Proceedings of FEDSM2007
5th Joint ASME/JSME Fluids Engineering Conference
July 30-August 2, 2007 San Diego, California USA

FEDSM2007-37403

ON THE ANALYSIS OF TURBULENT FLOW SIGNALS BY ARTIFICIAL NEURAL NETWORKS AND ADAPTIVE TECHNIQUES

F. López Peña
Grupo integrado de Ingeniería,
Universidade da Coruña, Ferrol, Spain
flop@udc.es

F. Bellas
Grupo integrado de Ingeniería,
Universidade da Coruña, Ferrol, Spain
fran@udc.es

R. J. Duro
Grupo integrado de Ingeniería,
Universidade da Coruña, Ferrol, Spain
richard@udc.es

P. Fariñas
Grupo integrado de Ingeniería,
Universidade da Coruña, Ferrol, Spain
fluidos@cdf.udc.es

ABSTRACT

Artificial Neural Networks (ANNs) and evolution are applied to the analysis of turbulent signals. In a first instance, a new trainable delay based artificial neural network is used to analyze Hot Wire Anemometer (HW) signals obtained at different positions within the wake of a circular cylinder with Reynolds number values ranging from 2000 to 8000. Results show that these networks are capable of performing accurate short term predictions of the turbulent signal. In addition, the ANNs can be set in a long term prediction mode resulting in a sort of non linear filter able to extract the features having to do with the larger eddies and coherent structures. In a second stage these networks are used to reconstruct a regularly sampled signal straight from the irregularly sampled one provided by a Laser Doppler Anemometer (LDA). The irregular sampling dynamics of the LDA signals is governed by the arrival of the seeding particles, superimposing the already complex turbulent signal characteristics. To cope with this complexity, an evolutionary based strategy is used to perform an adaptive and continuous on-line training of the ANNs. This approach permits obtaining a regularly sampled signal not by interpolating the original one, as it is often done, but by modeling it.

Keywords: Turbulent signals, dynamic reconstruction, Artificial Neural Networks, Evolutionary Algorithms

INTRODUCTION

Artificial Neural Networks emerge as a real tool in the early eighties just after the proposal of error back-propagation which solved the serious drawbacks of previous perceptron models. Very quickly and aided by the fast hardware developments and increasing processing capacities of that time, they become very popular as a practical tool in various scientific areas. Their use in turbulence analysis is not generalized, but some interesting applications can be found. For instance the work by Ferre-Gine et al. [1] and Giralt et al. [2] where a fuzzy artmap neural network is used to detect structures embedded in the far turbulent wake behind a circular cylinder and synthetically reproduce the sequence of individual classes of relevant events present in the wake. Some other examples are the work by Panigrahi et al. [3] where artificial neural networks and fuzzy-logic models are used to predict the statistical turbulence quantities measured by a hot-wire anemometer in the wake of a square cylinder, or the one by Chattopadhyay et al. [4] where a neural network is used to predict the flow intermittency from velocity signals in the transition zone of a boundary layer.

In the present work signals obtained by a HW and by a LDA are analyzed; both of these signals are time series, being the former sequential while the later is unevenly sampled. ANNs have been widely used for time series prediction in processes that can be somehow predictable [5, 6, 7]. Generally, the so-called feedforward ANNs are the ones most frequently applied to data processing; among these are MultiLayer Perceptrons (MLP), which are by far the best known and most frequently used of all neural networks. MLPs can construct approximations for unknown functions by learning from an input-output mapping example. This static way of learning makes MLPs quite unsuitable for time series prediction of chaotic-like phenomena.

On this basis, a new type of delay based ANNs was developed in our group as an analysis tool to be used in problems usually referred to as Dynamic Reconstruction. These types of problems involve obtaining some sort of description of a given chaotic time series obviating the need for detailed mathematical knowledge of the underlying processes that conform its dynamics. The network is similar to a standard MLP, but it introduces trainable time delays in its synapses in addition to the conventional weighing factors [8]. This particularity makes this type of network very suitable to analyze complex time dependent phenomena.

These networks have been used to analyze HW signals obtained in different points within the wake of a cylinder as well as in a free jet of air. Results show that the implemented trainable delay based artificial neural network is able to autonomously obtain the embedding dimension as well as the normalized embedding delay and permits performing short and long term predictions. The short term predictions are extremely accurate while the long term ones result in a sort of non linear filter able to extract the signal features having to do with the larger eddies and coherent structures [9].

A second application concerns LDA signal analysis, where the temporal irregularity in the sampling introduces strong difficulties. The fact of being unevenly sampled makes this temporal series unsuitable to be analyzed directly by the ANNs developed. Additionally, the superimposition of the timing dynamics inherent to the turbulent signal with the one concerning the sampling leads to a very complex non sequential time series. For this type of signals a method was implemented for adaptively and continuously training the ANNs on line on the irregularly sampled real data by using an evolutionary based strategy. Dynamic variable size memory buffers are employed allowing the networks to model the signal and thus to produce a regularly sampled signal straight from the irregular one. It is important to note that the signal is modelled, and not just interpolated; thus improving the spectra generated and the general knowledge of its features [11].

EXPERIMENTAL APPARATUS

The HW experiments in a cylinder wake have been carried out in the Low Turbulence Subsonic Open Jet Wind Tunnel (LTOJ-1) of the Fluid Mechanics Laboratory of the Centro de Investigaciones Tecnológicas of the Universidade da Coruña. This is a low speed low turbulence wind tunnel specially designed and built in house for air speed calibration and basic research purposes. It produces a 300 mm wide open free jet with a velocity uniformity of better than 1% and turbulence level of less than 1%. It is driven by a centrifugal blower provided with an 11 kW asynchronous AC motor coupled with an electronic inverter and able to provide a variable air speed from 0 to 45 m/s. A software package constituting a virtual instrument was specially developed in house to perform data acquisition and control of both the hot wire anemometer processor trough an RS232 line and the wind tunnel through the inverter control line. A set of sensors are arranged to measure the different physical magnitudes required within this virtual instrument to control the wind tunnel motor by means of a PID controller embedded in the software package. Specifically, a differential pressure transducer connected to a Pitot-static Prandtl type pressure probe, a barometric pressure sensor, and an ambient temperature sensor. A circular cylinder with a diameter of 8 mm is placed vertically in the test section at the open jet exit. The Reynolds number is used as the main control parameter. The virtual instrument has been developed to be able to calculate the Reynolds number in real time and to adjust the wind tunnel speed through the embedded PID controller to stabilize its value within 1%. Specific details of this experimental set-up can be found in [9].

An air free jet was used to make a second set of HW experiments. The air jet under analysis has a diameter of 16.5 mm and is coming out of a standard HW calibrator by TSI. This device takes air from the pressurized air supply of the lab. The density of the air in the jet is calculated by applying the perfect gas equation for air using the values of the temperature in the settling chamber and the ambient pressure. In order to be able of measuring these magnitudes, a barometric pressure sensor and a temperature sensor (a thermocouple) are used. This thermocouple is also used by the hot-wire anemometer to perform corrections in the velocity measurements by jet temperature fluctuations. The value of air density obtained under current test conditions is then applied to calculate the value the exit jet speed from the discharge equation of the settling chamber contraction and after measuring the difference in pressure between the settling chamber and the atmosphere by means of a differential pressure transducer. More details of this experimental set-up can be found in [10].

Turbulent velocity measurements are taken by means of a TSI Flowpoint HW anemometer. Values for the Reynolds number ranging from 2000 to 8000 are considered for the wake and of 5000 to 10000 for de jet. In these HW experiments we are particularly interested in extracting the signal features of the main structures under the extremely noisy conditions induced by the rest of the turbulent scales.

Concerning the LDV experimental data used in the present investigation, they were obtained in the Boundary Layer Wind Tunnel (BLWT) of the Fluid Mechanics Laboratory of the Escuela Politecnica Superior of the Universidade da Coruña. This is an aspirating open type wind tunnel having an 11:1 entrance contraction followed by a 1 x 0.3 x 0.25 (m) transparent test section, a diffuser, and a centrifugal blower driven by a 2.2 kW AC motor governed by an electronic inverter. The cylinder used to generate the wake under study is a rod with a diameter of 8 mm placed horizontally at mid height of the test section and spanning its whole width. LDV measurements were performed at two main stream velocities of 3.7 and 11.3 m/s, resulting in data for Reynolds numbers of 2000 and 6000 respectively, matching some of the conditions of the hot wire experiments. Data were taken at 10 and 20 diameters downstream of the cylinder at a mean sampling rate ranging from 900 to 3000 samplings per second. Specific details of this experimental set-up can be found in [11].

These measurements were performed using a fiber optic LDA system by DANTEC driven by a 500 mW Ar-ion laser source by ILT. Initially a DANTEC FVA 58N20 processor had been used but it was replaced by a DANTEC BSA F60 processor; measurements taken by both processors are presented here. In these experiments, the optical probe has been positioned by a traversing mechanism along a lateral wall of the test section. The probe was provided with a 400 mm focal length lens allowing it to measure in any position in the test section. The seeding system used was made in house based on the condensation of propylene glycol and provides an average drop size of one micrometer; it was replaced during the experimental campaign by a TSI model 9306 atomizer.

ANN-BASED APPROACHES

The artificial neural network (ANN) we consider consists of several layers of neurons connected as a Multiple Layer Perceptron (MLP) with trainable delay terms in addition to the classical weight terms [8]. As a consequence, the synaptic connections between neurons are described by a pair of values, (W, τ), where W is the weight, representing the ability of the synapse to transmit information, and τ is a delay, which in a certain sense provides an indication of the length of the synapses. The longer it is it will take more time for information to traverse it and reach the target neuron. This capability of managing temporal information is basic in this work.

The delay-based ANN is applied both in the case of hot-wire anemometer turbulent signals and in the irregularly sampled LDA signals, but using different learning methods. In the first case, we have used a variation of a gradient descent algorithm and in the second case, we have used and online learning procedure based on evolution and on the Multilevel Darwinist Brain system [13] developed in our group.

HOT-WIRE ANEMOMETER TURBULENT SIGNALS

In this case, the delay-based ANN presented before includes an additional difference with respect to the typical MLP configurations, as some of the nodes implement a product combination function instead of the traditional sum. Fig. 1 shows a schematic representation of the ANN.

As a consequence, to train the parameters of the ANN, we have developed an extension of the backpropagation algorithm, and have called it Pi Discrete Time Backpropagation (Π-DTB) [12]. This algorithm permits training the network through variations of synaptic delays and weights, in effect changing the length of the synapses and their transmission capacity in order to adapt to the problem in hand.

In addition, through the appropriate determination of the delay terms in the synapses the Π-DTB algorithm performs an automatic selection of the signal points to be correlated. Consequently, when speaking in the language of the dynamic reconstruction of signals, the network automatically obtains the embedding delay and embedding dimension.

If we take into account the description of the network in terms of synaptic weights and synaptic delays, the main assumption during training is that each neuron in a given layer can choose which of the previous outputs of the neurons in the previous layer it wishes to input in a given instant of time. Time is discretized into instants, each one of which corresponds to the period of time between an input to the network and the next input. During this instant of time, each of the neurons of the network computes an output, working its way from the first to the last layer.

Further details on the backpropagation algorithm used in these networks and on its training process for this particular application can be found in [10].

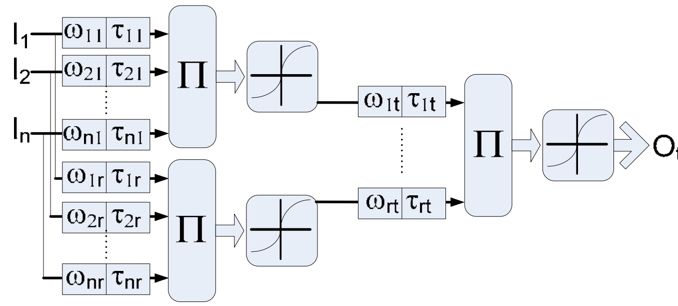

Fig. 1 The network used.

LASER DOPPLER VELOCIMETRY SIGNALS

Its processing is based on the Multilevel Darwinist Brain (MDB), which is extensively explained in [13]. This is an evolution-based control architecture originally designed for autonomous robots that permits a computational agent to learn from the interaction with its environment. To this end several concepts like Strategies, World Models, Internal Models and Action-Perception Pairs were considered. The problem confronted in this work does not require of the whole potential of the MDB as the system is going to be a simple spectator of the signals it is going to model without performing any actions over them. Consequently, the MDB provides only the basic procedure for learning a model on-line using evolutionary algorithms. This procedure requires three main elements:

- *Models:* encoded into delay-based MLP as commented before but, in this case, they don't include the product terms in the nodes. This kind of temporal ANN allows for the models to be able to predict time related phenomena without having to define a particular window or sampling regime.
- *Short Term Memory (STM):* small storage space that preserves a certain number of samples of the original data points. The STM is updated each time a new point is acquired. In this case, the replacement strategy of the points is simply a FIFO due to the highly local temporal information of the signals. The samples that are stored in the STM contain the velocity in instant t, the time until the next measurement and the velocity in instant t+1.
- *Evolutionary Algorithm:* the models are adjusted through a genetic algorithm that uses a set of models (population) to explore the search space.

The learning process in this case is as follows: when the STM is initially filled up, the evolutionary process starts from a population of delay-based ANNs that are initially random. After a fixed number of evolution steps (generations), the model (individual) that better predicts the sample points stored in the initial STM is selected as the *current model* and is applied for the on line prediction of the signal.

The procedure followed to evaluate the models in each generation of the evolutionary process consists in running them in a synchronous mode (as opposed to the random particle arrival time) for the time period corresponding to the sample points of the STM. When, for a given instant of time, there is a measured point in the STM, this point is used as input to the networks, and when there is no real point in the STM, the network uses its own previous output (its own prediction) as input in order to obtain a new prediction in a multi-step fashion until it finds a new real point. The predictions for real points present in the STM provide an error in terms of MSE whose inverse is used as fitness for the particular model.

When a new sample appears, it is stored in the STM and the evolutionary process starts again, but now the models are not randomly generated, instead they are the result of the previous evolution. This way, the learning process is accelerated and the creation of general models is promoted.

It is important to notice that the evolutionary process only runs for two to four generations between updates of the STM, this way, a generally good model of the signal can be achieved and not one that could over-fit the contents of the current STM.

This basic cycle of updating the STM, evolving the models, executing the current model and updating the STM is repeated and, as time progresses, the models become better adapted to the real signal and the predictions improve leading to networks that provide an evenly sampled signal with the same spectral characteristics as the original unevenly sampled one.

EXPERIMENTAL HW RESULTS

ANNs have been applied to analyze HW signals in two very different ways. As a first approach, they were applied to predict a few time steps in advance of the measured signals in both the wake and the jet cases. Our results show that the predictions obtained by the networks for all cases tested appear to be very good. An example of this multi-step prediction can be seen in Figure 2 representing the signal obtained by the HW in the cylinder wake at a position 20 diameters downstream of the cylinder when the Reynolds number value is 2000. Figure 3 presents the case of a turbulent jet with a Reynolds number of 5000 and the probe placed at 5 diameters from the jet exit and aligned to its edge. It can be seen that the performance achieved by the multi-step prediction process is adequate in both examples, the points are superimposed; this has been always like this in all test cases.

When the ANN is used as a signal generator, that is, as an analysis tool, the behavior can be different in both types of flows. In the wake case it is able to detect a main peak of the signal in conditions where a standard FFT is incapable of doing it. For instance, figure 4 presents the power spectra of the signal presented in figure 2 and of the signal generated by the ANN during a time of 0.2 s starting 0,1 s after the real signal input has been shut off. The spectrum of the real signal presents a maximum at a frequency of 96 Hz and so does the generated signal spectrum. However, the latter has lost a lot of the details. If the FFT is calculated with a later time window, everything but the main peak will vanish.

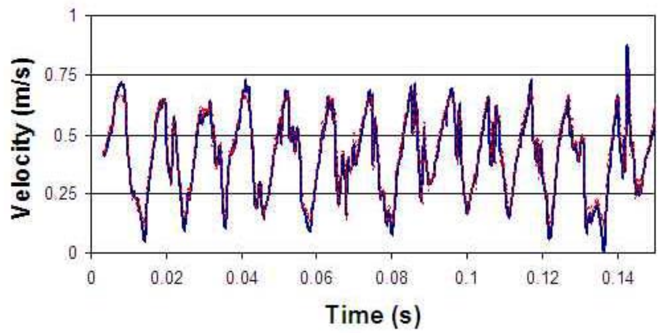

Figure 2. Measured (solid line) and predicted (dotted line) signal in a cylinder wake at 20 diameters downstream of the cylinder and with Re=2000.

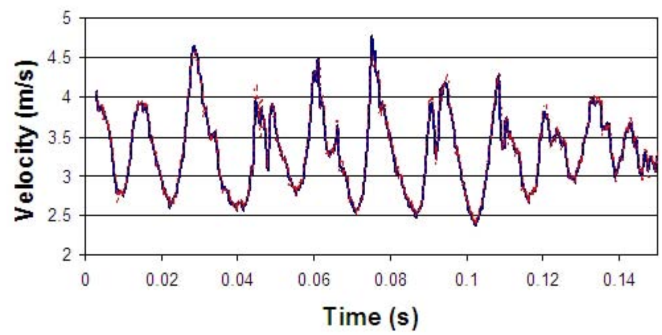

Figure 3. Measured (solid line) and predicted (dotted line) signal in an air jet at 5 diameters downstream of the jet exit and with Re=5000.

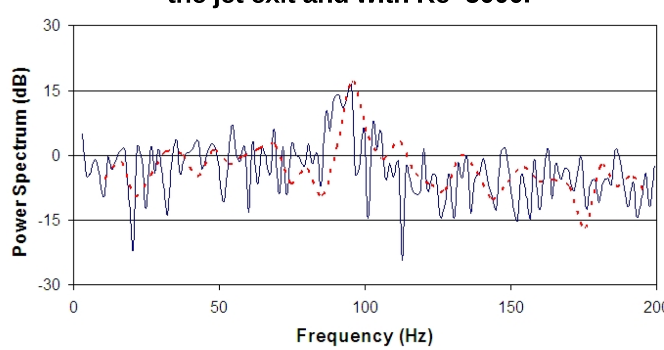

Figure 4. Power spectra of the measured (solid line) and self-generated (dotted line) signal in a cylinder wake at 20 diameters downstream of the cylinder and with Re=2000.

The analysis of the jet signals by this system have proven to be more difficult that the wake ones as in this type of flows the self-generated signal decays much more rapidly than in the other case and it always goes to a flat signal. Still, if a maximum exists, its decay is always slower than the rest of the spectrum. In many cases the system can also detect a maximum where no peak is perceptible in the real signal spectrum. Therefore, this analysis mode of the network appears to be a useful tool for detecting organized structures within the turbulent flow by looking exclusively at the signal generated in a single point and without having any other spatial information of the flow-field.

EXPERIMENTAL LDA RESULTS

Results obtained from turbulent signals measured with a LDA in the wake of a round cylinder and their subsequent analyses by the MDB model are presented. Two of the different test cases considered are presented here corresponding to Reynolds numbers of 2000 and 6000. In both cases, LDA signals were taken at a position 10 diameters downstream of the cylinder at an average sampling rate of 3000 samples per second. In both cases the Strouhal number should take a value close to 0.21. Thus, the first case must present a fundamental frequency close to 100 Hz while in the second one it should be about 300 Hz.

As for LDA the sampling of the signal is non-uniform then the Shannon theorem doesn't hold and thus it is possible to extract information in the frequency domain at values larger than half of the average sampling frequency. To check the ability of the MDB model for taking advantage of this characteristic, some reconstructions of the signals at synchronous time intervals shorter than the average sampling interval of the original LDA signal were performed. As an example, figure 5 displays the results of a test where the time interval used in the synchronous mode equals twice the average time interval of the LDA signal, resulting in an evenly sampled signal equivalent to the non-uniformly sampled original one.

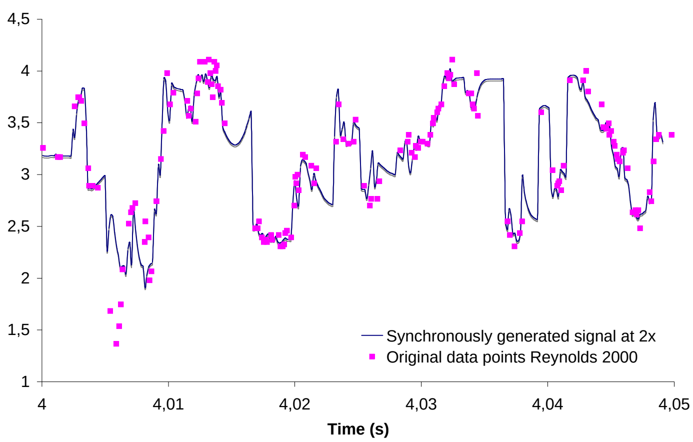

Figure 5. Synchronously sampled signal model obtained by the MDB (lines) for a Reynolds 2000 type signal (dots) using two times the average sampling rate of the original signal.

The figure shows that the signal reconstruction is very good while the non linear interpolation obtained from the MDB attempts to recover the chaotic character of the signal. It should be mentioned that in this 2x case, less than 10% percent of the synchronous time intervals have an actual signal point to correct the prediction. To obtain this result, the MDB-based procedure was applied with a delay-based ANN of 1 input node, two hidden layers of 6 neurons each and 1 output node. We used a genetic algorithm with a population of 1000 individuals, a STM of size 10 and a maximum delay of 8.

When the signals become more chaotic, as is the case of Reynolds 6000, these results still hold even at a 4x sampling pace. It is important to point out that, according to the considerations made in the next section; it does not make much sense to further increase the synchronous sampling rate –for instance to 8x- as the highest frequencies present are limited by the turbulence dynamics as well as by the LDV system.

POST PROCESING LDA RESULTS

Although the signal reconstruction presented in figure 5 shows a good performance, some discrepancies appear between the measured data and the predicted signals. Thus, it seems clear that the results can be improved by merging the measured data into the prediction. For this purpose some considerations need to be made; firstly, in the signal shown, the reconstruction of the target does not pass through all the measured points, even though it does capture the signal trends. Taking this into account, in our post processing scheme when two consecutive measured points are separated by a short time interval, the corresponding piece of reconstructed signal is shifted until the origin of the piece matches the first measured point. After this, the amplitude of all other points in the segment is varied by an amount proportional to its time distance to the first point with the condition that the last point of the segment must match the second measured point. In cases when two consecutive measured points are far apart, their corresponding predicted ones are shifted so as to coincide with them and a linear correction is applied to their three closest neighbours, leaving the rest of the predicted signal interval unaltered. Figure 6 displays the reconstructed signal presented in figure 5 after being corrected using the merging procedure with the real data. The small discrepancies found in the former figure have now disappeared after applying the proposed post processing scheme.

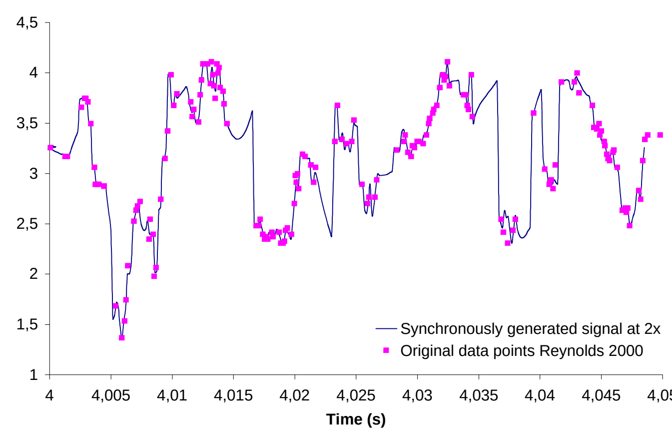

Figure 6. Signal reconstructed by applying the post processor

CONCLUSIONS

This paper presents some applications of ANN and evolutionary methods for the analysis of turbulent signals measured as time series at a single point for both HW and LDA. A new type of ANNs with trainable delay terms in their synapses is applied for the dynamic reconstruction of HW signals. Two different turbulent flows have been used as test cases; the wake of a cylinder and a free jet. The new network has been able to make a multi-step prediction of the signal in every case tested. The ANN is then used in an analysis mode in which, and after some time of predicting, the input signal is shut off and the network generates the learned signal by using as inputs its own predicted outputs. In many cases this signal presents during its decay clear peaks in its spectrum corresponding to the main characteristic frequencies of the original signal, even in cases where these peaks cannot be seen in the original power spectrum.

In the case of the LDA signals these ANNs are used within an evolutionary based method. It achieves its purpose by modelling and predicting the signals prior to re-sampling them at a regular pace. The strategy is based on the use of these delay based ANNs as models of the signals and an adaptation procedure inspired in the Multilevel Darwinist Brain which permits an agent to adapt to changing signals in real time through the production of adequate general non linear models of the processes involved. Analysis of real turbulent signals taken by an LDV system in the wake of a circular cylinder proves the ability of this model to correctly predict and non-linearly interpolate these signals. The model is able to generate an equivalent equally spaced sampled signal at several times the mean rate of the original one. As a final stage, a proposed post processing method shows that the small discrepancies between the reconstructed signals and the real data can be greatly diminished by applying a simple merging scheme.

ACKNOWLEDGEMENTS

This work was funded by the Xunta de Galicia under project PGIDIT04DPI166004PR and by the MEC of Spain under project TRA2005-09290-C02-01/TMAR.

REFERENCES

[1] Ferre-Gine, J., Rallo, R., Arenas, A., Giralt, F., 1996, “Identification of Coherent Structures in Turbulent Shear Flows with a Fuzzy Artmap Neural Network,” International Journal of Neural Systems, Vol. 7, No. 5, pp. 559-568.

[2] Giralt, F., Arenas, A., Ferre-Gine, J., Rallo, R., Kopp, G. A., 2000, “The simulation and interpretation of free turbulence with a cognitive neural system,” Physics of Fluids, Volume 12, Issue 7, pp. 1826-1835.

[3] P. K. Panigrahi; Manish Dwivedi; Vinay Khandelwal; Mihir Sen. Prediction of Turbulence Statistics Behind a Square Cylinder Using Neural Networks and Fuzzy Logic. Journal of Fluids Engineering. V. 125, Issue 2, pp. 385-387. March 2003.

[4] M. Chattopadhyay, J. Dey, V. Mani. Transitional intermittency detection by neural network. Experiments in Fluids, Volume 26, Number 6 / May, 1999

[5] Mozer N. Neural net for temporal sequence processing Time Series Prediction: Forecasting the Future and Understanding the Past. Weigend A, Gershenfeld N (eds), Addison-Wesley, 1993.

[6] Koskela T, Lehtokangas M, Saarinen J, Kaski K. Time series prediction with Multilayer Perceptron, FIR and Elman neural networks. Proc. World Congress on NNs., pp 491-496, 1996.

[7] De Falco, I., Della Cioppa, A., Iazzetta, A., Natale, P., Tarantino, E., 1998, “Optimizing Neural Networks for Time Series Prediction,” In: Roy, R., Furuhashi, T., Chawdhry, P.K., (eds.), Proceedings of the 3rd on-line World Conference on Soft Computing (WSC3), Advances in soft computing – engineering design and manufacturing Internet. Berlin Heidelberg New York, Springer.

[8] Duro, R. J. and Santos, J., 1999, “Discrete Time Backpropagation for Training Synaptic Delay Based Artificial Neural Networks,” IEEE Trans. Neural Networks, V.10, No. 4, pp. 779-789.

[9] López Peña, F., Duro, R.J. and Sánchez Simón, M. L., 2002, “Detecting Coherent Structures in a Turbulent Wake by Using Delay Based Networks,” Computer Stand. & Interfaces, No. 24, pp. 171–184.

[10] Bellas, F., Lopez Peña, F., Duro, R. J. and Sanchez Simon, M. L., 2005, “Analysis of Hot-Wire Anemometer Turbulent Signals by Means of Delay Based Networks,” Proc.3rd IEEE Workshop on Intelligent Data Acquisition and Advanced Computing Systems: Technology and Applications. Pp. 8-12.

[11] López Peña, F., Bellas, F., Duro, R. J. and Sánchez Simón, M. L., 2006, “Using Adaptive Artificial Neural Networks for Reconstructing Irregularly Sampled Laser Doppler Velocimetry Signals,” IEEE Transactions on Instrumentation and Measurement. Vol. 55, no. 3, pp. 916-922.

[12] Santos, J. and Duro, R.J., 2001, “Pi-DTB Discrete Time Backpropagation with Product Units, Connectionist Models of Neurons,” in Learning Processes and Artificial Intelligence, Springer Verlag, pp 207-214.

[13] Bellas, F., Faiña, A., Prieto, A., Duro, R.J., 2006, “Adaptive Learning Application of the MDB Evolutionary Cognitive Architecture in Physical Agents,” LNAI 4095, pp. 434-445.