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A fuzzy ARTMAP neural system for the prediction of turbulent velocity fields

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Abstract

An implementation of the FUZZY ARTMAP Neural Network has been used to generate a synthetic two-dimensional turbulent velocity field with local characteristics, statistical behaviour and structural distribution similar to the experimentally data measured simultaneously at different locations in a turbulent wake with eight X-wire anemometer probes. The net, formed by eight Fuzzy ARTMAP modules working in parallel, one for each experimental device measuring simultaneously two-component velocity signals at a given location in the wake flow, has been trained using the first 2000 instants of the real field. Training patterns have been constructed using historical and adjacent information of the velocity field. The predicted turbulent field properly describes the underlying turbulence structure of this free flow as well as its overall statistical behaviour.

1. Introduction

Turbulent wakes and shear layers have been the object of experimental and numerical analysis since the early studies of Townsend [1], Grant [2] and Brown and Roshko [3] showed the dominant effects that large scale coherent motions played in the dynamics of these turbulent flows. A turbulence field can be obtained either by experimentation or by direct numerical simulation. There have been attempts in the past to describe the fractal component of a single turbulent velocity [4]. In this paper we present a new method to obtain turbulent velocity data using a neural of Fuzzy ARTMAP system previously trained with velocity patterns measured by a rake of probes. The real and synthetic data are compared using correlations, pattern recognition with fuzzy ARTMAP [5] and Proper Orthogonal Decomposition (POD).

2. Real data and pre-processing

Two-component velocities measured by Prof. Antonia at the University of Newcastle (Australia) in the far region of a turbulent wake have been used to train the Network. Data were measured with eight X-wire probes placed in the horizontal homogeneous plane of the turbulent wake generated by a circular cylinder. Data files contained 84480 instants of digitalisation for each of the sixteen velocity components measured in pairs at eight spanwise locations. Fig. 1 includes a sample these time-dependent velocity signals.

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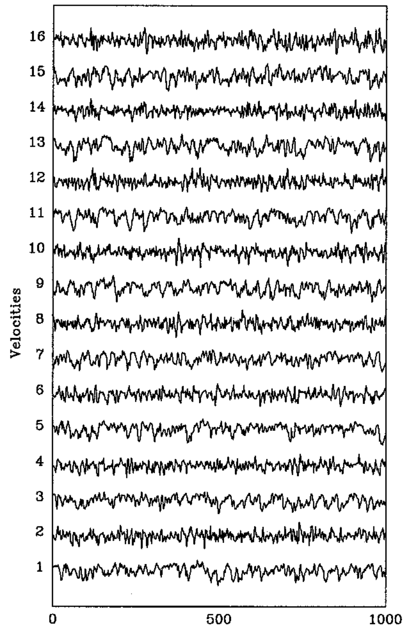

Figure 1. Samples of the time-dependent velocity records

These signals are grouped in pairs to represent the two-components, u and w, of each velocity vectors. The odd numbered signals in Fig. 1 correspond to the streamwise velocity component, u, and the even ones to the spanwise component, w. Fig. 2 shows the corresponding two-dimensional fluctuating velocity field, obtained by subtracting from each component its mean. This plot is equivalent to a snapshot taken by an observer moving at the average speed of the flow.

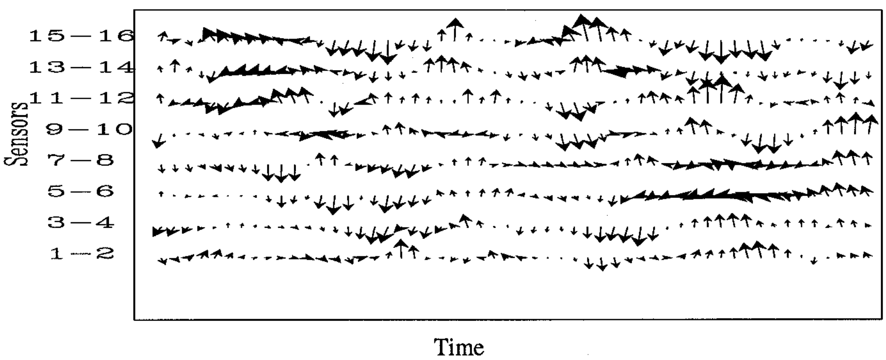

Figure 2. Sample of the two-dimensional fluctuating velocity field

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To fulfil the requirements of the net, the negative fluctuations were eliminated by adding a constant value to the data so that they expands the interval [0, 1].

3. The Fuzzy ARTMAP system

The fuzzy ARTMAP neural system [6] is based on the Adaptive Resonance Theory to avoid the so called stability-plasticity dilemma and consists of a pair of fuzzy ART modules, art_a and art_b, linked by an associative memory and an internal controller [7]. The controller is designed to create the minimal number of categories (or hidden units) to meet accuracy criteria. This is done by implementing a learning rule that minimises predictive error and maximises generalisation. The dynamics of fuzzy ARTMAP is determined by a choice parameter $\alpha > 0$, a learning rate parameter $\beta \in [0, 1]$, and a vigilance parameter $\rho \in [0, 1]$. The present system is constructed with 8 Fuzzy ARTMAP modules, one for each probe or two-component velocity signals measured simultaneously at a given location in the wake flow.

4. The process

Each module was trained using the first 2000 instants of real data for each velocity component. The training patterns were constructed using history temporal data for each velocity component (four previously sampled points) and spatial information from adjacent sensors (two points sampled by adjacent probes at the immediately preceding time) so that the spatio-temporal correlation of the velocity field was introduced in the learning stage. Since the spatial separation between sensors in the experiments was large compared to the microscale of the flow, the consideration of more points in the time-history or more information from adjacent sensors in the training patterns did not improve significantly the statistics and structural characteristics of the synthetic fields generated by the net.
The output from each module of the neural system is formed by the two velocity data points at the following instant of time. The lack of one adjacent signal for modules 1 and 8 was solved using as adjacent information signals from modules 3 and 6, respectively, to preserve the second order correlation.
During the performance phase the eight nets worked in parallel. Instants 2001-2004 were used as input to the nets and the produced output was added to the input forming a new input pattern (output + instants 2001-2003). The process continued until a data file of the same dimensions as the original 84480 instants of digitalisation was obtained. Thus, the trained nets were capable of producing a two-component velocity field with only one input from the old data file.

5. Results

The predicted and measured velocity fields for u and w are first compared using classical statistical tools. Fig. 3 shows the auto-correlations for the experimental and the predicted u-velocity component measured at a given location within the flow and generated by the corresponding net, respectively. The auto-correlations for the experimental and synthetic data are very similar, specially for small lag-times. The excellent agreement between the initial slopes indicates that the turbulent micro-scale is well predicted by the neural system.

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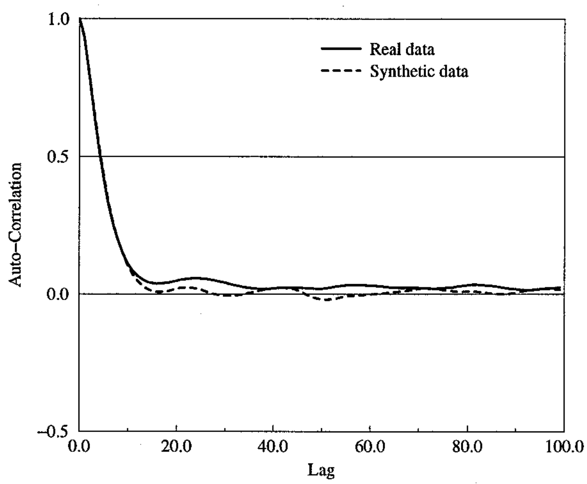

Figure 3. Auto-correlations for one u-component velocity signals

Table I. includes the mean and variance for each velocity signal. The average deviation for the mean values is 0.00863 and for the variances 0.00150. Statistical moments of higher order have not been considered because the size of the original data files was not enough.

		Mean		Variance	
Sensors	Velocity	Real	Synthetic	Real	Synthetic
1	1	0.56238	0.57775	0.01862	0.01866
	2	0.49769	0.49574	0.01398	0.01259
2	3	0.60530	0.62155	0.01858	0.01587
	4	0.50094	0.50252	0.01470	0.01236
3	5	0.55066	0.56437	0.01930	0.01818
	6	0.46471	0.46785	0.01325	0.01098
4	7	0.58463	0.60367	0.01925	0.01690
	8	0.52899	0.52671	0.01400	0.01213
5	9	0.58413	0.59569	0.02081	0.01690
	10	0.49992	0.50404	0.01545	0.01439
6	11	0.55281	0.56939	0.02234	0.01995
	12	0.48627	0.49958	0.01461	0.01379
7	13	0.53160	0.53909	0.02288	0.02315
	14	0.47058	0.47729	0.01339	0.01222
8	15	0.52606	0.52558	0.02384	0.02349
	16	0.49720	0.49268	0.01677	0.01677

Table I. Mean and variance values for the experimental and predicted data sets

The second method applied to compare the measure and predicted data sets is pattern recognising eight different types of coherent structures (Clockwise and anticlockwise eddies, sinks, sources and four types of saddle points) with an implementation of a fuzzy ARTMAP Neural Network [5]. Fig. 4 shows the vector skeleton of these eight structures. Table II includes the results of the classification when applied to both data sets.

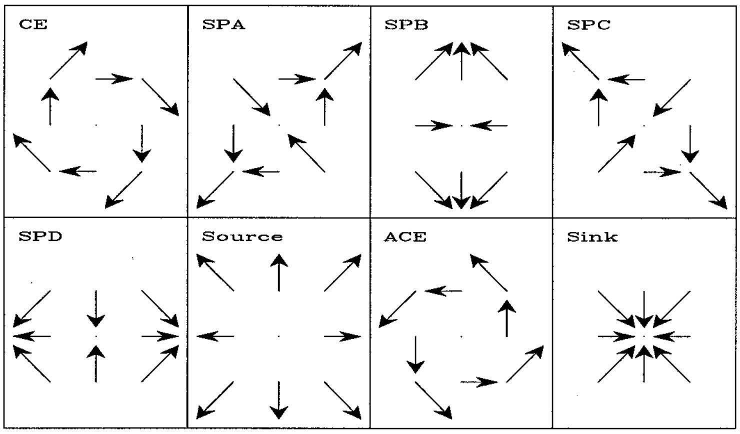

Figure 4. Structural characteristics of Clockwise Eddies (CE), Anti-Clockwise eddies (ACE), Saddle points (SPX), Sources and Sinks

	Anticlockwise eddies		Clockwise eddies		Saddle points		Sinks & Sources		Total	
ρ	Real	Synt.	Real	Synt.	Real	Synt.	Real	Synt.	Real	Synt.
0.90	251	194	196	142	253	249	10	21	710	606
0.91	219	167	165	104	200	195	6	16	590	482
0.92	173	131	141	76	135	143	4	9	453	359
0.93	138	97	103	50	88	104	3	5	332	256
0.94	101	64	69	30	48	62	2	3	159	137
0.95	64	31	46	20	23	28	2	2	81	93

Table II. Classification of patterns

The results in Table II show that the number of structures predicted for each value of the vigilance parameter of the net is closed to the distribution found in the experimental data with differences less than 15%.

Finally, the first eigenvector obtained from POD for the underlying structure of the velocity field predicted by the neural system projects to the one of the real data with a correlation coefficient of 0.96. For the second eigenvector this correlation only drops to 0.92. These correlation tensor results indicate that the proposed neural system is capable of capturing the highly non-linear dynamics of the turbulent wake flow.

6. Conclusions

We can conclude that the Fuzzy ARTMAP neural system proposed in the present study is capable of generating a velocity field with the same local characteristics and statistical behaviour as the original experimental data set used to train the net. This method has been applied also to turbulent velocity and temperature data files obtained experimentally in the wind tunnel facility at Tarragona with the same performance. The present system can thus be useful to analyse highly non-linear signals pertaining to other systems of practical interest and represents a step forward towards the control of complex devices.

7. Acknowledgements

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