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Employing the Hilbert–Huang Transform to analyze observed natural complex signals: Calm wind meandering cases

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HIGHLIGHTS

- We propose a new methodology to investigate the occurrences of turbulence and meandering movements.
- We use the Hilbert–Huang Transform to find the characteristic meandering time scale.
- We employ wind data measured in a PBL to obtain meandering marginal spectra.

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ABSTRACT

In this study we analyze natural complex signals employing the Hilbert–Huang spectral analysis. Specifically, low wind meandering meteorological data are decomposed into turbulent and non turbulent components. These non turbulent movements, responsible due to the absence of a preferential direction of the horizontal wind, provoke negative lobes in the meandering autocorrelation functions. The meandering characteristic time scales (meandering periods) are determined from the spectral peak provided by the Hilbert–Huang marginal spectrum. The magnitudes of the temperature and horizontal wind meandering period obtained agree with the results found from the best fit of the heuristic meandering autocorrelation functions. Therefore, the new method represents a new procedure to evaluate meandering periods that does not employ mathematical expressions to represent observed meandering autocorrelation functions.

1. Introduction

The analysis and the decomposition of non-linear complex natural signals into orthogonal components is a problem concerning distinct fields of the physical sciences. The Fourier and wavelet analyses represent classical decomposition methods that have been exhaustively and successfully applied to investigate natural signals [1,2]. Recently, a new method to analyze natural signals, known as Hilbert–Huang Transform, has been introduced [3]. Observed low wind velocity data,

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which are constituted by the atmospheric turbulence and low frequency motions, are typical examples of complex non-linear signals that occur for a significant percentage of time in different regions of the planet and therefore need to be investigated [4,5]. For instance, the enhanced dispersion of contaminants, associated to low wind speed conditions, is a frequent transport phenomenon occurring in the atmospheric boundary layer [6]. Under these conditions, often referred as "meandering", the simple task of determining a prevailing wind direction becomes difficult. In this particular flow pattern, the plume of contaminants is dispersed over a rather wide angular sector. As a consequence, traditional air pollution models, such as Eulerian and Lagrangian stochastic dispersion models become inadequate to simulate the observed contaminant dispersion. Wind meandering is characterized by low frequency horizontal atmospheric flow oscillations. Observational analysis accomplished by Anfossi et al. [4] shows that the meandering autocorrelation functions of the horizontal wind components, calculated for low wind situations, provide an oscillatory behavior characterized by the presence of large negative lobes. According to Steeneveld and Holtslag [7] a negative autocorrelation function means that particles become anti-correlated, i.e., a particle that has recently been released travels eastwards relative to the coordinate system, while the parcel that was released several hundred seconds before travels westwards. As a consequence, the above discussion stresses that correct air quality forecasting needs detailed physical information on the parameters describing the wind meandering. The meandering time scale is of fundamental importance to simulate meandering enhanced diffusion. The aim of the present study is to employ the Hilbert–Huang Transform (HHT) to obtain velocity and temperature meandering spectra to determine the magnitude of the meandering time scale (meandering period) for the horizontal velocity components and temperature and to compare it to other methods previously proposed for that task.

2. Hilbert–Huang marginal spectra

In general, the meandering time scale is determined from the fitting of heuristic mathematical formulations to observed meandering autocorrelation functions (ACF) [4]. Although this methodology has provided good results [8–10], it is dependent on the choice of the selected mathematical function to represent the experimental meandering data. To understand a complex phenomenon such as horizontal wind meandering, it is necessary to develop a new methodology to estimate parameters like wind and temperature meandering characteristic period ($T^*_{u,v,T}$) without the restrictions of a mathematical shape.

In low wind speed conditions, the turbulent fluctuations of the horizontal wind velocity components are smaller than under strong wind or convective conditions. Therefore, in situations of wind meandering, the spectral energy distribution of the horizontal components of the wind velocity is dominated by low frequency motions. As a consequence, the wind meandering period values can be obtained using a spectral representation. Mortarini et al. [9] showed that the period of occurrence of the velocity spectrum peak in the low-frequency region agrees with the meandering period estimated by the wind speed ACF fitting method. The Fast Fourier Transform (FFT) algorithm widely used to evaluate wind velocity spectrum is known to provide a coarse resolution in the low frequencies. Thus, the identification of the spectral peak associated to the wind meandering phenomenon is biased to occur in a few fixed frequency values in the low frequency region of the spectrum, determined by the length of the analyzed time series.

These spectral issues, associated to the low frequencies, are better solved by the Hilbert–Huang Transform which employs the concept of instantaneous frequency. The instantaneous frequencies are obtained applying the Hilbert transform to a specific set of functions called Intrinsic Mode Function (IMF). Such functions are characterized for the following properties: (a) the number of local maxima or minima is equal to the number of zeros crossings, or at most differ by one. (b) At any time, the local mean of the envelop built from the interpolation of the local maxima (upper limit) and minima (lower limit) is zero. The process used to decompose a non-linear and non-stationary signal $x(t)$ in a finite and reduced set of IMF is called Q4 Empirical Mode Decomposition (EMD). The EMD is based on a sifting process summarized in the following steps:

1. to identify the local maxima/minima;
2. to interpolate the local extrema to obtain the upper limit ($l_{upper}(t)$) and lower limit ($l_{lower}(t)$) of the envelop that constrains the signal;
3. to evaluate the envelop local mean $m_1(t) = 0.5 \times (l_{upper}(t) + l_{lower}(t))$;
4. to obtain the first protomode h_1 (IMF candidate): $h_1 = x(t) - m_1(t)$.

In general, the h_k do not satisfy the properties of an IMF in the first iteration. So, the sifting process (steps 1–4) is applied successively in $h_{k,j}$, with $j = 1, \ldots, n$, until a stoppage criterion is achieved [11,12]. Finally, $h_{1,n}$ is signed as the first (shorter period) IMF C_1. C_1 is removed from $x(t)$ and the first residue is obtained: $r_1 = x(t) - C_1$. The sifting process is applied repeatedly to each new residue r_k to extract the subsequent higher period IMFs. The EMD stops when no IMF can be extracted from the residual signal r_n. Hence, $x(t)$ can be represented by:

$$x(t) = \sum_{i=1}^{n} C_i + r_n. \quad (1)$$

The main advantages of the EMD in relation to the classical decomposition methods are that the decomposition is made in an adaptive base dependent on the local characteristics of the signal. Thus, the set of IMFs (C_i) represents the intrinsic natural modes of oscillation of the signal and the residue (r_n) is the natural trend.

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