Colour class identification of tracers using artificial neural networks

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Abstract

In this presentation a multilayer perceptron is used to classify coloured tracers. In fluid mechanics a non-intrusive measuring method delivering experimental information with a Lagrangian point of view (i.e. following the flow) would be extremely useful to clarify the origin, birth and development of vortical structures in technical systems. For this purpose Particle-Tracking-Velocimetry (PTV) might be employed.

In PTV small tracers are tracked by a multi camera setup over time. With the known position of the tracers in at least two camera images it is possible to compute the 3d position of a tracer in space. In doing so it is difficult to solve the temporal and the spatial correspondence problem at high tracer density. Using coloured tracer particles the problem becomes much easier because the colour information can be used to support the correspondence analysis.

To recognise the colour of particles, single chip cameras with a Bayer-Pattern are used. Because of the small diameter of the employed tracers (<0.1 mm), conventional interpolation methods do not work to reconstruct the colour information. Therefore, a multilayer perceptron with one or more hidden layers is employed to assign the tracers to their colour class. The feature vector of a tracer consists of the raw black/white-data of the Bayer-sensor as well as of structural attributes, such as the position of the tracer in relation to the camera pixel elements. The feature vector contains finally about 10 elements. In our example we have 4 colour classes. A training data set for one class has about 8000 feature vectors. The backpropagation-training converges in about 250 steps. The computational time of the recall is negligible. After training, the network is able to assign correctly about 90% of the tracers in each colour class.

1. Introduction

The primary aim of this paper is to improve the correspondence analysis in the Particle Tracking Velocimetry applying coloured tracers. There are two reasons to use artificial neural networks (ANNs) for classification. In one respect our group is very experienced with ANNs. Furthermore, the application of neural networks for the reconstruction of colours, especially in case of digital cameras is nowadays wide spread ([2], [6]). This paper also opens a further possibility for employing ANNs.

2. Flow measurements using Particle Tracking Velocimetry

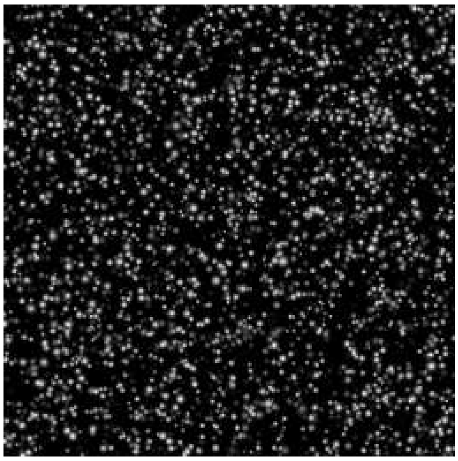


Figure 1. Typical Tracer distribution in a PTV-Image of a single camera [11].

Particle Tracking Velocimetry (PTV) is one of the most versatile techniques among the methods for flow measurements, allowing to determine pathlines and velocity fields. The method is based on a discrete visualisation of flows, usually mixing a large number of small (down to several times $10\mu m$) and buoyantly neutral particles to the flow. Pathlines are determined by the evaluation of multi camera image sequences of these particles. The recordings are carried out with the help of modern digital cameras.

The analysis of the recorded image sequences is based on the methods of digital image processing and digital photogrammetry. The PTV enables various investigations of flow phenomena. An overview of the different possible PTV-implementations is presented in [12].

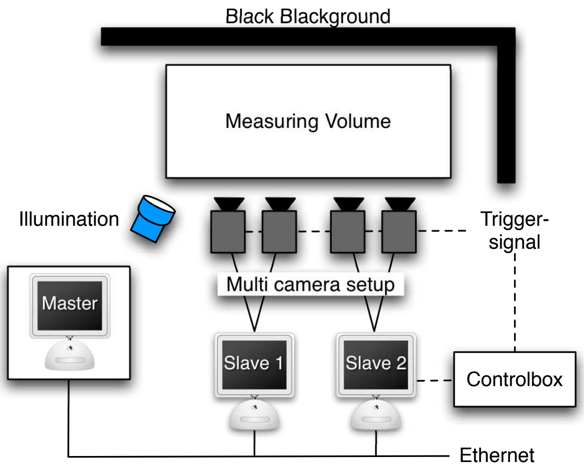


Figure 2. A typical schematic experimental setup.

An exemplary measuring setup is shown in Fig. 2. A suitable measuring volume is illuminated by convenient lighting. Images are recorded by several synchronized and calibrated cameras. Thereby usually a large number of image data is generated.

The first step of the analysis is to identify the particles in the image (for details see section 4.1). Afterwards a spatial (finding the mapping of a specific tracer in all images) and temporal correspondence analysis (flow of a specific tracer) must be executed. The spatial analysis consists of the establishment of stereoscopic correspondences using epipolar constraints ([8], see also Fig.3). Then the 3d coordinates of a tracer can be calculated with simple geometrical relations and the image-coordinates in at least two images using the camera calibration [4]. With this image and 3d information the tracking can be carried out (temporal analysis). Of course, both steps can be connected with each other. This has been shown in previous publications ([16], [14]).

2.1. Problems during the spatial and temporal correspondence analysis

The establishment of the spatial and temporal correspondence is a significant problem during the analysis of PTV-recordings ([7], see also Fig. 4).

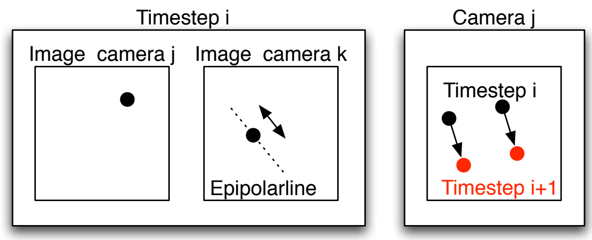


Figure 3. Left: Epipolar Geometry. The corresponding points can only lie on the epipolar line. Right: Temporal analysis in image space.

The ambiguity appears increasingly during the spatial correspondence analysis because of the high number of particles. The correlation of the particles in a time step is mainly based on geometrical conditions such as the epipolar geometry. The intersection between the image plane and a plane formed by the object point and the perspective centres of the cameras form a line. Only along this line a corresponding tracer can be found ([4], see also Fig. 3). This decreases the search area from 2d (the whole image) to 1d (a line in the image). Applying more than two cameras, the search-space is further limited. Nevertheless the ambiguities cannot be avoided. Most of all, their frequency depends on the number of particles per image.

To deduce the information concerning the flow field, a temporal correlation (tracking) is required. Thereby one wants to get trajectories as long as possible, without any interruption. A restriction of the search-space in successive time steps can be derived because of the restricted variations of velocity and acceleration and by considering the local correlation of the velocity vectors. Nevertheless, this does not suppress all ambiguities, leading to a reduced resolution of the flow features [7].

For our purposes a 3D-PTV system with a high temporal as well as spatial resolution is being developed, in order to be able to investigate gas flows at relatively high speeds and involving small eddies. In that case it is clear that PTV can only be successful with a lot of tracer particles, so that the particle concentration in the gas has to be very high.

To facilitate the temporal and spatial correspondence of the particles it would be useful to employ further parameters describing the tracers. In most cases, the size, form and brightness cannot be characterized explicitly (and these parameters depend less on the actual properties of the mapped particles than on the effect of the illumination, which can vary significantly for the single cameras). Therefore, such parameters are not suitable to improve correspondence and have been barely applied [16].

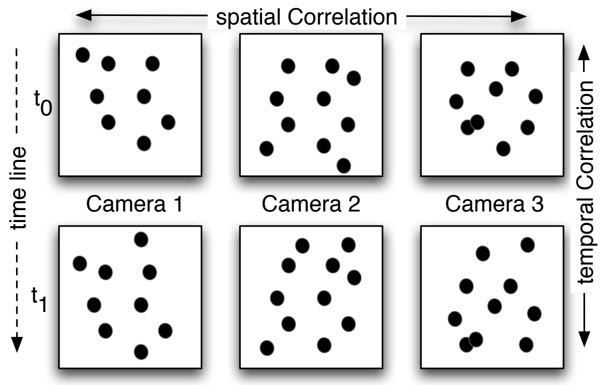


Figure 4. Two successive image triples with PTV, spatial and temporal correspondence.

The idea, which is followed now, is to colour the tracers and to use the colour information to simplify the correspondence analysis. When using coloured tracers, colour classes are created, which contain a lower number of particles, according to the total number of those classes. This way the correspondence analysis will be considerably improved (Fig. 5). The number of ambiguities decreases both for the spatial and the temporal correspondence. All color classes can be threaded separately. One gets decoupled systems for each class. The correspondence analysis becomes easier.

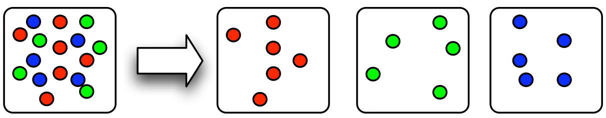


Figure 5. Decreasing the relative particle density with the help of colour classes.

2.2. Coloured tracer particles

Essential requirement for the particles is that they should follow the flow as accurately as possible, since their trajectories are tracked, but the velocity field of the flow is wanted. The diameter of the particles and the density difference between the continuous and dispersed phases are the two most influencing factors. As a matter of course the diameter should be as small as possible and the density the same as of the continuous phase. It is very difficult to find such solid particles, the density of which is similar to air. Furthermore, even for the lowest diameter, the particle colour classes must be identified by the cameras.

After intensive tests, Expanded Microspheres (EMS)

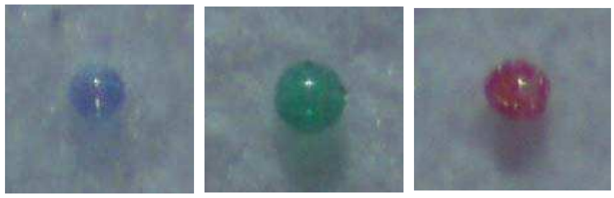


Figure 6. Blue, green and red tracer.

particles with a diameter of $80\mu m$ have been selected (for examples see Fig. 6). These particles follow air flows very accurately and can thus be used for accurate, quantitative measurements.

The selection of colours was complex. To achieve reliable separability these must clearly differ in their emission spectrum (see also Fig. 7). This is not completely the case with the current tracers. Further investigations are carried out. The final goal is to use up to ten different colours.

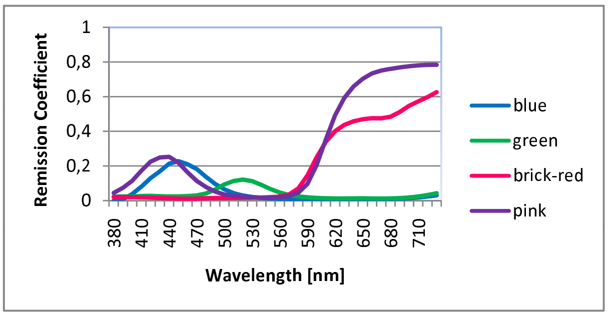


Figure 7. The emission spectrum of the 4 used colours.

3. Colour cameras, problems for determining colours

The most frequently applied colour cameras employ a Bayer-pattern [1], where a special colour filter with a so called Bayer-pattern is positioned in the front of a black and white sensor. It usually consists of 2x2 pixel structure elements, each with a filter of one red, two green and one blue (see also Fig. 8) elements. When further discussing the red, green or blue pixel of the Bayer-image, always the respective colour of the filter is meant, which is located on the corresponding sensor.

Starting from the black-white Bayer-raw-image the colour image can be interpolated from the individual pixels. This interpolation can be accomplished in different ways. Simple methods interpolate the colour value from the pixels of the same colours in the neighbourhood. As this procedure is first of all problematic perpendicular to the edges,

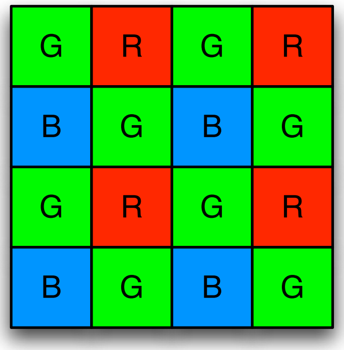


Figure 8. An exemplary Bayer-pattern. The subjacent pixel of a b/w sensor is respectively green, red or blue sensitive.

several methods try instead to carry out the interpolation along the edges.

Other algorithms are based on the assumption that the colour of a plane in the image is relatively constant, even in case of changing lighting conditions. Therefore at first the green channel is interpolated, followed afterwards by the red and blue channel, so that the colour conditions red-green and blue-green are constant respectively. A thorough overview of the usual interpolation methods can be found in [3] and [13].

As the tracers employed for the discretisation of the flow are very small (typically <0.1mm), their size in the image is only some pixels. Popular interpolation methods for the colour reconstruction fail in such cases. Note that the tracers has to be large enough that we do not get diffraction effects (which is the case with tracers smaller than 0.01mm).

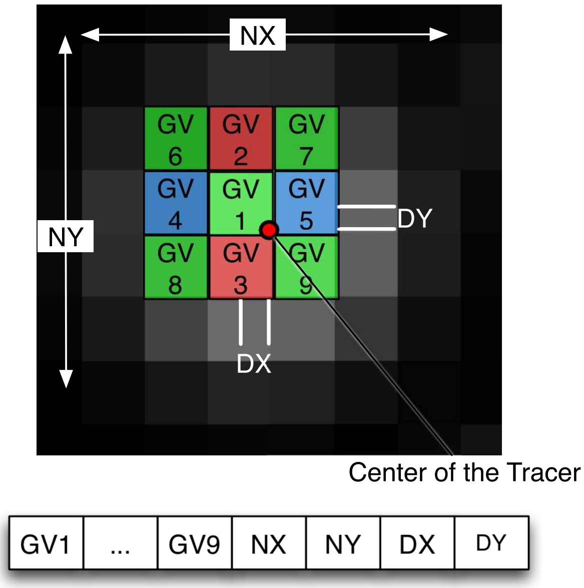
It can be seen in Fig. 9, that the colour of a tracer cannot be determined accurately after the Bayer-conversion in a simple way. So another approach should be selected for the colour classification.

4. Artificial neural networks for colour classification

In principle, it is not necessary to determine the colour of a tracer in the present case. It is only important to assign it to the appropriate colour class. These classes have to be sufficiently distinguished. The idea is to use an artificial neural network for the colour classification. In the followings the procedure is shown in details.

4.1. Feature vector

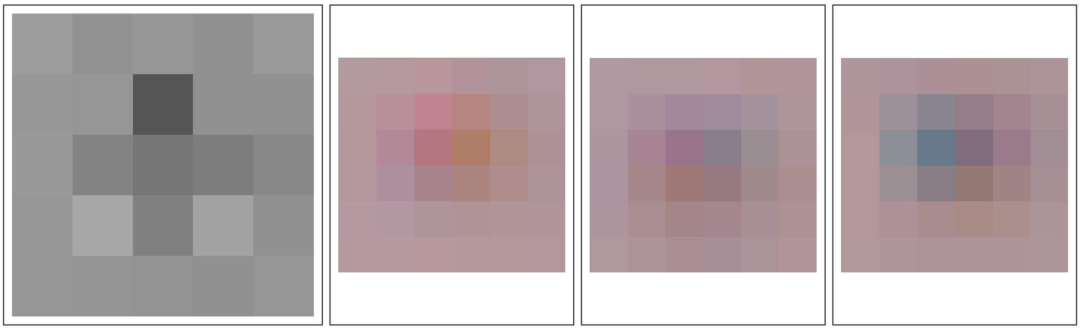
First we have to determine the centre of the tracer. There are various methods to locate the particles in the image. We use the Particle Mask Correlation (PMC) Method [15]. It can be started from the assumption that the image of a tracer corresponds to a Gaussian function. Then an appropriate template is correlated with all the pixels of the image. When there is a correlation maximum, a particle is assumed to be present at these coordinates.



Feature vector

Figure 10. Illustration of the Bayer pattern and the composition of a feature vector. We use the gray value of the nearest green pixel to the center of the tracer (GV1), the gray value of the surrounding green, blue and red pixels (GV2...GV9), the size of the specific tracer in x- and y-direction (NX and NY) and the distance in x- and y-direction from the green pixel to the center of the tracer (DX and DY).

The first elements of the feature vector consist of the assigned greyscale values of the Bayer-image. To decrease the influence of the varying intensity of the background, a background image is subtracted from the recorded image. This image is taken with an empty wind tunnel. To map a tracer the next green pixel will be searched in the Bayer-pattern starting from the centre of a particle. This and the surrounding 8 pixels form the first elements of the feature vector (see also Fig. 10). Of course, the pixels have to be arranged to get a specific order (5x green – 2x red – 2x blue).



(a) *Raw image.* (b) *Red Tracer.* (c) *Blue Tracer.* (d) *Green Tracer.*

Figure 9. Left, the unconverted mapping of a blue tracer on the sensor (the Bayer-pattern can be recognised). Next to it the colour image of three differently coloured particles with a smaller scale. While the colour of the red one can still directly recognised, the colour of the blue and green ones can barely be distinguished after the Bayer-conversion. The calculated colour depends on the position in the pixel raster. The conversion has been carried out with a simple interpolation of the greyvalues of a Bayer-image.

In addition to these image-based values some geometrical attributes of the imaged tracers are also used as feature such as its width or height or the distances in x- and y-direction from the green pixel to the centre of the tracer (this information is a result of the mentioned tracer search). This gives 13 features. Note that the analysed image of a tracer has to be at least 3x3 pixel wide.

4.2. Network setup

A fully connected multilayer network with back-propagation is applied. It consists of an input layers, one or more hidden layer and an output layer. The number of neurons in the input layer corresponds to the size of the feature vector and the number in the output layer to the colour classes. Because of its high numerical efficiency, the Fast Artificial Neural Network Library (FANN) [10] is applied. For the activation function the symmetric sigmoid function is used. Before training the initial weights are set to random values between -0.1 and 0.1.

4.3. Separability of the classes

A two-dimensional Self-Organizing Map (SOM) [5] has been used to get a general idea of the separability of the classes. The neurons have been arranged in a 5x5 grid. Fig. 12 shows the results of the separation of four classes with respective 500 vectors (the generation of the input data is explained in the next section). This shows that the colour classes are in principle separable and can be distinguished. But is shows also the one colour classes could fall into two classes. It appears to be important which pixel of the bayer-pattern is illuminated by the tracer.

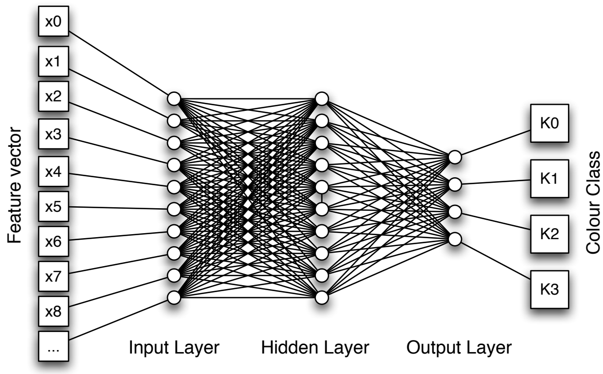


Figure 11. Architecture of the ANN using 4 colours classes and one hidden layer.

Additionally a Principal Components Analysis [9] was done with the data set of all colour classes. The total variability resulting from each principal component is illustrated in Fig. 13.

5. Experiments

The experimental setup consists of four glass sheets assembled in a distance of about 2 cm (this is a pre-arrangement setup for measurements in the windtunnel). The medium of the laminar flow was air. The employed camera is a Pulnix TMC 1400CL with a resolution of 1392x1040 pixels. For lighting standard halogen lamps are used. The complete experimental setup is shown in Fig. 14. There the fan controller regulates the flow, a control monitor

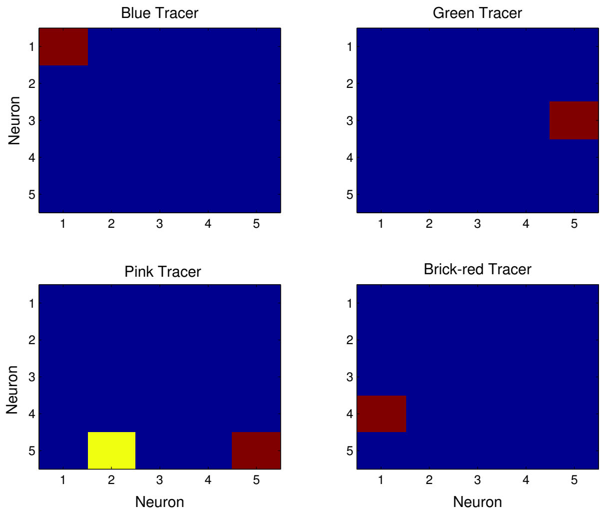


Figure 12. Result of the training of a 5x5 grid SOM. The feature vectors of four colour classes had been presented to it. The answer of the SOM after training is shown if only feature vectors of one class are presented to it. (Using of an indication threshold.)

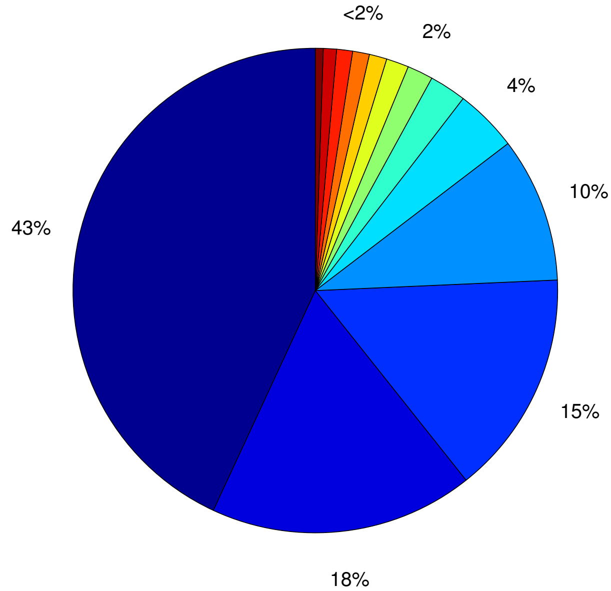


Figure 13. Amount of variance accounted for by each component after a Principal Component Analysis.

enables the control of the camera and the image recording. The tracers are in the velocity box. They are illuminated by several lights.

To acquire the training and test data, only tracers of a certain colour class have been mixed to the flow in each case. We used tracers of 4 colour classes (blue, green, brick-red and pink). Then the recordings have been carried out with constant illumination and recording conditions.

The centres of the particles are then determined using the previously mentioned PMC-method and the feature vectors are calculated for each tracer. So we had 12.000 feature vectors (8.000 for training, 4.000 for tests) for each colour class. Afterwards the training is executed with 8.000 datasets for every colour group (this gives a total amount of 32.000 feature vectors). The mean square error over the number of the training epochs is presented in Fig. 15.

Table 1 shows the results for the four applied colours. The recall-data contains 4.000 feature vectors for each class. It can be seen that about 90% of the tracers of each colour class are assigned to the correct colour group. The remaining of the answers of the network are usually in the most similar colour group (blue–green resp. brick-red–pink). It should be noted that the device could not always be cleaned entirely. Thus some (several percentage of the result) different-coloured tracers always remained in the flow. Of course, thats one reason for errors. Others are the difficult lightning conditions and the problematic colourisation of the tracers.

Fig. 16 shows the results for different ANNs setups. They were tested with the mentioned training- and test data. One, two or three hidden layers have been used. The number of neurons in the hidden layers was 10, 10-7 respectively 10-8-5. It can be seen that a net with only one hidden layer is not sufficient. As expected two hidden layers are optimal when considering both computational cost and accuracy. With 3 hidden layers we do not get a better result. In Fig.17 the results of the classification with different numbers of neurons in the hidden layer are presented.

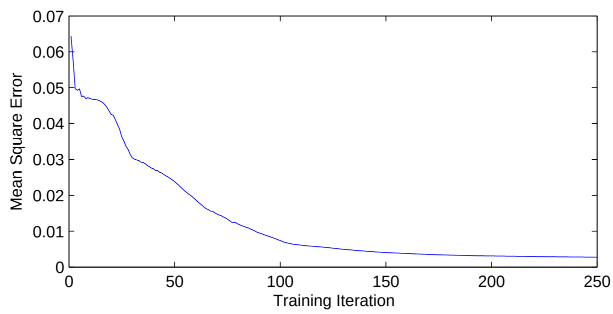


Figure 15. Progression of the mean square error during the training.

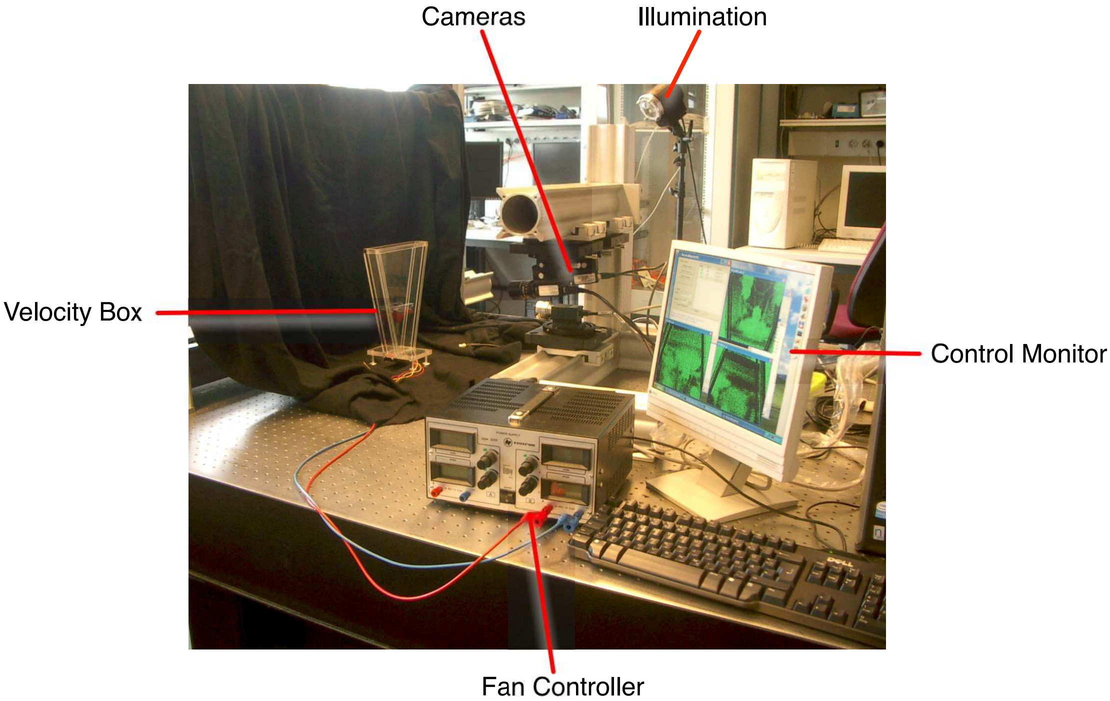


Figure 14. Experimental setup with 3 cameras (prearrangement for measurements in a wind tunnel).

Color of Tracer \ Recognized color	blue	green	brick-red	pink	vague
blue	**90.7%**	2.7%	0.3%	0.6%	5.8%
green	3.0%	**89.6%**	2.5%	0.0%	4.9%
brick-red	2.0%	1.1%	**86.0%**	5.2%	5.6%
pink	2.2%	0.1%	3.4%	**91.0%**	3.3%

Table 1. Results of a recall with test data. The bold number indicates the right answer. Vague means that the answer of the network was not clear enough.

6. Conclusions and Acknowledgment

PTV on the one hand and colour recognition with artifical neural networks on the other hand are known techniques. Our new approach is the determining the colour-classes of dyed tracers in PTV with ANNs. Therefore different architectures of ANNs have been investigated. The presented results show the suitability of the system for colour classification.

With the additional colour information temporal and spatial correspondence analysis are remarkably simplified. Hereby the number of tracers and consequently the resolution can be increased for PTV measurements in gas flow. At the same time higher flow velocities can be measured. It has been demonstrated in the present study that particles below 0.1 mm (as long as there are no diffraction problems and the images of the tracers are at least 3x3 pixel) can safely be employed. We used the 8-neighborhood of a central green pixel and some additional geometrical parameters to describe a tracer and build the feature vector. For classification a fully connected multilayer network with two hidden layers was used.

The further work shall concentrate on the direct integration of the colour information in the particle identification, to be able to determine the locations of the particles with a high accuracy. Furthermore more work will be done in analyzing the properties of the colour classes and we want to use more than four classes (up to 10).

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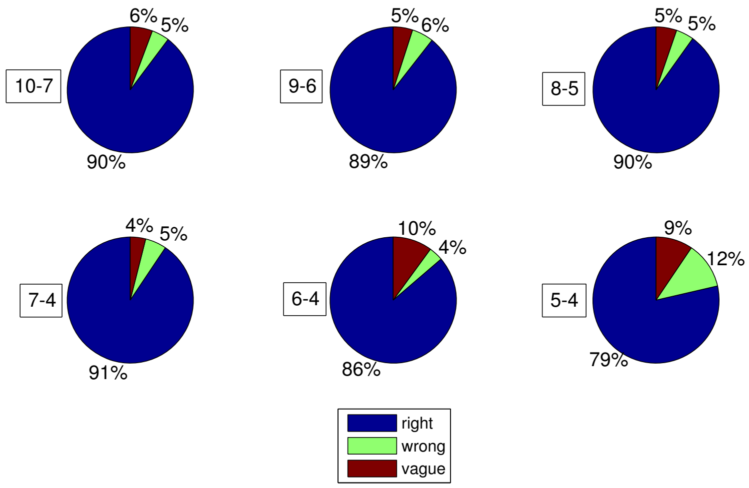

Figure 17. Comparison of the results using different numbers of neurons in the hidden layers (rounded).

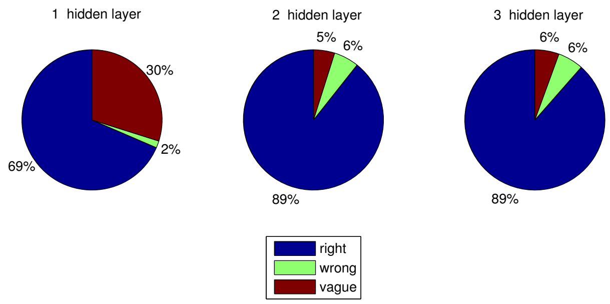

Figure 16. Comparison of the results using different numbers of hidden layers (rounded).

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