

CHARACTERIZATION METHODS FOR COHERENT STRUCTURES IN TURBULENT FLOWS AND THEIR POSSIBLE IMPACTS ON NUMERICAL SIMULATIONS

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ABSTRACT

A review of selected experiments on coherent structures in turbulent shear flow is performed. Different experimental approaches (conditional averages, filtering techniques, wavelets, Linear Stochastic Estimation and Proper Orthogonal Decomposition) are illustrated and their links with computations (LES, DNS, SDM,...) are emphasized. Particularly it is shown that some kind of universal behavior of the background turbulence can be retrieved from these various experimental methods.

INTRODUCTION

The existence of coherent or organized motions has been well admitted for at least the last two decades. Although there is no definitive consensus on the definition of Coherent Structures (CS), an organized character, at large scales (of the order of the characteristic gradient zones) of most turbulent flows is generally observed, mainly from visualizations. However, as far as turbulent flows are concerned, such CS are embedded inside a randomly distributed field and their identification and characterization is not straightforward. This identification has to be done for several purposes: first, for a simple energetic point of view, because CS can represent from 10 % (for boundary layers, far jets), up to 20 % (far wakes, plane mixing layers) or 25 % (near wakes or jets) (after Fiedler, 1998). Second, because the dynamical properties of CS play an essential role in mixing processes, drag, noise emission, etc. The energy content of CS

is not the only characteristic that has to be addressed, and their redistributive capacities are also of crucial importance. The impact on flow measurement and on data processing techniques is obvious. Simple, one-point statistics are not sufficient for a correct characterization of most turbulent flows. In addition, the choice of any predictive approach has also to be made with respect to the organized character of the flow.

The one-point statistical closure methods (RANS: Reynolds Averaged Navier Stokes), and among them the popular one-point statistics ($k - \epsilon$, RSM: Reynolds Stress Modeling) simulations ignore the CS influence. For many applications, these predictive approaches are successful but for others, it appears necessary to take into account the large scale structures for better predictions. This reasoning has led to the development of LES (Large Eddy Simulation: see Lesieur (1990), Lesieur and Métais (1996),... for reviews), and, more recently to the introduction of SDM (Semi-Deterministic Method: see Ha Minh, 1994, 1999), TRANS (Transient Averaged Navier Stokes: see Kenjeres and Hanjalić, 1999). Another recent concept, called CVS for Coherent Vorticity Simulation, has been built that is based on a partition of the flow into randomly distributed background and organized (the rest of the field) turbulence (see Farge *et al.*, 1999).

The RANS require only conventional statistics as initial conditions. In contrast, the other methods require more detailed information on the large scale instantaneous organization of the flows for initial conditions and also for validations. Then, it becomes more and more im-

portant to produce experimental data adapted to such constraints. Some efforts have already been devoted to such an approach (see Adrian *et al.*, 2000a, 2000b).

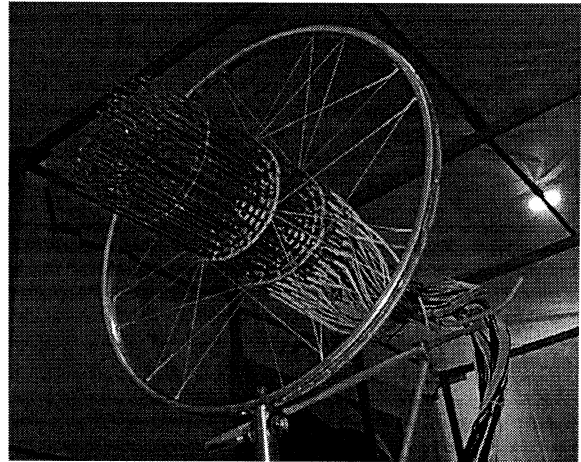
As far as the experiments are concerned, the main goal is to extract, from the overall turbulent fluctuating field, the so-called Coherent Structures. Several new tools have been intensively developed both for ad-hoc flow probing, for advanced data processing and for CFD purposes. Two point statistics have also been used from many years to evidence such large scale behavior (Townsend, 1976, Favre *et al.*, 1976). Rapid progresses in these fields have been recently observed. For example, the Particle Image Velocimetry (PIV) is now efficient; also, the number of Hot Wire (HW) probes that can be used simultaneously has drastically increased (Fig. 1).

The purpose of this paper is to present a review of Coherent Structures identification methods in turbulent flows and their possible influence on computational methods. As a first step, we review the different ‘filtering’ concepts used in several numerical methods. The counterpart for experimental approaches is then recalled and compared, with a particular emphasis on stochastic approaches based on two-point statistics. Lastly we present briefly some new applications of advanced data processing for the generation of realistic initial conditions that are able to represent the large scale behavior of turbulent shear flows.

FILTERING APPROACHES FOR NUMERICAL SIMULATIONS

As above mentioned, LES and SDM are among efficient methods for predicting most flows, in which the large scale organization plays an important role. These two approaches are similar in a sense that both involve a filtering process: a low-pass filtering (LES) or a more global filtering approach (SDM). Figure 2, after Ha Minh illustrates, these concepts. LES takes into account the unresolved scales (at the level of the computational mesh) by a specific closure, relating these small scales to the resolved quantities. LES involves a ‘low-pass’ filter, in a conventional Fourier decomposition sense. SDM postulates that the turbulent field can be decomposed in term of a coherent (deterministic) part, directly related to the flow configuration, on which a random (more universal) part is superimposed. In this case, the applied filter does not correspond to a cutoff filter as for LES. Indeed, as we

(a)



(b)

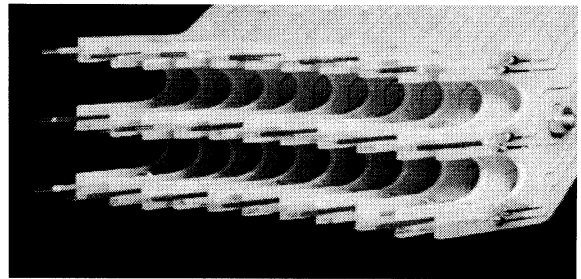


Figure 1: Examples of multi-probes rakes of hot-wire. (a) 138 single wires, measurements in a round jet – after Citriniti (1996); (b) 33 X-wire probes (66 wires), measurement in a turbulent mixing layer – after Druault (1999)

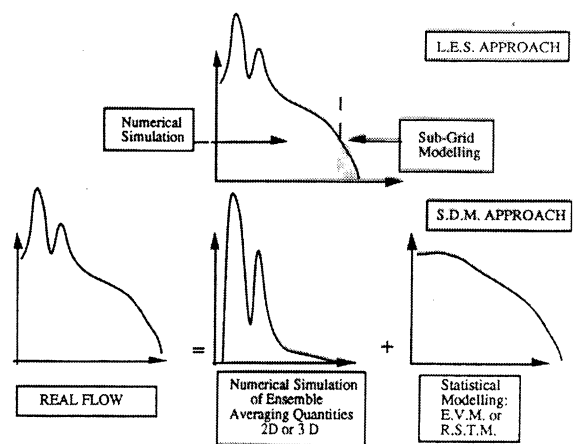


Figure 2: Schematic description of LES and SDM, after Ha Minh (1994). Vertical axis: turbulent energy, horizontal axis: wave number (arbitrary units)

will demonstrate in the following, experimental results show that any coherent structure covers the whole spectrum. The filter used by SDM can be considered as a ‘structure filter’. Following this approach, the filtered part is resolved by schemes comparable to DNS. Additional universal transport equations are to be used for the random part, the coherent and random fields being coupled by a specific closure. Farge and co-workers have recently proposed a new simulation approach (CVS) based also on the representation of turbulent flows in two parts: one part considered as being out of equilibrium, the other being considered as ‘thermalized’ motion (Farge *et al.*, 1999). In some sense, these two last approaches are both based on a structure filter, but the SDM uses the CS as the major definition (the random part being the rest of the fields), when CVS considers that the random field is the thermalized part, the CS part being considered as the rest of the field. LES, SDM and CVS are related to the so called triple decomposition introduced by Reynolds and Hussain (1972) where the instantaneous turbulent field u , is separated in an average contribution (in the sense of the conventional Reynolds decomposition) and a fluctuating part u' . This contribution is itself decomposed into a coherent part u_c and a random part u_r :

$$u = \bar{u} + u', \quad \text{where : } u' = u_c + u_r.$$

As above mentioned, the respective definitions of u_c and u_r will depend upon the method considered. In this decomposition, the coherent part can be used to build an ensemble average that corresponds either to the averaging of similar events or to a phase average (this last method being particularly efficient in excited flows). An important notion is implicitly included in the definition of this approach: coherent and random parts are not correlated (i.e. $\langle u_c \cdot u_r \rangle = 0$).

There is no formal difference in the form of the filtered equations which are used for both approaches. Because only the applied filter differs, then comparable terms appear (e.g. Leonard’s terms...).

COHERENT STRUCTURE FILTERING

The detection methods can be classified depending on the associated CS definition, that is not universal (Bonnet *et al.*, 1998) and depends on the available information. Table 1 provides a general overview of the different methods. We do not, in the present paper, address the

Table 1: A tentative of classification of CS identification methods

RAW VISUALIZATIONS	
<ul style="list-style-type: none"> - Particle Image Velocimetry (PIV) - Pseudo Flow Visualization (PFV) - Iso-Vorticity - Sectional Streamlines 	
CONDITIONAL	Non-CONDITIONAL
<ul style="list-style-type: none"> • Detection: (\Leftrightarrow CS definition) <ul style="list-style-type: none"> - Fluctuation Levels - 4 Quadrants - Variable Integration Time Averaged (VITA) - Gradients - Window Averaged Gradient (WAG) - Contaminant: temperature,... - Visualizations - Critical Points • Pattern Recognition (PRA) • Linear Stochastic Estimation (LSE) • Wavelets 	<ul style="list-style-type: none"> • Space-Time Correlation & Spectral Analysis & Filters • POD
STATISTICS	
<ul style="list-style-type: none"> - Ensemble Average - Multiple Decomposition - CS Dynamics - Statistical Properties 	<ul style="list-style-type: none"> - Most Probable Charac. - POD - Dynamical Systems
DYNAMICAL SYSTEM IDENTIFICATION	
	<ul style="list-style-type: none"> Lyapounov Exponent High Order Statistics

conditional sampling approaches more or less related to the initial double/triple decomposition. Examples of typical coherent patterns obtained by such an approach are shown for a backward facing step and a turbulent plane mixing layer on Fig. 3. Fig. 3.a illustrates the use of the Delocalized Conditional Sampling (DCS) in a plane turbulent mixing layer, on Fig. 3.b, the Vorticity Based detection has been carried out in the case of a backward facing step and on Fig. 3.c a WAG detection is applied to the turbulent mixing layer.

A consensus on which type of event (CS) can be deduced from the various approaches generally used has been established. For example, on a common data base, obtained with HW-rakes in a plane turbulent mixing layer (available as a database in the AGARD WG21 (1998)), we compared in a collaborative manner (six research teams were involved at this occasion) different detection schemes: Delocalized Conditional Sampling (DCS: Bellin 1991, Vincendeau 1995), Window Averaged Gradients (WAG: Antonia and Bisset, 1995), Vorticity based (Hussain and Hayakawa 1987), Wavelets (Kevlahan *et al.*, 1993). An illustration of this comparison can be found in Fig. 4. On this figure, the different times of detections obtained from different methods are compared within a given time sample. It was concluded

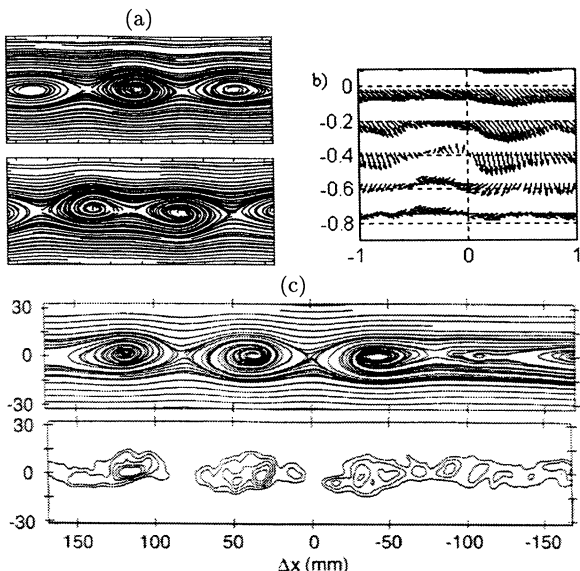


Figure 3: Examples of conditional averaged structures. Vertical axis: transverse direction (mean gradient direction); horizontal axis: time or space direction (using Taylor hypothesis). (a) turbulent mixing layer, all events cumulated (top) and corresponding to a pairing stage (bottom) – after Vincendeau (1995); DCS detection. (b) shear layer of a backward facing step ($X/H=4.2$); vorticity based detection – after Aubrun (1997). (c) ‘large scale structures’ of the turbulent mixing layer: sectional streamlines (top) and iso-vorticity (bottom) – after Bisset and Antonia (Bonnet *et al.*, 1998); WAG detection.

that, even if the actual detection times can be slightly different, the same CS are globally extracted by these schemes. Moreover, all these detections pointed out more or less to the same events as unconditional ‘stochastic methods’ like POD or LSE.

Note that, from a conditional sampling, mainly ensemble averages are obtained and typical patterns of CS can be deduced. Moreover, a description or contribution of the CS can be obtained only when a CS is present. This approach is therefore not well designed to provide a temporal, ‘continuous’ description of the contributions of the coherent and random parts. Continuous time filtering methods are then required for such a purpose and some kind of ‘structure filtering’ process needs then to be introduced.

In the following, we focus on signal decompositions based on non-conditional approaches, that can be of help for *structure filtering* the turbulent field. These approaches also make it possible a dynamical analysis of CS.

HARMONIC AND ADAPTATIVE FILTERS

The first decomposition that can be used is naturally the harmonic (Fourier modes) decomposition. This decomposition can either be used for low-pass/high-pass filtering (as in a

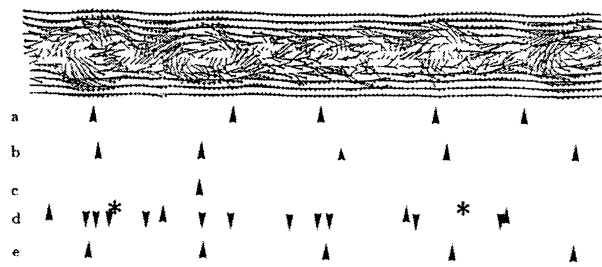


Figure 4: Comparison of different *detection procedures* applied to the same time sample, measured in a plane turbulent mixing layer (rake of 12 X-wire probes, lying across the mixing layer); after Bonnet *et al.* (1998). Top: instantaneous plot of velocity vector (in a $x-y$ plane); vertical axis: transverse direction; horizontal axis: time (the total duration of the presented sample corresponds to 0.128 second). Bottom: time stamps of detections for: (a) Wavelets; (b) PRA; (c) Vorticity based; (d) WAG: \blacktriangle detection based on v ; \blacktriangledown detection based on spanwise vorticity at the mixing layer axis; $*$ pairing; (e) DCS.

LES approach) or for a band-pass/band-reject filtering. It is of interest in the case where a clear typical frequency (in space or time) is present within the experimental signal. This is the case for shedding wake, artificially excited flow, etc. However, this approach is limited in nature and requires to separate, for the given bandwidth, the part which is attributed to CS and the part which is due to the background turbulence. This represents an orthogonalization problem. The following examples illustrate this approach. First, in an attempt to build what they call a turbulence filter, Brereton & Kodal (1994), Fig. 5, used a filtering procedure of PIV data based on an adaptive filter. Second, a similar approach was applied by de Souza (1996), in the case of the wake of a cylinder, by using a Fourier filtering of the time series of the signals obtained with a rake of hot wires (see Fig. 6). These methods are generally limited to one-point information. In most flows however, the typical frequency can depend upon the quantity observed (e.g. the corresponding velocity component, the vorticity,...), an on the location in space; then more sophisticated filtering methods, such as wavelet-based methods have been developed.

WAVELETS FILTERS

When spatial representation of the flow is available in time (for example time resolved PIV, rakes of HW-sensors), an alternative is to use the wavelet transform in a 2D plane. By using a ‘mask’ (equivalent to a band-pass filter), we can extract the CS signature (Lewalle *et al.*, 2000). An example of the statistics of the CS and background signals obtained in a mixing layer (still obtained on the above men-

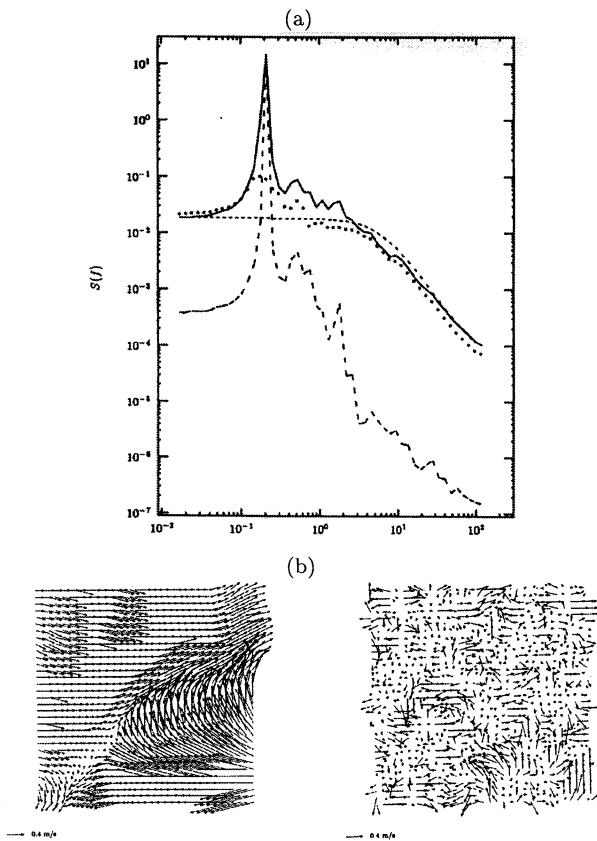


Figure 5: CS extraction via Adaptive Filters after Brereton and Kodal (1994). (a) Measured energy spectra of $u(t)$ and estimated coherent and random energy spectra in a flat-plate boundary layer undergoing forced sinusoidal free-stream oscillations. Horizontal axis: frequency. —, spectrum of u ; - - - coherent part spectrum, . . . random part spectrum. (b) Vector plots of the coherent and random part (from a PIV measurement at the edge of a jet flow).

tioned data base) is given by Fig. 7. This figure shows that the background turbulence has a spectra close to homogeneous grid turbulence one and that its probability density function can be assumed to be quasi-Gaussian. This result corroborates the results of Farge *et al.* (1999), who use this concept as a definition for CS as discussed earlier for the CVS method. These decompositions also perfectly correspond to the SDM proposed by Ha Minh.

Alternative concepts not based on frequency signature but based on stochastic properties, can also be introduced.

LINEAR STOCHASTIC ESTIMATION

In the Linear Stochastic Estimation (LSE), introduced by Adrian (1975), some *reference* signals are considered as conditioning the rest of the signals. In this approach, one tries to linearly estimate $\tilde{u}(x, t)$, the conditional flow field from the knowledge of N_r references p_r . This estimation is performed through the knowledge of the two-point correlation tensor. Symboli-

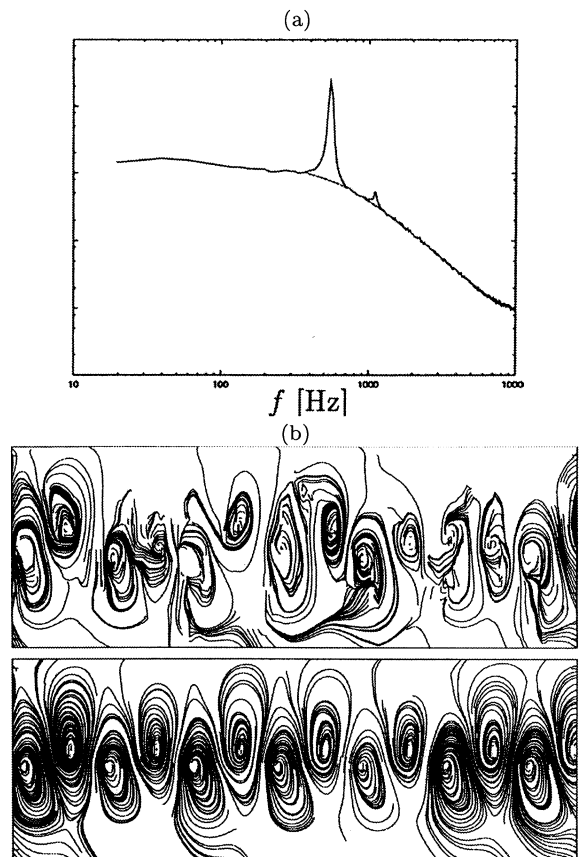


Figure 6: CS extraction via Fourier Filters in the near wake of a cylinder, after de Souza (1996). (a) typical spectrum of the u velocity component exhibiting a sharp peak. (b) Sectional streamlines of the raw (top) and filtered (bottom) velocity. Vertical: transverse direction; Horizontal time (sample length 10 ms); measurements are performed 4.25 diameter downstream the cylinder trailing edge.

cally, the LSE can be written as:

$$\tilde{u}(x, t) = \sum_{r=1}^{N_r} a_r(x) p_r(t).$$

An illustration of this method is given on Fig. 8. By combining pressure transducers placed in the vicinity of a turbulent jet, and a rake of hot wires lying in the shear zone of the jet mixing layer, estimated velocity fields, induced by the instantaneous longitudinal pressure distribution was obtained by Picard and Delville (2000).

Such a method is very useful for simple estimation of instantaneous field, this estimation being considered as a conditional one. The important difference with conventional conditional method is that LSE does not require any thresholding or adaptation procedure. The only parameter to be chosen is the location and nature of the reference signal(s). Another advantage is the possibility of association with other methods, particularly with the POD.

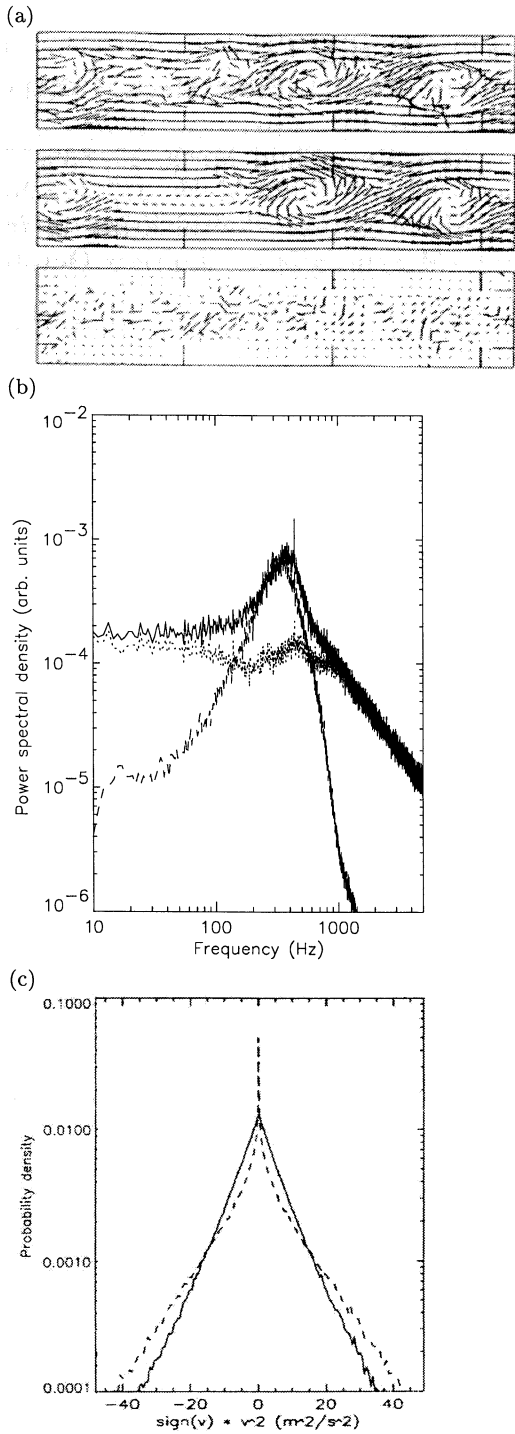


Figure 7: CS extraction via a wavelet mask in a plane turbulent mixing layer. (a) Vector plots of original velocity field, wavelet-filtered (coherent) field and random field. Vertical axis: transverse direction; horizontal: sample duration 10 ms; (b) Power spectra of the original (solid), coherent (dashed) and random (dotted) traces of the v component at the mixing layer center; (c) Probability densities for the v -component of the coherent (dashed) and background (solid) at the mixing layer centerline. The range shown covers about 5 standard deviations on either side of the mean. After Bonnet *et al.* (1996) and Lewalle *et al.* (2000).

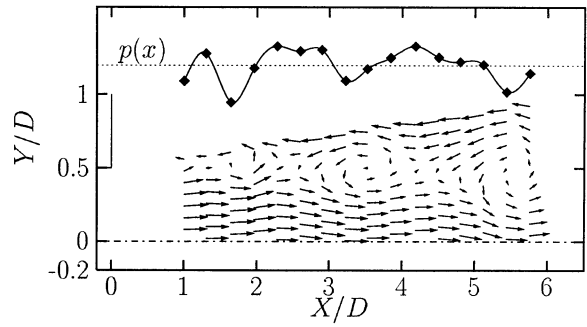


Figure 8: CS eduction from LSE. Estimated velocity vector field induced by the instantaneous axial pressure distribution in the near field of a round jet – after Picard and Delville (1999): 16 microphones + 12 X probes are simultaneously used.

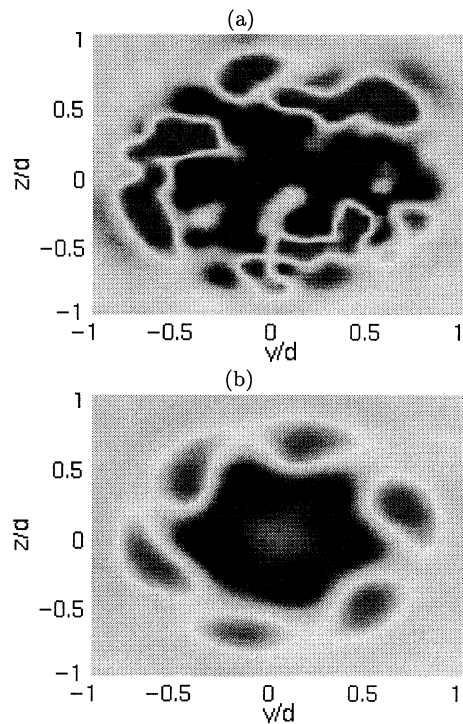


Figure 9: CS extraction in an axisymmetric jet (measurements through a rake of 138 probes) via POD after Citriniti (1996). (a) Raw fluctuating longitudinal component of velocity; (b) Contribution of the first radial POD mode and the first 6 azimuthal modes.

PROPER ORTHOGONAL DECOMPOSITION

Another type of decomposition is the Proper Orthogonal Decomposition (POD: Lumley, 1967) or its generalization, the Bi-Orthogonal Decomposition (BOD: Aubry *et al.*, 1991). In this case, the modes on which the ‘signal’ is projected are the own, intrinsic, modes of the flow. These modes are representative of energetic events. They are determined from the two-point correlation tensor by solving an eigenvalue problem. Symbolically the instantaneous contribution of the POD mode can be

written:

$$u^{(n)}(x, t) = a_n(t) \Phi^{(n)}(x),$$

where $a_n(t)$ is obtained by projecting the flow realization $u(x, t)$ onto the POD eigenvectors $\Phi^{(n)}(x)$:

$$a_n(t) = \int_{\mathcal{D}} u(x, t) \Phi^{(n)}(x) dx,$$

where $\Phi^{(n)}$ is solution of the eigenvalue problem:

$$\int_{\mathcal{D}} \langle u(x, t) u(x', t) \rangle \Phi^{(n)}(x') dx' = \lambda(n) \Phi^{(n)}(x).$$

This method can be applied to turbulent data coming either from hot wire rakes (in this case the conventional POD is used), or from snapshot results (from PIV for example). In this last case, the snapshot POD is used (Sirovich, 1987).

Intensive experimental studies on POD, applied to the axisymmetric mixing layer, have been performed in Clarkson University and in SUNY Buffalo. A nice illustration of these studies, obtained by use of a home-made hot wire rake with 138 probes (see Fig. 1a), is shown by Fig. 9. A spectacular illustration of the capacity of POD to capture the energetic modes of turbulent flows is given on this figure.

In the case of plane turbulent mixing layers, recent results have been obtained by Delville *et al.* (1999) from two rakes of 12 X-wires probes lying in the (y, z) plane (i.e. normal to the mean convection velocity). A 3D description of the first POD mode was then provided (Fig. 10-a). This mode, exhibits a Λ -shape spatial organization which compares quite favorably with several direct visualizations of mixing layers obtained either from experiments or from numerical simulations (Lesieur, 1990). From the same data, Druault (1999) computed the ‘coherent’ and ‘random’ spectra that can be defined by truncating the series to the four first POD modes. The first modes clearly extracts the typical frequency peak associated to the Kelvin-Helmoltz 2D instability. The rest of the signal (corresponding to the remaining modes) exhibits a spectrum corresponding to an homogeneous (equilibrium) turbulence. A comparable behavior has been observed from the wavelet mask method (Fig. 7-b). However, from the POD approach, the coherent part (here the four first modes contribution) is more broad-band than for wavelet filtering. This characteristic shows that the CS detected from

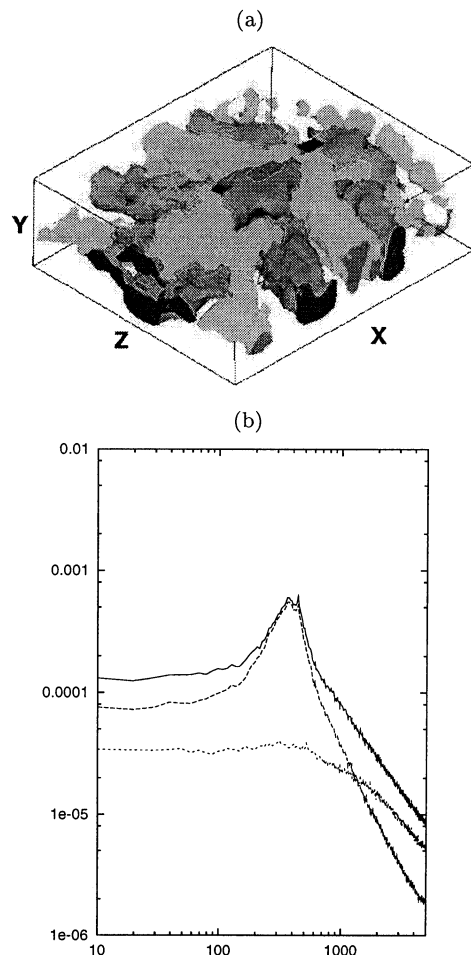


Figure 10: CS extraction via POD in a plane turbulent mixing layer. (a) after Delville *et al.* (1999). Iso-surfaces of constant velocities (v component). Plotted is the contribution of the first POD mode obtained via a shot-noise description. Dark grey $v > 0$, light grey $v < 0$. (b) after Druault (1999). Here are plotted, vs. frequency, — the directly measured v spectrum (original), - - - the contribution of first four POD modes to this spectrum (coherent) and ... the spectrum of the remaining modes (incoherent).

POD are not spectrally localized, they correspond to multiple scales and cannot be seen as usual filtering in time or space. A recent comparable comparison has been performed by Yilmaz and Kodal (2000), in a forced jet flow. They also showed that the POD ‘filtering’ gives more broad band CS when compared to adaptive filtering.

POD/LSE COMPLEMENTARY TECHNIQUE

The determination of the correlation tensor requires only a two-point measurement procedure. However, the projection (equivalent filtering) process needed for CS eduction via POD (or BOD) necessitates the knowledge of instantaneous velocity in several points. De-

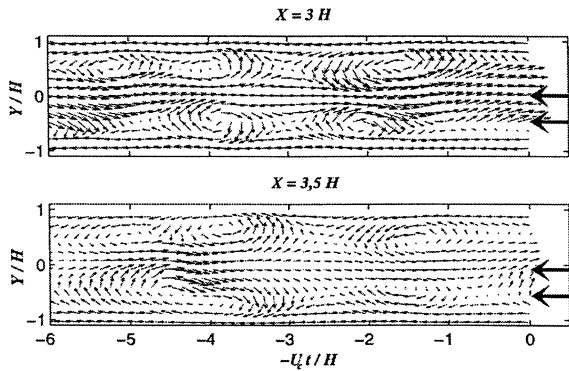


Figure 11: CS extraction via the Complementary Technique obtained at the end of the potential core of a turbulent plane jet after Faghani (1996). Plotted are samples of the instantaneous contribution of the first two POD obtained from only two X probes (arrows).

pending on the measurement apparatus, this is not always possible. For example, it is sometimes difficult to operate simultaneously several hot wire probes. In this case, the LSE, also based on two point correlations, allows to estimate the raw data on which POD can be used as a structure identification process (by retaining only a few number of modes). This approach, called complementary method has been introduced by Ukeiley *et al.*, (1993) and Bonnet *et al.*, (1994). It has been recently used by Faghani (1996). From the measurements obtained with only 2 probes, it is then possible not only to reconstruct the entire dynamical behavior of the CS, but also to apply the POD in his wider extend. Figure 11 gives an example of such an analysis obtained in a plane turbulent jet.

In conclusion, stochastic methods are powerful tools for large scale structures analysis in turbulent flows. Moreover this is not the only use of these methods. We develop in the next sections some other applications.

EXTENSIONS OF THE STOCHASTIC METHODS: GENERATION OF INITIAL CONDITIONS

When LES or DNS are concerned, the determination of initial conditions, dynamically representative of the CS is crucial. It is clear that prescription of the correct initial value of the one-point statistics (such as RMS values of velocity fluctuations) is not sufficient. The generation of time series with correct spectral distribution improves the results and limits the adaptation time of LES. However, it becomes clearer and clearer that the large scale dynamical behavior of the initial conditions has to be known for ideal LES (Adrian *et al.*, 2000a). Recent approaches based on

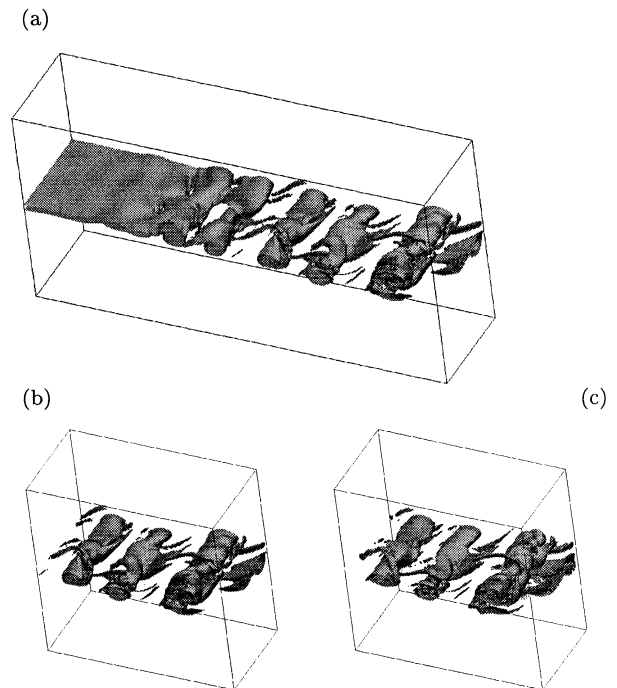


Figure 12: Generation of upstream conditions for a DNS by using LSE after Druault (1999). (a) A plane mixing layer is simulated on a large domain: inlet conditions are then *conventional ones* — mesh: $301 \times 97 \times 48$; (b) A new simulation is performed by using as inlet conditions the velocity *measured* at a given section of the first computation ($X \sim 0.5 * L_x$). Information retained: 3 components on 97×48 points. ; (c) A simulation is performed by using as inlet conditions the estimated velocity (through LSE). Information retained: 2 components on 3×15 points. Data compression ratio: 155.

CS eduction/characterization have been applied in order to retrieve, from a minimum amount of data, the realistic dynamics of the CS that are needed for initializing LES or DNS computations. Two examples, in a turbulent plane mixing layer and in a turbulent boundary layer are given on Figs. 12 and 13 respectively. In these examples, initial conditions for DNS (Fig. 12) and LES (Fig. 13) are generated from the knowledge of the correlation tensor and a limited number of time series (see figures captions). The correlation tensor used for LES purpose can be obtained either from precursor computation as was done by Druault (Fig 12) or from an a-priori knowledge of the flow as was done by Peneau (Fig. 13). Even if a few time series are obtained from precursor computations, the resulting storage requirements are very low. It appears that the LSE can be a powerful tool for an efficient use of DNS/LES, allowing for a minimal ‘adaptation period’ of these methods.

CONCLUDING REMARKS

The concept of CS, initially introduced for a better understanding of the flow, has evolved

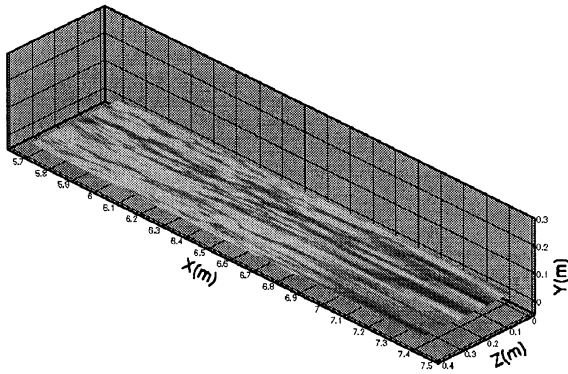


Figure 13: Generation of initial conditions for a LES of a turbulent boundary layer by using LSE after Peneau (1999). Instantaneous XZ plane shot of the u velocity field at $y^+ = 8$.

towards wider ranges of application. It is now an essential concept for experimental approaches, that makes it possible to define the measurement method and apparatus as well as the appropriate data processing methods. It is also an essential concept for choosing the more adapted computational approach, essentially RANS, TRANS, DNS, LES, SDM, CVS,... Most of these methods take mutual benefit of their rapid improvements. The experiments are now well resolved in time or space. Unfortunately, right now, space and time resolutions are not easy to obtain. For example, rakes of hot wires have excellent time resolution, they can collect long duration time histories, and are able to evidence 'rare' events of practical importance. However, even with a huge number of probes, this method remains relatively badly resolved in space (although the spatial resolution can be close to several industrial type simulations) and remains intrusive. On the other hand, the spatial resolution of PIV is well defined. However, for most flows, PIV is not able to provide time series essential for the analysis of CS dynamical behavior. The 3D character of any turbulent flow is also difficult to address (multiple hot-wires, Holographic PIV are under progress). The combination of several experimental methods is now possible and can overpass the individual drawbacks. In addition, the combined use of advanced data processing and huge data storage capacities can also solve these limitations. The combination of several advanced experimental approaches and LES-type CFD is a promising issue, that may reconcile the experimental and CFD communities for the next decade.

Aknowledgements. The authors dedicate this paper to Pr. H. Ha Minh and Pr. H. E. Fiedler.

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