Volume : 2 | Issue : 6 | June 2013 • ISSN No 2277 - 8160

Research Paper | Computer Science

Visual Enhancement of Under Water Images Using Empirical Mode Decomposition

Dr. M. Nandhini Department of Computer Science, Pondicherry University, Puduherry-14

Avinash Anand Department of Computer Science, Pondicherry University, Puduherry-14

ABSTRACT *Most of the underwater vehicles are now-a-days equipped with vision sensors. However, it is very likely that underwater images are captured using optic cameras have poor visual quality due to lighting conditions in real-life applications. In such cases it is useful to apply image enhancement (IE) methods on underwater images to increase visual quality of the images as well as enhance interpretability and visibility. This algorithm is proposed to improve image quality, compensate attenuation effects, enhance contrast, adjust colors, suppress noise and blur, while preserving and possibly even enhancing edges and its potentiality is proved with better performance.*

KEYWORDS: IE, empirical mode, IMF, genetic algorithm

1. Introduction

Most of the underwater vehicles are now a day's equipped with vision sensors. However, it is very likely that underwater image is captured using optic cameras having poor visual quality due to lighting conditions in real-life applications. In such cases it is useful to apply IE methods for underwater images [1], [2] and [6] to increase visual quality of the images as well as enhance interpretability and visibility.

Existing solutions are limited by fidelity or generality. The number of pixels and colors does not determine if an image looks realistic. Common global IEs often cause artifacts or enhance noise [1] or unwanted parts of the image. As human vision perception is based upon stereo vision, without consideration and respect of this important fact, any enhancement will suffer from bad quality condition.

In the proposed approach, initially each spectral component of an underwater image is decomposed into intrinsic mode functions (IMFs) [4] and [5] using EMD [4] and [5]. Then the enhanced image is constructed by combining the IMFs of spectral channels with different weights in order to obtain an enhanced image with increased visual quality. The weight estimation process is carried out automatically using a genetic algorithm (GA) [7] that computes the weights of IMFs so as to optimize the average gradient of the reconstructed image.

2. Literature Survey

Sangkeun Lee (2006) proposed a method for content based IE in the compressed domain based on multi- scale α-routing algorithm. It is for compressing image dynamics and enhancing image details in the discrete cosine transform (DCT) domain. The content measure using the energy distribution of the DCT coefficients is defined directly in each DCT block of an image. Then, the reflectance component is altered by a multi-scale α-rooting method for enhancing image details based on human visual perception.

Laurence Likforman-Sulem et al (2011) proposed a method for Enhancement of historical printed document images by combining total variation regularization and non-local means filtering with total variation framework and cleaning image as steps and consists of a filter based on Non-local Means.

Xiangzhi Bai et al (2011) presented a algorithm for Infrared IE through contrast enhancement by using multiscale new top-hat transform. The overall algorithm is divided in to three phases, firstly, multiscale new top-hat transform are constructed to extract multiscale light and dark image regions; secondly, the final light and dark image regions are obtained from the extracted multiscale light and dark image regions and finally, infrared image is enhanced through enlarging the contrast between the final light and dark image regions.

Weiguo Zhao (2011) presented a method for Adaptive IE based on gravitational search algorithm.This method improves the degraded image according to the image characteristics, using the Gravitational Search Algorithm (GSA) for optimizing the parameters of Beta function.

From the survey, it is observed that IE are environment specific and they work either for enhancing color, lightening contrast and removing blur, enhancing edges; but they did not give the optimized algorithm after taking consideration of viewer insight but did not concern for viewers point of view. This proposed algorithm focus on considering each pixel of the image and try to optimize its color and denoise blur and enhance edges, so that better perception can be achieved.

3. Design of Enhanced Methodology

This new proposed has been implemented to improve image quality, compensate attenuation effects, enhance contrast, adjust colors, suppress noise and blur, while preserving and possibly even enhancing edges. Here GA is applied to optimize the constructed Enhanced Image.

In this algorithm, initially each spectral component of an underwater image is decomposed into IMFs using EMD. Then the enhanced image is constructed by combining the IMFs of spectral channels with different weights in order to obtain an enhanced image with increased visual quality. The weight estimation process is carried out automatically using GA that computes the weights of IMFs so as to optimize the average gradient of the reconstructed image.

3.1 Visual Enhancement Algorithm for Underwater Images

3.1.1 Band Separation: -

Firstly, The Input Image is broken down in the separate spectral component because each color image is having a separate color band for Red, Green, Blue band (or Spectral Component).

3.1.2 IMF Generation: -

In this Algorithm, initially each spectral component of an underwater image is decomposed into IMFs using EMD.

EMD is applied to break an image in to IMF's.

1. Find all points of 2D local maxima and all points of 2D local minima of $input_{lk}(i,j)$.
2. Produce the upper envelope ($e_{max}(i,j)$) by 2D spline interpolation of local maxima and the lower envelope ($e_{min}(i,j)$) by 2D spline interpolation of local minima.
3. Compute 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. Compute the stopping criterion. It is defined in equation (a)

$$eps = \frac{\sum_{i=1}^{H}\sum_{j=1}^{W}|e\_mean_{lk}(i,j)|}{H \times W} \quad \text{---------(a)}$$

Where H and W show the dimensions of the image. Check if the envelope mean satisfies the iteration stop criterion for the current IMF. If eps < s, where s is a small threshold, the sifting process is stopped for the current IMF the current IMF is obtained as $IMF_l(i, j) = h_{lK}(i, j)$. If the stop criterion is not met, 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 $R_l(i, j) = input_{l1}(i,j) - IMF_l(i,j)$. If the residue does not contain any more extreme points the EMD decomposition process is terminated. Otherwise the next IMF is computed from step 1 using the residue as input, i.e. $input_{(l+1),1}(i,j) = R_l(i,j)$.

The EMD process decomposes the original image into several IMFs, and a final residue R_l. The original image is actually the sum of these components. It is defined by the equation (b)

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

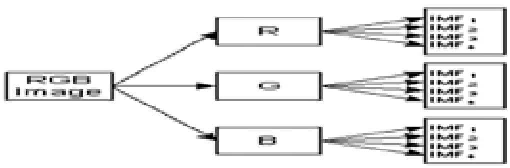


Fig. 3.1 EMD is applied to RGB channel

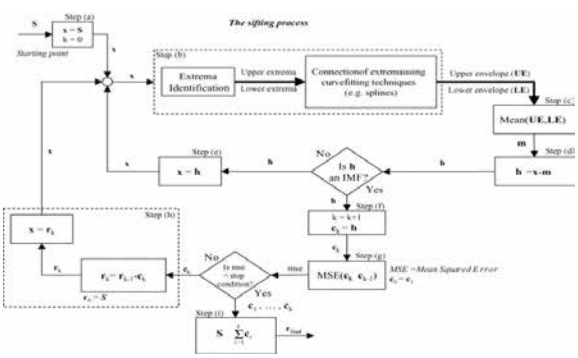
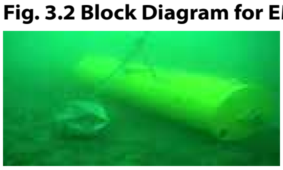


Fig. 3.2 Block Diagram for EMD Process

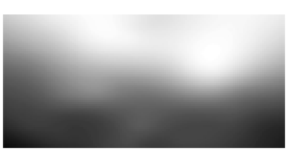


1. Input Image

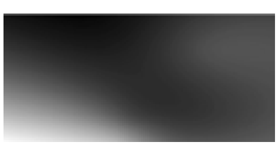
2. Green Channel

3. First IMF

4. Second IMF



5. Third IMF



6. Fourth IMF

7. Final Residue

Fig.3.3 Conversion in IMF

3.1.3 Fitness Value Evaluation: -

This approach uses a GA to obtain the weight set automatically in an optimum way. In the proposed approach GA is employed to find the optimum weight set which maximizes the average gradient of the reconstructed image; so that the richness of information and contrast of the information can be easily enhanced.

The average gradient of an image of size W_H pixels is defined in equation (c).

$$grad\_avg = \frac{1}{W \times H}\sum_{i=1}^{W}\sum_{j=1}^{H}\sqrt{\left(\frac{\partial I(i,j)}{\partial i}\right)^2 + \left(\frac{\partial I(i,j)}{\partial j}\right)^2} \quad \text{----(c)}$$

The data set used for proving the potentiality of the proposed work is,[3],

Methods	Average Gradient
Original image	0.96
Proposed approach	5.84
Contrast stretching	2.13
Histogram equalization	3.70
(Bazeille et al., 2006)	1.62

Table 3.1 Average Gradient

3.1.4 Initialize Population: -

Generate the initial population (values) randomly between 0 and 1 for the initial weight set. The number of the weight set is equal to the number of IMF generated, and then normalize the values so that their sum equals unity. Each weight set represents an individual in the GA.

3.1.5 Combine weight with IMF:-

In order to obtain an enhanced image, the individual IMFs will be summed using different weights. The enhancement approach can therefore be expressed by the equation (d).

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

--------(d)

Here, F(x,y) is the final enhanced image, t is used as index of IMFs and w_t shows the weight of the t_{th} IMFs. IMF^R_t , IMF^G_t and IMF^B_t show the t_{th} Red channel IMF, the t_{th} Green channel IMF and the t_{th} Blue channel IMF, respectively.

3.1.6 GA Operators: -

Crossover: -

In crossover there will be two different weight set as parent and there will be generating two different weight set generating as children.

Mutation: -

In Mutation there will be two different weight set as parent and there will be generating two different weight set generating as children. Here, new population is generated through the use of GA by using 80% crossover and 20 % mutation.

3.2.7 New population –

In this process, the average gradient of the image is found. If it is greater than the input image's average gradient, the input image is replaced by this image otherwise the next generation of the weight set is generated and its fitness value is calculated. This step is continuously goes until final enhanced image with maximum average gradient is found.

3.2.8 Terminate: -

The stop criteria is depend on either visibility of image and perceptibility of the user and user can select our final image as having maximum average gradient value.

4. Result: -

Here, first image is taken as input and the proposed algorithm separate the red, green and blue channel separate then breaks each channel into different IMF using Empirical mode decomposition. Then, algorithm generate initial population using random number thereafter normalize the population and get the enhanced image after combining IMF's using different weight set and later apply 0GA to optimize the image for due consideration of viewers point of view. In GA we apply crossover 80 times and mutation 20 times.

5. Conclusion

The proposed enhanced image is constructed by summing the IMF's of R,G and B channels by an optimum weight set obtained using GA. It gives better visual performance than conventional enhancement methods, alternative methods and filtering methods. It is used for enhancing underwater image; military, scientific field, under water vehicle, sub marine. It can be further enhanced for satellite, X-ray and camera images under bad circumstances.

REFERENCES

1. Arnold-Bos, A., Malkasse, J. P., & Kervern, G. "A preprocessing framework or automatic underwater images denoising". In European conference on propagation and systems, Brest, France, 2005. | 2. Bazeille, S., Quidu, I., Jaulin, L., & Malkasse, J. P. "Automatic underwater Image pre-preprocessing". In Proceedings of the Characterization du Milieu Marin, Brest, France, 2006. | 3. Bhagavatula, R., & Savvides, M. "Analyzing facial images using empirical mode decomposition for illumination artifact removal and improved face recognition". In IEEE international conference on acoustics, speech and signal processing, Honolulu, Hawaii, USA, pp.505–508, 2007. | 4. Demir, B., & Ertürk, S. "Empirical mode decomposition pre-process for higher accuracy hyperspectral image classification". In International conference on geoscience and remote sensing symposium, Boston, Massachusetts, USA, pp. 939–941, 2008. | 5. Hariharan, H., Gribok, A., Abidi, M., & Koschan, A. "Image fusion and enhancement via EMD". Journal of Pattern Recognition Research, Vol. 1, No.1, pp. 16–32, 2006. | 6. Iqbal, K., Abdul Salam, R., Osman, A., & Talib, A. "Underwater image enhancement using an integrated colour model". IAENG International Journal of Computer Science, Vol. 34, pp. 2–8, 2007. | 7. Mitchel, M. "An introduction to genetic algorithms". MIT Press , 1999. | 8. Sangkeun Lee. "Content-based image enhancement in the compressed domain based on multi-scale α-rooting algorithm". Pattern Recognition Letters Vol. No.27, pp.1054–1066, 2006. | 9. Laurence Likforman-Sulem, Jérôme Darbon, Elisa H. Barney Smith. "Enhancement of historical printed document images by combining Total Variation regularization and Non-local Means filtering". Image and vision computing, Vol. No. 29, pp. 351-363, 2011. | 10. Xiangzhi Bai, Fugen Zhou, Bindang Xue. "Infrared image enhancement through contrast enhancement by using multiscale new top-hat transform", Infrared physics and technology Vol No. 54 pp. 61-69, 2011. | 11. Weiguo Zhao. "Adaptive Image Enhancement based on Gravitational Search Algorithm". Procedia Engineering Vol No. 15, pp. 3288 – 3292, 2011.