Solving Engineering Problems with Neural Networks

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EXTRACTION OF STRUCTURES EMBEDDED IN THE VELOCITY FIELD OF A TURBULENT WAKE

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Abstract

The flow analysed here was generated in a low turbulence wind tunnel at the University of Newcastle (Australia). Two component velocity data were measured with an array of anemometers (eight X-wire probes) at 420 diameters downstream of a circular cylinder ($D = 3.25$ mm.) at Re ($DU_o\rho/\mu$) = 1600 (U_o = 7.8 m/). Voltage signals were low pass filtered and sampled at 4 KHz. per channel during 30 s. A small part of the u, v velocity field obtained was pre-processed to extract a set of relevant patterns from the data in order to train an implementation of the FUZZY ARTMAP Neural Network. After the net was trained, the complete data files were tested with the net, obtaining eight different kinds of structures: Clockwise and anticlockwise eddies, sinks, sources and four types of saddle points. The characterisation of these structures using artificially generated classes for training instead of extracting these classes by pre-processing directly the velocity fields of real leads to poor classification results due to the intrinsic irregularity of turbulence. Present results provide further evidence about the occurrence of double rollers in free turbulent shear flows and also suggest the procedure for characterising three dimensional turbulent flows.

1. Introduction

An implementation of the Fuzzy ARTMAP Neural Network [1] is used to identify eddy motions present in the horizontal (homogeneous) spanwise direction of a turbulent wake flow. The aim of the present paper is to develop an automatic procedure to classify the different structures and motions embedded in two-component velocity signals sensed in a turbulent flow. A pre-processing procedure is proposed to pre-classify vortex-like patterns net and to obtain a training set before data is presented to the. This procedure is based on the geometric characteristics of the set of vectors representing an eddy motion.

2. Data preconditioning

Pre-processing of data, which is a usual practice in Neural Network field analysis has two objectives. One is to transform data so that vortical characteristics within two-dimensional frames of data are enhanced. The other is directed to obtain a good and reduced set of real patterns to train the net. The first step in the pre-processing of data is to transform the velocity field into a field of fluctuating velocities with zero mean, by subtracting from each vector component its mean. This transformation is equivalent to taking snapshots of the fluctuations of the turbulent motions with a camera moving at a velocity adjusted to eliminate the average motion of the fluid. These fluctuations are the ones analysed here. To obtain a training set and to simplify the final classification procedure, frames F of 3x3 consecutive velocity vectors were considered, and patterns were constructed with the angular components of these vectors.

3. The ARTMAP system

The Fuzzy ARTMAP neural network [1] is powerful in difficult classification problems. It's based on the Adaptive Resonance Theory, which avoids the so called stability-plasticity dilemma. We have implemented a supervised Fuzzy ARTMAP net for our purposes. A Fuzzy ARTMAP neural network consists of a pair of Fuzzy [2] modules, art_a and art_b, linked by an associative memory and an internal controller. 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. Our implementation forces the art_b module to have only one category representing Clockwise eddies. Another fictitious category considered is the one corresponding to the "I do not know" answer by the net. All inputs that do not pass the reset for a given vigilance parameter ρ are included in this category and considered not to be eddy motions.

4. Geometric Transformations and Method

Geometrical properties of the vectors in a frame allows that a net trained to recognise only Clockwise Eddies (CE) is able to extract 8 kinds of coherent structures in a turbulent wake, without further training. $S = \{I, s_1, s_2, s_3, s_4, g_{\pi/2}, g_\pi, g_{3\pi/2}\}$ is the group of movements leaving invariant a square [3]. In the group there are four symmetries and four rotations, with $g_{2\pi} = I$. We have chosen a frame of 3X3 so as to identify the core of eddies present in the wake flow. Applying this transformations on the vectors in a frame representing a CE, we obtain the following results:

s_1(CE) = Saddle point of type A (SPA)
s_2(CE) = Saddle point of type C (SPC)
s_4(CE) = Saddle point of type D (SPD)
$g_{\pi/2}$(CE) = Source
g_π(CE) = Anti-clockwise eddies (ACE)
$g_{3\pi/2}$(CE) = Sink

These events and the CE are depicted in Fig. 1. The relationship between the four saddles and the CE in Fig. 1 confirms previous turbulence studies in the sense that searching for saddles is appropriate to identify eddies in three-dimensional flows.

The movements s_1, s_2, s_3, s_4, g_π have order two in the group and, thus, they are inverses of themselves, while $g_{\pi/2}$, $g_{3\pi/2}$ are mutually inverse. The rotations are also a subgroup of fourth order and each symmetry together with the identity movement form a subgroup of second order. Hence several procedures can be followed to identify all these structures. One of these procedures consists in the following steps: (i) The net is trained to recognise CE; (ii) the net extracts the CE from the data; (iii) all frames extracted as CE are discarded from the velocity field; (iv) the remaining original data is transformed by g_π. Steps (ii), (iii) and (iv) are iterated changing the transforming movements sequentially, so that the remaining structures are obtained according to

$g_\pi \longrightarrow$ ACE $\qquad s_1 \longrightarrow$ SPA
$s_2 \longrightarrow$ SPB $\qquad s_3 \longrightarrow$ SPC
$s_4 \longrightarrow$ SPD $\qquad g_{\pi/2} \longrightarrow$ Sinks
$g_{3\pi/2} \longrightarrow$ Sources

This procedure can be accelerated, using information about the nature of the. Using the fact that the movements are elements of a group it is possible to transform data without going back to the original sets at the end of each transformation. For instance, applying the movements I, g_π, s_3,, $g_{\pi/2}$, $g_{\pi/2}$, $g_{\pi/2}$, s_1, g_π in this order, the results are equivalent to those obtained from the procedure given above.

5. Results

The two-component velocity data used here were measured by Prof. Antonia (University of Newcastle, Australia) at x/D = 420 in the wake behind a circular cylinder. These data have been also analysed by Kopp et al. [4] using POD and template matching. The experimental conditions of these data are equivalent to those reported by Giralt et al. [5].

The Table given below summarises the results obtained here, with the number of structures classified and percentages.

TYPE OF STRUCTURE	NUMBER OF STRUCTURES CLASSIFIED	PROPORTION OF FLOW CLASSIFIED
CE	7589	10,16
ACE	6745	9,03
SPA	955	1,28
SPB	2352	3,15
SPC	993	1,33
SPD	1667	2,23
SOURCE	36	0,05
SINK	100	0,13
	TOTAL	**27,37**

Figure 2 shows one example of each class of structures extracted from the turbulent wake data in this study.

6. Conclusions

A Neural System based on Fuzzy ARTMAP has been successfully applied to recognise coherent structures in the velocity field of a turbulent wake without the need of using initial external templates for pattern recognition. The patterns obtained corroborate the results reported in previous pattern recognition analysis. The Fuzzy ARTMAP system is a good classifier for multi-sensor patterns. Present results also suggest that searching of saddle points may be the best choice to classify three-dimensional turbulent flows.

6. Acknowledgements

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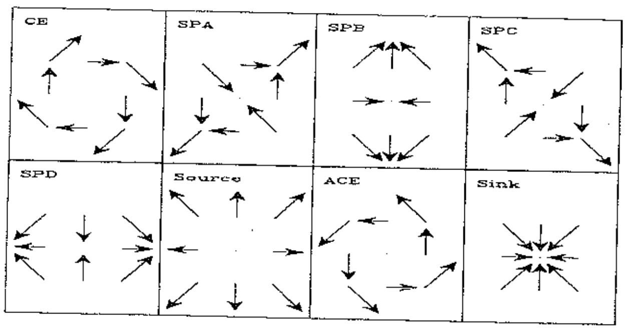

Fig. 1 Transformations of an eddy

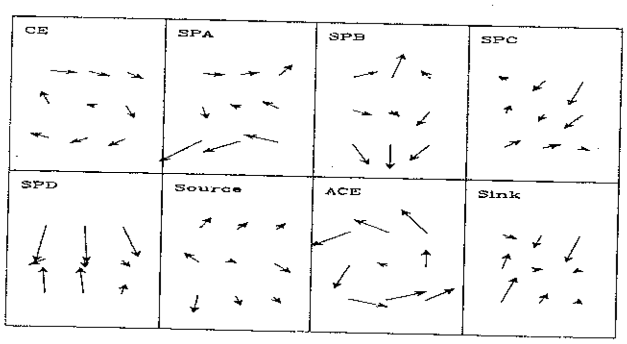

Fig. 2 Found structures