxels along the line of sight were estimated, which were then used to perform the voxel based reconstruction. The volumetric reconstruction was carried in the voxel domain of 20*20*10 mm^3 and the variation of voxel intensity was observed during the reconstruction process. The voxel grid size was fixed at 360*260*200 voxels, with the voxel size being 0.01mm^3.

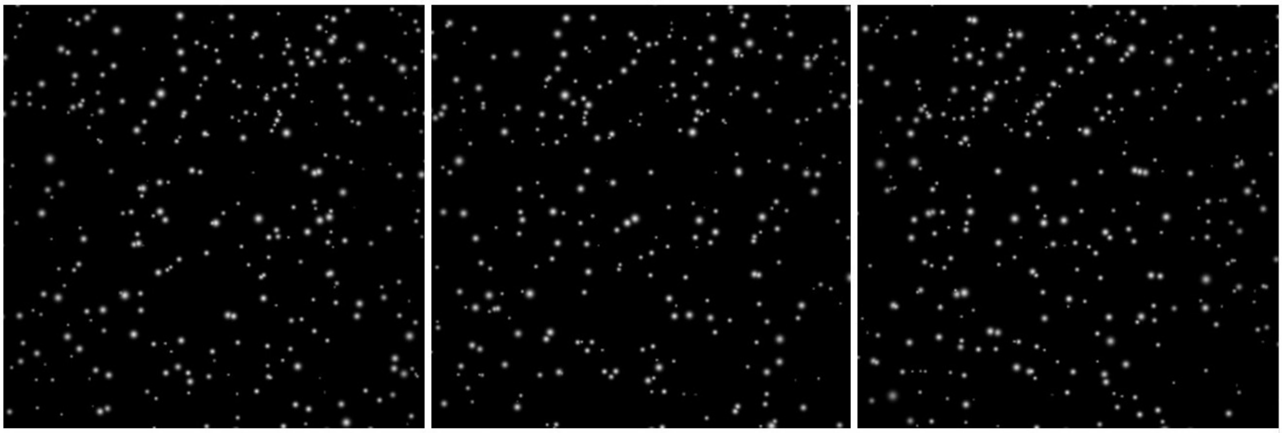

Fig. 2 PIV standard images (Series 352) viewed by three cameras with viewing angles of 30° (left), 0° (center) and -30° (right)

The voxel intensity was initialized as unity at all the voxels and then iteratively updated according to the MART or SMART algorithm. This update calculation was generally completed in 10 iterations for a fixed value of relaxation factor μ of 2.0. After this step of reconstruction, the voxel intensity was normalized in the range from 0 to 1.0. Then, the global threshold or dynamic threshold binarization [11] was applied to the reconstructed voxel intensity, followed by the 22-neighbors labeling process and the centroid calculation of individual particles. Finally the calculated centroid coordinates were checked by a new back-projection based validation scheme with the concept of multiplicative first guess [13]. A typical set of reconstruction results are shown in Fig. 3, which are obtained from the PIV standard image #352 and the particle number density is 0.0046 ppp. In this figure, the particle constellation is displayed in the form of normalized and color-coded voxel intensity. The threshold level of the global threshold binarization (left) is 0.19.

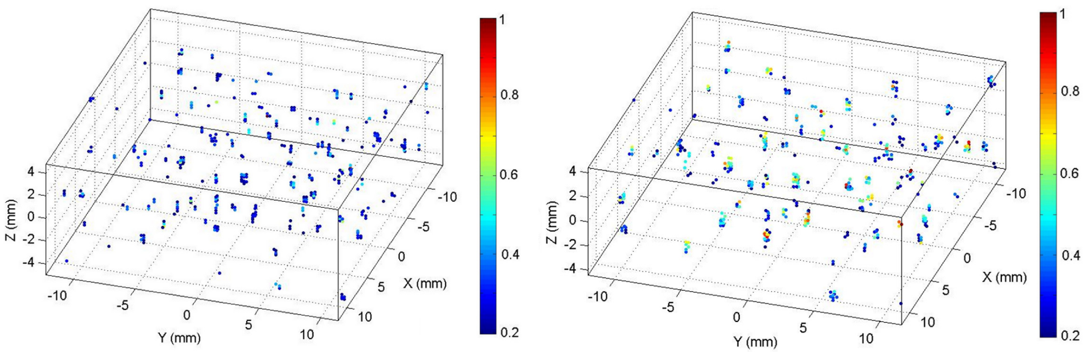

Fig. 3 Reconstruction of particles constellation performed by the global threshold binarization based (left) and the dynamic threshold binarization based (right) schemes for standard image #352.

It is observed from this figure that with these improved reconstruction scheme, the ghost particles are effectively filtered out and there is appreciable increase in the number of the particles which nearly corresponds to the real number of particles. The accuracy of this ghost particle suppression scheme is ascertained by a direct comparison of centroids between the detected particles and the actual (theoretical) particles. From this comparison it is confirmed that the rms error of the reconstructed particle coordinates falls within a 0.10 mm range. In the next step, to check the quality of reconstruction furthermore with a larger number of particles, the particle image data of the PIV standard image #351 were also investigated with the same processing method. It is observed from this second test that the larger number of particles gives rise to increase in the computation time for the voxel intensity reconstruction as well as for the particles extraction process. The particle reconstruction results with the global threshold binarization based and the dynamic threshold binarization based schemes are shown in Fig. 4, which also indicates a good quality of reconstruction even for the higher particle number density of 0.03 ppp. But the rms error of the particle centroid coordinates is also increased up to a level of 0.27 mm.

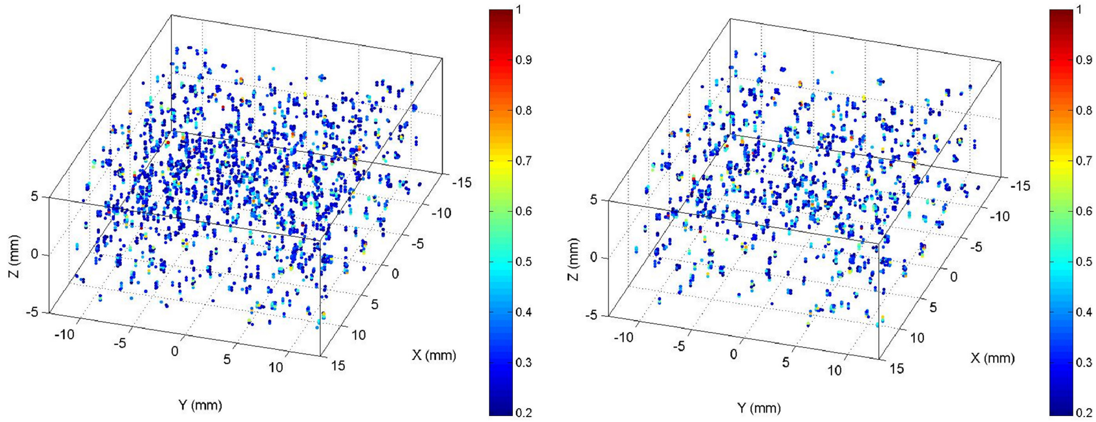

Fig. 4 Reconstruction of particles constellation performed by the global threshold binarization based (left) and the dynamic threshold binarization based (right) schemes for standard image #351.

CONCLUSION. A new tomographic reconstruction scheme of the particles constellation in a 3D measurement volume based on the multiple instantaneous camera views of the observation volume has been developed for the use in 3D particle tracking velocimetry. The points of the new scheme are the new simplifed method of the weighting matrices estimation, the dynamic threshold binarization based particle extraction method and the back projection based validation method using the epipolar constraints and the concept of multiplicative first guess. The performance of the new tomographic reconstruction scheme was tested with the PIV standard images. The new scheme appears to have significantly improved the reconstruction quality by decreasing the number of ghost particles and increasing the precision for the estimation of the particle centroids. The major issue in the current implementation is the computation time required for the enhancement of recontructed voxel intensity and the detection of particle centroid.

References

1. Adrian R.J. *Twenty Years of Particle Image Velocimetry.* Experiments in Fluids. 2005, **39**, pp.159-169
2. Willneff J. Grün A. *A new spatio-temporal matching algorithm for 3D particle tracking velocimetry,* Proc. of the 9th Int. Symp. on Transport Phenomena and Dynamics of Rotating Machinery. Hawaii, USA, 2002
3. Malik N.A. Dracos Th. Papantoniou D.A. *Particle tracking velocimetry in three-dimensional flow.* Experiments in Fluids. 1993, **15**, pp.279-294
4. Elsinga G.E. Wieneke B. Scarano F. Schröder A. *Tomographic 3D-PIV and Applications.* in Particle Image Velocimetry: New Developments and Recent Applications, Springer, 2008
5. Maas H.-G. Westfeld P. Putze T. Bøtkjær N. Kitzhofer J. Brücker C. *Photogrammetric techniques in multi-camera tomographic PIV.* Proc. of the 8th Int. Symp. on Particle Image Velocimetry. Melbourne, Australia, 2009
6. Atkinson C. Soria J. *An efficient simultaneous reconstruction technique for tomographic particle image velocimetry.* Experiements in Fluids. 2009, **47**, pp.553-568

7. Kitzhofer J. and Brücker C. *Tomographic particle tracking velocimetry using telecentric imaging.* Experiements in Fluids. 2010, **49**, pp.1307-1324
8. Novara M. Batenburg K.J. Scarano F. *Motion tracking enhanced MART for tomographic PIV.* Measurement Science and Technology. 2010, **21**, p.035401
9. Atkinson C. Buchmann N. Stanislas M. Soria J. *Adaptive MLOS-SMART improved accuracy tomographic PIV.* Proc. of the 15th Int. Symp. on Applications of Laser Techniques to Fluid Mechanics. Lisbon, Portugal, 2010
10. Joshi B. Ohmi K. Nose K. *Investigation of volumetric reconstruction technique for 3D particle tracking velocimetry,* Proc. of the Pacific Symposium on Flow Visualization and Image Processing, Moscow, Russia, 2011
11. Ohmi K. Li H.-Y. *Particle tracking velocimetry with new algorithms*. Measurement Science and Technology, 2000, **11**, pp.603-616
12. Okamoto K. Nishio S. Saga T. Kobayashi T. *Standard images for particle image velocimetry*. Measurement Science and Technology. 2000, **11**, pp.685-691
13. Worth N.A. Nickels T.B. *Acceleration of Tomo-PIV by estimating the initial volume intensity distribution*. Experiments in Fluids. 2008, **45**, pp847-856
14. Soloff S.M. Adrian R.J. Liu Z.-C. *Distortion compensation for generalized stereoscopic particle image velocimetry*. Measurement Science and Technology, 1997, **8**, p.1441-1454