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Improvement ocean wave spectra estimation using the temporal structure of wave systems

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ABSTRACT

Sea states are usually the combination of several time-evolving wave systems whereas the classical spectral estimation methods assume stationarity. A method that adapts to the dynamical evolution of the spectral components is proposed to improve both omnidirectional and directional sea wave spectral estimations. In this method, periodograms are computed for each sea state as in the conventional methods, and rather than only smoothing individual periodograms, the overall time-history of periodograms are simultaneously smoothed in frequency and time dimensions. Since a simple two dimensional averaging would not be appropriate because the temporal evolution of the wave systems reflects typical non-stationary behaviors, we use either kriging or adaptive 2D kernel density estimators that allow the taking care of the spectral component frequency–time evolutions. The method is successfully validated on sequences of spectra typical of sea-state conditions in West Africa. The comparison with the simple 2D averaging method and individual periodogram smoothing method shows that the proposed method gives higher effective numbers of degrees of freedom, better estimates of the spectral shape and reliable spectral moments. The method also provides a tool for sea wave spectra interpolation and may thus be used to fill in missing values and improve wave systems tracking for storm identification purposes.

1. Introduction

A description of random ocean waves is of vital importance for many activities and therefore a considerable effort is spent on the collection and analysis of wave data. The most frequent approach for analyzing the characteristics of random ocean waves is spectral analysis (Goda, 2010; Borgman, 1967). In that approach, a sea state is defined for a suitable short-term period of time (from half hour to several hours), and is considered fully characterized by its directional spectrum which provides the distribution of the wave energy as a function of frequency and direction. Reliable sea state spectral estimation is therefore important, especially in coastal engineering and other marine applications. Two types of methods are available for estimating the spectrum of a sea surface elevation time series: non-parametric and parametric methods. Non-parametric sea wave spectral estimation generally consists of periodogram smoothing with frequency windows (Schuster, 1898; Welch, 1967), or Fourier transformation of smoothed or truncated auto-covariance function (Blackman and Tukey, 1959). In parametric spectral estimation, the task is to estimate the parameters of a model that describes the spectrum of the sea state (Phillips, 1985; Hasselmann et al., 1973). Parametric estimation is generally satisfactory for unimodal spectra, but much weaker when the spectrum exhibits many peaks (Olagnon et al., 2013).

In many cases, the sea state is a superimposition of coexisting wave systems (swells and wind sea) and the resulting spectra have many peaks. One often needs in such cases to partition the sea state into its wave systems for an accurate characterization (see (Aarnes and Krogstad, 2001; Gerling, 1992; Hanson and Phillips, 2001; Portilla et al., 2009)). Furthermore, some of the successive wave systems are created by the same meteorological event (storm, hurricane, pressure low, etc.) and thus, one can track in time the evolution of wave systems in order to link them to the same event (see (Hanson and Phillips, 2001; Aarnes and Krogstad, 2001)). Indeed, when looking at the time-history of periodograms, it is possible to observe temporal coherence in the spectral components. As an illustration, Fig. 1 shows on the left panel a periodogram for individual sea state (in dark) and on the top right panel the time-history of periodograms off Angola. Linear patterns can be observed in the low frequency ranges, corresponding to the time evolutions of swell systems. Some coherent patterns can also be observed in high frequency ranges, corresponding to local wind effects. It

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is legitimate to expect that taking into account the temporal coherence of the spectral components may be a good way to improve sea wave spectra estimation. That allows the overcoming of the limits imposed in the estimation quality by strict stationarity conditions.

This study proposes methods that adapt to the dynamical evolution of the spectral components to improve both omnidirectional and directional sea wave spectral estimations. Periodograms are first of all computed for each sea state as in the conventional methods. Yet, rather than only smoothing individual periodograms, we consider the overall time-history of periodograms as a random field that depends on frequency and time, and we smooth this field simultaneously in frequency and time dimensions. Since the temporal evolution of the wave systems reflects typical non-stationary behaviors, as for instance the linear increasing trend of the pic frequency of swell components, a simple two dimensional averaging would not be appropriate. Two techniques that allow the consideration of the dynamical evolution of wave systems are therefore proposed in this study to smooth the time-history of periodograms:

- Kriging that is a spatial optimal interpolation method based on the idea that the value at an unknown point should be a weighted average of the known values at its neighbors, where the optimal weights are calculated using the time and frequency correlations (Stein, 1999);
- Adaptive 2D kernel density estimator i.e. imposing a kernel that adapts to the dynamical evolution of wave systems (Silverman, 1986).

The addition and the use of the time dimension, taking into consideration the dynamical evolution of the wave systems, improve the sea state spectral estimation. Spectra estimates using the proposed approach dramatically enhance the temporal tracking of wave systems for sea storm identification purposes. Moreover, in situ wave measurements often suffer from missing data in consequence of instrument loss, malfunction, or delayed maintenance. For the many marine applications that need continuous measurements, the approach provides a straightforward way to interpolate spectra when faced with missing data (see Fig. 1 right panel). The extension of the method to directional spectra improves also the estimation of the directional spreading which is important in some marine applications (Table1).

The paper is organized as follows. A brief description of the data used for this study is given in Section 2. In Section 3, we present the proposed method for omnidirectional spectral estimation. We then show some comparison results of the estimated spectra with those that are estimated by only smoothing individual periodograms, and with spectra that are estimated using a naive two dimensional averaging. The ability of the proposed method to interpolate the missing spectra is finally shown. Section 4 presents the extension of the methods to the directional spectral estimation. Conclusions are given in Section 5.

Table 1
Summary of the method used to generate synthetic time series of sea surface elevation.

Observed sea surface elevation	⟹	Observed spectrum	⟹	Parametric fitted spectrum	⟹	Synthetic sea surface elevation simulation

2. Data

The data used for this study are re-simulated times series of sea surface elevations derived from a time-history of parametric spectra in order to validate the proposed methods in an idealized situation where the "true" spectra are known. The measurement data, covering period from March 2001 to April 2004 are obtained from a directional waverider buoy, sampled at 1.28 Hz, and anchored by 1450 m water depth off the coast of Angola. Half hourly successive spectra derived from in situ measurements are first partitioned using a "dynamical partitioning algorithm" (Ailliot et al., 2013). Synthetic spectra are then obtained as linear combinations of parametric models fitted to the partitions. A wind sea component is fitted by a JONSWAP parametric model and swell components are fitted by log-normal parametric models as recommended in Forristal et al. (2013), Olagnon et al. (2013) for West Africa conditions (see Fig. 2). The resulting time-history of synthetic spectra provides a realistic sequence of spectra (reference spectra). From each synthetic spectrum, time series of sea surface elevation $z(\tau)$ are finally simulated, assuming that $z(\tau)$ is a Gaussian process, as described in Goda (1977) and Olagnon and Robin (1990). The goal is to estimate the spectra from the re-simulated sea surface elevation time series with the proposed methods and the conventional ones and to compare the results with the reference spectra.

3. Proposed method for omnidirectional spectral estimation

3.1. Method

The method consists of two steps:

1. block the data by short stationary periods (typically 30 min) and compute periodograms for recorded sea elevation time series using discrete Fourier transform on each block;
   - kriging, or
   - two dimensional kernel density estimator by imposing a kernel that follows the dynamical evolution of wave systems (adaptive kde2D).
2. smooth the time-history of log-periodogram using either.

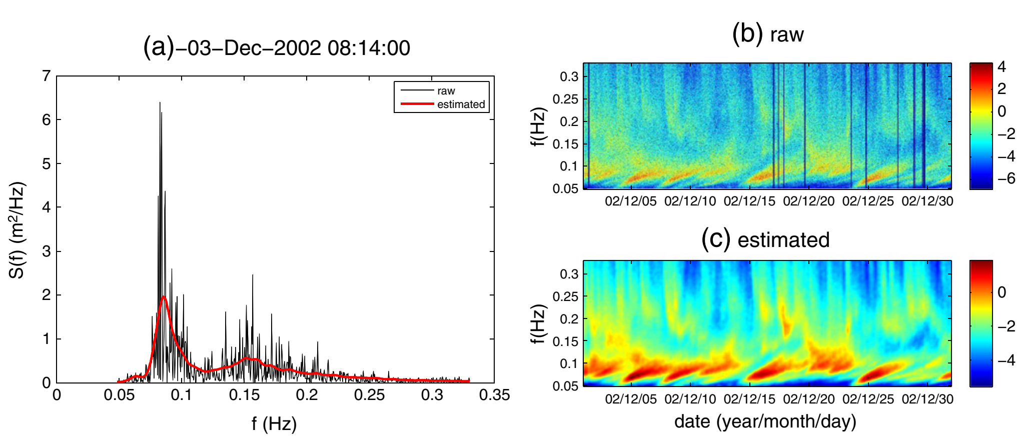

Fig. 1. Sea wave spectra estimation and interpolation applied to in situ data: (left) example of periodogram and estimated spectrum; (right) time-history of periodogram (up) and estimated spectra (below).