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Time dependent intrinsic correlation analysis of temperature and dissolved oxygen time series using empirical mode decomposition

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ABSTRACT

In the marine environment, many fields have fluctuations over a large range of different spatial and temporal scales. These quantities can be nonlinear and non-stationary, and often interact with each other. A good method to study the multiple scale dynamics of such time series, and their correlations, is needed. In this paper an application of an empirical mode decomposition based time dependent intrinsic correlation, of two coastal oceanic time series, temperature and dissolved oxygen (saturation percentage) is presented. The two time series are recorded every 20 min for 7 years, from 2004 to 2011. The application of the empirical mode decomposition on such time series is illustrated, and the power spectra of the time series are estimated using the Hilbert transform (Hilbert spectral analysis). Power-law regimes are found with slopes of 1.33 for dissolved oxygen and 1.68 for temperature at high frequencies (between 1.2 and 12 h) with both close to 1.9 for lower frequencies (time scales from 2 to 100 days). Moreover, the time evolution and scale dependence of cross correlations between both series are considered. The trends are perfectly anti-correlated. The modes of mean year 3 and 1 year have also negative correlation, whereas higher frequency modes have a much smaller correlation. The estimation of time-dependent intrinsic correlations helps to show patterns of correlations at different scales, for different modes.

1. Introduction

Generally in geosciences, but especially in the marine environment, many fields have fluctuations over a large range of spatial and temporal scales. To study their dynamics and estimate their variations at all scales, high frequency measurements are needed (Chang and Dickey, 2001; Chavez et al., 1997; Dickey, 1991). Here a time series obtained from automatic measurements in a moored buoy station in coastal waters of Boulogne-sur-mer (eastern English Channel, France) is considered, recorded every 20 min from 2004 to 2011 (Zongo and Schmitt, 2011; Zongo et al., 2011). This fixed buoy station can record various biogeochemical parameters simultaneously. Here, mainly to illustrate the application of a new method for multi-scale data analysis there is a focus on two parameters: temperature, due to its obvious importance, influenced by the dynamics, by meteorology, and as a link with ecosystem forcing, and dissolved oxygen time series, due to its important role in biological processes, and also for the probable growing importance of this parameter to assess the quality of coastal waters, in the framework of European directives (Best et al., 2007).

These physical and biogeochemical time series are nonlinear, and non-stationary, and may possess interactions at different scales. In order to consider their multi-scale dynamic properties and explore their correlations at different scales, the empirical mode decomposition (EMD) framework is applied here (Huang et al., 1998).

EMD and the associated Hilbert spectral analysis (resp. Hilbert–Huang Transform, HHT) have already been applied in marine sciences (Dätig and Schlurmann, 2004; Hwang et al., 2003; Schmitt et al., 2009; Veltcheva and Soares, 2004). For example, Hwang et al. (2003) applied the HHT method to ocean wave data. They found that the HHT method detects more energy in lower frequencies, leading to a lower average frequency in HHT spectra than using the Fourier framework. Dätig and Schlurmann (2004) showed that the HHT method can used to study nonlinear waves using instantaneous frequencies. Schmitt et al. (2009) applied the HHT method to characterize the scale invariance of velocity fluctuations in the surf zone. They observed that the scale invariance holds for almost two decades of time scales.

In the following, the methodology is presented and then its application is illustrated on the chosen time series. Section 2 presents the Hilbert–Huang Transform method and the fairly recent time dependent intrinsic correlation; Section 3 presents the data base; Section 4 presents the analysis of the intrinsic correlation and Section 5 draws the main conclusion of this paper.

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2. Hilbert–Huang transform and time dependent intrinsic correlation

In this section, the Hilbert–Huang transform and the empirical mode decomposition based time dependent intrinsic correlation are presented. These time series analysis techniques have been applied, since their introduction in 1998 (Huang et al., 1998), in several thousand different studies in natural and applied sciences. Here the main idea is recalled but the method is not presented in too much detail.

The HHT consists of two steps. The first step is the so-called 'empirical mode decomposition', which separates a multi-scale time series into a sum of intrinsic mode functions without a priori basis assumption (Flandrin and Gonçalvès, 2004; Huang et al., 1998). In the second step, the Hilbert spectral analysis is applied to each mode function to extract the time-frequency information. The so-called Hilbert spectrum and the corresponding Hilbert marginal spectrum are then introduced to characterize the time-frequency distribution of a given time series (Chen et al., 2010; Huang, 2009; Huang et al., 1998, 2008).

2.1. Empirical mode decomposition

Empirical mode decomposition is a fully adaptive technique to study the nonlinear and non-stationary properties of time series (Flandrin and Gonçalvès, 2004; Huang et al., 1998, 1999; Huang et al., 2011). The main idea of EMD is to locally separate a given multi-scale signal into a sum of a local trend and a local detail, respectively, for a low frequency part and a high frequency part (Rilling et al., 2003). The latter is called the intrinsic mode function (IMF), and the former is called the residual. The procedure is repeated to the residual, considered as a new times series, extracting a new IMF using a spline function, and obtaining a new residual until no more IMF can be extracted (Flandrin et al., 2004; Huang et al., 1998, 1999; Rilling et al., 2003). The EMD method then expresses a multi-scale time series as the sum of a finite number of IMFs and a final residual (Flandrin et al., 2004; Huang et al., 1998).

To be an IMF, an approximation to the so-called mono-component signal, it must satisfy the following two conditions: (i) the difference between the number of local extrema and the number of zero-crossings must be zero or one; and (ii) the running mean value of the envelope defined by the local maxima and the envelope defined by the local minima is zero (Huang et al., 1998, 1999; Rilling et al., 2003). The so-called empirical mode decomposition algorithm is then proposed to decompose a signal into IMFs (Huang et al., 1998, 1999; Rilling et al., 2003):

1. identify the local extrema of the signal $x(t)$;
2. construct upper envelope $e_{\max}(t)$ by using the local maxima through a cubic spline interpolation (other interpolations are also possible). Construct a lower envelope $e_{\min}(t)$ by using the local minima;
3. define the mean value $m_1(t) = (e_{\max}(t) + e_{\min}(t))/2$;
4. remove the mean value from the signal, providing the local detail $h_1(t) = x(t) - m_1(t)$;
5. check if the component $h_1(t)$ satisfies the above conditions to be an IMF. If yes, take it as the first IMF $C_1(t) = h_1(t)$. This IMF mode is then removed from the original signal and the first residual, $r_1(t) = x(t) - C_1(t)$ is taken as the new series in step 1. If $h_1(t)$ is not an IMF, a procedure called the "sifting process" is applied as many times as necessary to obtain an IMF (not detailed here).

By construction, the number of extrema decreases when going from one residual to the next; the above algorithm ends when the residual has only one extrema, or is constant, and in this case no more IMF can be extracted; the complete decomposition is then achieved in a finite number of steps. The analyzed signal $x(t)$ is finally written as the sum of mode time series $C_i(t)$ and the residual $r_n(t)$:

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

Based on a dyadic filter bank property of the EMD algorithm, the number of IMF modes is estimated as

$$N \leq \log_2(L) \tag{2}$$

where L is the length of the data in points (Flandrin et al., 2004; Huang et al., 2008; Wu and Huang, 2004). Unlike Fourier based methodologies, e.g., Fourier analysis and wavelet transform, this method does not define the basis a priori (Flandrin and Gonçalvès, 2004; Huang et al., 1998, 1999). It thus possesses full adaptability and is very suitable for non-stationary and nonlinear time series analysis (Huang et al., 1998, 1999).

2.2. Hilbert spectral analysis

To characterize the time-frequency distribution of the IMF mode, a complementary analysis technique namely Hilbert spectral analysis (HSA) is then applied to each IMF mode to extract the local frequency information (Huang, 2009; Huang et al., 1998, 1999, 2011; Long et al., 1995). In this complementary step, the Hilbert transform is used to construct the analytical signal, i.e.,

$$\tilde{C}(t) = C(t) + j\frac{1}{\pi}P\int_{-\infty}^{+\infty} \frac{C\left(t'\right)}{t-t'} dt' \tag{3}$$

in which P is the Cauchy principle value (Cohen, 1995; Flandrin, 1998; Huang et al., 1998; Long et al., 1995). The above equation can be rewritten as

$$\tilde{C}(t) = \mathcal{A}(t)\exp(j\theta(t)) \tag{4}$$

in which $\mathcal{A}(t) = \left|\tilde{C}(t)\right|$ is the modulus and $\theta(t) = \arctan\left(\mathrm{IM}\left(\tilde{C}(t)\right)\Big/\mathrm{RE}\left(\tilde{C}(t)\right)\right)$ is the instantaneous phase function (Cohen, 1995; Flandrin, 1998; Huang, 2009; Huang et al., 1998, 2011; Long et al., 1995). The instantaneous frequency is then defined as

$$\omega(t) = \frac{1}{2\pi}\frac{d\theta(t)}{dt}. \tag{5}$$

Note that the instantaneous frequency ω is very local since the Hilbert transform is a singularity transform and the differential operator is used to define the frequency ω (Huang et al., 1998, 1999; Huang, 2009). It was found experimentally that the Hilbert-based methodology is free with the Heisenberg–Gabor uncertainty and can be used to describe nonlinear distortions by using an intrawave-frequency-modulation mechanism, in which the frequency can be varied with time in one period (Huang, 2005; Huang et al., 1998, 2011). Therefore, the method is free with high-order harmonic components, which are required in Fourier-based methods to capture the non-stationary and nonlinear characteristics of the data (Huang et al., 1998, 1999; Huang, 2005; Huang et al., 2011).

Note that several methods exist, that could be applied to estimate the instantaneous frequency, e.g., direct quadrature, and teager energy operator; see more detail in (Huang et al., 2009a). In practice, the Hilbert method already provides a good estimation of ω in a statistical sense (Huang et al., 2010, 2011).

A Hilbert spectrum $H(\omega, t) = \mathcal{A}^2(\omega, t)$ can be designed to represent the energy of the original signal as a function of frequency ω and time. It can be taken as the best local fit to $x(t)$ using an amplitude and phase varying trigonometric function (Huang, 2005). This corresponds to a