Multiscale Characterization of Bathymetric Images by Empirical Mode Decomposition

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ABSTRACT: In this work the characterization of seafloor using a multiscale analysis of bathymetric images is proposed. The proposed scheme is based on the Empirical Mode Decomposition (EMD) [1]. Bathymetric image is considered as a set of oriented sand wave profiles generated, in general, by unidirectional currents. Seafloor may be viewed as a superposition of fast sand oscillations superimposed to slow ones, and their separation is an important step in geophysical and geological explorations. The method considers bathymetric profiles, which are less correlated in the orthogonal direction of the water currents, at the scale of their local oscillations. Each profile is decomposed into oscillations called Intrinsic Mode Functions (IMFs). The EMD is applied separately to each profile, and images called Empirical Images (EIs) are constructed IMF-per-IMF. These EIs can be associated to bedforms such as ripples, sand waves or dunes (Megaripples). The proposed analysis is tested on real multibeam echosounder images.

1 INTRODUCTION

New improvements in acoustic systems such as high-frequency multibeam echosounders provide new seabed images of good quality for seafloor characterization, which is a major issue in geological and geophysical explorations. The bottoms of shallow seas, characterized by the presence of tidal currents and large deposit of sand, exhibit a variety of regular and irregular morphological patterns of different length scales. These bedforms are superimposed and classified on the basis of their length, height and steepness. Among these bedforms, one may find ripples, megaripples (small dunes), sand waves and antidunes. Sand waves are rhythmic features and their profile is symmetric unless either strong residual currents are present or the tidal wave is asymmetric. Ripples may be symmetrical or asymmetrical depending on the flow type. Megaripples are a product of the peak tidal currents and tend to increase in size toward the top of sand waves. Thus, bathymetric profile may be viewed as a superposition of fast oscillations (ripples) superimposed to slow oscillations (sand waves). This superposition of oscillations demonstrates clearly that the bathymetric images are inherently multicomponent, and may be considered to comprise different locally narrowband components. More particularly, bathymetric images contain complicated and non-stationary texture structures. Since these images are wideband, a multiband filtering must be applied to isolate locally the components. In this work a multibeam echosounder system is used to obtain bathymetric profiles. The aim is to separate bathymetric oscillations using multiband filtering method based on a new decomposing data tool called Empirical Mode Decomposition (EMD) [1]. The EMD decomposes a profile into oscillating components called Intrinsic Mode Functions (IMFs). In some sense, the decomposition can be compared with time-varying filter bank. For two-dimensional data or images processing, the IMFs are called Empirical Images (EIs) [2],[3]. Each EI may be associated to a given bedform and some physical parameters can be calculated for its characterization. Most of bedforms such as sand waves, dunes or ripples, are generated by unidirectional water currents and thus the corresponding bathymetric images are oriented ones. Consequently, profiles are less correlated in the orthogonal direction and the EMD decomposition is only performed along the principal direction of water currents. The problem of decomposing bathymetric images, which are of practical interest, is particularly challenging. It is a difficult problem, and no general solution has been formulated. In this paper a new multiscale method using the EMD for quantitative characterization of bathymetric images is proposed.

2 EMD ALGORITHM

The IMFs of a given signal, x(t), are obtained by means of an iterative process called the *sifting* algorithm [1]. The name IMF is adapted because it represents the oscillation mode embedded in the data. With this definition, the IMF in each cycle, defined by the zero crossings, involves only one mode of oscillation, no complex riding waves are allowed. An IMF can be both amplitude and frequency modulated. In fact, it can be non-stationary (AM-FM component). The essence of the EMD is to identify the IMF by characteristic time scales, which can be defined locally by the time lapse between two extrema of an oscillatory mode or by the time lapse between two zero crossings of such mode. The EMD picks out the highest frequency oscillation that remains in the signal. Thus, locally, each IMF contains lower frequency oscillations than the one extracted just before. Furthermore, the EMD does not use any pre-determined filter or wavelet function [1]. It is fully data driven method. It has been shown experimentally that the EMD acts essentially as a dyadic filterbank [4]. Since the EMD is based on local characteristics time scale of a data, it is applicable to nonlinear and non-stationary processes. The signal x(t) is decomposed into a sum of IMFs that: (R1) have the same numbers of zero crossings and extrema; and (R2) are symmetric with respect to the local mean. The first condition is similar to the narrow-band requirement for a stationary Gaussian process. The second condition modifies a global requirement to a local one, and is necessary to ensure that the instantaneous frequency will not have unwanted fluctuations, as induced by a symmetric waveform. The sifting is defined by the following steps:

Step 1: Fix the threshold ε and set $j \leftarrow 1$ (j^{th}IMF)
Step 2: $r_j(t) \leftarrow x(t)$ (residual)
Step 3: Extract the j^{th}IMF :

(a): $h_{j,i-1}(t) \leftarrow r_{j-1}(t)$, $i \leftarrow 1$ (i number of sifts)

(b): Extract local maxima/minima of $h_{j,i-1}(t)$

(c): Compute upper and lower envelopes $U_{j,i-1}(t)$ and $L_{j,i-1}(t)$ by interpolating, using cubic spline, respectively local maxima and minima of $h_{j,i-1}(t)$

(d): Compute the mean of the envelopes:

$$\mu_{j,i-1}(t) = (U_{j,i-1}(t) + L_{j,i-1}(t))/2$$

(e): Update: $h_{j,i}(t) := h_{j,i-1}(t) - \mu_{j,i-1}(t)$, $i := i+1$

(f): Calculate the stopping criterion: SD(i)

$$SD(i) = \sum_{t=1}^{T} \frac{|hj,i-1(t) - hj,i(t)|^2}{(hj,i-1(t))^2}$$

(g): Repeat Steps (b)-(f) until $SD(i) \leq \varepsilon$ and then put $IMF_j(t) \leftarrow h_{j,i}(t)$ (j^{th}IMF)
Step 4: Update residual: $r_j(t) := r_{j-1}(t) - IMF_j(t)$.
Step 5: Repeat Step 3 with $j := j + 1$ until the number of extrema in $r_j(t)$ is ≤ 2.

Where T is $x(t)$ time duration. The sifting is repeated several times (i), in order to get h true IMF that fulfills the conditions (R1) and (R2). The result of the sifting is that $x(t)$ will be decomposed into a sum of C IMFs and a residual $r_c(t)$ such that:

$$x(t) = \sum_{j=1}^{C} IMF_j(t) + r_C(t) \qquad (1)$$

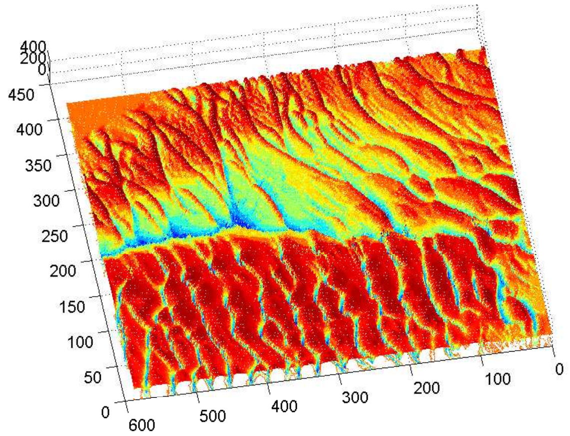
C value is determined automatically using SD (Step 3(f)). The sifting has two effects: (a) it eliminates riding waves and (b) it smoothes uneven amplitudes. To guarantee IMF components retain enough physical sense of both amplitude and frequency modulation, we have to determine SD value for the sifting. This is accomplished by limiting the size of the standard deviation SD, computed from the two consecutive sifting results. Usually, SD (or ε) is set between 0.2 to 0,3 [1].

Different methods of varying complexities have recently been proposed to extend the 1-D EMD to analyze two-dimensional data (images) [2],[3],[5]-[6]. There are several challenging difficulties that need to overcome. One of them is the computation efficiency. As pointed out by Xu et al. [6], for a medium-sized two-dimensional data, e.g. a 512 x 512 image, the number of the local extrema can be tens of thousands. Owing to the iterative nature of the EMD method, the decomposition of such a dataset is rather time-consuming, and could be unacceptable for many applications [6]. However, in the present work, the principal characteristic of the bathymetric images is that they are oriented ones. The principal direction corresponds to the sediment (sand,) movements (current ripples, water flowing, ...) [7]. Thus, one can make the assumption that the profiles are less correlated. Consequently, the EMD is applied separately to each profile and EIs are constructed IMF-per-IMF.

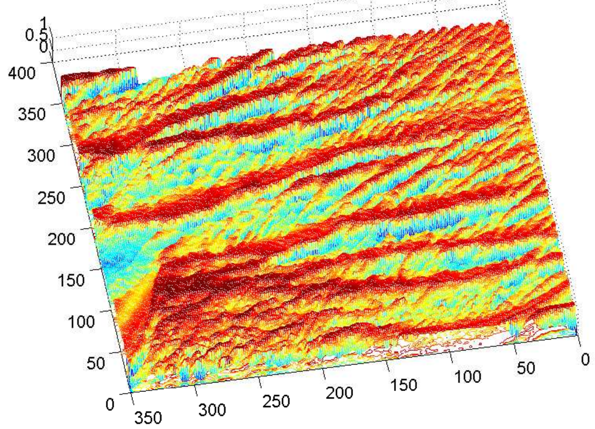
3 RESULTS

Since bathymetric images are oriented ones, EMD decomposition is performed profile-per-profile. Figure 1 shows two real multibeam echosounder images of two regions ("A": Schôle Bank, West of Normandy; "B": very large, large and small dunes of Le

Trieux, North of Brittany) with different water current directions. Sizes of images "A" and "B" are 588 x 405 pixels and 350 x 356 pixels respectively. Note that for each image, globally all the bathymetric profiles have the same direction. Images are shown in a perspective view to evidence the different sand waves. The principal direction of each image, roughly defined as the direction of the currents (water flows constantly in one direction), is used for the decomposition of the profiles, and the reconstruction of the EIs IMF-per-IMF.



(a) Image of region “A”



(b) Image of region “B”

Figure 1. Original multibeam echosounder image

The EMD is applied separately to each profile. An example of a profile and its sequential extraction into local oscillations (IMFs) is shown in figure 2. Top graph of figure 2 corresponds to the profile number 45 of the image of region "A". IMFl and IMFs correspond respectively to the highest (fast oscillation) and to the lowest (slow oscillation) components of this profile (Fig. 1(a)).

Six and five EIs are extracted from region "A" (Fig. 1(a)) and "B" (Fig. 1(b)) respectively. For each image, the first El extracts the locally highest spatial frequency in the bathymetric image, while the second IMF holds the locally next highest spatial frequency, etc. While ground truth is not available for these images, the decomposition results appear to be in excellent qualitative agreement with human visual perception.

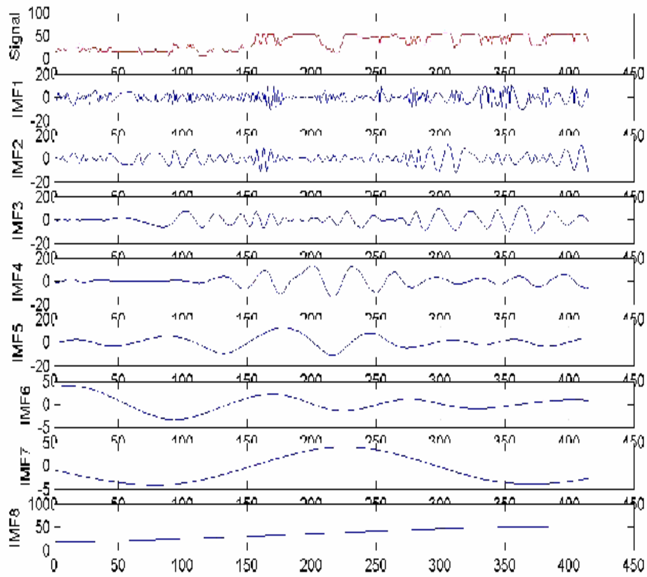
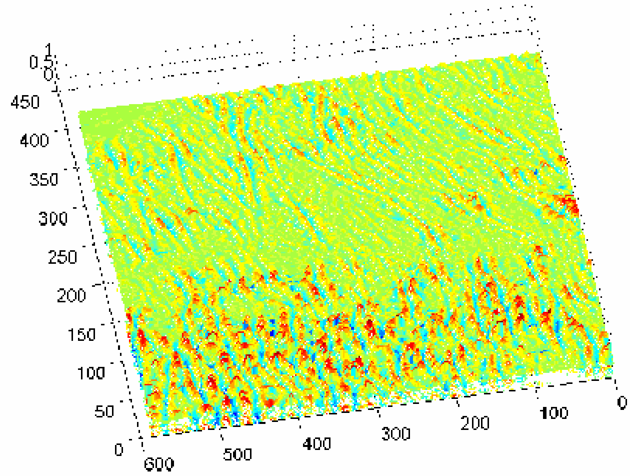
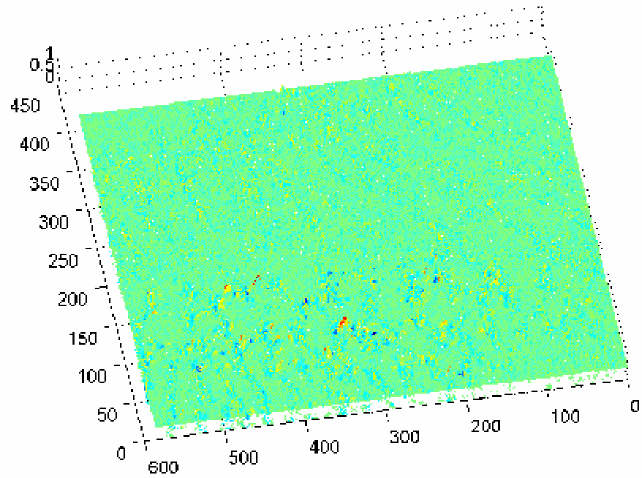


Figure 2. EMD applied to profile 45.

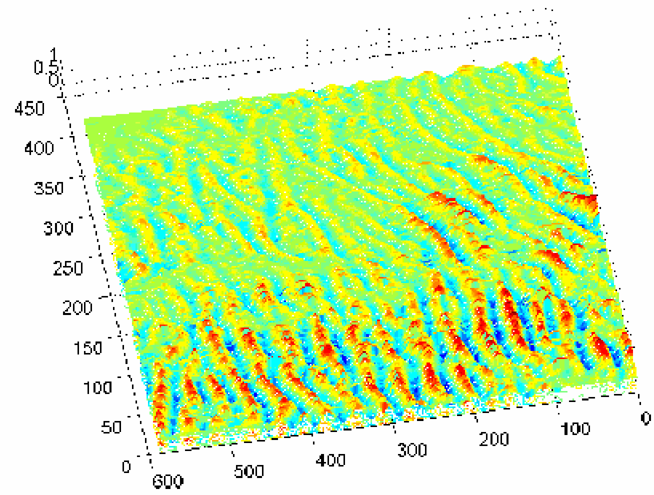
Examination of figures 3 and 4 shows that fast oscillations of EIs of figures 3(a)-(c) and 4(a)-(b) can be attributed to ripple bedforms, while middle oscillations of figures 3(d) and 4(c) can be associated to sand waves bedforms. Low oscillations of figures 3(e) and 4(d) can be classified as dunes (megaripples) class. Finally, figures 3(f) and 4(e) can be affected to plane (flat) bed. It is truly remarkable that the essential structures or bedforms of the images are captured with a reduced number (C = 6, C = 5) of EIs or non-stationary locally coherent AM-FM components. The processed images shows clearly the power of the EMD as a signal decomposition tool to capture the essential and perceptually structures in bathymetric images, which are complicated images. The images are displayed with a 256 colour look-up table where red colour corresponds to the maximum oscillation value (very high spatial frequencies), and the blue colour to the minimum one (very low spatial frequencies). Globally, for the two real images (Fig. 1), starting from the first El (Figs. 3(a), 4(a)) to the last one (Figs. 3(f), 4(e)), the colours of the corresponding oscillations values decrease from red to blue. These results also indicate that the fact that profiles are globally less correlated is a valid hypothesis, and that the sifting can be reduced to one dimension. While, the 1-0 sifting is certainly not optimal to process several classes of images, for oriented images such as bathymetric images, the obtained results show that the 1-0 method is in practice effective. The advantages of the proposed decomposition method are simplicity and low computational complexity. Based on the EMD, the proposed multi-scale characterization of bathymetric images shares the same limits as the EMD. Thus, the decomposition results and the classification in bedforms are sensitive to the original image sampling, and to the interpolation method used in the sifting process.



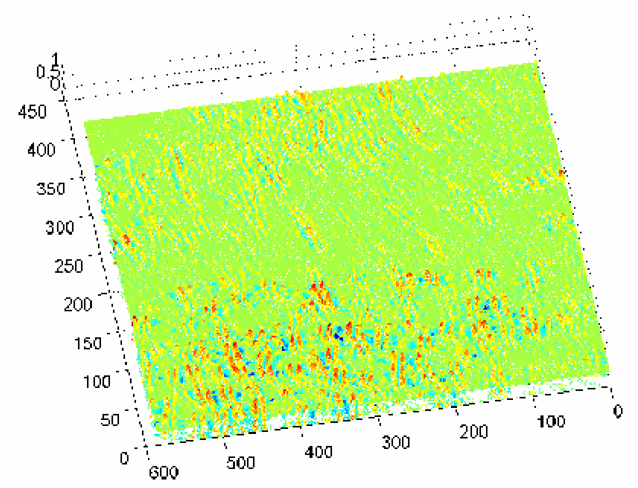
(Figure 3c)



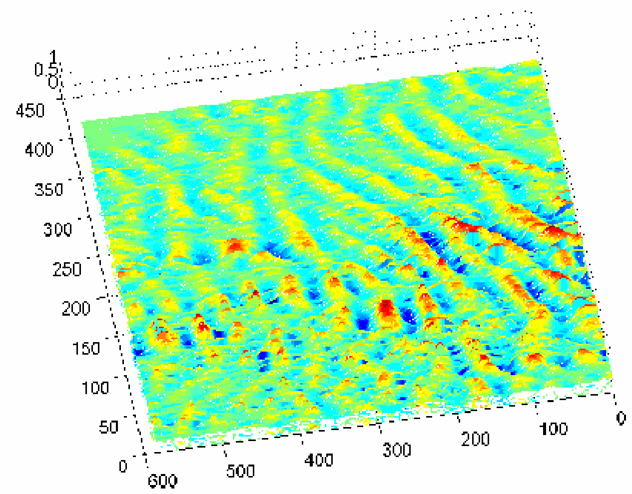
(Figure 3a)



(Figure 3d)

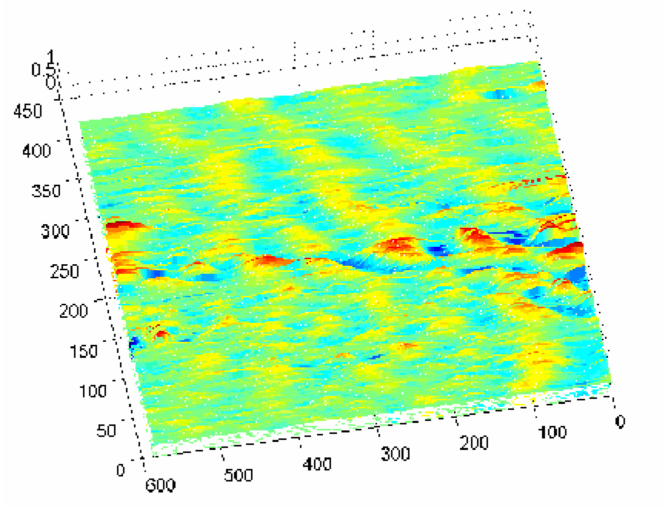


(Figure 3b)

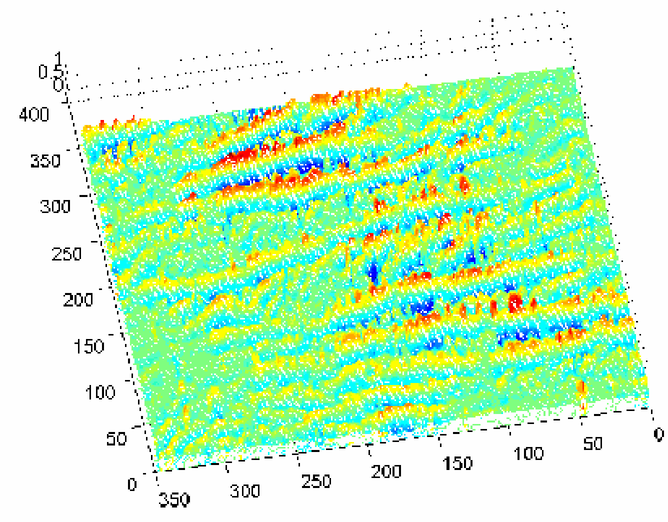


(Figure 3e)

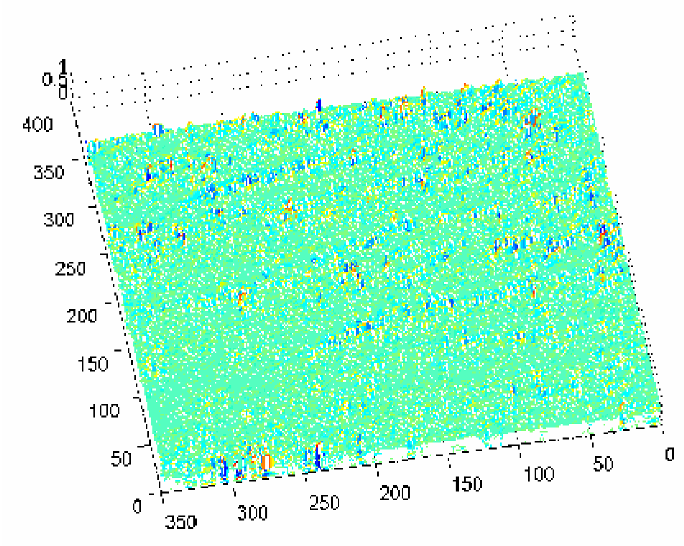
Figure 3. EIs extracted from image of region “A”



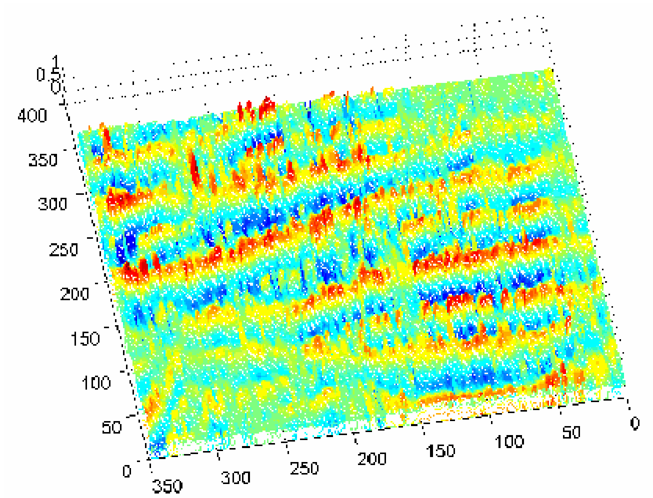
(Figure 3f)



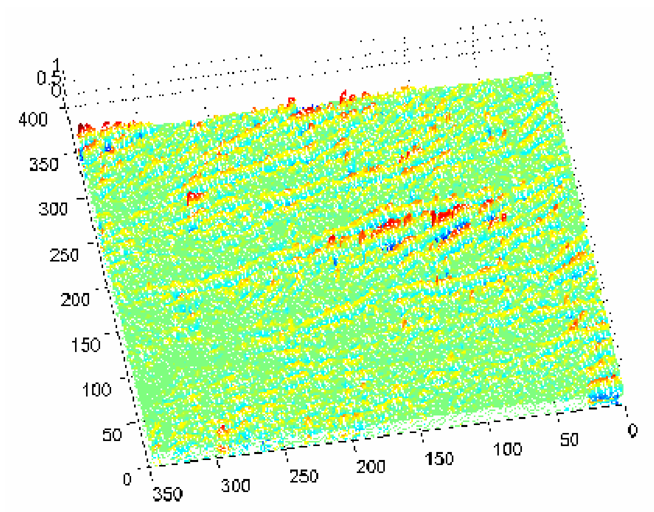
(Figure 4c)



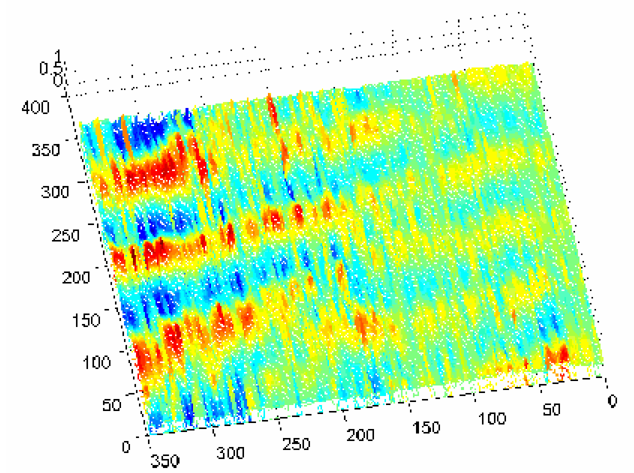
(Figure 4a)



(Figure 4d)



(Figure 4b)



(Figure 4e)

Figure 4. EIs extracted from image of region “B”

CONCLUSION

In this paper a new method for seafloor characterization by bathymetric images analysis, is proposed. The multi-scale approach uses the EMD as a signal decomposition method, to capture the essential and perceptually structures in bathymetric images, which are complex images. Even limited to one direction, the obtained results show that the essential structures or bedforms of the bathymetric images are effectively captured with a small number of components by the EMD. These results clearly demonstrate the power of the EMD as a signal decomposition tool. Also, these results indicate that the fact that profiles are globally less correlated is a valid hypothesis. Each of the obtained empirical images corresponds to a given bedform. The presented results show that the method identifies the main bedforms such as the sand waves or the ripples. A large class of real bathymetric images is necessary to confirm these results. As future works, we plan to estimate the instantaneous frequency and amplitude from the extracted empirical images to calculate features such as wave length and steepness in order to quantitatively classify the bedforms.

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