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Abstract

This paper is concerned with the problem of analyzing turbulent flow signals that are irregularly sampled by a Laser Doppler velocimeter. The temporal irregularity of the sampling is the main problem addressed due to the difficulties it introduces in the use of traditional analysis techniques. The main contribution of this work is to assess the adequateness of introducing a signal modeling strategy by means of temporal delay based Artificial Neural Networks (ANNs) that are adaptively and continuously trained on line on the irregularly sampled real data using an evolutionary based strategy called the Multilevel Darwinist Brain. The networks are used to model the signal and thus are able to produce a regularly sampled signal straight from the irregular one. It is important to note that they are being trained to model the signal, and not just interpolate it; they are able to generate spectral signatures that are very close to that of the original signal.

1. INTRODUCTION

Laser Doppler Velocimetry (LDV), also known as Laser Doppler Anemometry (LDA), is an optical non intrusive flow measuring technique widely used as a standard in many fluid research laboratories all over the world. This technique measures the velocity of small particles (typically of about one micrometre) seeded within the flow, while they cross a small region of interest where two laser beams intersect. These seeded particles should be big enough to scatter sufficient light for signal detection but small enough to be conveyed by the fluid flow under measurement. As the particles pass through the intersection of the two laser beams, they scatter light modulated in intensity with a frequency equivalent to the Doppler shift between the incident and scattered light. Thus, the frequency of this modulation is proportional to the component of the particle velocity lying in the plane of the two laser beams and which is perpendicular to their bisector. This technique, or better, a slightly different one known as reference-beam LDA, was first introduced by Yeh and Cummins in 1964 [1], and the dual beam LDA as described before was proposed after subsequent developments during the late sixties and the seventies as reported by Drain [2] or Durst et al [3]. Further improvements in detectors, Doppler signal analysis, or the inclusion of fiber optic probes, have transformed

LDA into a well established flow diagnosis technique which is extensively used in fluid flow studies to perform spatially precise point measurements at speeds ranging from mm/s to supersonic, as well as to serve as a bench-mark validation tool for other velocimetry techniques. Examples of the wide variety of applications where LDA has been used are combustion studies, turbomachine flows, atmospheric turbulence measurement, or aerodynamic and hydrodynamic studies for vehicles. A comprehensive review of the principles, evolution, applications and techniques related with LDA can be found in the book by Albrecht et Al [4].

In Accordance with the description above, LDA is a single point measuring technique in which data sampling times are dictated by particle arrival in the measuring volume, resulting in a non uniformly sampled signal with timing governed both by flow velocity and by particle seeding distributions. Consequently, the problem of estimating the power spectrum from irregularly sampled data arises. This problem is also present in many other technical applications of practical interest, and it has received a lot of attention during the last decade. Early attempts to obtain the power spectral density of LDA data were performed by Adrian and Yao [5] and Boyer and Serby [6] by holding each sampled velocity value until another valid signal point was acquired. This procedure provides reasonable results; nevertheless it leads to a low-pass filtering of the spectra at the mean sampling rate (which can be quite low), a fact that was already reported by Adrian and Yao [5]. Furthermore, it introduces white noise in the spectra due to the steps in the sample-and-hold operation. Some improvements to this procedure were introduced by Nobach et Al. [7] and Ouahabi et Al. [8]. The latter replace the sampling and hold procedure by a polynomial interpolator of the sampled data after assuming that these sampled data points are Poisson distributed, while in the former the improvement on the sample and hold reconstruction procedure is achieved by using the knowledge of the particle arrival statistics to correct the estimates.

In the present work, the reconstruction of the signal is achieved through a different non linear model based approach characterized by the on line adaptation of neural networks with trainable synaptic delays acting as models to the unevenly sampled signal. When an adequate model is obtained the network is used to produce the whole signal in a synchronous manner in order to generate an appropriate power spectrum. To achieve a good model we have taken inspiration from the Multilevel Darwinist Brain introduced by Bellas et Al. [9]. The approach is founded in the ability of Artificial Neural Networks for modeling and reconstructing chaotic signals generated by turbulent flows, as shown by López Peña et Al. [10].

The flow behind a circular cylinder is used as a benchmark problem because it has been extensively studied in the past and it is being used as a test bench for experimental and numerical studies. It has the advantage of being governed by a single control parameter; the Reynolds number, which is defined as the ratio between inertial and viscous forces. For a cylinder of diameter D moving at velocity V in a fluid of density ρ and viscosity μ, the Reynolds number has a value $\mathrm{Re}=\rho VD/\mu$. When this Reynolds number presents values in the few thousands range, the wake is turbulent but it displays a known dominant frequency corresponding to large embedded coherent structures. This characteristic is used in this study to check for the correct behavior of the proposed model.

A Multilevel Darwinist Brain (MDB), which is extensively explained in [9] [11], is an approach to implement a mechanism that allows an organism to interact with the environment and learn from it, leading to the improvement of its performance in time in a computationally efficient way. 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 a simple spectator of the signals it is going to model without performing any actions over them. Consequently, the action generation part of the MDB will not be required.

In the reduced version of the MDB used for this work the models are implemented through trainable delay based ANNs which are evolved in real time using a Promoter Based Genetic Algorithm (PBGA). The basic idea is that when a measured point is produced, it is introduced in the short term memory and a few generations of evolution take place on the Delay Based ANNs that conform the evolving population using as fitness the average prediction ability of the models for the values in the short term memory. The evolution generations that take place between interactions with the world, that is, evolutionary steps carried out every time a new measured point is obtained, are very few (around four) and it will take many interactions with the world for a good model to be obtained. This permits avoiding any overfitting to a given content of the short term memory, which in this case means a given portion of the signal instead of the whole process underlying it. As demonstrated by Bellas et Al. [9] the implicit learning inertia thus generated permits using small short term memories, with the consequent reduction of computation, and still obtain a good generalization of the non linear models.

The initial results using this technique for modeling unevenly sampled signals are quite encouraging in the sense that good models may be obtained for this type of signals, especially with regards to the more periodic aspects which can be very well represented in the delay patterns of the synapses in Delay Based ANNs. When more chaotic signals are considered the resulting models represent the underlying periodic terms which in this problem is what is required for the production of the most relevant terms in the power spectrum.

2. EXPERIMENTAL SET-UP

The experimental data used in the present investigation were obtained in the Boundary Layer Wind Tunnel (BLWT) of the fluid mechanics laboratory of the Escuela Politecnica Superior of the Universidade da Coruña. A schematic view of the facility and the experimental set-up is presented in Figure 1. 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. Data were taken 10 diameters downstream of the cylinder at a mean sampling rate of 3000 samplings per second.

Measurements were performed using a fibre optic LDA system by DANTEC. This system has a hardware analyzer specifically designed for Doppler signal processing and is schematically represented in figure 2. The first component of the LDA system is a 500 mW Ar-ion laser source mounted on an optical bench together with a transmitter unit. This unit consists basically of a Bragg cell and a colour separator. The laser beam coming from the laser source enters the transmitter unit where is split into two beams by the Bragg cell, one of these is a zero order beam while the other is a first order diffracted beam having its frequency shifted by 40 MHz with respect to the incoming beam. These two beams are then passed through optical fibres going to an optical probe which includes the emitting and the receiving optics. The emitting beams cross each other at the focal point forming a small measuring volume with the shape of an ellipsoid. When a particle seeded in the flow crosses this volume, the receiving optics collect the optical signal and send it through an optical fibre to a photomultiplier transforming it into an electrical signal ready to be used as input by the processor. The LDA raw signal is a burst having a sinusoidal component modulated in amplitude by a Gaussian envelope due to the intensity profile of the laser beams. The frequency of the sinusoidal component equals the Bragg frequency plus the Doppler frequency, being the latter proportional to the velocity of the particle crossing the volume. The LDA processor determines this velocity after obtaining the Doppler frequency by means of a Fast Fourier Transform (FFT). The DANTEC BSA F60 processor used in our experiments can measure Doppler frequencies up to 100 MHz in windows of bandwidths ranging from 15 kHz to 30 MHz, and is able to extract reliable velocity information from bursts shorter than 100 ns.

In our experimental set-up, the optical probe is positioned by a traversing mechanism along a lateral wall of the test section. The probe is provided with a 400 mm focal length lens allowing it to measure in any position in the test section. The LDA measurement system needs the air to be seeded with small particles in order to be able to perform measurements, so a seeding system is placed at the wind tunnel entrance to seed the air in the mainstream. This seeding is made up of small drops obtained by condensation of propylene glycol with an average size of one micrometre.

3. MULTILEVEL DARWINIST BRAIN

As explained earlier, a MDB is an approach to implement a mechanism that allows an organism to interact with the environment and learn from it in a computationally efficient way so that it can improve its performance in time without the designer predetermining future behaviours,. It is based on the on-line limited evolution of populations of models that adapt in real time to sensor information. It was originally developed as a cognitive mechanism for autonomous robots [9] but it is now being applied to other types of problems, such as signal modelling and processing.

The operation of the MDB consists in a sensing stage, a model adaptation stage and an action determination stage. The sensing stage is devoted to the acquisition of information from the environment (in this case from the signal) and its introduction in a Short Term Memory (STM). This STM is limited in size and is used as the representation of reality against which the models are evaluated. The second stage, that is, the adaptation stage, is in charge of the evolution of models. To this end, this stage consists of an evolutionary algorithm working over a model base. In our case, the models are implemented as Delay Based Artificial Neural Netoworks (DBANNs). Initially all the models in the model base are random DBANNs. Every step of the interaction with the world, that is, every sensing stage, a few steps of evolution are carried out over the model base using as fitness value for each model the mean squared error of its prediction of the current contents of the STM. As the interaction with the world progresses, the models become better adapted to the world (signal in this case) as a whole, and not to a particular part of it. When applied to systems that require actions on the environment, the MDB has another stage where using the best current models the system seeks the most appropriate action it must perform in order to satisfy its motivation. Obviously, this stage will not be necessary in the application considered here, as no action will be taken over the signal. The objective is just to obtain a good model of it.

Thus, in this particular application, the main objective of the mechanism is to obtain in real time from unevenly spaced samples a non linear model of the signal so that it can be reconstructed in an evenly sampled way. Consequently, from the original MDB we are only going to consider two elements:

- *World model (*W*)*: function that relates the sensory inputs of the agent in instant of time t to the sensory inputs in instant t+1. Basically the model of the signal under study.

- A*ction-perception pair*: is a set of values made up by the sensorial inputs and the internal state obtained after the execution of a strategy in the real world. It is used when perfecting world and internal models. An action-perception pair represents the information we have on the real signal.

The MDB is basically an on-line evolution based strategy to obtain models from processes as they are taking place. To do this it must have information on the real data obtained and it must be able to manage populations of models to effectively evolve them. Thus, in order to make it work appropriately two elements are needed:

- A *World Model Evolver,* which is a structure that manages world models through evolution. This structure evolves a population of world models and each moment of time selects the best one according to the information it has available about the real world. The selected model is the current model.

- A Short term memory STM, which is a small storage space that preserves a certain number of action-perception pairs corresponding to reality. They are used as local fitness functions of the world model evolver through a comparison of the outputs predicted by the world models and the reality for a given period of time provided by the STM. The reason for the existence of a STM is that it is not feasible, or even convenient, to store all the values obtained from reality and use them to test models. As time passes and the number of points increases this approach would become impractical. Thus, the function of the STM is to store relevant points that are used to evaluate possible models.

The evolutionary process starts from a population of models stored in a memory (*World Model Mem*ory). In our case, the models are obtained in the form of Delay Based Artificial Neural Networks. The contents of this memory are initially random for the first iteration of the mechanism. These contents are maintained from an iteration to the next in order to obtain a generally good population of models and not a superindividual. The individual with the highest fitness value after evolution according to the information of the short-term memory is selected as the current model and is applied for the prediction of the signal. It is important to note that the evolutionary process only runs for two to four generations between data interactions with the world, this way a generally good model of the signal can be achieved.

The models are encoded into feedforward artificial neural networks which contain, in addition to the traditional weights, trainable delays in the synapses. This allows for the models to be able to predict time related phenomena without having to define a particular window or sampling regime.

Thus, the procedure followed for obtaining the models consists in running the models in the population in a synchronous mode for the time span encompassed by the STM. When for a given instant of time there is a real measured point in the STM this point is used as input for the networks. However, when for an instant of time 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 are compared to reality as stored in the Short Term Memory, the mean squared error for the points stored in STM is calculated and its inverse used as fitness for the given network. After all the networks present in the world model memory have been evaluated this way, the steps of a Promoter Based Genetic Algorithm are carried out in order to obtain a new generation of models and the cycle is repeated between two and four times. Having finalized these generations of evolution, an interaction with the world takes place, which means that a new point from reality is inserted in the STM and the oldest one is eliminated. A new set of two to four generations of evolution are the run. This basic cycle is repeated and, as time progresses, the models become better adapted to the real world and the predictions improve leading to networks that provide an evenly sampled signal with the same spectral characteristics as the original unevenly sampled one.

4. THE ARCHITECTURE OF SYNAPTIC DELAY BASED ARTIFICIAL NEURAL NETWORKS

The architecture of the artificial neural network we consider for training is the one shown in figure 3. This network was introduced in [12] and it consists of several layers of neurons connected as a Multiple Layer Perceptron (MLP). Consequently, every neuron of one layer is connected through a synapse to every neuron of the next layer. Each neuron performs a sum of its inputs and passes these values through some non linear function, (in this case a sigmoid). It is obviously a feed-forward network. The only difference with respect to a traditional MLP is that the synapses are represented by two trainable parameters:

the classical weight term and a delay term. Thus, the synaptic connections between neurons are now characterized by a pair of values, (w_{ij}, τ_{ij}), where w_{ij} is the weight describing the ability of the synapse to transmit information from neuron i to neuron j and τ_{ij} is a delay, which in a certain sense provides an indication of the length of the synapse between neurons i and j. The longer it is, it will take more time for information to traverse it and reach the target neuron. The addition of the delay term provides a way to allow decisions based on events occurring in different instants of time.

Therefore, in order to obtain the trained network, both the weight and the delay terms must be calculated in such a way that they adapt to the generation of the signal. The main application of these types of networks is in the generation of models of signals as they can be trained to a point where by inputting the outputs they generate as inputs for the next iteration they provide their version of the signal on which they were trained.

This capacity was demonstrated in [12] and [13] with different types of signals. The results in these papers show that these networks could be used to generate signals through multistep type predictions for very long time spans. In the application presented here, these multistep predictions only need to be carried out between real asynchronously sampled points. What is really important here is that the predictions provided by the network are not just a consequence of some type of function taking into account the neighboring samples, but a more global process where the whole signal up to the current instant of time has been considered and used for the training of the network as a model.

5. RESULTS

Results obtained from turbulent signals measured with a LDV in the wake of a round cylinder and their subsequent analyses by the MDB model are presented. As our goal is to show the fitness of the model, we have decided to present here just two of the different test cases considered. Both were measured under ambient conditions, but the first case was with free air speed V = 3.7 m/s, matching a Reynolds number of around 2000 while the other was at V = 11.3 m/s corresponding to a Reynolds number of about 6000. In both cases, LDV signals were taken at a position 10 diameters downstream of the cylinder at an average sampling rate of 3000 samples per second. Previous experimental results from many sources prove that at these regimes this type of flow is dominated by a main oscillation embedded in the turbulence having a fundamental frequency f. The dimensionless shedding frequency is called the Strouhal number; St=fD/V, which, according to the experimental evidence, in both cases takes a value close to 0.21. In view of this, the first case must present a fundamental frequency close to 100 Hz while in the second one it should be about 300 Hz. This known characteristic of the benchmark flows used is going to be applied to check the performance of our analysis model.

One advantage of having a non-uniformly sampled signal is that the Shannon theorem doesn't hold and thus it is possible to extract information in the frequency domain at values exceeding the Nyquist limit. To check the ability of the MDB model for taking advantage of this characteristic, d some reconstructions of the signals at synchronous time intervals shorter than the average sampling interval of the original LDV signal were performed. As an example, figure 4 displays the results of applying the MDB analysis model to LDV signals corresponding to the above mentioned cases. This figure presents the results of a test where the time interval used in the synchronous mode equals four times the average time interval of the LDV signal, resulting in an evenly sampled signal equivalent to the non-uniformly sampled original one. The figure shows that the signal reconstruction is very good while the non linear interpolation obtained from the MDB attempts to recover the real chaotic character of the signal. It should be mentioned that in this 4x case, less than 10% percent of the synchronous time intervals have an actual signal point to correct the prediction.

Figure 5 presents the power spectra obtained by direct application of FFTs to the reconstructed signals corresponding to a Reynolds number of 2000 and synchronously sampled at 1x, 2x and 4x the average frequency of the original LDV signal. It can be clearly seen that the fundamental frequencies mentioned earlier are well captured in all cases. More importantly, when the signals become more chaotic, as is the case of Reynolds 6000, these results still hold as can be appreciated for the reconstruction of the signal displayed in figure 6 and its power spectrum in figure 7. 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.

6. POST PROCESSING

Although the signal reconstruction presented above shows a good performance, some discrepancies appear between the measured data and the predicted signals. Thus, it seems clear that the result can be improved by merging the measured data into the prediction. Nevertheless, directly merging both data sets is not possible as it would introduce spurious peaks in the reconstructed signal leading to artefacts in its spectrum. Consequently, a merging strategy should be assessed. 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.

To better understand how the time intervals used for corrections are chosen, it is necessary to highlight some aspects of turbulence dynamics. Turbulence can be seen as a mixture of eddies of different sizes embedded in the main stream. Turbulent energy starts in the larger vortices and passes on to the smaller ones as the big ones break down into smaller and smaller sizes until a minimum scale is achieved –namely the Kolmogorov scale- where this turbulent energy is dissipated under the action of viscosity. The sizes of the largest vortices are of the same order as the size of the perturbing object –in our case 8 mm- while the ratio between the sizes of the Kolmogorov scale and the larger scale is of the order of $Re^{-0.75}$; thus, in both test cases this minimum scale is of the order of the hundredths of a millimeter. Nevertheless, the measuring system is not able to capture these small scales because each measurement of velocity corresponds to the average speed of a particle while crossing a measuring volume created by the intersection of the laser beams and having the shape of an ellipsoid with a diameter of 0.19 mm and a length of 4.1 mm. Therefore, the measurements are taken as speed averages along paths as large as several tenths of a mm. Considering all this in the frequency domain, the experimental results show that the lower frequencies –which correspond to the larger turbulence scales- are of 100 Hz for the case of Re = 2000 and 300 Hz for the Re = 6000 case. Turbulence theory shows that the highest frequencies –corresponding to the Kolmogorov scales- are of the order of $Re^{0.5}V/D$; then, for our test cases these high frequencies are of the order of 10^4 Hz and 10^5 Hz respectively, while the measurements are low-pass filtered by the LDV system at crossover frequencies just above 10^3 Hz and 10^4 Hz respectively. Accordingly, the time intervals considered above for correcting the generated signal by merging the predicted and real data are taken to correspond to the center of the frequency range for each case. Figure 8 displays the reconstructed signals presented in figures 4 and 6 after being corrected using the merging procedure with the real data. The small discrepancies found in the former figures have now disappeared after applying the proposed post processing scheme.

7. CONCLUSIONS

An evolutionary based method using ANNs for the non-linear reconstruction of non-uniform sampled LDV signals is presented. The type of reconstruction proposed is adequate for the chaotic character of the turbulent flows. It achieves its purpose by modeling and predicting the signals prior to re-sampling them at a regular pace. The strategy is based on the use of artificial neural networks with trainable delay terms in their synapses as models of the signals and an adaptation procedure inspired in the Multilevel Darwinist Brain which permits an agent to adapt to changing environments, in this case 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 four 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:

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FIGURE CAPTIONS

Figure 1: Experimental set-up.

Figure 2: Basic schematics of the LDV system. (After Dantec Dynamics web site drawing).

Figure 3: Delay Based Artificial Neural Network.

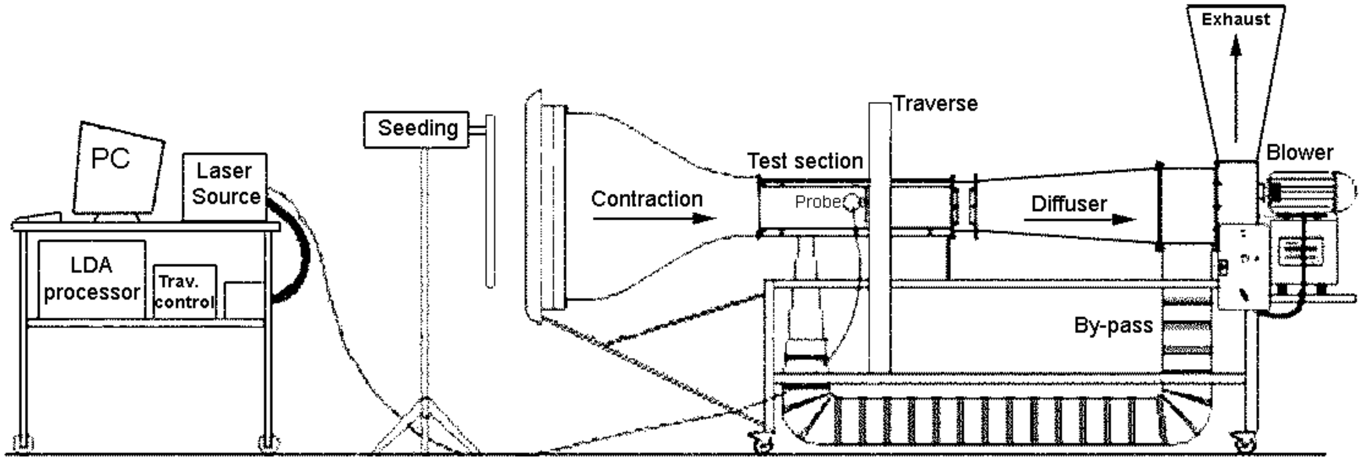
Figure 4: Synchronously sampled signal model obtained by the MDB (lines) for a Reynolds 2000 type signal (dots) using four times the average sampling rate of the original signal.

Figure 5: Power spectrum of a Reynolds 2000 signal generated by the MDB at sampling rates of 1, 2 and 4 times the average sampling rate of the original unevenly sampled signal.

Figure 6: Synchronously sampled signal model obtained by the MDB (lines) for a Reynolds 6000 type signal (dots) using twice the average sampling rate of the original signal.

Figure 7: Power spectrum of a Reynolds 6000 signal generated by the MDB at a sampling rate of 2 times the average of the original unevenly sampled one.

Figure 8: Reconstructed signals after applying the post processor. The one at the top corresponds to figure 4 (Reynolds 2000) and the bottom one to figure 6 (Reynolds 6000).



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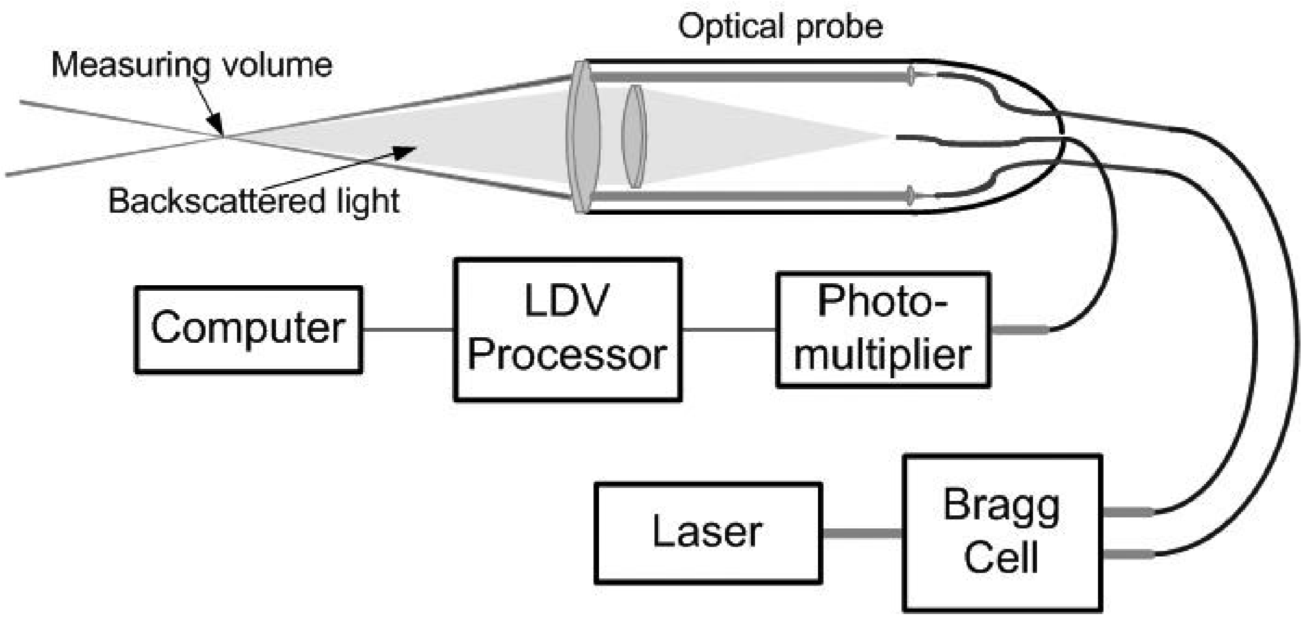


Figure 2: Basic schematics of the LDV system. (After Dantec Dynamics web site drawing).

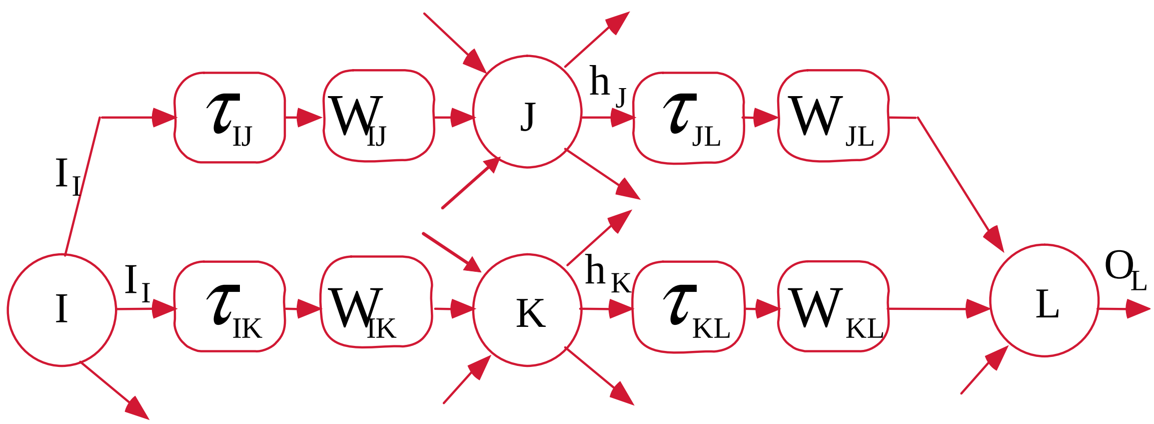


Figure 3: Delay Based Artificial Neural Network.

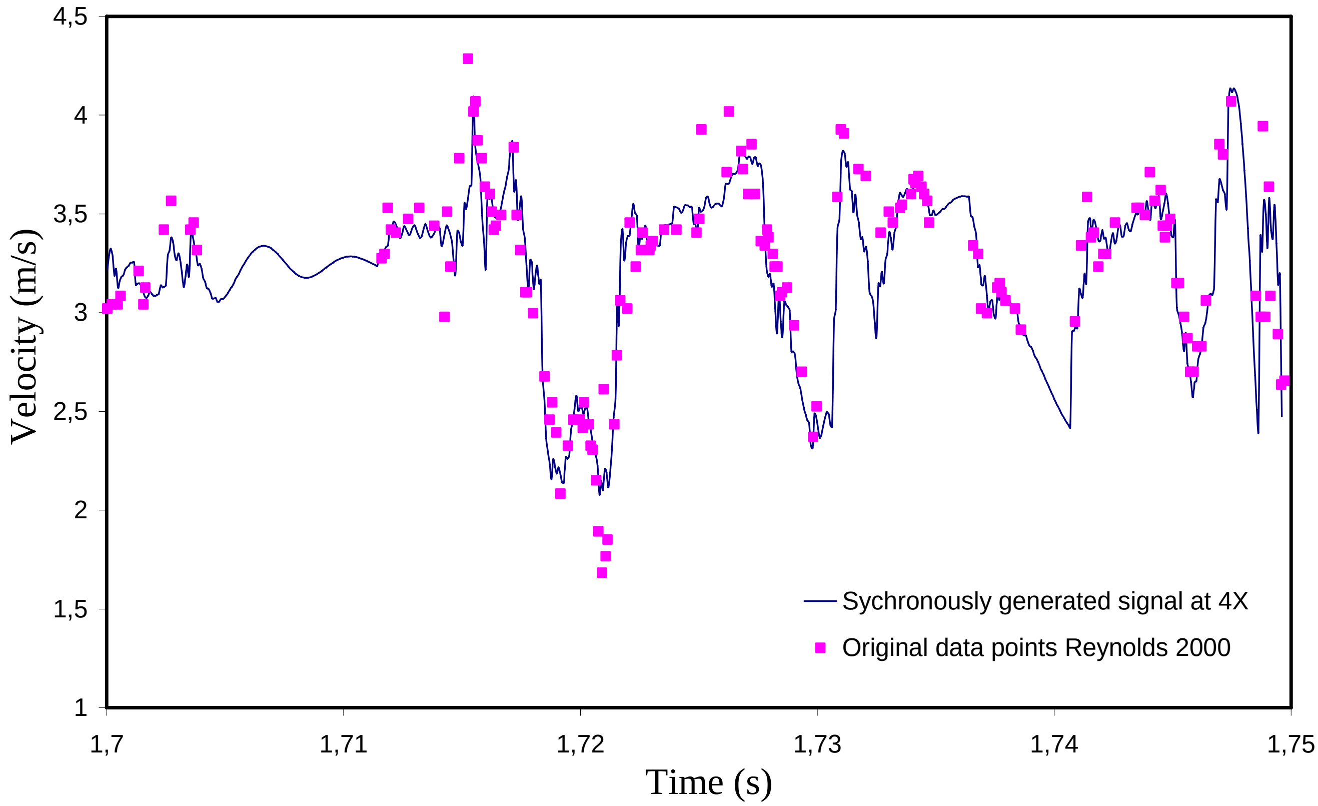


Figure 4: Synchronously sampled signal model obtained by the MDB (lines) for a Reynolds 2000 type signal (dots) using four times the average sampling rate of the original signal.

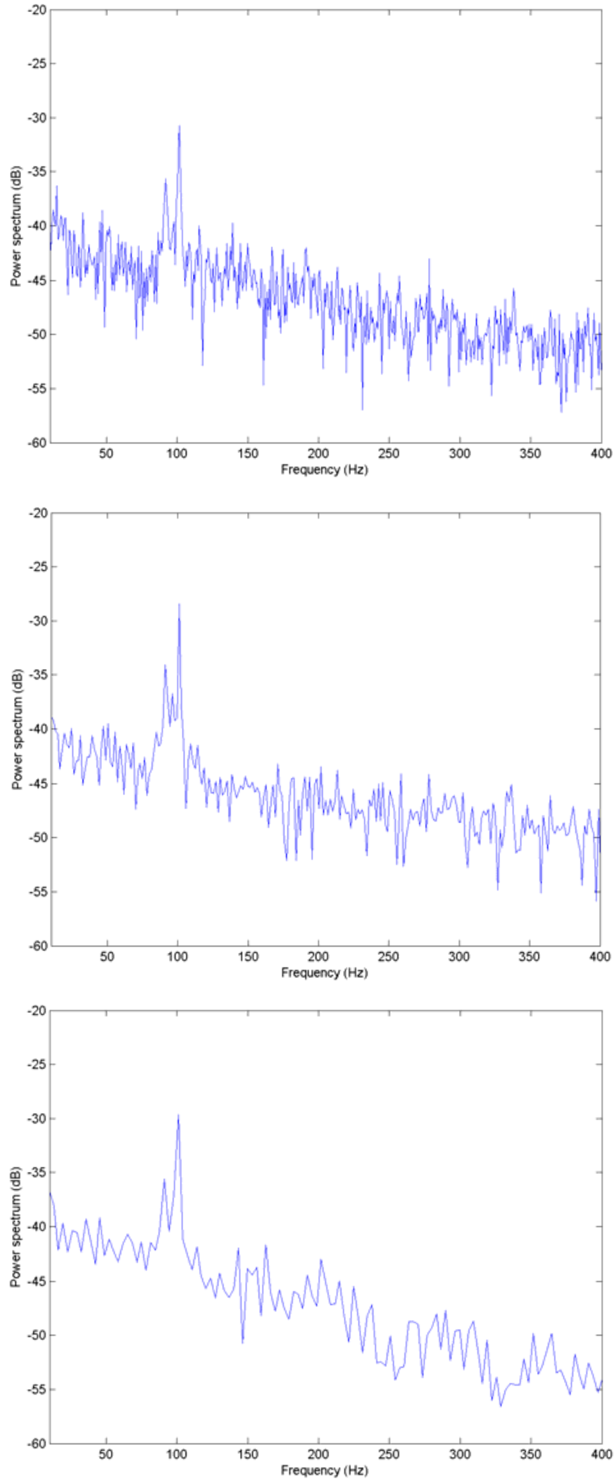


Figure 5: Power spetrum of a Reynolds 2000 signal generated at 2 by the MDB at sampling rate2 of 1, 2 and 4 times the average sampling rate of the original unevenly sampled signal.

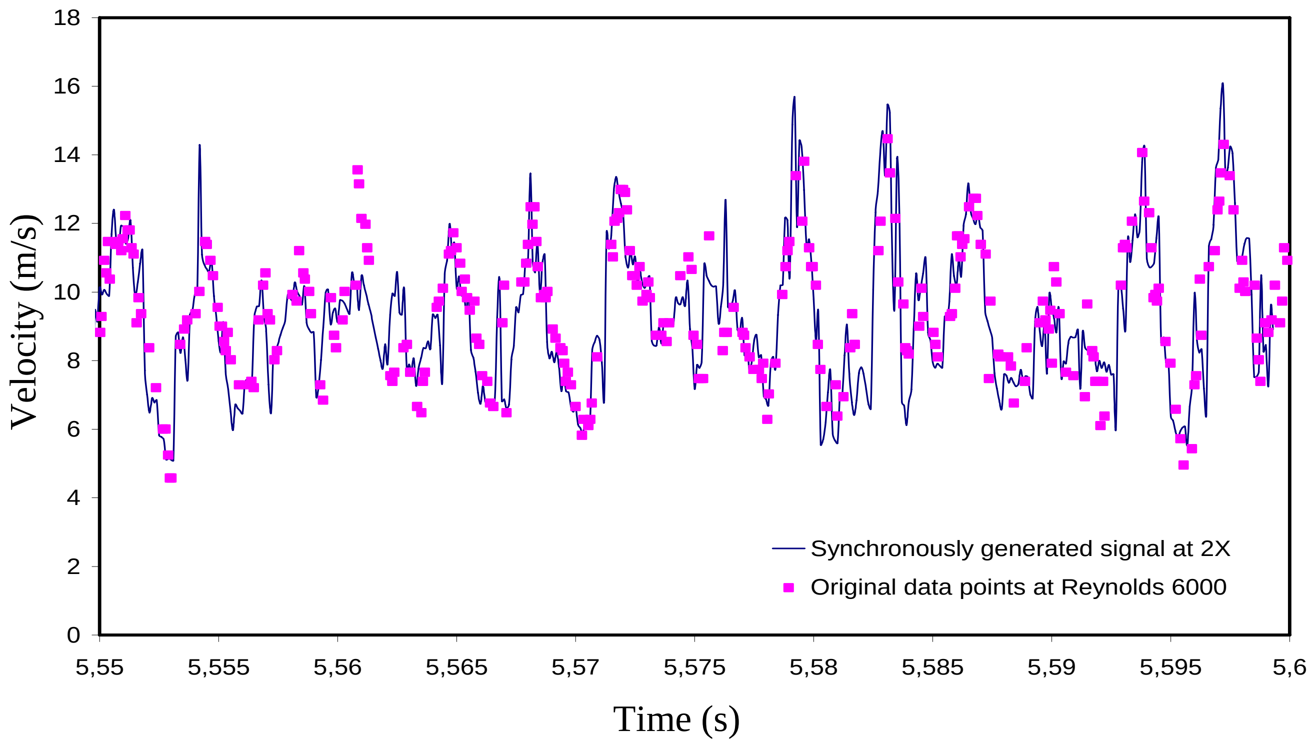


Figure 6: Synchronously sampled signal model obtained by the MDB (lines) for a Reynolds 6000 type signal (dots) using twice the average sampling rate of the original signal.

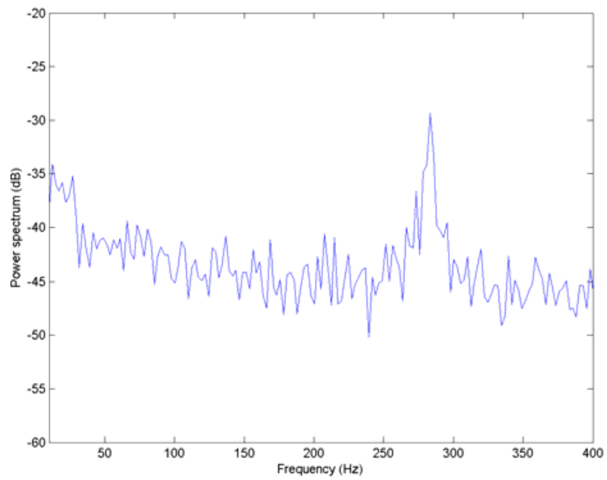
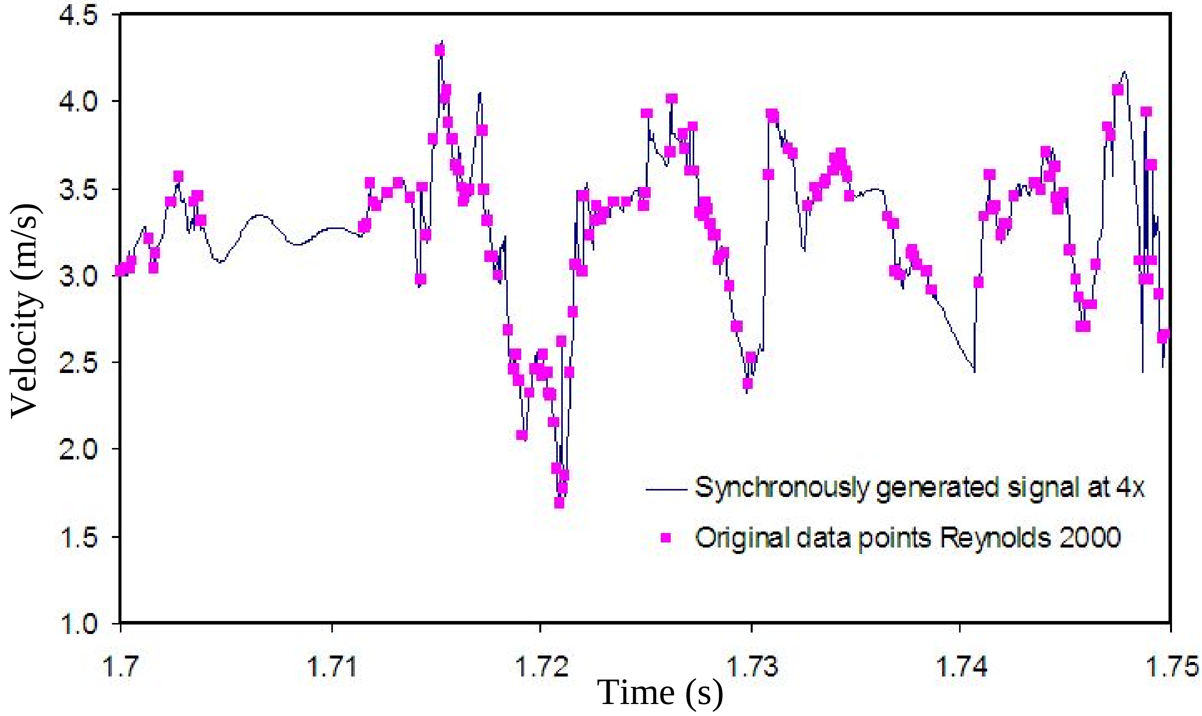


Figure 7: Power spetrum of a Reynolds 6000 signal generated at 2 by the MDB at a sampling rate of 2 times the average of the original unevenly sampled one.



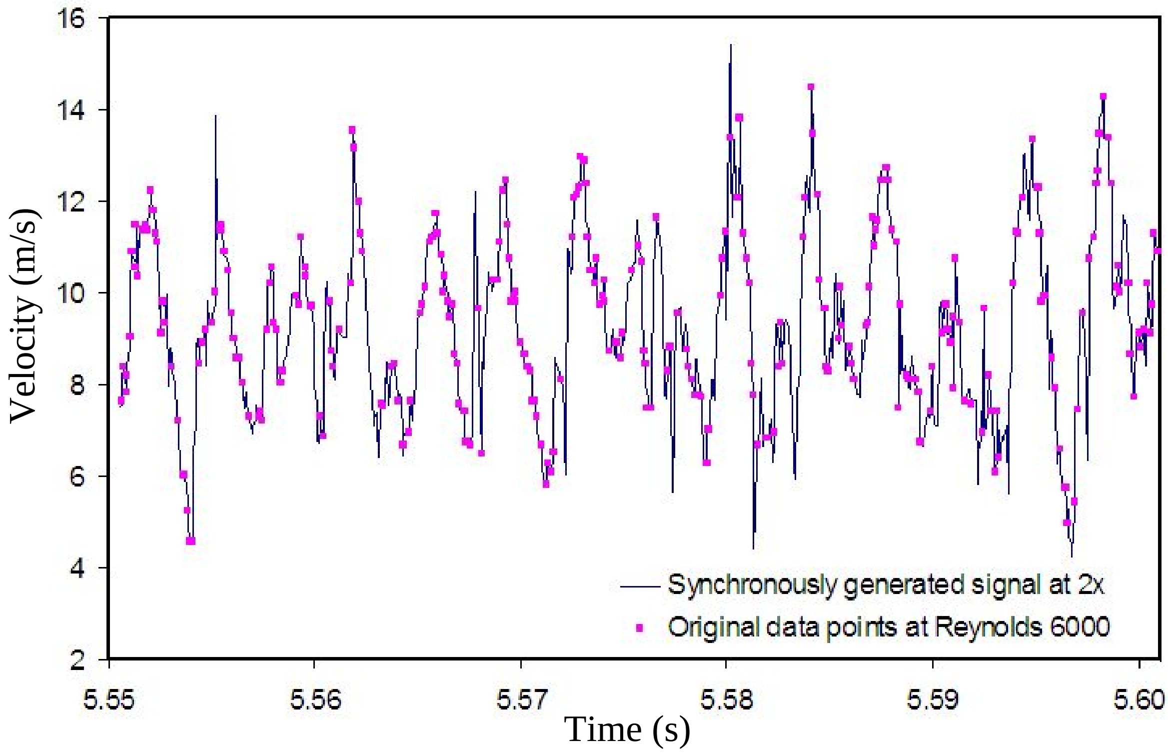


Figure 8: Reconstructed signals after applying the post processor. The one at the top corresponds to figure 4 (Reynolds 2000) and the bottom one to figure 6 (Reynolds 6000).