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Performance of Particle Tracking Velocimetry (PTV) with Streak Images

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Abstract

A new concept developed for the performance of Particle Tracking Velocimetry by using sysnthetic streak images. To evaluate the PTV performance with long exposure particle images, synthetic particle streaks of Hill's vortex are generated by integration of Gaussian particle image profile with normalized exposure time. To evaluate the performance of PTV algorithm, the match yield and the match reliability in quantitative analysis of PTV are adopted. In addition, the performaces of PTV and PIV for particle streak images are compared with variations of particle image diameter, particle image intesnity and particle image density with different exposur times. The results show that reliabilty and match yield were 98% and 75% and dropped to 50% and 35%, respectively, due to long exposure time. PTV performance can be justified with its peak-finding criteria for normalized exposure time up to 0.05. The range of the appropriate normalized exposure time tested in this study is from 0 to 0.14. As the exposure time increases from 0.43 to 1.0, PTV can not longer efficiently resolved the flow. The comparision with PIV shows that the mesurement uncertainity is higher as compared to PTV. PTV performance validate the results only for short exposure time whereas PIV performed also with longer exposure time, with the measurement uncertainity range form 0.3 to 7.32. Under the appropriate exposure range, PIV performs as good as PTV for long exposure images.

1-Introduction

In the last decades, the great invention in the fluid mechanics obtained for the flow visualization are the Particle Image Velocimetry (PIV) and Particle Tracking Velocimetry(PTV). As described in Raffel et al. (2018) and Adrian et al. (2011), PTV and PIV are nonintrusive, whole-field, quantitative flow visualization techniques for veloicty measurements of the flows. The main difference in the two methods is that PTV tracks the motion of individual particles whereas PIV measures the average displacement of a cluster of particles. PIV method will be preffered in the case of high density medium and small velocity gradient inside a cross-correlation interrogation window. The computational process is very fast because the cross-correlation function is the simple algebraic product of logical variables. The advantages and disadvantages of this method as compared to the four-frame method; the speed and the velocity recovery ratio are improved. The cross-correlation algorithm performs less accurate to strongly rotation and/or high shearing flow images. On the otherhand, PTV is prefferd for low density medium and moderately distributed particles, and with the same particle image it can achieve higher spatial resolution than PIV.
In the last two decades, different particle tracking algorithms proposed by the researchers as Nishino et al. (1989) described the automated digital image processing technique in three-dimensional particle tracking velocimetry. With the help of this technique three dimensional instantaneous velocity components were measured in an unsteady laminar Couette flow between two concentric cylinders. The results was justified with the measurement uncertainties evaluated systematically. Another type of particle tracking algorithm is the cluster matching. In this technique, the first frame particle and the candidate particle of the second frame forms a cluster together with their respective neighbours. Best matches criteria based on the deformation index specified between every pair of clusters. The deformation index proposed by Okamoto et al. (1995) propose a spring model technique using the elastic restoring force. This algorithm is applied on the flow fields which charactarized such as rotation, shear and expenstion. This technique was verified with the synthetic data for both 2D and 3D-flow, and high degree of accuracy can be achieved for 2D and 3D evaluation. A Muti-layer neural network proposed by Grant et al. (1995) is designed for double-exposure single frame particel images. The basic concept can be extended for the use of single-exposure image pairs.

The demerit point is that only basic learning of the estimation on the flow field to be considered. A relaxation method proposed by Baek et al. (1996) finds the most sutable connection with the reference particle with the assumtion that the displacements are similar with its neighbour particles (also called quasi-rigidity condition). This algorithm has an ability to evaluate wide range of deformation of particle distribution. A hybrid digital particle tracking velocimetry technique by Cowen et al. (1997) used in digital particle tracking velocimetry (DPTV) based on cross-correlation digital particle image velocimetry (DPIV). This approach provide the alternative method of interpolation of randomly located velocity vectors. This technique allows the the direct measurement of mean squared fluctuating gradiaents and capable to measure the turbulence statistics.

Another concept used in particle tracking is the use of different types of cost functions. One example is the PTV using Hopfield neural network proposed by Knaak et al. (1997). With this approach, the fluid mechanics of hydraulic turbomachinery and artificial heart valves were investigated. For valid particle matching, a particular cost function is elaborated and then mapped onto a two-dimensional Hopfield network. In comparison with classical nearest neighbor technique, Hopfield neural network provides better amount of correct match pairs. Shen et al. (2001) utilizes fuzzy logic on particle tracking velocimetry for simultaneously measuring the velocities and sizes of falling particles. This method can recognize particles from the image not only with high recognition ratio but also with high precision even the particles are overlapped very heavily. The method is examined by a numerical experiment with computer-generated images. Genetic algorithm (GA) implemented by Ohmi et al. (2009) is based on the movement of a group of particles and it is more feasible for increased particle image density. In this study, the particle images are recorded and identified to be used for GA, and the best-match in particle pairs are found by minimization of the fitness function depends upon the total sum of squares of particle displacements or some other geometrical distances. The results are acceptable if the physical problem can be carefully solved by genetic encoding. The disadvantage of this genetic algorithm is the high usage of random numbers in the computation, which results in high computational cost. Ohmi et al. (2010) described ant colony optimization (ACO) method for the particle tracking. In this approach particle cluster matching in its mechanism of individual particle matching. This method works well with the minimization strategy of the particle cluster relaxation.

In Particle Image Velocimetry(PIV), two types of lasers are used continuous wave (CW) and pulsed lasers. Most commonly used lasers in continuous wave are argon–ion lasers producing in the range of few watts whereas, pulsed lasers are frequency-doubled Nd:YAG (neodymium: yttrium aluminum garnet). The pulsed lasers have short duration of the laser pulse, typically a several nanoseconds, which produces short exposure time and expensive in cost whereas, the low cost lasers have long exposure time approximately in milliseconds and lower cost. Particle image generated by long laser exposure elongates into streak. PTV performance depends on how precise the individual particle image can be identified and located by the peak-finding algorithm. In practice, hardware limitations sometimes cause image streaking due to long exposure time, but few studies have been focused on effect of image streaking to the performance of PTV. In this paper, the performance of PTV is evaluated by synthetic streak images. The goal of this study is to understand how the particle image streak is created and discuss the influence of the particle image streaking to the performance of PIV and PTV using synthetic particle images. The comparison between PIV and PTV is also discussed by setting the parameters particle image diameter, particle image density and particle image intensity with different exposure time.

2-Method

2.1-Synthetic Particle Image Generation

In this research the prerequisit step to produce particle streak is the particle image generation. Because the particle streak can be simulated as a normal particle image with a minimum exposure time (integration by time) and stretch by extending the integration time interval to the extreme condition (long streak). Synthetic particle image generation is based on the known characteristics: diameter, shape, dynamic range, spatial density and image depth with respect to each other. The shape of the individual particle image is described by the Gaussain intensity profile as described in Raffel et al. (2018),

$$I(x,y)= I_0 \exp\left[\frac{-(x-x_0)^2-(y-y_0)^2}{(\frac{1}{8})(d_\tau)^2}\right] \tag{1}$$

where the center of the particle image is located at (x_0, y_0) with a peak intensity of I_0. For simplicity the magnification factor between object plane and image plane is chosen to be unity, such that (x, y) ≡ (X, Y). The particle image diameter, d_τ, is defined by the e^{-2} intensity value of the Gaussian bell which by defination contains 95% of the scattered light.

To evaluate the PTV performance with streak images, synthetic images of Hill's vortex are generated by MATLAB code. Hill's vortex is highly rotational and has strong velocity gradient as compared to a simple pipe or duct flow. Therefore, it is adopted as a good evaluation tool for the PTV performance. The method is used to generate the random particle coordinate list for four consecutive frames with constant time interval of 0.6. The analytical solution of Hill's vortex in terms of velocity components V_x and V_y are

$$V_x = U \cdot \left(\frac{x}{R}\right) \cdot \left(\frac{y}{R}\right) \tag{2}$$

$$V_y = U \cdot \left(1 - \frac{y}{R}\right)^2 - 2 \cdot \left(\frac{x}{R}\right)^2 \tag{3}$$

where x and y are the random particle center coordinates(pixels), U is the velocity of random particles which was set to pixels / time = 15. R is the radius of the vortex set to 700 pixels.

2.2- Synthetic Streak Generation

Particle streak (PS) is defined as the tracer particles imaged by the long exposure time t_{exp}. Particle image streak is produced by the integration of 2D-Gaussian function which represents a particle traveling along a trajectory X(t) and Y(t), t∈ $(0, t_{exp})$ during the exposure time t_{exp}. Streaks of this vortex was produced by the time-integral to model the 2D Gaussian function described Voss et al. (2012) as,

$$G(x,y) = \frac{1}{t_{\exp} - t_0} \int_{t_0}^{t_{exp}} G\Big(\big(x - X(t)\big) + \big(y - Y(t)\big)\Big)\, dt \tag{4}$$

where G (x,y) is a two-dimensional Gaussian distribution. The result is an image that contain information on the particle trajectories recorded during the exposure time as shown in Figure 1.

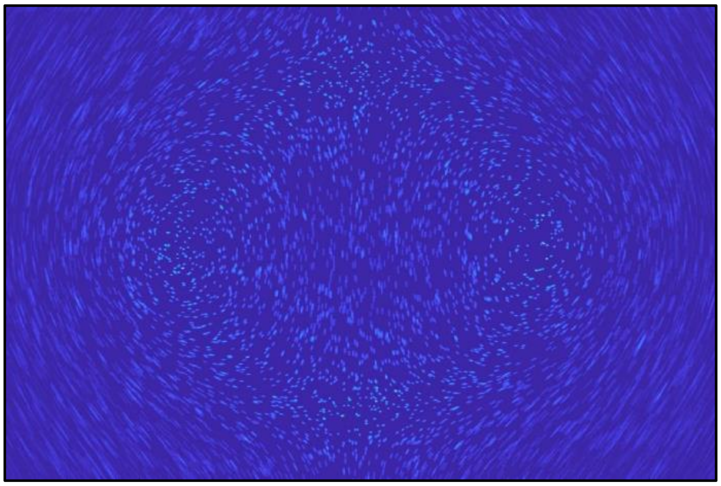


Figure 1: Particle streaks generation with 8340 particles at the normalized exposure time of 0.4

2.3- PTV-Algorithm and The Performance Evaluation Method

Particle image tracking algorithm tested in this study is the vision-based PTV (VB-PTV) algorithm by Lei et al. (2012). This vision-based PTV algorithm is based on three matching rules: proximity, exclusion and similarity. Proximity prefers a smaller distance match as compared to a long one. Exclusion requires one-to-one mapping between characteristics in multiple frames. Similarity matches particle images to the similar ones. To evaluate the performance of VB-PTV algorithm, two commonly used parameters in quantitative analysis of PTV were adopted in this study: reliability(M_R) and match yield (M_Y) defined as,

$$M_R = \frac{\text{Matches Correct}}{\text{Matches Found}} \quad (5)$$

where matches correct is the total number of correct vectors found by tracking algorithm and matches possible is the total number of particle pairs between the frames.

$$M_Y = \frac{\text{Matches correct}}{\text{Matches Possibles}} \quad (6)$$

where matches found is the total number of vectors (correct and incorrect) identified by the PTV algorithm. Each match results in a vector found by the tracking algorithm, which is one pairing of particle center locations from two consecutive frames.

All tests were done by increasing the normalized exposure time from 0 to 1.0. For the PTV tracking algorithm tested in this study, the interrogation window size is set to 64 by 64 pixel^2, the Mask size is 5 pixels, the particle diameter is 3 pixels. The contrast threshold is set to 1, outlier tolerance is 1 and the outlier threshold is set to 1.5. In the present work, the number of particles are 8340 and the image area 1000 by 1000 pixels^2. Therefore, the particle image density is 0.0083. This low value suggests that the synthetic image is free from the two-phase flow effect (Lei et al. (2012)).

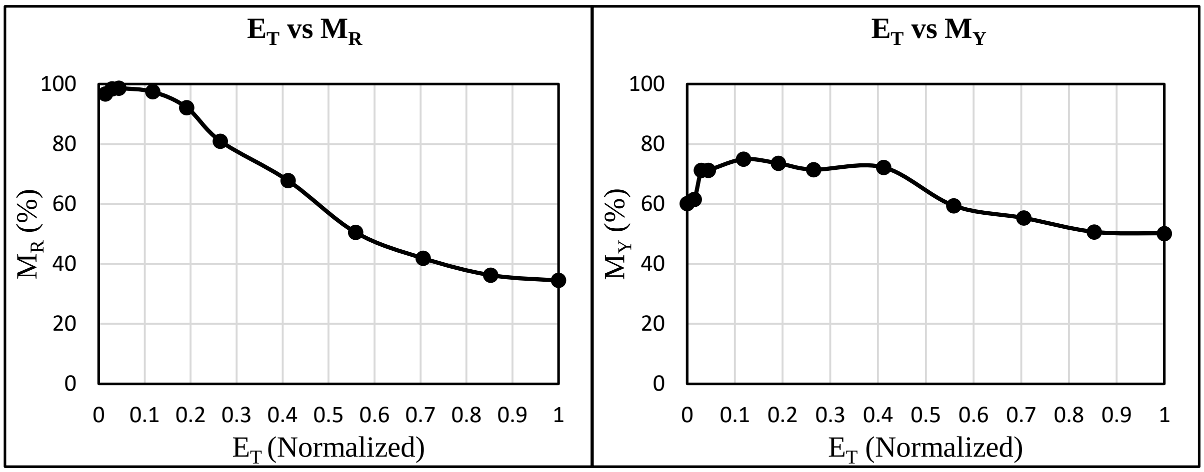
This research evaluated the reliability and match yield of the PTV algorithm as well as to compare the PIV and PTV performance on the basis of exposure time by the variation in four parameters particle image diameter, particle image intensity, particle image density and kept the other two parameters constant simultaneously and discussed in results section. To compare the performance between PTV and PIV, the particle image diameter was set within the range from 2 to 6 pixels with constant particle image intensity of 0.5 pixel and particle image density 0.01 for PTV and 0.02 for PIV, respectively. For particle image intensity set within the range from 0.1 to 1.0 pixel, the constant particle image diameter is 2 pixels and the particle image density is 0.02. For the case of particle image density within the range from 0.01 to 0.05 pixel, particle image diameter was fixed to 2 pixel and particle image intensity was set to 0.5 pixel. Detailed discussion is presented in the following result section.

3-Results

3.1 PTV performance

a. Match Yield and Reliability

The results of the streak images analyzed with PTV performance show that the match reliability (M_R) and match yield (M_y) are kept at 98% and 75%, respectively, for the range of the normalized exposure time(E_T) is from 0 to 0.1. As the normalized exposure time increases from 0.1 to 1, the match reliability and match yield drop to 50% and 35%, respectively, as shown in Figure 2. Based on these results, the threshold of exposure time in this study is proposed to be smaller than 0.05, since the particle image center location from the elongated particle image still satisfies the PTV peak-finding criteria and the high PTV performance can be kept.



(a) Reliability (b) Match Yield

Figure 2: Streak analysis by Reliability and Match yield on the basis of exposure time

b. Particle Image Diameter

Table 1 and Figure 3 illustrates the measurement RMS (root-mean-squared) uncertanity with respect to particle size and exposure time. The results suggest the existance of an optimum particle image diameter for the evaluation of PTV performance at constant particle image intensity of 0.5 and particle image density of 0.01 (1/pixel^2). Observations shows that with small particle size of 2 and 3 pixel in diameter, the PTV performance can be justified for long exposure time due to less particle overlaping and easier particle image identification by peak-finding algorithm. For larger particle size from 4 to 6 pixels, results in table 1 shows the worse results for long exposure time because of high overlaping ratio and PTV unable to identify the particle locations.

Table 1 The effect on PTV results from the normalized exposure time on the particle image diameter

Particle Image Diameter	Exposure Time	RMS	Exposure Time	RMS	Exposure Time	RMS	Exposure Time	RMS	Exposure Time	RMS
2	0	1.42	0.14	1.25	0.43	1.83	0.71	1.78	1	1.87
3	0	1.18	0.14	1.78	0.43	1.86	0.71	1.92	1	NA
4	0	1.34	0.14	1.77	0.43	1.89	0.71	NA	1	NA
5	0	1.77	0.14	1.61	0.43	NA	0.71	NA	1	NA
6	0	1.56	0.14	1.92	0.43	NA	0.71	NA	1	NA

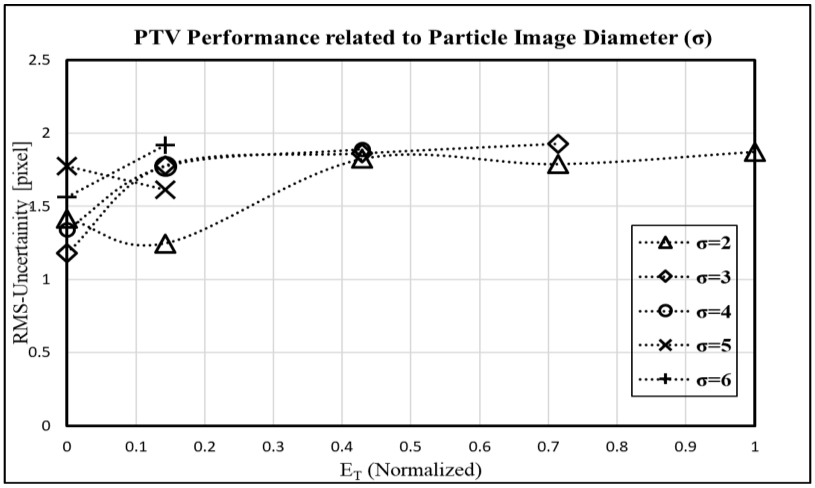


Figure 3: Measurement Uncertainity (RMS random error) for PTV with particle image diameter with respect to varying exposure time

c.Particle Image Intensity

To illustrate the PTV results with respect to particle image intensity by varying exposure time with constant particle image diameter of 2 pixel and image density of 0.02 (1/pixel^2) as shown in Table 2 and Figure 4. PTV performance were evaluated by changing the normalized particle image intensity from 0.2 to 1 with different exposure times. The results show that PTV performance is justified from intensity 0.2 to 0.4 for long exposures because the image intensity within the range is good for particle image identification, whereas worse conditions was observed for the range of 0.5 to 1.0 due to over exposure.

Table 2 The effect on PTV results from the normalized exposure time on the particle image intensity

Particle Image Intensity	Exposure Time	RMS	Exposure Time	RMS	Exposure Time	RMS	Exposure Time	RMS	Exposure Time	RMS
0.2	0	1.29	0.14	1.82	0.43	1.69	0.71	1.78	1	1.74
0.3	0	2.76	0.14	1.56	0.43	1.89	0.71	1.53	1	1.67
0.4	0	1.54	0.14	1.41	0.43	1.38	0.71	1.31	1	1.79
0.5	0	2.11	0.14	1.49	0.43	1.59	0.71	1.59	1	NA
0.6	0	0.79	0.14	2.74	0.43	2.46	0.71	1.01	1	NA
0.8	0	3.14	0.14	1.42	0.43	NA	0.71	NA	1	NA
1.0	0	2.15	0.14	1.42	0.43	NA	0.71	NA	1	NA

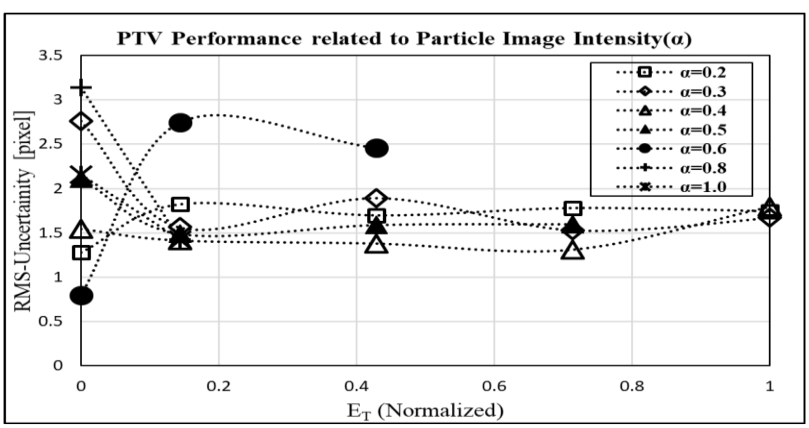


Figure 4: Measurement uncertainity (RMS random error) for PTV with particle image intensity with respect to varying exposure time

d.Particle Image Density

PTV performance was also investigated by changing the particle image density from 0.01 to 0.05 (1/pixel^2) with different exposure times at constant particle size of 2 pixel and normalized particle image intensity of 0.5 as shown in Table 3 and Figure 5. The results show that the probability of valid displacement detection increases when more particle image pairs enter into the tracking algorithm for short exposure time of 0.01 and 0.015, whereas the worst performace was found at high image density from 0.02 to 0.05 (1/pixel^2) and long exposure time. This is because PTV is based on the peak-finding algorithm to identify the particle image locations, and it is difficult to identify the particle image locations accurately with particle streaks generated by long exposure time.

Table 3 The effect on PTV results the normalized exposure time on the particle image density

Particle Image Density	Exposure Time	RMS	Exposure Time	RMS	Exposure Time	RMS	Exposure Time	RMS	Exposure Time	RMS
0.01	0	1.35	0.14	1.62	0.43	1.84	0.71	1.61	1	2.17
0.015	0	2.29	0.14	1.06	0.43	1.52	0.71	1.58	1	1.77
0.02	0	0.91	0.14	1.97	0.43	1.32	0.71	1.50	1	NA
0.025	0	2.62	0.14	1.17	0.43	1.02	0.71	NA	1	NA
0.03	0	4.02	0.14	0.98	0.43	1.12	0.71	NA	1	NA
0.04	0	0.71	0.14	NA	0.43	NA	0.71	NA	1	NA
0.05	0	0.74	0.14	NA	0.43	NA	0.71	NA	1	NA

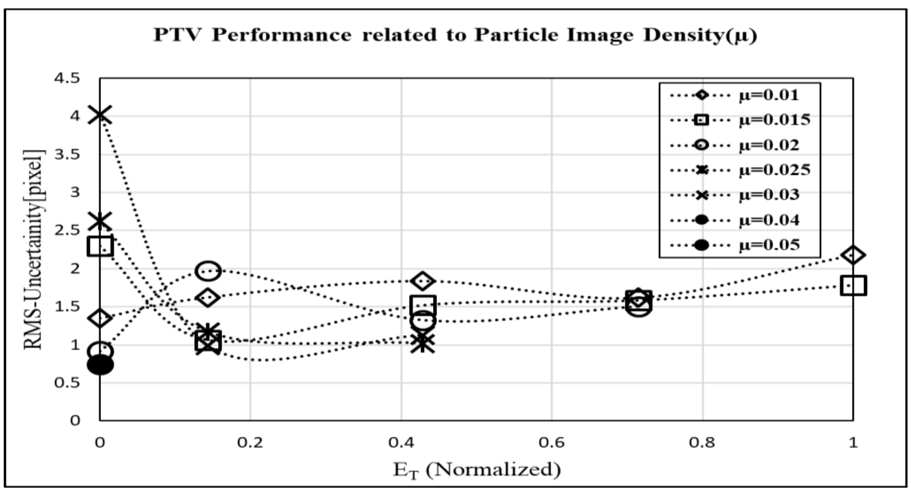


Figure 5: Measurement uncertainity (RMS random error) for PTV with particle image density with respect to varying exposure time

3.2 PIV Performance

a.Particle Image Diameter

Figure 6 shows the PIV performance evaluated by measurements of RMS-uncertainity on the basis of the particle image diameter range from 2 pixels to 6 pixels with different exposure times. The results show that RMS-uncertainity increases as the particle size increases with exposure time. The reason behind this may be due to the "peak-locking" effect, which means the displacement bias error has a periodic pattern on integer pixel intervals. Mostly it is caused by improper sub-pixel displacement estimation.

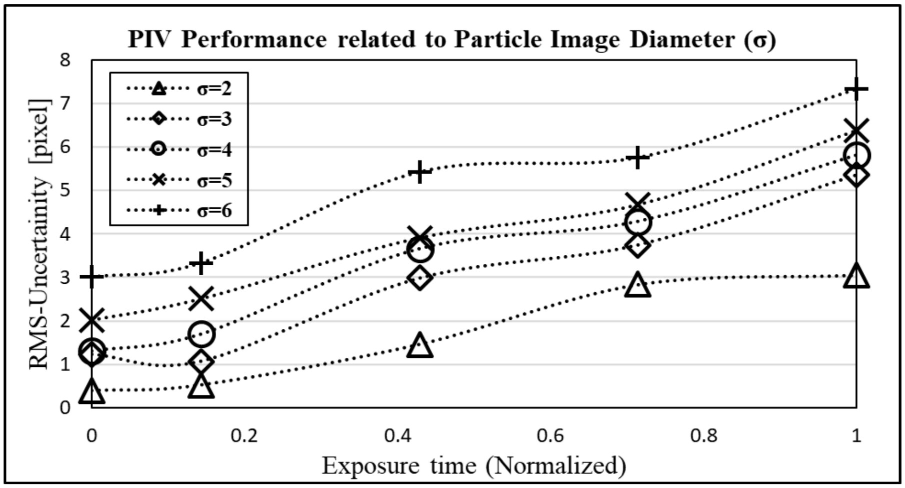


Figure 6: Measurement uncertainity (RMS random error) for PIV with particle image diameter with respect to varying exposure time

b.Particle Image Intensity

Particle image generation based on Gaussian function and its peak depends upon the particle image intensity. Therefore, it is necessary to study the effect of intensity of particle image to the performance of PIV. Figure 7 represents the measurments of RMS-uncertainity on the basis of particle image intensity with different exposure times. The results show that RMS-uncertainities increase with the increase of exposure time, because exposure time based on the time-integral of the Gaussaain function. Therefore, as the length of streak increases, the intensity also increased. PIV performed a better space whereas for short exposure time and justify the partcle image intensity.

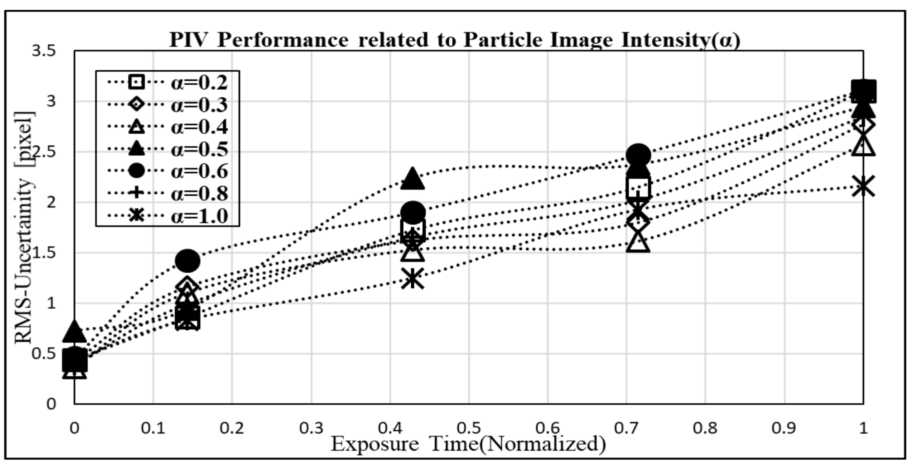


Figure 7: Measurement uncertainity (RMS random error) for PIV with particle image intensity with respect to varying exposure time

c.Particle Image Density

To evaluate the PIV images, the particle image density represents two effects. One effect is the probability of the correct diplacement detection increses with the increase of particle image density that is more image pairs involved in the correlation calculation . Other effect is the direct influence on the measurement of uncertaininty. Figure 8 represents the measurements of uncertainity on the basis of particel image density with different exposure time at constant particel size of 2 pixel and intensity of 0.5. The results show that at high image density and short exposure time PIV performs better.

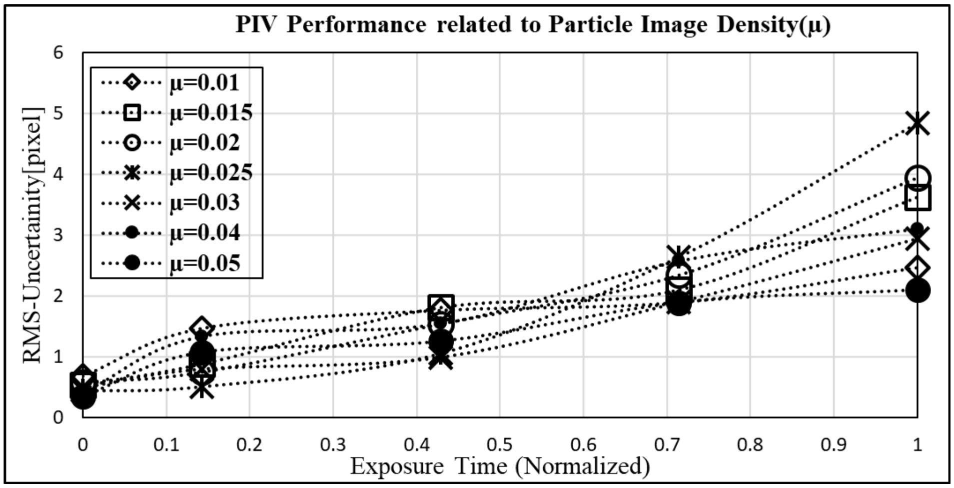


Figure 8: Measurement uncertainty (RMS random error) for PIV with particle image density with respect to varying exposure time

4-Comparision between PTV and PIV

From the above discussion, comparision between PTV and PIV can be made based on three parameters: particle image diameter, particle image intensity and particle image density with respect to exposure time. Observation of the results shows that PTV performed better at low values of the above parameters and low RMS-uncertianity values obtained for long exposure time as compared to PIV. In case of higher values of these parameters, the PTV stopped but PIV still worked with higher RMS-uncertainity values. It suggests that PIV performs good as compared to PTV in the cases of long exposure time, but it also depends upon the justification of high RMS-uncertainity values for PIV either.

5- Conclusion

In conclusion, the performance of PTV on synthetic images generated to simulate particle streak due to long exposure time was successfully evaluated in this study. Synthetic particle streak can be generated by integration of Gaussian particle image profile with normalized exposure time. The results of analytical Hill's vortex show that reliabilty and match yield were 98% and 75% and dropped to 50% and 35%, respectively, due to long exposure time. PTV performance can be justified with its peak-finding criteria for normalized exposure time up to 0.05. For the effects of different particle image parameters with particle streaks on PTV performance, the PTV performance were obtained for diameter range from 2 to 6 pixel, intensity range from 0.2 to 1.0 pixel and density range from 0.01 to 0.05. The range of the appropriate normalized exposure time tested in this study is from 0 to 0.14. As the exposure time increases from 0.43 to 1.0, PTV can no longer efficiently resolved the flow. The comparision with PIV shows that the mesurement uncertainity is higher as compared to PTV. PTV performance validate the results only for short exposure time whereas PIV performed also with longer exposure time with the measurement uncertainity range form 0.3 to 7.32. Under the appropriate exposure range, PIV performs as good as PTV for long exposure images.

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