Empirical mode decomposition based visual enhancement of underwater images

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***Abstract*— Most underwater vehicles are nowadays equipped with vision sensors. Underwater images captured using optic cameras can be of poor quality due to lighting conditions underwater. In such cases it is necessary to apply image enhancement methods to underwater images in order to enhance visual quality as well as interpretability. In this paper, a Empirical Mode Decompostion (EMD) based image enhancement algorithm is novelly applied to underwater images for this purpose. EMD has been shown to be particularly suitable for non-linear and non-stationary signals in the literature, and therefore provides useful in real life applications. In the approach presented in this paper, initially each R, G and B channel of the RGB underwater image is separately decomposed into Intrinsic Mode Functions (IMFs) using EMD for. Then, the enhanced image is constructed by combining the IMFs of the R, G and B channels with different weights, so as to obtain a new image with increased visual quality. It is shown that the proposed approach provides superior results compared to conventional methods such as contrast stretching.**

***Keywords*—Underwater images, Image enhancement, Empirical Mode Decomposition.**

I. INTRODUCTION

In recent years, there is an increasing interest in underwater remotely operated vehicles (ROV's) and autonomous underwater vehicles (AUV) for submarine and military operations. These vehicles are typically equipped with optical sensors (cameras) to acquire underwater images. The main difficulty in employing optical cameras in underwater applications is limited visibility that can be restricted to about twenty meters in clear water and less than a few meters in turbid and coastal waters such as in harbors [1].

Because underwater image quality can be poor because of specific propagation properties of light in water, image enhancement is necessary to enable effective interpretation means for operators. The most important cause of underwater image degradation is due to transmission properties of light in water, such as absorption (light disappears) and scattering (light changes direction). Another problem is related to depth. Due to the nature of underwater optics, red color disappears at the depth of about 3m and orange color starts diminishing a little further while yellow color is lost at a depth of about 10m and finally the green goes off at further depths thus producing blue to grey like images [2]. As a result, the underwater images are getting darker, have non-uniform lighting, low-contrast, diminished colors and blurring of image features. Some of the effects are even observed with external lighting is used. In the literature, enhancement methods have been proposed to improve image quality, suppress noise and blur, while preserving and possibly even enhancing edges.

In literature, the number of methods proposed or applied to underwater images for enhancement and pre-processing is rather limited. The most widely used enhancement methods are conventional histogram equalization [3] and contrast stretching [4]. Alternative methods proposed in the literature are adaptive smoothing techniques [5], and some filtering methods such as homomorphic filtering, anisotropic filtering, and wavelet denoising by average filtering [5,6]. In this paper, an Empirical Mode Decomposition (EMD) based enhancement method is novelly applied to underwater images.

EMD is a signal decomposition technique which is particularly suitable for the analysis of non-linear and non-stationary data [7]. In EMD, the signal is decomposed into components called Intrinsic Mode Functions (IMFs) and a final residue. EMD has some important advantages compared to Wavelet [8] and Fourier transform techniques [9]. For example, many real-life systems are non-linear and non-stationery, but in the Fourier Transform data is assumed to be stationary and linear. For the wavelet transform it is possible to use different wavelet types and the performance can change according to this selection. On the other hand, EMD does not have basis functions and decomposes a signal based on its intrinsic properties. The IMFs obtained by EMD can contain both high and low frequency detail at different signal locations depending on signal characteristics.

EMD has been applied in several areas of signal processing. In [8], EMD and wavelet decomposition are used to detect human cataract using ultrasound signals. EMD is applied to 2D face images as a pre-processing approach to remove illumination artifacts for a face recognition application in [10]. EMD is used for image compression in [11]. EMD has been applied to hyperspectral image data to increase classification accuracy of hyperspectral images in [12]. [13] presents an effective algorithm for removing noise in sonar images utilizing EMD. It has been proposed to use EMD for increased target detection capabilities in sonar images in [14]. [15] describes a technique for image fusion and enhancement, using Empirical Mode Decomposition where images from different imaging modalities are decomposed into their IMFs and fusion is performed at the decomposition level and fused IMFs are used to obtain the reconstructed image.

In this paper it is used two dimensional empirical mode decomposition (2D-EMD) for underwater image enhancement. The paper is organized as follows: Section 2 briefly describes the EMD method, Section 3 presents the proposed approach for underwater image enhancement, Section 4 shows experimental results and Section 5 provides conclusions and discussions

II. EMPIRICAL MODE DECOMPOSITION

Empirical Mode Decomposition (EMD) has been proposed by Huang [7] as an adaptive time-frequency data analysis method. The procedure of EMD is very simple, and the main purpose is to apply sifting to the original data series until the final data series are stationary.

This decomposition process starts from the original image $(I(x,y))$ and the initial input to the EMD process can be shown as

$$input_{lk}(x,y) = I(x,y)$$

where $(l = 1,2,...,L)$ is used as index to show the *l*-th IMF, $(k = 1,2,...,K)$ shows the iteration number of the process and (i, j) shows the spatial location.

The decomposition procedure of 2D-EMD is as follows:

1- Find all points of 2D local maxima and all points of 2D local minima of $input_{lk}(i, j)$.

2- Create the upper envelope ($e_{\max}(i, j)$) and the lower envelope ($e_{\min}(i, j)$) by 2D spline interpolation of local maxima and 2D spline interpolation of local minima, respectively.

3- Calculate the mean of the upper and lower envelopes: $e\_mean_{lk}(i, j) = (e_{\max}(i, j) + e_{\min}(i, j))/2$.

4- Subtract the envelope mean from the input signal: $h_{lk}(i, j) = input_{lk}(i, j) - e\_mean_{lk}(i, j)$.

5- Calculate the stopping criterion such as $eps = \dfrac{\sum_{i=1}^{H}\sum_{j=1}^{W}\left|e\_mean_{lk}(i, j)\right|}{H \times W}$ where H and W are the dimensions of $e\_mean_{lk}(i, j)$. Check if the envelope mean ensures the iteration stop criterion for the current IMF. If the stop criterion for the current IMF falls below a small threshold such that $eps < \tau$, where τ is a small threshold, the sifting process is stopped for the current IMF [16]. If the stop criterion is met, assume at step $k = K$, the current IMF is obtained as $IMF_l(i, j) = h_{lK}(i, j)$. If the stop criterion is not met, the next iteration is started with $input_{l(k+1)}(i, j) = h_{lk}(i, j)$ and this process is repeated from step 1 to find the current IMF.

6- If the current IMF is obtained successfully, the residue signal $R_l(i, j)$ is computed as given below. If the residue does not contain any more extreme points the EMD decomposition process is finished.

$$R_l(i, j) = input_{l1}(i, j) - IMF_l(i, j)$$

In this way, the original image is decomposed into a total of *L* IMFs, and a final residue R_l. The ultimate expression can be given as follows:

$$I(i, j) = R_l(i, j) + \sum_{l=1}^{L} IMF_l(i, j)$$

III. UNDERWATER IMAGE ENHANCEMENT USING EMD

In this paper, the 2D-EMD is applied to color underwater images to decompose the R, G and B channels, and their IMF's are obtained separately as shown Fig 1.

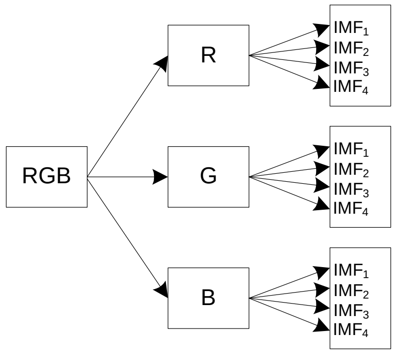


Fig. 1. EMD is applied to the R, G, B channels separately.

The enhanced image is constructed by retaining the lower order IMFs that are multiplied by a set of weights to reconstruct the final image. Higher order IMFs that basically contain low-frequency underwater imaging impairments are discarded in this process. The enhancement method is given by the following equation.

$$F(x,y) = \sum_{t=1}^{T}[w_t \times IMF_t^R + w_t \times IMF_t^G \times w_t * IMF_t^B]$$

where $F(x,y)$ is the final enhanced image, and w_t shows the weight of the *t-th* IMF. IMF_t^R, IMF_t^G and IMF_t^B are the *t-th* Red channel IMF, the *t-th* Green channel IMF and the *t-th* Blue channel IMF, respectively. It has been observed in the experiments that the utilization of three IMFs provides the best performance and this process is shown in Figure 2.

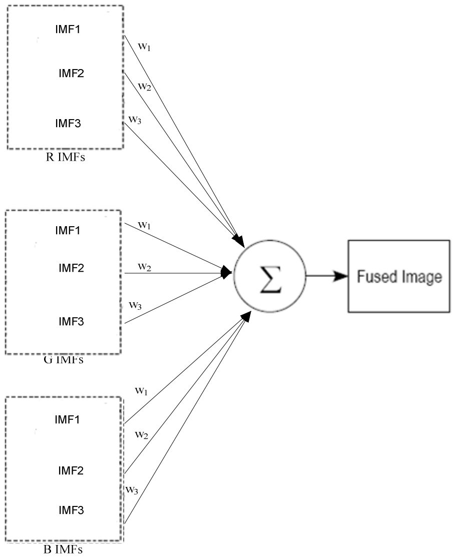
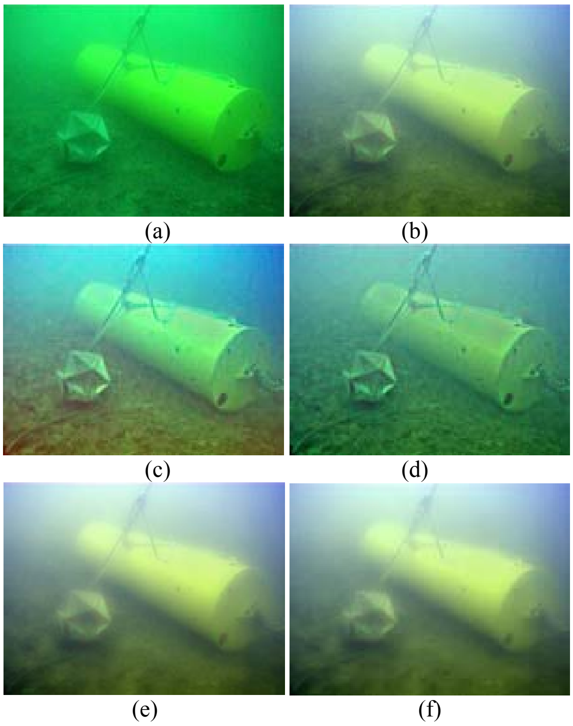


Fig. 2. The proposed underwater image enhancement scheme.

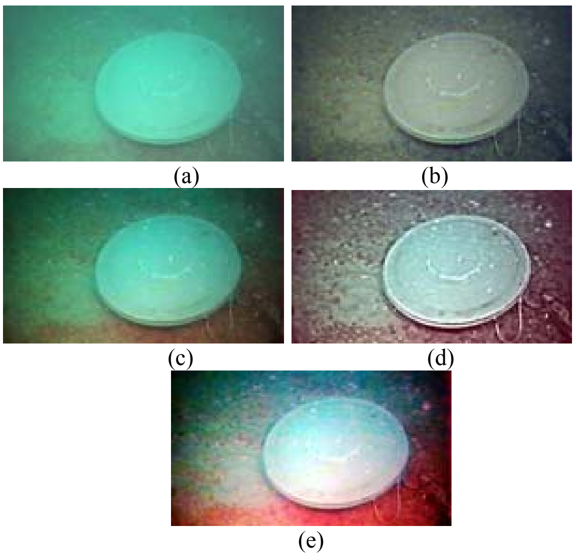
IV. EXPERIMENTAL RESULTS

In this paper, the proposed method is applied to underwater images for enhancement. The enhanced images presented in this Section were constructed using different weighting sets to enable evaluation. Fig.3 shows examples of reconstructed enhanced images using different weights for a sample image. In order to obtain the best performance, many weight sets were evaluated and the weight set that provided the best visual image quality was finally selected in practice. As observed in Fig. 3 when the weight of the first IMF is larger, the enhanced image is typically visually superior. It has been found experimentally that using the first three IMFs is typically sufficient for this purpose and the most adequate weight set is [0.7 0.2 0.1], which is also used in the remaining enhancement results presented in this Section.



(a) (b) (c) (d) (e) (f)

Fig. 3. (a) Original underwater image, (b) IMF1×0.33 + IMF2× 0.33 + IMF3×0.33 (c) IMF1×0.5 + IMF2× 0.3 + IMF3×0.2, (d) IMF1×0.7 + IMF2× 0.2 + IMF3×0.1, (e) IMF1×0.3 + IMF2× 0.5 + IMF3×0.2, (f) IMF1×0.2 + IMF2× 0.3 + IMF3×0.5,



(a) (b) (c) (d) (e)

Fig. 4. (a) Original underwater image, (b) image obtained after applying the proposed method, (c) image obtained after contrast stretching, (d) image obtained after applying the method presented in [5], (e) image obtained after applying histogram equalization to R, G and B channels separately.

The reconstructed enhanced image includes more visual detail and has better image quality compared to the original image. The most important problem of underwater images is low contrast. As shown in the results, this problem is resolved using the proposed method.

In Fig 4. the visual performance of four alternative methods, namely contrast stretching, the presented in [5], histogram equalization for R, G and B channels separately and the proposed method are shown. Note that [5] proposes an enhancement algorithm that is composed of different processes such as homomorphic filtering, wavelet denoising and anisotropic filtering, contrast adjustment and color compensation. It is observed that the proposed enhancement using EMD provides good visual quality compared alternative methods.

Fig. 5 presents results of the proposed approach for different underwater images to enable visual comparison between underwater images before and after processing. It is clearly seen that images obtained after enhancement provide better interpretability, visibility and perception of objects in the images.

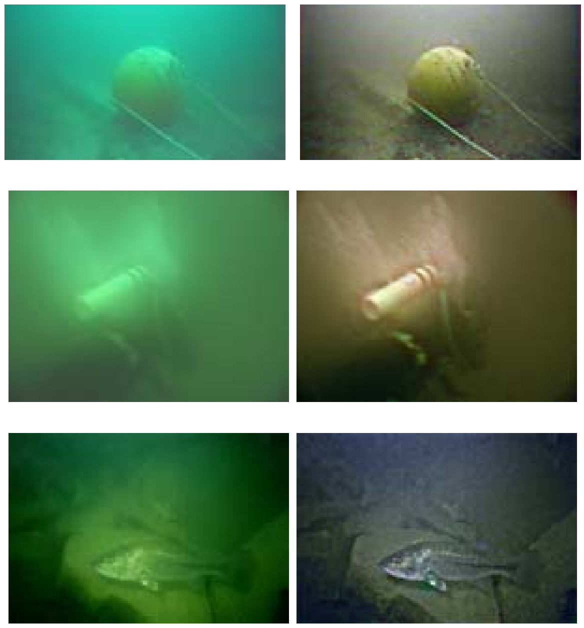


Fig. 5. Original images at left side, images after pre-processing using proposed method at right side.

V. Conclusion

In this paper, a novel enhancement algorithm based on 2D-EMD is proposed for underwater images. The enhanced image is constructed by summing the IMF's of R, G and B channels by a pre-defined weight set. The enhanced image obtained using the proposed method gives better visual performance than conventional enhancement methods such as contrast stretching and even more successful multi-process approaches as presented in [5]. The low contrast problem widely encountered in underwater images is resolved with the proposed approach.

V. Acknowledgement

This work was supported by Turkish State Planning organization project DPT 2008K-120800.

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