RETRIEVAL OF THE TURBULENT AND BACKSCATTERING PROPERTIES USING A NON-LINEAR FILTERING TECHNIQUE APPLIED TO DOPPLER LIDAR OBSERVATION

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ABSTRACT

We present a new algorithm for the provision of real time estimations of turbulent parameters (TKE and EDR) as we filter the perturbed data of a Doppler lidar. The algorithm uses stochastic models for the atmospheric turbulence and for the remote sensor observation. The results show that we are able to catch fine and fast structures in the Boundary Layer. Here we applied our method to the experimental data of the BLLAST experiment which used a vertical lidar. We finish by comparing the structure of the estimated TKE profiles to the TKE profiles of a Meso-NH simulation.

1. INTRODUCTION

There is presently no proven ground-based instrumental technique able to measure automatically vertical profiles of turbulence properties (Turbulent Kinetic Energy, TKE or Eddy Dissipation Rate, EDR) in the boundary layer. The best approach consists in using aircraft or tethered balloons. The use of remote sensors has been considered for quite some time. Some works have also been done with Doppler lidars that confirms the great potential of this type of instrument for the observation of small-scale, fast evolving, atmospheric flows. They suggest that the Doppler lidar is a possible and interesting remote sensing technique for the characterization of turbulence ([1; 2]).

We have been working on the characterization of turbulent media (at the aerological scale) using non-linear filtering technique and stochastic modelling of the turbulence or/and the sensor measurements. These techniques are based on the particle approximation of the probability laws conditioned by the actual observation. These laws make it possible to denoise the observations and retrieve turbulence parameters. We will present the application of these works to Doppler lidars. This highlights the real possibility to retrieve wind, TKE or EDR in the Boundary Layer probed by this instrument.

We show the ability of our method to learn the vertical profiles of turbulence parameters from real data. We take examples during the experiment BLLAST held in June-July 2011 and we compare our results with slow estimations of EDR or TKE using tethered balloon. We also show how to compare our estimated profiles to numerical simulations using the Meso-NH model.

2. LEARNING THE RANDOM MEDIA PARAMETERS USING NON-LINEAR FILTERING

Before presenting the technological application, we outline the theoretical background with the acquisition process of a random field along a random path. A more precise presentation may be found in [3]

Here we consider a configuration space $E \subset \mathbb{R}^d$, $d \in \mathbb{N}^*$, a metric locally compact space and a phase space $E' \subset \mathbb{R}^{d'}$, $d' \in \mathbb{N}^*$, a vector space, both endowed with some $\sigma-$algebra, $\mathcal{E}$ and $\mathcal{E}'$. Then for any time $t \in [0,T]$ where $T < \infty$ we consider X_t a $(E,\mathcal{E})$-valued random variable called the acquisition path and for any point $x \in E$ we consider $X'_{t,x}$ a $(E',\mathcal{E}')$-valued random variable family (random vector field). Then we define the pair of applications $(X_t, X'_{t,x})$ as the Acquisition System of the random vector field and we define for any measurable function F the Acquisition Process by $A_t \stackrel{def}{=} F(X'_{t,X_t})$. As an easy example, the Lagrangian modelling could be seen as the Acquisition Process of an Eulerian field along the particle trajectories.

For a locally homogeneous medium, given a familly of balls $B^\varepsilon_t(x)$ along the random path X_t, we may compute the expectation $\mathbb{E}(f(X_t, A_t) \mid X_t \in B^\varepsilon_t)$. One may show [3] that there is a Feynman-Kac [4] structure to this conditional expectation. By this way, we can propose some algorithm to estimate the probability laws of this mean-field process with stochastic particle approximations. This is a two-step scheme. The first one is the Markovian prediction of the medium evolution. The second step is a Markovian state selection using a potential function given by the Acquisition Path. The selection kernel is composed of an acceptance/rejection part and a resampling for the rejected states. This update meets the conditioning of the medium to the Acquisition trajectory.

Using this background the filtering problem is then an overlay, the Markovian dynamics being driven by the Acquisition Process estimation (see [3]). The non-linear filtering consists in the computation of the probability laws of an hidden Markov process $\mathcal{X}_t$ conditionally to the observations $\mathcal{Y}_{[0,t]}$. Then the filtering learning retrieves the Markov components, including the non-observed ones. In this manner we realize the learning of the random medium as well as the filtering of the dynamical state.

What kind of prediction model should we use for the acquisition process estimation? If we have local observations of a random medium, it may be interesting to use a local model, such as Stochastic Lagrangian Model (SLM). The numerical domain is covered with a collection of local models. These models have local or global interactions. This is often the case when we have sparse observations. It is more powerfull to have adjusted local models instead of a global one with a mean adjustement. We use this type of dynamics in the case of lidar observations.

3. STOCHASTIC FILTERING FOR VERTICAL LIDAR OBSERVATIONS

The theoretical background being settled, the adaptation of the general problem to the lidar observation concerns mainly the management of a 1D medium observed by point measurements. In this study the lidar beam is vertical, therefore we use bounded column model splitted in several segments centered on the lidar measurement points. Therefore we have regular intervals driven by the observation with a minimum level and a maximum level. We use a stochastic particle approximation to feed a Stochastic Lagrangian Model, a conditionning to the finite size column and a filtering with respect to the observations. The SLM for the vertical velocity is derived from the SLM that we have developed for our pointwise filtering [3]:

$$
\begin{aligned}
X^i_{n+1} &= X^i_n + W^i_n \Delta t + \sigma^X \Delta B^{X,i}_n \\
W^i_{n+1} &= W^i_n + A_n - C_1 \frac{\varepsilon_n}{k^i_n}[W^i_n - < w >]\Delta t \\
&\quad + C_2 \frac{\theta^i_n - < \theta >}{< \theta >}\Delta t + \sqrt{C_0 \varepsilon_n}\Delta B^{W,i}_n
\end{aligned}
$$

where (X^i_n, W^i_n) is the location and the vertical velocity of any particle $i \in [1, N]$, θ^i_n is its associated absolute temperature and $(\Delta B^{X,i}_n, \Delta B^{W,i}_n)$ its Brownian perturbation. The Eulerian average $< w >$ (resp. $< \theta >$) is the expectation $\mathbb{E}(W_n | X_n = x)$ (resp. $\mathbb{E}(\theta_n | X_n = x)$) approximated with the particle using a Gaussian interaction kernel. This local mean is also used for k^i_n is the local Turbulent Kinetic Energy. Δt is the time mesh and C_0, C_1 and C_2 are fixed constants. For the filtering step, for each segment the observations select the stochastic particles keeping alive the most adapted. For this selection phase, we have chosen to adopt a genetic kernel in order to minimize the variance errors [4]. At each step and for each segment, A_n and ε_n are learned as the mean and the quadratic mean of the velocity time increments. In this model ε_n is the Eddy Dissipation Rate. In order to not have to model the temperature θ_n, we drown out the whole term $\dfrac{\theta_n - < \theta >}{< \theta >}$ in a random variable and we have chosen a truncated normal distribution with a support $[-1, 1]$ and a standard deviation about 0.01.

In our method we use a stack of SLM and the stochastic particles are free to leave their segment. This may have (at least) two consequences. We have to deal with overloaded or underloaded segments. This is particularly true at the limits of the domain. The outgoing particles are randomized into the domain using an importance rule favouring the less loaded segments. The management of the particle number in the different segments is performed using min and max bounds around a mean profile determined at the beginning of the experiment using the atmospheric density. This profile is computed with a rough estimation of the temperature gradient. It is only used for the determination of the bound numbers for each segment. Using the max bounds if a segment overshoots the particle number, we withdraw particles and randomize them in other segments according to the importance rule. Using the same idea, if a segment is starved of particles, we withdraw some particle to the most filled segments using the importance rule. These different rules linked to the particle numbers ensure we have enough particles for the conditional expectation estimations. But whatever the precautions, the accuracy of the first and last level are affected by the algorithmic choices and suffer of the lack of physical sense. We will give some clues in the conclusion in order to improve this situation.

4. APPLICATION TO THE BLLAST EXPERIMENT LIDAR DATA

We present some results using the vertical lidar data recorded between 12h41 and 14h05 UTC the June 18th, 2011 at Lannemezan, France during the BLLAST experiment (`http://bllast.sedoo.fr/`). We have vertical profiles every 6 seconds with 10 stacked lidar observations (from 100m to 500m with 50m steps). They are used as a reference signal or truth for the mean vertical velocity. We add a numerical noise to get perturbed observations. Then the challenge to our filter consists in denoising the perturbed signal to retrieve the turbulent parameter and a realization of the original medium. Therefore we can compare the results with the signal considered as a reference. Obviously the main advantage of the method, besides the denoising, lies in the on-line estimation of the turbulence parameters with our SLM. For each time step, i-e every 6s, we have an estimation of Eulerian quantities like TKE or EDR.

First we examine time series (figure 1) of the vertical wind with the three kind of values (reference, perturbed and filtered) at the altitude of 250m. One can see that the general shape is well estimated, steep variations are also retrieved. The original signal and the filtered one are two realizations of the same random medium if the turbulent parameters are correctly assessed by the filter. This is the reason why they do not superimpose exactly. To extend the analyzes we can examine the Power Spectral

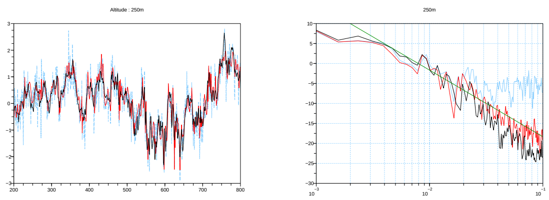

Figure 1: Detail of the vertical wind reference series at 250m (black), observations (cyan), filtered signal (red), with their PSD, sample number as x-axis. Data recorded the June 18th, 2011 every 6s between 12h41 and 14h05 UTC at Lannemezan, France.

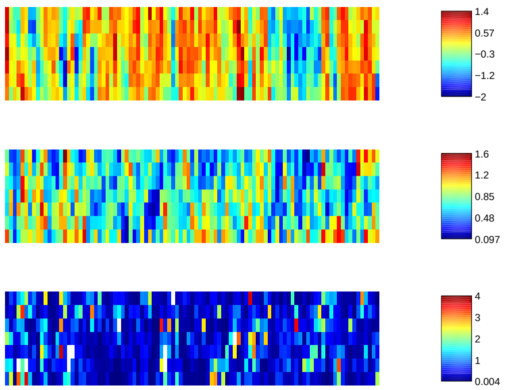

Figure 2: Time profiles averaged on 60s (10 time step) of filtered wind (above), estimated TKE (middle) and EDR (bottom). Data recorded the June 18th, 2011 between 12h41 and 14h05 UTC in Lannemezan, France.

Density (PSD) to have a look on the energy properties. The figure 1 presents the three PSD with the same colorcode. Clearly the spectrum of the filtered signal is better than the reference spectrum. The noise has been really switched off and we see that the lidar spectrum is perturbed by the spatial average of the instruments.

We may present (figure 2) the results as vertical profiles with a 1 minute (10 time steps) average, for the filtered velocities (upper part), the TKE (middle part) and the EDR (lower part). For the wind profiles, positive values are in red, negative are in blue. It is difficult to have an opinion on the behavior of the TKE or EDR with respect to the wind structures. We can notice that the TKE is more important at the transition between upward and downward stream.

5. COMPARISONS WITH CLASSICAL METHODS OR MESO-NH MODEL OUTPUTS

5.1. Balloon-borne in-situ measurements

For a first comparison we consider data taken from an aerodynamic ballon at Lannemezan on 19 June 2010

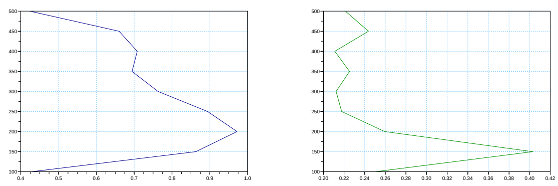

Figure 3: Mean profiles of wind variance (left) and TKE (right). Data recorded the June 19th, 2011 every 6s between 13h26 and 14h49 UTC at Lannemezan, France.

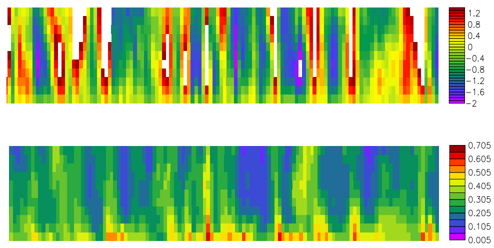

Figure 4: Time profiles produce by a Meso-NH simulation (time step 60s) of vertical wind (above), TKE (bottom).

between 13h26 and 14h49 UTC in the vicinity of the lidar location. The sonic anemometer shipped by the balloon provides 10 Hz relative wind measurements. The ground speed estimated using the INS/GPS information is substracted from the relative wind to obtain an absolute wind. The ballon flew at 60m during the period. Then using the lidar observation, we compute the filtered wind and the TKE, the first level at 100m is representative of the 75-125m segment, and we compare.

The aerodynamical balloon measurements of the wind is at 0.1s. We subsample the wind at 6s and we compute a variance about 0.39 $m^2 s^{-2}$. We can compute directly the variance of the filtered lidar signal at 100m and we obtain 0.42 $m^2 s^{-2}$. The two values are very close. For the same period, the average TKE is assessed at 0.25 $m^2 s^{-2}$. It is possible to produce a mean profile of wind variance with respect to the height and a mean profile of TKE. The figure 3 shows these profiles which are typical of a convective boundary layer.

5.2. Meso-NH profiles outputs

We have some difficulties to analyze the figure 2 because it is too early to assess the structures of the TKE or EDR in the boundary layer at this rate. In order to evaluate the realism of the TKE or EDR structures seen by lidar, we compared lidar profiles to a Meso-NH simulation. The code is not ready yet for the BLLAST experiment, therefore we use a numerical experiment of a well-know and published case [7].

The simulation is a Large-Eddy Simulation realised with Meso-NH over a domain of $10 \times 10 \times 5km^3$

with a horizontal resolution of 100m. This simulation represents a clear boundary layer observed over the Southern Great Plains during one day (June 14th, 2002) of the IHOP field campaign. It starts at 07h00 LT from an observed radiosounding profile and uses prescribed surface fluxes. It has been evaluated with observations up to 14h00 LT (see [7]). This simulation is run for 14 hours. Profiles have been extracted every 60s from this simulation and are compared to the observations.

In this comparison, we only examine the general shape of TKE and the order of the value both for the simulation and the 18th of June estimation. On the vertical wind, we have both for the filtered profiles and for the simulation, downward structures. It is consistent with advected ascending columns or descending areas seen by a vertical profile and the upper part of the advected structure is first observed. The simulation and the filtered signal have the same range of values. About the TKE, the structures are different with greater values in the bottom. While the simulation of the TKE is smoother, the filtered TKE reacts faster and gives profiles with more dynamical small scales. But is the reality smooth or coarse ? we have no answer at the moment. However we can remark that the structures are the same for the simulation and the filtering, with higher values of TKE at the transitions between upward and downward winds, with the same range of values.

6. OUTCOMES AND FURTHER DEVELOPMENTS

We have presented a new algorithm to estimate the turbulent parameters using lidar measurements. This algorithm is based on non-linear filtering, on a stochastic modeling of the medium and on a stochastic modeling of the sensor behavior. Applying our method to real data demonstrated the capability of the algorithm to estimate not only the vertical wind but also turbulent parameters such as the TKE or the EDR. The comparisons with pointwise balloon measurements and with a Meso-NH simulation are qualitatively and quantitatively good.

We have to improve the processing of the first level to avoid the algorithmic perturbations. A nice idea may be to use a ground anemometric measurement (for instance with sonic anemometer) with a particle approximation of the turbulent parameters. Therefore this ground system would be considered representative of the 0-75m layer and used to feed the first layer (75-125m) of the lidar particle system. It would be better than the current and purely algorithmic solution.

We intend to complete the measurement system with an X-band radiometer to provide some temperature vertical profiles. This slow observation would be helpful in order to include in the system an equation on temperature that will guide the vertical motions.

We have develop some mock-up for 3D estimations using lidars scanning the atmosphere within an hemisphere ([8]). In this work, the vertical interactions have not been taken into account. With the present studie about vertical lidar, we have developed the algorithmic solutions to finish the job and have full 3D estimations of wind, TKE and EDR.

At the same time we have to continue the work of comparison with other BLLAST cases and we are waiting for the Meso-NH simulations for the same experimental cases. It will end the qualification of our methodology.

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REFERENCES

1. Lothon M., Lenschow D. and Mayor S. 2009 : Doppler Lidar Measurements of Vertical Velocity Spectra in the Convective Planetary Boundary Layer. *Boundary-Layer Meteorology*, **132**, 205-226.
2. O’Connor E., Illingworth A., Brooks I., Westbrook C., Hogan R., Davies F. and Brooks B. 2010 : A method for estimating the turbulent kinetic energy dissipation rate from a vertically pointing doppler lidar, and independent evaluation from balloon-borne in situ measurements. *J. Atmos. Oceanic Technol.*, **27**, 16521664, doi: 10.1175/2010JTECHA1455.1.
3. Baehr, C. 2010 : Nonlinear Filtering for observations on a random vector field along a random path. *M2AN - ESAIM*, **44 (5)**, pp. 921-945, DOI No: 10.1051/m2an/2010047 .
4. Del Moral, P. *Feynman-Kac Formulae, Genealogical and Interacting Particle Systems with Applications*. Springer-Verlag, Berlin, 2004.
5. Pope, S.B. *Turbulent Flows*. Cambridge University Press, 2000).
6. Das S. and Durbin P. 2005 : A Lagrangian stochastic model for dispersion in stratified turbulence. *Phys. of Fluids*, **17**, 025109.
7. Couvreux F., Guichard F., Redelsperger J., Kiemle C., Masson V., Lafore J. and Flamant C. 2005 : Water-vapour variability within a convective boundary-layer assessed by large-eddy simulations and IHOP_2002 observations *Q. J. R. Meteorol. Soc.*, **131**, 2665-2693, DOI: 10.1256/qj.04.167.
8. Suzat F., Baehr C. and Dabas A. 2011 : A fast atmospheric turbulent parameters estimation using particle filtering. Application to lidar observations *J. Phys. Conf. Ser.*, **318-7**, doi:10.1088/1742-6596/318/7/072019