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A method for underwater image analysis using bi-dimensional empirical mode decomposition technique

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Abstract. Recent developments in underwater image recognition methods have received large attention by the ocean engineering researchers. In this paper, an improved bi-dimensional empirical mode decomposition (BEMD) approach is employed to decompose the given underwater image into intrinsic mode functions (IMFs) and residual. We developed a joint algorithm based on BEMD and Canny operator to extract multi-pixel edge features at multiple scales in IMFs sub-images. So the multiple pixel edge extraction is an advantage of our approach; the other contribution of this method is the realization of the bi-dimensional sifting process, which is realized utilizing regional-based operators to detect local extreme points and constructing radial basis function for curve surface interpolation. The performance of the multi-pixel edge extraction algorithm for processing underwater image is demonstrated in the contrast experiment with both the proposed method and the phase congruency edge detection.

Keywords: underwater image; bi-dimensional empirical mode decomposition; edge feature detector; phase congruency; multiple pixel edge extraction

1. Introduction

With the development of science and technology, the image processing technique has been widely used in some areas such as ocean surveillance, seabed prospect, underwater targets (for instance, oil platform, ships on the ocean bottom, etc.) detection and the fish culture. Consequently, underwater image processing technique plays an important role in modern ocean engineering. In general, underwater image with high resolution can be obtained by underwater camera in underwater environment. In deep-sea or turbid water, however, illumination conditions are bad and the real environment of images are very noisy, the application of underwater image is limited accordingly, the primary limitations for its applications result from the light scattering and absorption in water. In the past decades, scientists have long sought numerous underwater imaging designs, and believing that they would overcome these difficulties (Jaffe 1998, 2001, Nevis 1999). In order to reduce the effects of the light scattering and absorption on the produced image, especially in turbid water, underwater acoustic imaging (Boyle 2003, Blair 2006) and underwater laser imaging (Chen 2002, Chen and Wu 2004, Nevis 1999) have experienced a spectacular increase in application over recent years. But they are also mild drawbacks, in other words, these approaches depend heavily on their

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imaging systems. As far as most underwater images are concerned, the underwater optical images always inevitably to be encountered; in this case, a method must be found in image itself. For this reason, this paper will introduce a new image analysis method, namely, combining bi-dimensional empirical mode decomposition (BEMD) with Canny operator technique.

The BEMD is a two dimensional extension of the concept of one-dimensional empirical mode decomposition (EMD), the EMD (Huang *et al*. 1998) approach was first proposed by Huang et al. for analyzing non-linear and non-stationary data. This method is initially limited to real-valued time series, and then it has been extended to complex-valued time series (Rilling *et al*. 2007), and has been extended from one dimension to two dimension, this two-dimensional data decomposition method has received large attention by the image analysis (Bhuiyan *et al*. 2008b, Damerval *et al*. 2005, Nunes *et al*. 2003a, Nunes *et al*. 2005, Nunes *et al*. 2003b, Xu *et al*. 2006), therefore this promising image processing technique can be applied in various real problem, for example, image texture analysis (Nunes *et al*. 2003a, Nunes *et al*. 2005, Nunes *et al*. 2003b, Xu *et al*. 2006), image feature detection (Bhuiyan *et al*. 2008a, Guangtao *et al.* 2007), image de-noising (Bhuiyan *et al*. 2008c), medical image analysis, pattern analysis, multi-spectral image fusion (Xu *et al*. 2007), and so on.

The purpose of underwater optical image analysis is to distinguish objects in water and to catch underwater environment information. But the problem, due to underwater ambient noise, which can reduce the quality of image, and makes image blurry. Thus, the features of objects in image can not be extracted out clearly, so aiming at this problem, we present an improved feature detection algorithm based on the BEMD method to extract the multi-pixel edge features in underwater image, and make preparations for further analyzing underwater image.

For convenience of discussion, this paper is organized as follows. First, the regular EMD principle and BEMD principle is briefly reviewed in section 2 of this paper. Section 3 briefly introduces two method of edges detection, namely the Canny operator and the phase congruency edge detection. In Section 4, two groups of experiments are performed to verify the effectiveness of the proposed algorithm: one is decomposing the test image into IMFs and residues by the BEMD algorithm, the other is detecting the edge information in the first IMF by Canny operator. Next the contrast experiments are followed to verify the feasibility of our proposed method. Finally, Section 5 gives concluding remarks.

2. Empirical mode decomposition principle

2.1 The one-dimensional (1D) empirical mode decomposition

The one-dimensional empirical mode decomposition (EMD) algorithm is a sifting process. This method requires two steps in adaptive multi-scale analyzing the data as follows:

The first step is to preprocess the data by the EMD algorithm, and the data are decomposed into a finite number collection of intrinsic mode functions (IMFs) components, the so-called IMF was innovatively introduced by Huang et al. which based on local properties of the signal and possessed the instantaneous frequency meaningful. The IMF represents the oscillation mode imbedded in the data and is defined by the zero crossings, involves only one mode of oscillation, complex riding waves are not allowed, thus the IMF requires two conditions (Huang *et al*. 1998): (a) in the whole data set, the number of extremes and the number of zero crossings must either equal or differ at most by one; and (b) at any point, the mean value of the envelope defined by the local maxima and the envelope defined by the local minima is zero. The second step is to apply the Hilbert transform to the decomposed IMFs and constructs a full energy-frequency-time distribution of the data; such a representation of the results is designated as the Hilbert spectrum.

The decomposition by means of EMD method is called sifting process. The sifting procedure is based on the assumptions: (a) the single has at least two extremes, viz. one maximum and one minimum; (b) the characteristic scale is defined by the trailing edge of time domain signal between the extremes; (c) if the data sets were totally devoid of extremes but contained only inflection points, then it can be rebuilt the extremes by first or higher derivation of the data sets.

2.2 The bi-dimensional empirical mode decomposition

According to the principle of 1D empirical mode decomposition, the following we will extend 1D empirical mode decomposition to two dimension case, and introduce the bi-dimensional empirical mode decomposition (BEMD) in detail.

Similar to 1D empirical mode decomposition approach, the BEMD must be based on three constraints: (a) The two-dimensional data plane included at least one maximum and one minimum extremes; (b) If the two-dimensional data plane were totally devoid of extremes but it can be differentiated once or more times to reveal the extremes: one maximum and one minimum; (c) The characteristic scale was defined by the distance between the extremes.

Now we define a bi-dimensional sifting process similar to the 1D empirical mode decomposition, the sifting procedure as follows:

First we assume that $f(x, y)$ is an image function, and identify all the local extremes including maxima and minima. By interpolating the local maxima and minima we will get envelop surface of maximum $E_{max}(x, y)$ and envelop surface of minimum $E_{min}(x, y)$, and then compute the mean of these envelop surface, $E_{mean}(x, y)$ denotes average value of envelop surface of extreme, the formula of it is shown as the following

$$E_{mean}(x,y) = \frac{E_{max}(x,y)+E_{min}(x,y)}{2} \tag{1}$$

The difference between the original image data $f(x, y)$ and $E_{mean}(x, y)$ is the first component, which is designated as $H_1(x, y)$, that is

$$H_1(x,y) = f(x,y) - E_{mean}(x,y) \tag{2}$$

Since the sifting process serves two purposes, viz. to eliminate riding waves and to make the wave-profiles more symmetric. We should repeat the procedure above k times, until H_{1k} is an IMF, that is

$$H_{1(k-1)}(x,y) = E_{mean,k}(x,y) - H_{1k}(x,y) \tag{3}$$

Set $C_1(x, y) = H_{1k}(x, y)$, then $C_1(x, y)$ is the first IMF component separated from the original image data. Similar to the 1D EMD, we must determine a criterion for each layer of the sifting process to stop. This step can be accomplished by limiting the size of the standard deviation (SD), computed from the two consecutive sifting results $H_{i(k-1)}(x, y)$ and $H_{ik}(x, y)$ for the i th mode as (Nunes *et al*. 2003b)

$$SD = \sum_{x=1}^{X}\sum_{y=1}^{Y}\left[\frac{\left|h_{i(k-1)}(x,y) - h_{ik}(x,y)\right|^2}{h_{i(k-1)}^2(x,y)}\right] \tag{4}$$

generally, the value of SD is equal or greater than 0.2 meanwhile equal or lesser than 0.3.

After that, $C_1(x, y)$ is separated from the original image data, the rest part is the residue, $R_1(x, y)$, it is treated as the new data and subjected to the same sifting process as similar described to the EMD method, this procedure can be repeated n times, we will finally get the superposition expression

$$f(x,y) = \sum_{i=1}^{n} C_i(x,y) + R_n(x,y) \tag{5}$$

where $f(x, y)$ denotes the original image data, $C_i(x, y)$ is designated the information of the smaller scale after the decomposition, $R_n(x, y)$ denotes the finally coarsest scale mean trend.

3. Improved BEMD algorithm for multi-pixel edge detection of underwater image

In order to identify all the local extreme points of the given image $f(x, y)$, there are many methods available for them, such as morphological operators (Nunes *et al*. 2003, 2005), sliding window (Bhuiyan *et al*. 2008). These extreme points data interpolation is usually performed by the Delaunay triangulation, the bi-cubic spline, finite element algorithm and two order statistics filters estimation (Bhuiyan *et al*. 2008). In this paper, we have choice the regional-based operators to find the local maxima and minima points from the underwater image data. The method of the regional-based operator is that one pixel of image is considered as a local extreme point, if its value is lower or higher than all of its neighbors, through scanning each pixel of all image line by line. The surfaces interpolation is realized using the radial basis functions (Carr *et al*. 2001).

Edges are significant image features because of edges carrying the main information. Edge detection is an efficient means of finding boundaries of objects or their parts in an image. Edges represent sharp changes in image intensities, which could be due to discontinuities in scene reflectance, surface orientation and depth. In this paper, we decompose the test images into IMFs and residues using the improved BEMD algorithm, while the first IMF (IMF1) very closely resembles the edge map of an image, so we perform edge detecting in IMF1 image by Canny operator. For comparison purposes, we also take another edge detector, that is phase-based edge detection (Kovesi 1999), as the image edge features extraction tool.

The Canny algorithm detects edges by looking for local maxima of the gradient of image. The gradient's amplitude and orientation are calculated using the derivative of a Gaussian filter. The Canny operator belongs to primarily gradient-based method. In this paper we developed a method based on the improved BEMD and Canny operator; that is the BEMD-C algorithm. Image features including step edges, lines, and Mach bands all give rise to points where the Fourier components of the image are maximally in phase. The use of phase congruency for marking image features has significant advantages over gradient-based method, since phase congruency is an illumination and contrast invariant measure of image feature, unlike gradient-based feature detectors, which can only detect step features. Consequently, we will also take this method as an example for comparison in section 4, and analyze the diversity of the two methods in detail.

4. The results and discussion of preliminary experiment

4.1 Multi-scale decomposition of the underwater image based on BEMD algorithm

In order to prove the practicability of this algorithm, in this section the contrast experiment for edge detection of underwater optical image has been done. The proposed method is tested for various real underwater images, among which results for two images, the original test images shown in Fig. 1 and 2 are as follows:

The Fig. 3 displays three layers decomposition of the original image based on BEMD, this process could separate natural scale from the original image to achieve image decomposition from low to high frequency. To begin with, the first intrinsic mode function (IMF1) is isolated from the

Fig. 1 Test Image 1

Fig. 2 Test Image 2

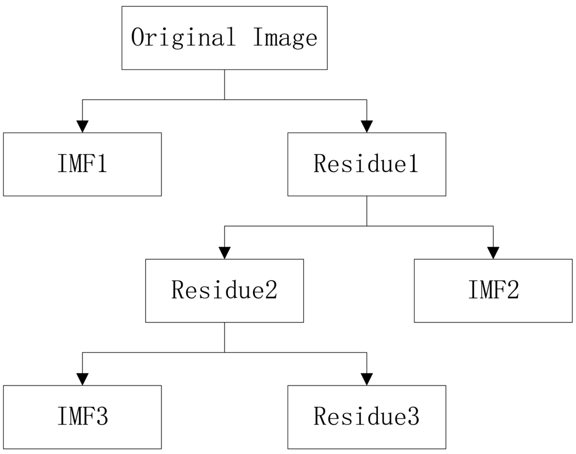

Fig. 3 The block diagram of Original Image based on BEMD

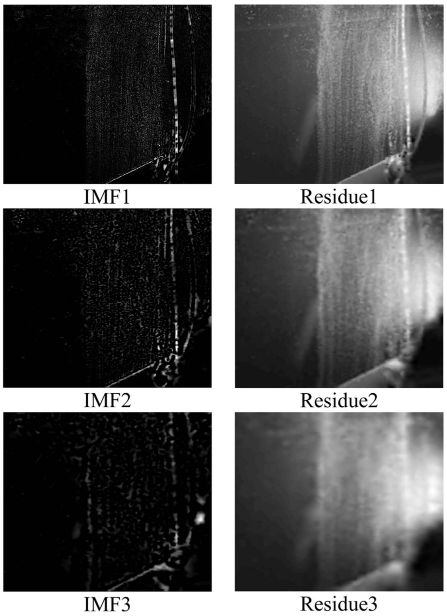

Fig. 4 The multi-scale decomposition of Test Image1 into three IMFs and three Residues. The left column is the IMFs from finer to courser scales; the right column is the Residues corresponding to the IMFs

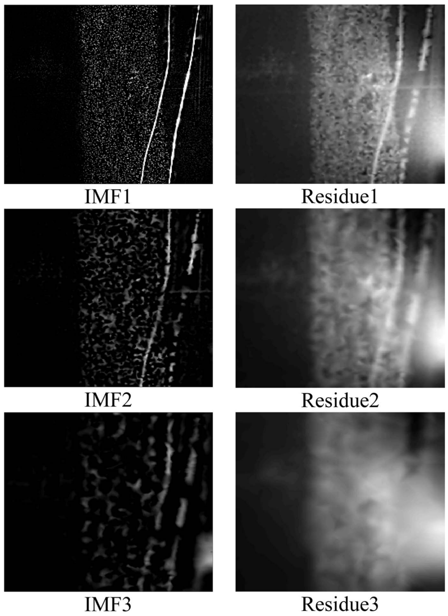

Fig. 5 The multi-scale decomposition of Test Image2 into three IMFs and three Residues. The left column is the IMFs from finer to courser scales; the right column is the Residues corresponding to the IMFs

original image, which corresponds to the image with the highest spatial frequency. The residual viz. Residue1, is the remainder which the IMF1 is subtracted from the original image, it corresponds to the image with the lowest spatial frequency. The next step is to extract the IMF2 in the Residue1 and obtains the Residue2. Finally, we can obtain the IMF3 and Residue3 based on such method. Every IMF is obtained by decomposing the upper residue, as shown in Figs. 4 and 5, the test image is decomposed into three intrinsic mode functions and three residues by BEMD algorithm. The IMFs represent texture, noise and edges information of the image, especially, the first IMF obviously exhibits the edges information of the image. Then the residual present the basic structure and eventual trend of the image.

4.2 Results of edge features detection

Figs. 6 and 7 is the edge detection map of the test image. In Figs. 6 and 7, we first separate the IMF1 from the original image, and then detect the edge information in IMF1 by BEMD-C method. From the Figs. 6 and 7, we can see that the BEMD-C method is symmetrical along the edge, this imply that Canny operator is sensitive to the edge of image. In this section, the phase congruency algorithm is adopted for comparing with the proposed method, from the color-map in Figs. 6 and 7, we can see that the IMF1 color-map images have distinct edges texture, and the phase images are ambiguous, although the phase symmetry image has good visual effect over IMF1 gray level image, edge features detection for IMF1 image has not been effected yet, on the contrary, the edge information in IMF1 is greater than in phase image. In the next steps, therefore, it is desired to use

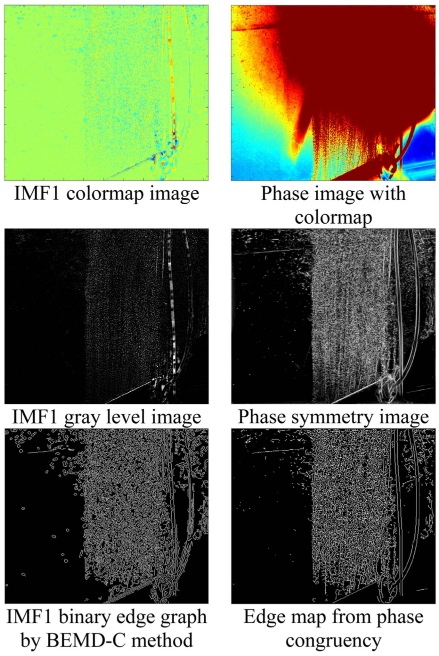

Fig. 6 Comparison picture of the Test Image1, the left column is image of IMF1 and its Canny edge detection, the right column is phase-based image and edge map

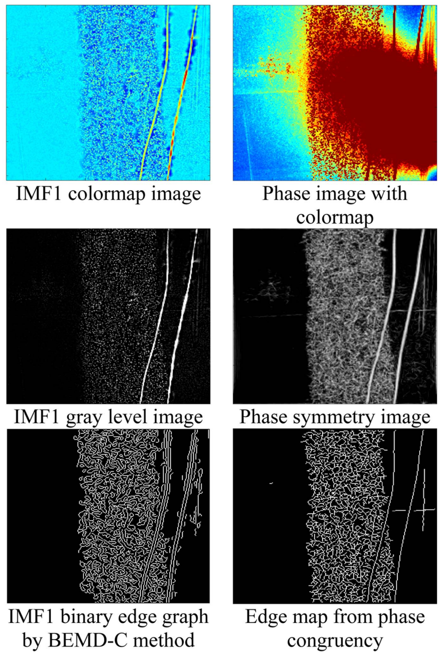

Fig. 7 Comparison picture of the Test Image2, the left column is image of IMF1 and its Canny edge detection, the right column is phase-based image and edge map

this edge detection results for counting the bubbles.

Fig. 6 and Fig. 7 are a group of gas curtain images in water, though we are not able to distinguish the sizes and amounts of bubbles in image, yet we access vast quantities of texture information of objects. Generally, there are some problems with non-structured objects such as bubbles and rocks; it is difficult to extract robust information from underwater images. In Figs. 6 and 7, however, by comparing analysis, we can conclude that edge features detection by BEMD-C method is better than phase-based algorithm in this condition.

5. Conclusions

In this paper, an image processing method has been introduced for analyzing underwater image, namely BEMD algorithm. The BEMD method is a potential image processing algorithm, which is not only robust and adaptive, but also totally data-driven. The contrast experiment has shown that, the proposed method can detect edge feature for underwater image, even for unclear image. A particular image processing method may be suitable for certain types of images. But as far as underwater optical image is concerned, there is not a versatile method for processing it. In this paper, the proposed method can process not only the ordinary optical image better, but also underwater image. Combining with Canny operator, we adopt a novel method which can detect the edge features of image. To compare the performance of this edge detection method, phase congruency edge detection is applied to the original test image, and the experiments has shown that the advantage of the proposed method, just as section 4 describes. Though the BEMD method is simple and applicable, there are still some mild drawbacks with this algorithm such as boundary effects etc. The proposed method tries to solve this problem by extending boundary before using the BEMD algorithm.

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