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ASSESSMENT OF FUZZY LOGIC BASED DATA VALIDATION TECHNIQUE FOR 3-D PARTICLE TRACKING VELOCIMETRY

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ABSTRACT

A data validation technique for 3-D particle tracking velocimetry is proposed. Rule based fuzzy logic system has been used. In the proposed scheme, the PTV pairing results will be provided as an input to the validating system. Then, velocity vectors of the particles in the neighborhood are measured, in terms of velocity gradient, direction and magnitude. The distance between vector midpoints, difference in vector magnitudes, average value of vector magnitude and the sum of the squares of the differences of the x, y and z-components of the velocity vectors are used as reference parameters for evaluation. Depending upon the combination of the values of these different parameters the fuzzy logic system will check how much the vectors are likely to be declared as true vectors in terms of numerical parameter called *confidence*. Higher value of confidence shows that the vectors under consideration as true while the vectors are likely to be erroneous for lower value of confidence. The results are tested with various PTV results. The validation results are encouraging with very low possibility of false vector being accepted and true vector being rejected with reasonable values of confidences..

Keywords: Fuzzy logic, PIV, PTV, Flow visualization

INTRODUCTION

Over the years, fuzzy logic and neural networks have been successful mathematical tools for various types of scientific applications. They are replacing many conventional concepts of computations including optimization, image processing and pattern recognition, and thus hold the potential applications in the field of particle tracking velocimetry (PTV).

Fuzzy sets are a generalized form of conventional set theory to represent vagueness existing in various phenomena which involve a decision somewhere in between perfectly true and completely false. Flow measurement through particle tracking involves on of such phenomena where the certain projections can be made in advance though the exact solution itself may not be distinct. In this context, Wernet (1993) implemented the concept of fuzzy model to particle tracking velocimetry. But, in this method, the successful results are affected by the data density and the search region size for the candidate particles. Similarly, the method requires priori knowledge of flow field to effectively determine the search area.

Similarly, if looked over the recent approaches, Knaak *et al.*(1997) implemented Hopfield neural network (Hopfield, 1982) to particle pairing process. Hopfield neural network's inherent demerit of long computation time with the increase in number of particles per frame makes it reluctant to implement for the case of relatively higher number of particles per frame. This fact is evident from the experimental results reported by present authors (Ohmi and Sapkota, 2004) that only around 150 particles per frame were successfully matched within the tolerable computation time. In order to overcome this problem the present authors suggested the idea of implementing cellular neural network in which neuron units' connections are limited to units in local neighborhood of individual units (Chua and Yang, 1988). This implementation gave fruitful results of significant improvement in computation time with adequate accuracy which showed a comfortable way to use such networks for particle pairing. However, this methodology has the limitation associated with the dependency of true solution over the weight constants. Similarly, it is difficult to say that in what extent the constraint conditions imposed are satisfied making difficult for the algorithms to get tested in practical environment. Moreover, in all of these methods, there is still a lack of proper mechanism do determine whether the final results are true or not.

Taking all the things mentioned above in mind, the authors here propose the idea of using fuzzy logic for the validation of PTV results obtained by different algorithms. This methodology which is aimed at the combined use of computational abilities of neural networks and fuzzy logic overcomes the limitation of their standalone presence in PTV systems

FUZZY LOGIC AND PTV DATA VALIDATION

Fuzzy logic works with the rules supplied by the users according to the required systems or expected phenomena. The fuzzy systems convert these rules to their mathematical equivalents. If the system is understandable these rules are easy to write and as many rules as necessary can be supplied to describe the system adequately. Wernet suggested the following mechanism to deal the particle tracking problems using fuzzy logic. The particle centroids on first time-step are used as starting points for possible particle displacements. The user specifies a search region of certain radius to search for certain particles. Each particle in the second frame within a radius R from the initial particle centroid is a candidate displacement vector. All possible displacements of the initial particle to the second particle locations within the search region are recorded and stored as lists of candidate displacement vectors for each initial particle. If two separate initial particles do claim the same second particle, then all possible vectors pairs between these two initial particles are compared. The main assumption is that if two initial particles are close enough to interact (claim the same second particle) then the pair of vectors that look the most similar (in direction and magnitude) must be correct pair of displacement vectors for the two separate initial particles. Taking the reference of this point the authors here now have proposed a validation scheme where the basic assumption is that the velocity vector of any particle in the first time-step frame is similar in direction and magnitude to the velocity vector of the particle physically nearest to it.

In the proposed scheme the PTV pairing results will be provided as an input to the validating system where each particle in the first frame will search for the particle nearest to it. The velocity vectors originating from these two physically nearest particles are then measured in terms of distance between the vector midpoints in pixels (Sep); average vector magnitude (Mag); difference in vector magnitudes (MagDif); and the sum of the squares of the differences of the x, y and z- components of the two velocity vectors (Delta). The “Sep” and “MagDif”, when combined, act as a measure of velocity gradient where “Delta” operates in the opposite manner to the dot product. Depending upon the combination of the values of these different parameters, the fuzzy logic system will check how much the vectors are likely to be declared as true vectors in terms of numerical parameter called *Confidence* where higher value of confidence shows that the vectors under consideration as true while the vectors are likely to be erroneous for lower the value of confidence.

Each input measure, Sep, Mag, MagDif and Delta, has three elements in its set named as fuzzy set:{Small, Med, Large}, where the degree of membership for each element varies between 0 and 1. Standard 50% overlapping triangular input membership functions is used as shown in Figure 1 for this purpose.

The degrees of membership for each input are then processed through a rule base of "IF...THEN" blocks as shown in Table 1. For a given vector pair, up to 16 rules may fire depending on the number of unique combinations of membership values. Equation (1), as shown below, is used to determine the output of the fuzzy PTV processor.

$$Confidence = \frac{\sum_{i=1}^{n} \mu\_out(i) \times conf\_out(i)}{\sum_{i=1}^{n} \mu\_out(i)} \qquad (1)$$

Where *Confidence* is the output of the fuzzy processor and is the crisp estimate of the confidence in the velocity vector pair, ranging from 0 (low confidence) to 1 (high confidence). μ_out and *conf_out* are the membership values and confidence level determined by each fired rules. n is the number of rules fired. As mentioned earlier this value of confidence shows the degree of validity where higher value of confidence shows that the vectors under consideration as true while the vectors are likely to be erroneous for lower the value of confidence.

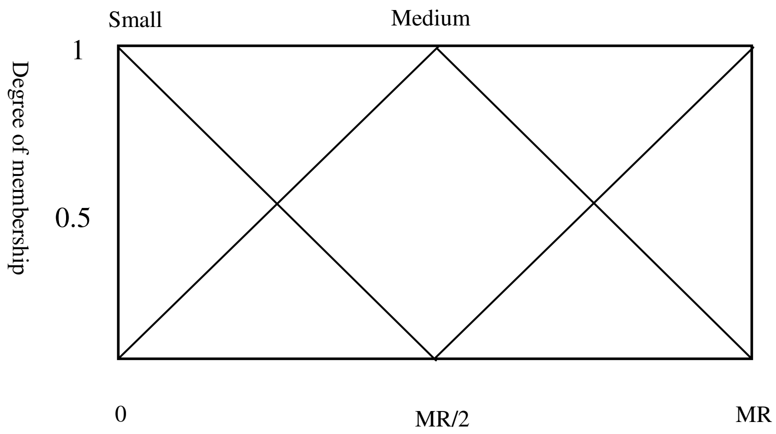

Figure 1. Input membership function with 50% overlap

Table 1 Rule base for fuzzy PTV processor

Sep Small	MagDif Small			MagDif Med			MagDif Small		
	Mag Small	Mag Med	Mag Large	Mag Small	Mag Med	Mag Large	Mag Small	Mag Med	Mag Large
Delta Small	High	High	High	High	Med	Med	Med	Med	Low
Delta Med	High	Med	Low	Med	Med	Med	Low	Low	Low
Delta Large	Med	Low	Low	Low	Low	Low	Low	Low	Low

Sep Med	MagDif Small			MagDif Med			MagDif Small		
	Mag Small	Mag Med	Mag Large	Mag Small	Mag Med	Mag Large	Mag Small	Mag Med	Mag Large
Delta Small	High	Med	Med	Med	Med	Low	Med	Low	Low
Delta Med	Med	Med	Low	Med	Med	Low	Low	Low	Low
Delta Large	Low	Low	Low	Low	Low	Low	Low	Low	Low

Sep Large	MagDif Small			MagDif Med			MagDif Small		
	Mag Small	Mag Med	Mag Large	Mag Small	Mag Med	Mag Large	Mag Small	Mag Med	Mag Large
Delta Small	Med	Med	Low	Med	Low	Low	Low	Low	Low
Delta Med	Low	Low	Low	Low	Low	Low	Low	Low	Low
Delta Large	Low	Low	Low	Low	Low	Low	Low	Low	None

EXPERIMENTAL RESULTS

The Visualization Society of Japan (VSJ) offers a variety of comprehensive synthetic particle images for the performance check of various PIV systems (Okamoto *et. al*,) From their library of particle images, the standard image #351 is used for testing of the results of the 3-D particle tracking algorithms.

Table 2 shows the average and standard deviation of the values of confidences of the entire vector pairs for different input of PTV results with varying error levels. These PTV results were obtained by varying the weight constants in the Cellular Neural Network based PTV algorithm developed previously by the present authors (Ohmi and Sapkota, 2006). High, Med, Low and None of the rule table are assigned the numerical value of 1.0, 0.6, 0.1 and 0 respectively. As it is shown in Table 2 the average value of confidence has been increased for less erroneous PTV results with low deviation from the average. That is result of false vectors producing low values of confidences.

Table 2 Measure of confidence for different PTV results

S.No.	Number of particles	Errors in matching	Average confidence	Standard deviation
1	300	5	0.63	0.11
2		32	0.52	0.25
3		88	0.39	0.29
5	500	36	0.6	0.23
6		65	0.55	0.24
7		96	0.48	0.29
9	700	26	0.65	0.20
10		112	0.53	0.28
11		161	0.47	0.3
13	1000	68	0.67	0.23
14		198	0.54	0.30
15		367	0.42	0.32

Similarly, by setting the certain threshold errors can be traced as shown in the Figures 2 and 3. Figure 2 is the case of 500 particles of #351 series VSJ images with 7.2% and 19.2% errors in measurement. Similarly, figure 3 is the case of 1000 particles of same image series with 6.8% and 12.8% errors respectively. The error vectors are represented by red lines. These red lines are obtained by setting the confidence threshold of 0.6 in the output of fuzzy validator. Hence, in this way the error vectors can be removed from the results by using such threshold as shown in Figure 4 and 5. It is also observed that there is very low possibility of false vectors being accepted and true vectors being rejected for the reasonable value of confidence threshold.

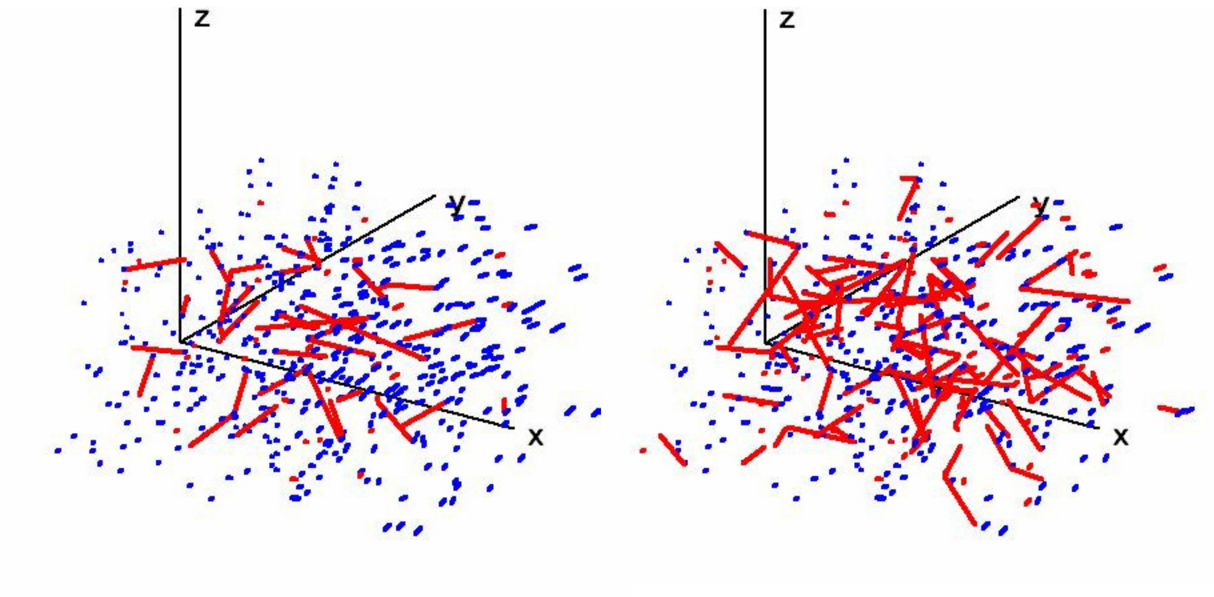

Figure 2. #351 series images with 500 particles

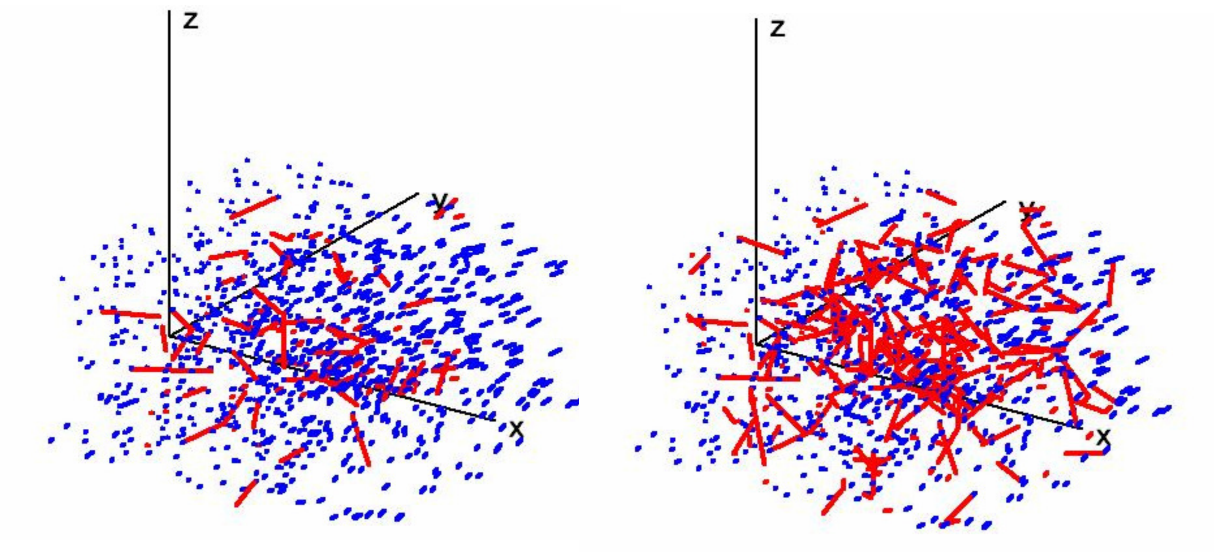

Figure 3. #351 series images with 1000 particles

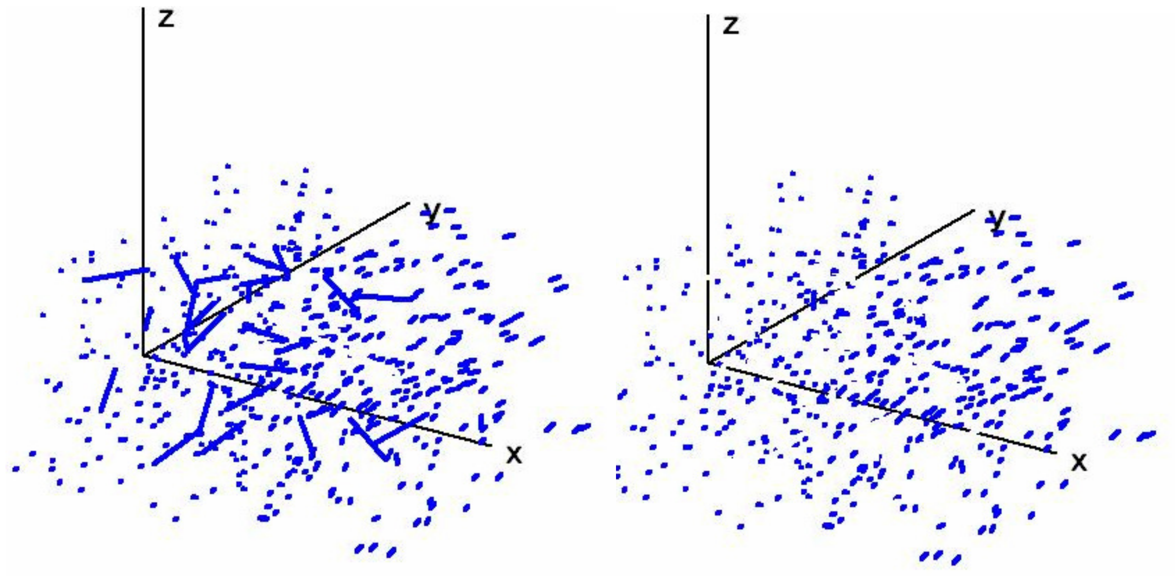

Figure 4. Outliers removal using threshold of 0.6 for 500 particles with 7.2% error

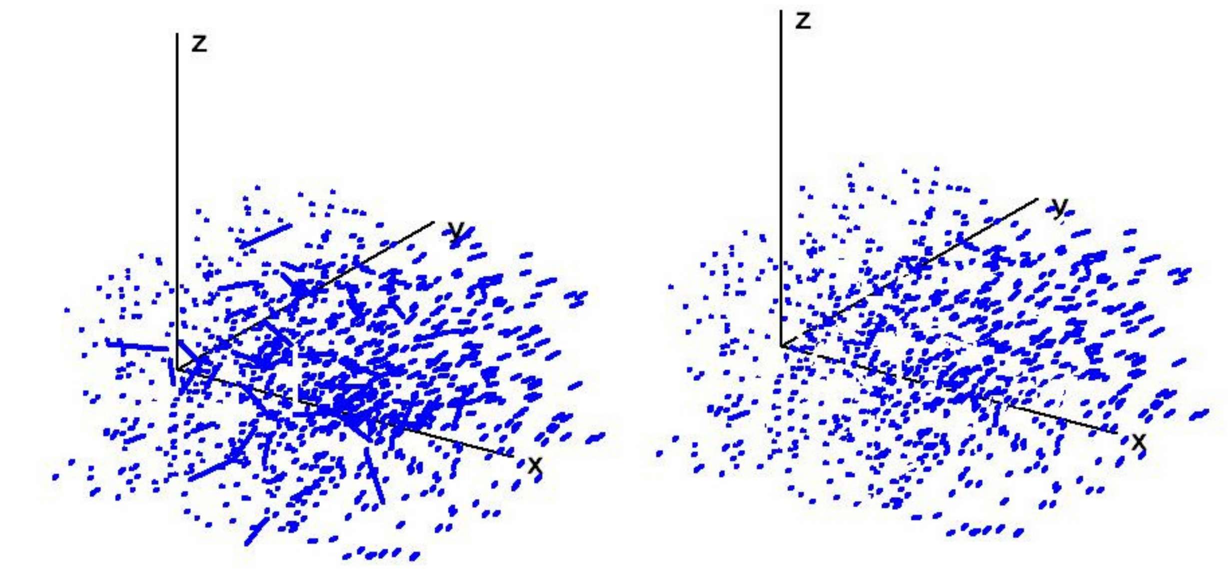

Figure 4. Outliers removal using threshold of 0.6 for 1000 particles with 6.8% error

CONCLUSIONS

The rule-based fuzzy logic method proposed here seems to be a reliable method for the detection of the outliers present in the 3-D PTV results. In the proposed methodology, the vectors are considered valid on the basis of multiple components of constraint of coherence of particle motion. There is very low possibility of false vectors being accepted and true vectors being rejected for the reasonable value of confidence threshold. There are still avenues for the improvement in the assignment of membership values by using some statistical approaches so as to enhance the simplicity and reliability of the validation system.

REFERENCES

Wernet M P. (1993), "Fuzzy logic particle tracking velocimetry," *NASA Technical Memorandum.* 106194

Knaak M , C. Rothlübbers and R. Orglmeister (1997), A Hopfield neural network for flow field computation based on Particle Image Velocimetry/ Particle Tracking Velocimetry image sequences, *Proc IEEE International Conference on Neural Networks*

Hopfield J J (1982), Neural networks and physical systems with emergent collective computational abilities, *Proc. Nat'l Acad. Sci. USA*, **97**, 2554-2558

Ohmi K and A. Sapkota (2004), Particle tracking velocimetry using a Hopfield neural network, *Proc 15th International Symposium on Transport Phenomena*, Paper number: 20

Chua L O and L. Yang (1988), Cellular neural networks: theory and applications, *IEEE Trans. on Circuits and Systems*, **35**, 1257-1290

Ohmi K and A. Sapkota (2006), Particle tracking velocimetry using cellular neural network, *Proc. IEEE International Joint Conference on Neural Networks, Vancouver, Canada,* 3963-3969

Okamoto K, S. Nishio, T. Kobayashi and T. Saga (1997), Standard images for particle imaging velocimetry, *Proc. PIV-Fukui*, 229-236