Analysis of Hot-Wire Anemometer Turbulent Signals by Means of Delay Based Networks

F. Bellas [2], F. López Peña [1], R. J. Duro [2], M. Sanchez Simon [1]
1) Grupo de Ingeniería de Fluidos, 2) Grupo de Sistemas Autónomos
Universidad de La Coruña, Escuela Politécnica Superior, Mendizabal s.n., 15403 Ferrol, Spain
fran@udc.es, flop@udc.es, richard@udc.es, marisass@udc.es

Abstract: *A Neural Network based system for reconstructing turbulent signals obtained by a Hot Wire Anemometer in the shear layer surrounding a turbulent free yet of air is presented. The flow-field used as work bench presents very complex turbulence dynamics making the measured signals very difficult to predict. The results presented here show a very good agreement in prediction and present a high potential as an analysis tool.*

Keywords: - Turbulence, Turbulent Jet, Hot-wire anemometer, Signal Reconstruction, Signal Analysis, Artificial Neural Network.

1. INTRODUCTION

Most fluid flows of practical interest for scientists and engineers are turbulent ones. Depending on the particular application, the engineering design some times tries to increase and some others to reduce their turbulence level. Delaying the transition to turbulence in a boundary layer, for example, can allow engineers to reduce the propulsive force needed to move an automobile or a commercial airliner; but increasing the turbulence level inside a combustion chamber can improve the fuel efficiency of an engine. Both examples evidence one of the main characteristics of turbulence; it produces a large amplification of the transfer processes of momentum, heat and mass [1].

Turbulence is one of the most notoriously difficult problems of classical physics; still today remarkably little of a quantitative nature is known about it. Any turbulent flow motion can be considered as a spatial-temporal chaotic phenomenon having many degrees of freedom [2]. Regardless of these intrinsic characteristics, the analysis of turbulent flows by approaches other than statistical have been attempted only during the last two or three decades. The Reynolds number, defined as de ratio between inertial and viscous forces, is the fundamental parameter governing turbulent flows. For a round jet of a fluid of density ρ and viscosity μ, having diameter D and coming out at velocity V, the Reynolds number has a value of

$$(1) \qquad Re = \frac{\rho V D}{\mu}$$

In our study a hot wire anemometer is used to perform measurements in a round air jet exhausted into the atmosphere. The hot wire anemometer is a basic tool very suitable for experimental characterization of turbulent flows due to its ability to measure flow fluctuations up to the hundred thousand Hertz range [3]. In the present investigation, the temporal signals obtained by this device while measuring in a given spatial point are reconstructed and analyzed through delay based artificial networks.

Turbulent jet flow is a classical free shear flow problem that can be found in many practical applications, due to its interest it has been widely studied by many researchers [4] [5] [6]. Jets attain a region of universal self-similar velocity profiles at a position about 15 jet exit diameters downstream of the exhaust. A near-field region appears just after the exit which is dominated by an axisymmetric mixing layer governed by vortex rings generated by Kelvin-Helmholtz instabilities which promote coherent structures. Is in this near-field region where the tests presented here are performed.

2. EXPERIMENTAL SET-UP

The experimental set-up is shown in Fig. 1. The air jet under analysis has a diameter of 16.5 mm and is coming out of a device made by a settling chamber followed by a contraction. 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

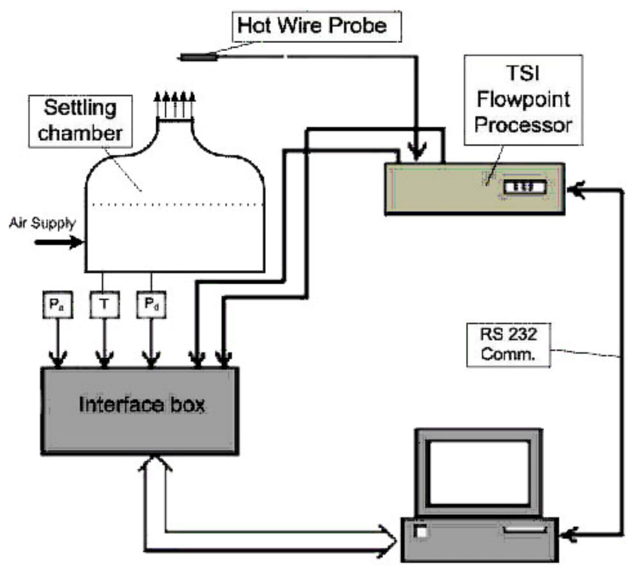

Fig. 1- Experimental set-up.

measuring the difference in pressure between the settling chamber and the atmosphere by means of a differential pressure transducer.

All the above mentioned sensors, as well as the hot wire anemometer processor (a Flowpoint model by TSI), are connected trough an interface box to a National Instruments PCI-MIO-16XE-50 data acquisition board installed in a personal computer. The interface box contains all the filters and amplifiers needed to condition the signals coming from the different transducers and sensors. A RS232 communication cable is used to control the hot wire anemometer processor from the computer. A specific virtual instrument has been developed under the Labview environment to perform all the acquisition and control tasks in an appropriate way.

3. DYNAMIC RECONSTRUCTION

The problem of Dynamic Reconstruction involves obtaining some type of description of a given chaotic time series obviating the need for detailed mathematical knowledge of the underlying processes that conform its dynamics. Basically, what is required is some type of function that can autonomously adapt to the signal under study to the level of detail required so that after some type of training or parameter adjustment, it can generate it. This is the approach followed here in order to study turbulent signals. These signals are used as training set for a neural network that learns to predict them and which is quite efficient when performing multi-step prediction processes. After the network is trained, it is disconnected from the signal and it uses its own outputs as inputs for the next predictions. Thus, the network has become a signal generator. In this work, we demonstrate that these types of artificial neural networks learn the regularities in these signals and thus can reproduce them to the level of detail required in order to obtain the most significant spectral peaks the original signals present, especially those related with the underlying processes.

4. THE NEURAL NETWORK

The artificial neural network we consider for training consists of several layers of neurons connected as a Multiple Layer Perceptron (MLP). It is represented schematically in Fig. 2. There are two differences with respect to traditional MLPs. The first one is that the synapses include a delay term in addition to the classical weight term [7]. That is, now 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. The second one is that some of the nodes implement a product combination function instead of the traditional sum.

We have developed an extension of the backpropagation algorithm for training both parameters of the connections, and have called it Pi Discrete Time Backpropagation (Π-DTB) [8]. 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.

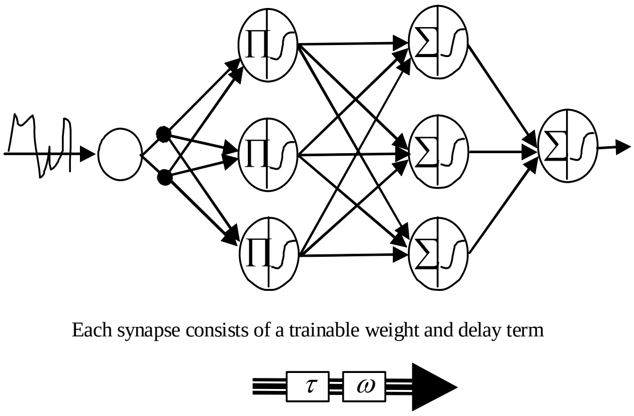

Fig. 2 - Network used

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. Thus, for each input, there is an output assigned to it.

As we show, by discretizing the time derivative we obtain simple expressions for the modification of the weights and delays of the synapses, in an algorithm that is basically a back-propagation algorithm where we have modified the transfer function of the neuron to permit a choice of inputs between all of the previous outputs of the neurons of the previous layer.

Here we summarize the basis of the algorithm, explained in detail in [8], concentrating in the new equations for the Π-units.

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. Thus, for each input, there is an output assigned to it.

In order to choose from the possible inputs to a neuron the ones we are actually going to input in a given instant of time, we add a selection function to the processing of the neuron. This selection function could be something as simple as:

$$\delta_{ij} = \begin{cases} 1 \rightarrow i = j \\ 0 \rightarrow i \neq j \end{cases} \quad (2)$$

so that the output of a traditional (3) and a product (4) node k in an instant of time t is given by:

$$O_{kt} = F\left(\sum_{i=0}^{N}\sum_{j=0}^{t}\delta_{j(t-\tau_{ik})}w_{ik}h_{ij}\right) \quad (3)$$

$$O_{kt} = F\left(\prod_{i=0}^{N}\sum_{j=0}^{t}\delta_{j(t-\tau_{ik})}w_{ik}h_{ij}\right) \quad (4)$$

where F is the activation function of the neuron, h_{ij} is the output of neuron i of the previous layer in instant j and w_{ik} is the weight of the synapse between neuron i and neuron k. The first sum (or product) is over all the neurons that reach neuron k (those of the previous layer) and the second one is over all the instants of time we are considering (let´s say since the beginning of time, although in practical applications the necessary time is finite).

The result of this function is the sum or product of the outputs of the hidden neurons in times t-τ_{ik} (where τ_{ik} is the delay in the corresponding connection) weighed by the corresponding weight values.

Now that we know what the output of each neuron is as a function of the outputs of the neurons in the previous layer and the weights and delays in the synapses that connect these neurons to it, what we need is an algorithm that allows us to modify these weights and delays so that the network may learn to associate a set of inputs to a set of outputs. The basic gradient descent algorithm employed in traditional backpropagation may be used, but we must now take into account the delay terms when computing the gradients of the error with respect to weights and delays.

As shown in [8], these gradient terms are:

$$\frac{\partial E_{total}}{\partial w_{jk}} = \Delta_k h_{j(t-\tau_{jk})} \quad (5)$$

$$\frac{\partial E_{total}}{\partial \tau_{jk}} = \Delta_k w_{jk}\left(h_{j(t-\tau_{jk})} - h_{j(t-\tau_{jk}-1)}\right) \quad (6)$$

being E_{total} the total squared error for all the training vectors and

$$\Delta_k = \frac{\partial E_{total}}{\partial O_k}\frac{\partial O_k}{\partial ONet_k} = 2(O_k - T_k)F'(ONet_k) \quad (7)$$

where T_k is the desired output, O_k the one really obtained and O_{Netk} is the combination of inputs to neuron k, when we consider output neurons. For hidden neurons connected to the input layer, and defining as before

$$\Delta_k = \frac{\partial E_{total}}{\partial hNet_k} = F'(hNet_k)\sum_r \Delta_r w_{kr} \quad (8)$$

where index r represents the neuron of the next layer, whether output or hidden, we have the following derivatives for the weights and connections:

$$\frac{\partial E_{total}}{\partial w_{jk}} = \frac{\partial E_{total}}{\partial hNet_k}\frac{\partial hNet_k}{\partial w_{jk}} = \Delta_k I_{j(t-\tau_{jk})} \quad (9)$$

$$\frac{\partial E_{total}}{\partial \tau_{jk}} = \frac{\partial E_{total}}{\partial hNet_k}\frac{\partial hNet_k}{\partial \tau_{jk}} = \Delta_k w_{jk}\left(I_{j(t-\tau_{jk})} - I_{j(t-\tau_{jk}-1)}\right) \quad (10)$$

where the second derivative in (9) is the result of:

$$\frac{\partial hNet_k}{\partial \tau_{jk}} = \frac{\partial\left[\sum_{i=0}^{N}\sum_{n=0}^{t}\delta_{n(t-\tau_{ik})}w_{ik}I_{in}\right]}{\partial \tau_{jk}} \quad (11)$$

when considering neurons in a hidden layer. It may be observed that the derivative in $hNet$ of equation (11) has been discretized in order to obtain (10), implicitly assuming there is a certain continuity in the temporal variation of the outputs of the neurons, which in practice turns out to be a valid assumption.

Regarding the product units in the first hidden layer, we have:

$$hNet_k = \prod_{r=0}^{N} w_{rk}\ I_{r(t-\tau_{rk})} \quad (12)$$

and the derivatives are

$$\frac{\partial hNet_k}{\partial w_{jk}} = \frac{\prod_{r=0}^{N} w_{rk}\ I_{r(t-\tau_{rk})}}{w_{jk}} \quad (13)$$

$$\frac{\partial hNet_k}{\partial \tau_{jk}} = \frac{\prod_{r=0}^{N} w_{rk}\ I_{r(t-\tau_{rk})}}{I_{j(t-\tau_{jk})}}\left(I_{j(t-\tau_{jk})} - I_{j(t-\tau_{jk}-1)}\right) \quad (14)$$

where index r denotes the input nodes connected to the corresponding product hidden unit. The importance of the procedure is that now the appropriate delays for these connections, and consequently the temporal values that make up the product terms in the *pi* units are obtained automatically, and are not imposed beforehand.

As we show, by discretizing the time derivative we obtain simple expressions for the modification of the weights and delays of the synapses, in an algorithm that is basically a backpropagation algorithm where we have modified the transfer function of the neuron to permit a choice of inputs between all of the previous outputs of the neurons of the previous layer.

5. RESULTS

Neural networks have been applied to analyze hot wire signal in two very different ways. At first they were applied to predict the measured signals. Our results show that the prediction obtained by the networks for different

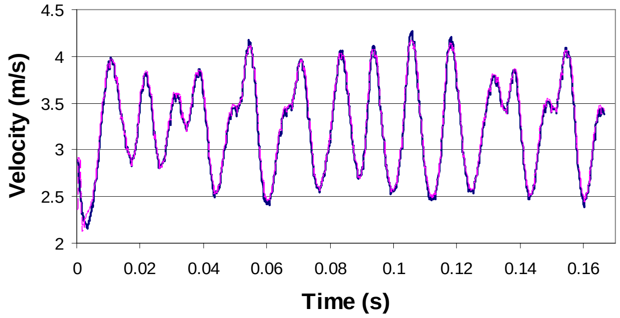

Fig. 3 - Original signal (continuous line) and signal predicted by the network (dotted line) corresponding to a turbulent signal of Reynolds number 5000

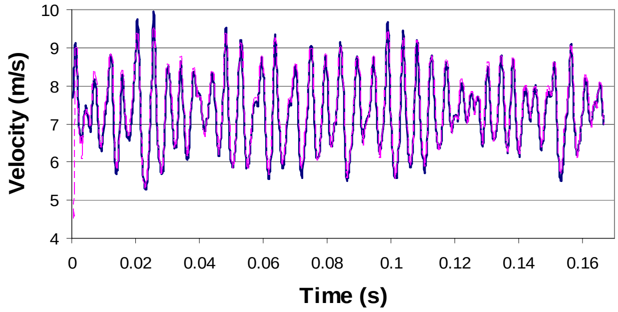

Fig. 5 - Original signal (continuous line) and signal predicted by the network (dotted line) corresponding to a turbulent signal of Reynolds number 10000

jet cases appears always to be very good. As a second analysis application, the networks have been trained on a real signal and then they were used as signal generators. In this case no signal input was provided to the networks from a certain point on and they were allowed to run using their previous outputs as inputs for the next predictions. That is, they were run as multistep predictors or signal generators. This was done in order to see how well they managed to capture the basic dynamics of the process. This type of application was used in [9] to capture coherent structures in a turbulent wake.

As an example, Fig. 3 shows the comparison between the prediction of the turbulent signal and the signal itself in a case for which the Reynolds number is 5000 and the position is of 2.4 jet exit diameters downstream of the jet exit and at a radial position of one radius, that is just in the middle of the mixing layer where the instabilities are generated. The applied network has 2 hidden layers of 30 neurons each. The achieved prediction results to be excellent in all test cases considered.

For this test case, Fig. 4 shows the power spectra of the original signal (dotted line) and the prediction of its main features made by the network (continuous line) when the system is used as signal generator as explained earlier. In this case, the network provides a successful result with two main frequencies in 64 Hz and 117 Hz while the original ones are in 67.6 Hz and 114 Hz. As we can see, the higher frequency is not clearly defined in the original signal, but in the prediction there is a clear peak.

Figs. 5 and 6 are equivalent to the previous ones but correspond to a turbulent signal for which the Reynolds number is 10000 and the same axial distance of 2.4 jet exit diameters. The prediction is highly accurate and the power spectrum shows a main frequency in 198 Hz.

It is important to notice that the analysis system is able to capture more than one fundamental frequency corresponding to the coherent structures embedded in the turbulent flow.

The detection of two fundamental frequencies is an indication of the extreme complexity of the flow-field used in the test. In some other test case flows, as in the case of the wake use in previous research work [9], or in most part of the present one, only a fundamental frequency appears. In any case where the fundamental frequencies can be detected by means of traditional linear methods, their values coincide with the ones obtained by our non linear detector, but this later is able to detect this frequencies corresponding to coherent structures in many cases where traditional methods only show noise like patterns.

6. CONCLUSIONS

In this paper we present a new approach for the dynamic reconstruction of hot wire anemometer signals through artificial neural networks. This network is trained on the real signal on line and after that it is able to accurately predict the signal. In a second stage, and after some training time, the input signal is shut off and the network generates the learned signal by using as inputs its own predicted outputs. The signals thus generated reproduce the basic spectral features corresponding to the

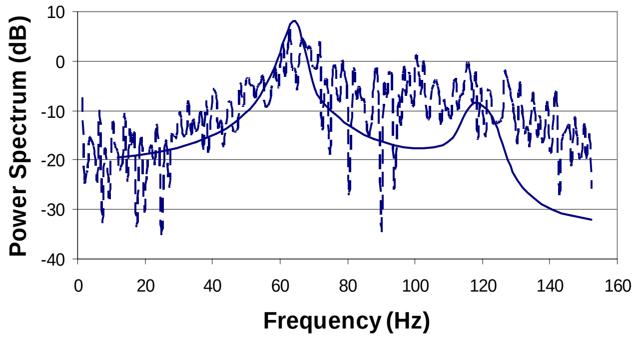

Fig. 4 - Power spectrum of the original signal (dotted line) and the feature extraction made by the network (continuous line) corresponding to a turbulent signal of Reynolds number 5000

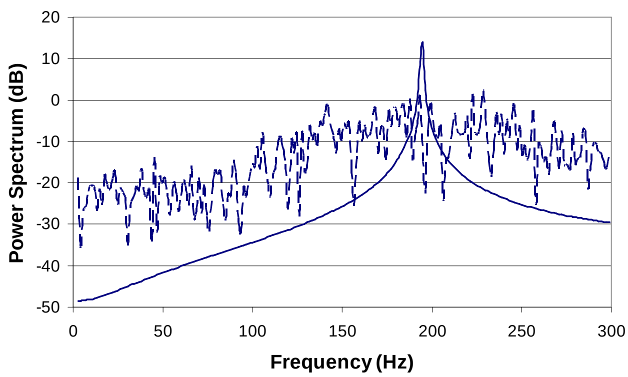

Fig. 6 - Power spectrum of the original signal (dotted line) and the feature extraction made by the network (continuous line) corresponding to a turbulent signal of Reynolds number 10000

coherent structures embedded in the flows under consideration, even in cases where the power spectrum of the original signal does not present any well defined peak.

7. ACKNOWLEDGEMENTS

This work was funded by the MCYT of Spain thorugh project VEM2003-20088-C04-01 and Xunta de Galicia through projects PGIDIT03TIC16601PR and PGIDIT04DPI166004PR.

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