International Journal of Advanced Technology in Engineering and Science
Volume No.05, Issue No. 09, September 2017
www.ijates.com
ijates
ISSN 2348 - 7550

UNDERWATER IMAGE FUSION FOR ENHANCEMENT

Mr.Surender Kumar[1], Dr.Mahendra Kumar[2]

[1,2]*University College of Engg & Technology*

[1,2]*Guru Kashi University, Talwandi Sabo*

ABSTRACT

The inability of humans to dive deep into the ocean for lengthy periods of time has compounded the difficulties of underwater study. This research introduces a novel single picture improvement technique based on an image fusion mechanism. The process begins by applying white balance and picture sharpening techniques to the original image, then weighting these two modified copies of the original image with specialised maps such as gradient magnitude form and jet mapping. We get the improved results by computing the per-pixel weight total of the two inputs using three picture fusion strategies: Laplacian fusion, Wavelet transform based image fusion, and Multi - band image compression based on frequency unmixing. These approaches have distinct characteristics that deconvolve the pixels in both the input and output pictures, which are assessed using six numerical metrics: MSE, PSNR, noise density, entropy, UIQI, and UCIQE. The three fusion problems that arise are convex, and they can be solved quickly with the alternating direction approach of pixel multipliers. Experiments are carried out on both real and semi-real satellite imagery. When compared to state-of-the-art combined laplacian fusion and wavelet methods, the proposed unmixing-based fusion technique enhances both abundance and end member estimates.

Keywords: Image Fusion; Remote Sensing Image; Wavelet Transform

1. Introduction

Poor visibility under water is a major drawback for oceanic applications of computer vision. In order to know the underwater world better, we regularly use photovoltaic systems to objects under water for imaging. In fact, light interaction with the medium obscures underwater scenes: light absorption and dispersion result in poor contrast, low luminance, and limited visibility. The bigger the quantity of scattering component, the turbider the water is. Pre-processing is required before any analysis or comprehension, because data obtained beneath the water frequently suffers from huge defaults. In order to get the quality enhancement image, the effect of the attenuation has to be compensated and restore color balance between physical and images. In the literature, a few approaches have been proposed to improve the underwater image based on physics-based methods. Using the polarization imaging to improve the visibility of underwater color images which are obtained through natural lighting, automatic underwater image pre-processing, underwater image enhancement by attenuation inversion with quaternion's , underwater image enhancement using an integrated color model comparison and validation of point spread models for imaging in natural waters, retinex enhancement algorithm and so on. This paper proposes a fusion-based strategy that can enhance underwater image with high efficiency, low complexity. The method includes three main steps: initial, how to produce appropriate inputs. Second, choose effective fusion methods. The last, effectively integrates the inputs and fusion methods. Now we'll go over some background material and associated algorithms. The remainder of this work is arranged in the following manner. Section 2 contains a literature review for underwater photographs, while Section 3 has an explanation of the method. The proposed approach is thoroughly shown in section 4. Section 5 displays the simulation findings.

2. Literature Survey

Various methods are used for enhancing underwater images. Some of them are discussed below.

2.1 Underwater Image Restoration Based on Image Blurriness and Light Absorption

Yan-Tsung Peng et al. [2] an accurate depth estimation method for restoring underwater images based on image blurriness and light absorption was proposed. It can be used in the image formation model to enhance and restore the degraded underwater image. As scene depth is not estimated via color channels, it is possible to restore underwater images properly. More precise BL and depth estimates are offered by the suggested technique. To begin, BL is selected from hazy areas in an underwater picture. The depth map and TMs are then created based on the BL in order to restore scene radiance.

Blurriness is a key indicator of depth. Picture blurriness isn't used to assess depth alone; both image blurriness and light absorption are taken into account. Candidate BLs calculated from blurry zones are used to define the blurriness BL. After that, the most thorough underwater picture restoration techniques are utilised. Artificial illumination may be handled via depth estimate based on light absorption when BL is taken into account. Because light rays travel a longer distance in water, it absorbs more light. Artificial lighting is occasionally used to give enough light for underwater photography and videography. In an underwater photograph, artificial illumination creates a vivid foreground. Foreground objects reflect the light emitted by an artificial lighting source. It goes less distance in the water and is absorbed and dispersed less. A restoration approach improves artificially lighted bright foreground pixels less than background pixels. The restoration utilising the depth map obtained from the red channel map would perceive such bright pixels as being close and not over-compensate their colour if the BL of an underwater image with dim artificial lighting. When BL is strong, the red light from the background pixels attenuates more than the red light from the foreground pixels, indicating scene depth. In comparison to current underwater picture restoration approaches, the suggested method may produce better restoration and enhancement outcomes in a variety of underwater colour tones and lighting circumstances.

2.2 Low Complexity Underwater Image Enhancement

Based on Dark Channel Prior Hung-Yu Yang et al. [3] proposed low complex and efficient underwater image enhancement method based on dark channel prior. This approach consists of two main procedures. First, estimation of air light by calculating dark channel prior and depth map is generated by using median filter.

International Journal of Advanced Technology in Engineering and Science
Volume No.05, Issue No. 09, September 2017
www.ijates.com
ijates
ISSN 2348 - 7550

Second, to further enhance the visual quality of underwater image, an unsupervised color correction method is used to improve the color contrast of the object. The low intensities in the dark channel are mainly due to the factors like shadows, colorful objects, dark objects etc. In the dark channel prior method, the soft matting algorithm is employed to eliminate the block effect of the transmission and to reconstruct a better image. It requires heavy computing resources and several iterations for smoothing and optimizing the transmission. In order to solve the problem, median filter is employed for the observed image directly to obtain the smoothed transmission. The top brightest pixels in the dark channel are picked out and among these pixels with highest intensities are selected as the atmospheric light. Then an efficient color correction method is used. Since underwater images have high blue color when compared with remaining colors, the blue color can be used to increase the green and red colors for making the image balanced. The highest blue color is put as a target mean and therefore the remaining color channels are determined with a multiplier to get a color balanced image.

2.3 Underwater Image Enhancement by Wavelet Fusion

Amjad Khan et al. [4] projected a wavelet-based fusion method to enhance the hazy underwater images by addressing the low contrast and color alternate problems. Initially, the hazy degraded underwater image is replicated into two classes. These categories are processed in parallel to improve the image contrast and quality. The wavelet based fusion process consists of a series of high pass and low pass filter banks. Contrast limited adaptive histogram equalization is a form of adaptive histogram equalization. It is adopted for enhancing the contrast and quality of underwater image by clipping the unnecessary region from the histogram. The limit for clipping is defined by the normalization of the histogram.

B. A. Levedahl and L. Silverberg propose a general formulation of the problem of control of underwater vehicles in full unsteady flow is presented. The first step is to create a reduced-order model of the coupled fluid vehicle (CFV) system. Because it is impossible to witness fluid motion, a fluid compensation control (FCC) technique adjusts for hydrodynamic loads derived from surface measurements. The FCC contains a tracker, a regulator, and a fluid compensator. There is a condition that ensures vehicle stability. In addition, the tradeoff between control and fluid compensation is investigated. The results are illustrated using a numerical example of an elliptically shaped vehicle.

3. Underwater Image Capturing

Due to the absorption and scattering, the light crossing the water is attenuated and dispersed. Fig 1 based on the common and popular optical model, the captured image can be modeled as two components: the direct reflection of light from the object and the reflection from the particles of the medium. The model is described as follow:

$$I(x) = J(x)\, T(x) + B\,(1 - T(x)) \text{ ----------- } (1)$$

Where x is a point in the underwater scene, T(x) be the image captured by the camera, J (x) be the scene radiance at point x. B is the homogeneous background light.

International Journal of Advanced Technology in Engineering and Science
Volume No.05, Issue No. 09, September 2017
www.ijates.com
ijates
ISSN 2348 - 7550

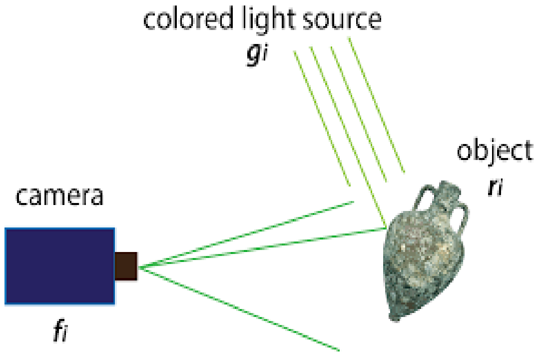


Fig. 1 Process of image capturing

T (x) is the residual energy ratio of after reflecting from point x in the underwater scene and reaching the camera. Assuming a homogeneous medium, the transmission T is determined as

$$T(x) = e\ (-\beta\ d(x)) \text{ ------- } (2)$$

With d representing the distance between the observer and the considered surface and being the medium attenuation coefficient owing to scattering. The degradation of scene radiance in the water is described by the direct attenuation term J(x) T(x), while the background light created by multi-scattering is described by the second portion B(1-T(x)). We utilise white as a baseline and restore colour offset since they are the sources of colour divergence. The contrast is thus increased, which improves the performance of the details. This theory is theoretically capable of achieving our desired outcomes.

4. Image Fusion techniques

The image fusion process is defined as acquiring all relevant data from several photos and combining it into a smaller number of images, generally only one. This one image has all of the relevant information and is more accurate than any single source image. The goal of picture fusion is to create images that are more acceptable and intelligible for human and machine perception, not just to minimise the amount of data. Multisensor Image Fusion is a procedure in computer vision that combines pertinent information from two or more pictures into a single image. The image that results will be more informative than any of the input photographs.

The increasing availability of space-borne sensors in distant sensing applications provides inspiration for various picture fusion methods. In image processing, a variety of circumstances necessitate great spatial and spectral resolution in a single picture. The majority of the equipment on hand is incapable of delivering such information persuasively. Image fusion methods allow for the integration of several information sources. The spatial and spectral resolution features of the merged picture are complimentary. Normal image fusion approaches, on the other hand, damage the spectral information of multispectral data when combining.

The major three types of fusion are

1. Wavelet transform
2. Laplacian fusion
3. Multiband image fusion

4.1 Wavelet Transform Based Image Fusion

The raw pictures are divided into approximation and detailed coefficients at the desired level in a wavelet image fusion approach utilising DWT. Once the picture has been deconstructed using the wavelet transform, a composite multi-scale representation is constructed using a selection of the prominent wavelet coefficients. The maximum of the absolute values or an area-based maximum energy are frequently used in the choices. The final step is to perform an inverse discrete wavelet transform on the composite wavelet representation. The inverse discrete wavelet transform (IDWT) was employed to create the fused picture, as illustrated in figure. The fusion algorithm simply averages the approximation coefficients and selects the detailed coefficient with the greatest Magnitude in each sub band.

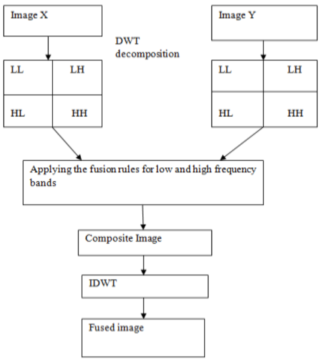


Fig. 2 Wavelet transform based fusion algorithm

4.2. Laplacian Fusion Algorithm

In this approach, the Laplacian pyramids for every image component (IR and Visible) are used. Where Laplacian pyramid (fundamental tool in image processing) of an image is a set of band pass images in which every image is a band pass filtered copy of its forerunner. Calculating the difference between low pass pictures at various layers of a Gaussian pyramid yields band pass duplicates. A strength metric is used to determine which pixels contribute to each sample location from which source. Add the averages of the two pyramids that correspond to each level. The generated image is a simple average of two low quality photographs at each level. Expanding, then summing all the layers of the fused pyramid, which is achieved by simple averaging, is how a picture is decoded. The Laplacian pyramid is derived from the Gaussian pyramid representation, which is basically a sequence of increasingly filtered and down sampled versions of an image.

The process of face detection is accomplished by using simple and efficient algorithm for multi-focus image fusion known as Laplacian pyramid algorithm. Multiresolution signal decomposition scheme is efficiently used for further applications like gestures, texture, pose and lighting conditions while taking an image.

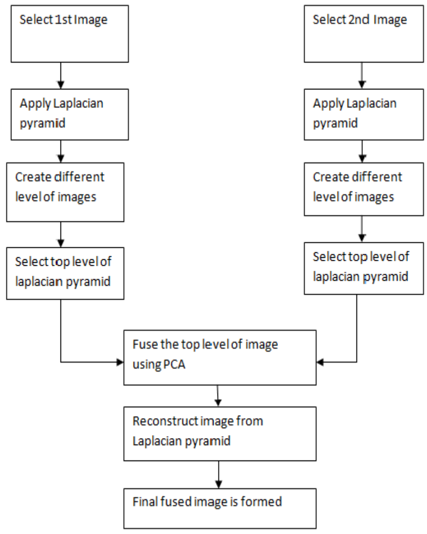


Fig. 3 Laplacian Fusion algorithm

A kind of fusion approach is very useful for applications like Hand Gesture. Hand gestures play a major role in Human Computer Interaction. They provide primary interaction tools for gesture based computer control.

4.3. Multiband Image Fusion Based on Spectral Unmixing

Based on unsupervised spectral unmixing for combining a high-spatial–low-spectral-resolution image and a low-spatial– high-spectral-resolution image is that the multiband image fusion algorithm. The commonly used linear observation model (with additive Gaussian noise) is combined with the linear spectral mixture model to create the likelihoods of the observations. The nonnegative and sum-to-one constraints resulting from the intrinsic physical properties of the abundances are introduced as prior information to regularize this ill-posed problem. The joint fusion and unmixing problem is then formulated as maximizing the joint posterior distribution with respect to the end member signatures and abundance maps. The two subproblems that arise are convex and can be solved quickly using the alternating direction multiplier approach. An alternating optimization approach is used to combat this optimization flaw. When compared to state-of-the-art joint fusion and unmixing algorithms, simulation results reveal that the proposed unmixing-based fusion approach improves abundance and end member estimates. Experiments using synthetic and semi-real data are carried out.

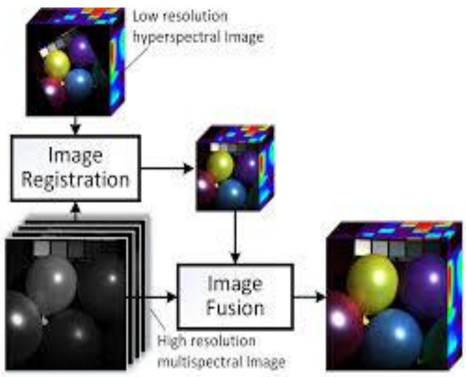


Fig. 4 Multiband image Fusion algorithm

International Journal of Advanced Technology in Engineering and Science
Volume No.05, Issue No. 09, September 2017
www.ijates.com
ijates
ISSN 2348 - 7550

5. Proposed Methodology

5.1. Architecture

In this approach we employ a single image based approach built on fusion principle. This approach is a simple and fast, that the visibility of underwater images are increased. The considered weights and specified inputs were carefully taken to overcome the limitation of such environments yet specialized optical models are not used.

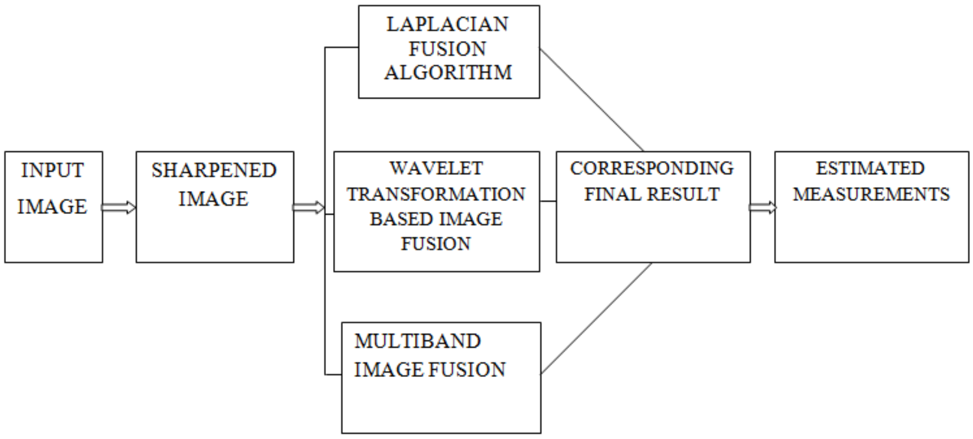


Fig. 5 Proposed Methodology

5.2. Implementation

Image Fusion aims to enhance the information apparent in the images as well as to increase the reliability of the interpretation by integrating disparate images. This leads to more clear data and increased visualizes in application fields like medical imaging, foggy images, etc. Depending from low visibility mainly in those regions dense haze and lowlight conditions. The idea that global contrast enhancement techniques are limited to dealing with hazy scenes has been remarked previously by Fattal. In order to overcome this limitation, we introduce three measures (fusion methods). Image Fusion aims to enhance the information apparent in the images as well as to increase the reliability of the interpretation by integrating disparate images. This leads to more clear data and increased visualizes in application fields like medical imaging, foggy images, etc.

Thus, we can conclude that fusion algorithm with pixel level and fusion methods.

A combination of fusion methods including luminance map, chromatic map, saliency map. Which increase the clarity of foggy image this approach may be the correct way to find out which fusion algorithm is most appropriate for an application.

For the multi-scale fusion, the number of decomposition levels depends on the image size, and is defined so that the size of the smallest resolution reaches a few tenths of pixels (e.g. 7 levels for a 600×800 image size). The results obtained on ten underwater images, by several recent (underwater) dehazing approaches.

6. Results and Discussions

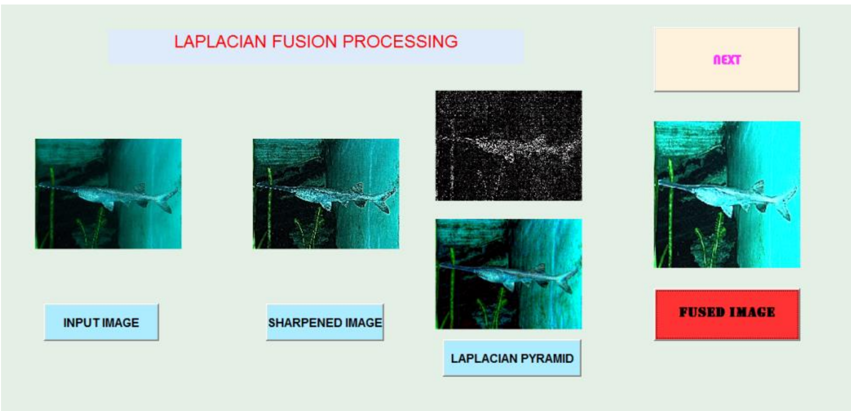
Two test photos are given in Fig.6 to demonstrate the performance of our technique. When the picture quality of the three enhancement approaches is compared, it is clear that the suggested method may significantly improve the underwater image. The first group consists of comparative studies with the literature; this approach uses MSR computations for the luminance channel of a colour underwater picture to decrease water scattering and boost actual characteristics of underwater objects. The results of the comparison are displayed in Fig. 7. Our result is more satisfying when compared to the group of comparison photos in Fig.7, whether the degree of vivid colour or the presentation of details. Deconvolution is used in the literature, but we compute the weight total of the two inputs per-pixel, which improves computing efficiency. Underwater picture improvement based on dark channel prior is discussed in the literature. The approach starts by estimating the depth map with the median filter, then combining the black channel to produce the scene picture, and then applying colour enhancement. However, there is an estimating inaccuracy with this procedure. As a result, the colour integrity will be compromised. The colour fidelity may be maximised saved under the premise of boosting the underwater image, as shown in Fig. (b).

Two sample images are taken for the processing which are implemented in the project also as colour fusion is given below.

(a) (b)

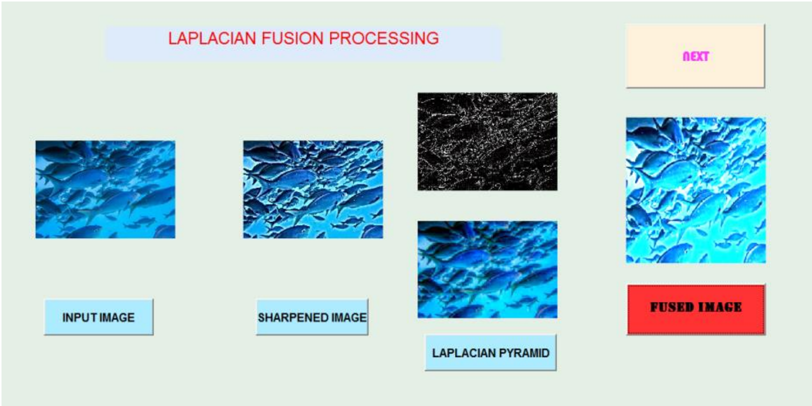
Fig. 6 Input Images

Fig.7 shows laplacian fused image, the Laplacian pyramid (fundamental tool in image processing) of an image is a set of band pass images; in which each is a band pass filtered copy of its predecessor.



International Journal of Advanced Technology in Engineering and Science
Volume No.05, Issue No. 09, September 2017
www.ijates.com
ijates
ISSN 2348 - 7550

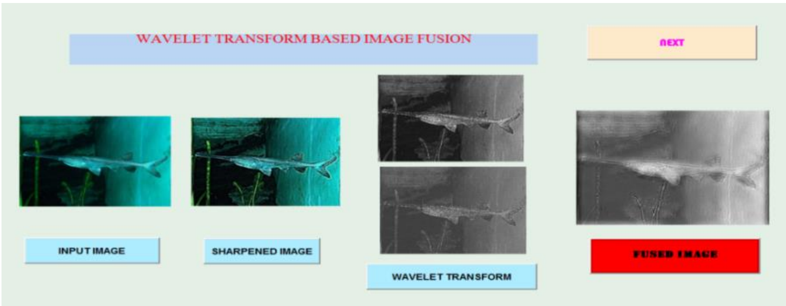
(a)



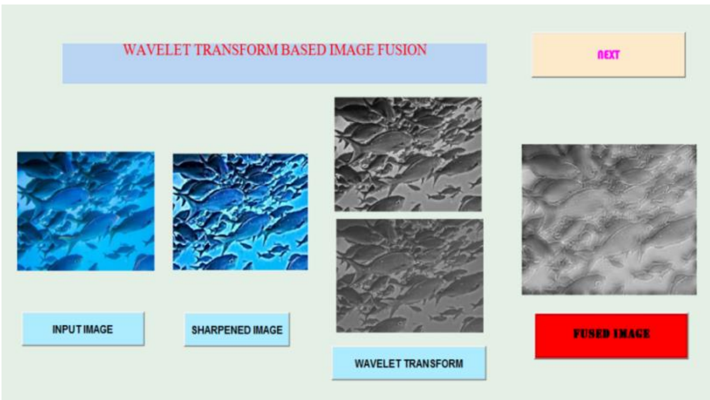
(b)

Fig. 7 Laplacian Fusion Processing of Input Images

The source pictures are split into approximation and detailed coefficients at the desired level in a wavelet image fusion system, as shown in Fig.8. A multiband image fusion approach based on unsupervised spectral unmixing for fusing a high-spatial–low-spectral-resolution picture and a low-spatial–high-spectral-resolution image is referred to as a multiband fused image. The simulation results from the multiband picture fusion approach are shown in Fig.9.



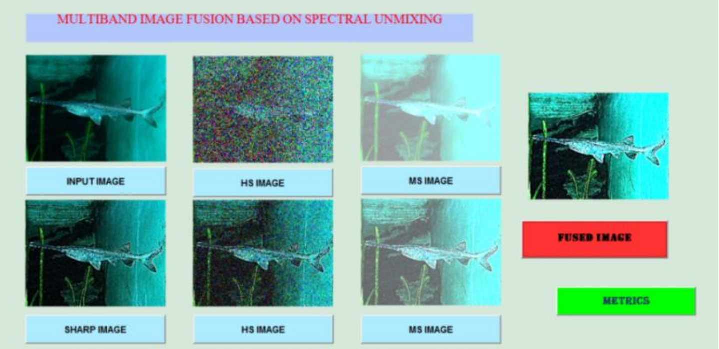
(a)



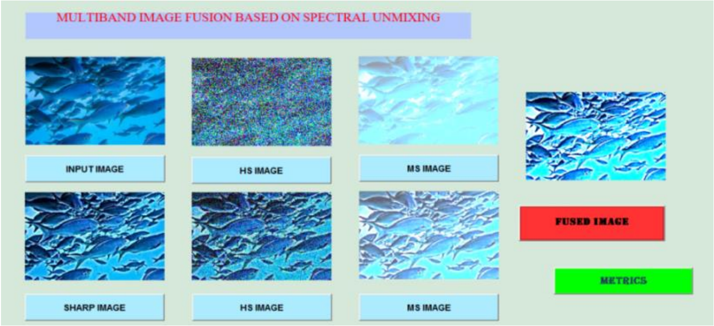
(b)

International Journal of Advanced Technology in Engineering and Science
Volume No.05, Issue No. 09, September 2017
www.ijates.com
ijates
ISSN 2348 - 7550

Fig. 8 Wavelet Transform Based Image Fusion of Input Images



(a)



(b)

Fig. 9 Multiband Image Fusion Based On Spectral Unmixing

MSE – Mean Square Estimation, PSNR – Peak Signal to Noise Ratio, NOISE DENSITY, ENTROPY, UIQI – Universal Image Quality Index, and UCIQE – Underwater Color Image Quality Assessment are the evaluation metrics. Table 1 lists the metrics for the picture Fig (a).

Table 1 Various metrics obtained from three algorithms for Input image (a)

	Laplacian (dB)	**Wavelet (dB)**	**Multiband (dB)**
MSE	183.42	101.61	175.51
PSNR	54.65	28.10	55.09
N.D	678.00	198.01	237.01
ENTR	6.99	-3.40	7.02
UIQI	1.61	1.01	1.57
UCIQE	0.38	0.33	0.39

International Journal of Advanced Technology in Engineering and Science
Volume No.05, Issue No. 09, September 2017
www.ijates.com
ijates
ISSN 2348 - 7550

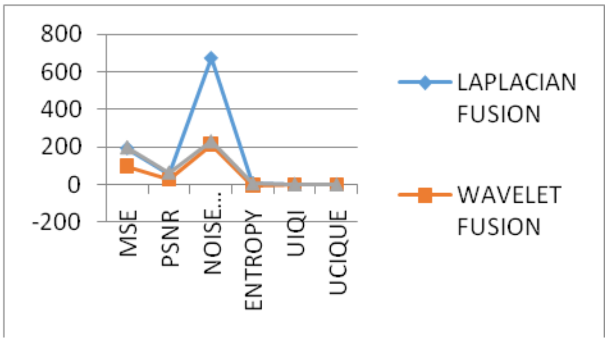


Fig. 10. Comparative study of three methods for image (a)

The above graph indicates that metrics are examined. In comparison to the three fusion methods, MSE valves are in the range of 200dB for multiband image fusion, 190dB for laplacian fusion, and 100dB for wavelet fusion, PSNR valves are in the range of 0 - 100 dB, noise density valves are in the range of 2200dB for multiband image fusion, 690dB for laplacian fusion, and 180dB for wavelet fusion, noise density valve Entropy ranges from 0 to 30 decibels, UIQI valves from 0 to 10 decibels, and UCIQUE valves from 0 to 10 decibels. All three fusion approaches, laplacian fusion, wavelet fusion, and multiband picture fusion, are assessed for these values.

For the image Fig (b) the metrics are given in Table 2.

Table 2. Various metrics obtained from three algorithms for Input image (b)

	Laplacian (dB)	**Wavelet (dB)**	**Multiband (dB)**
MSE	193.00	98.35	188.91
PSNR	54.14	28.22	54.36
N.D	672.01	214.01	231.01
ENTR	6.68	-4.05	6.58
UIQI	1.39	0.98	1.32
UCIQE	0.51	0.73	0.54

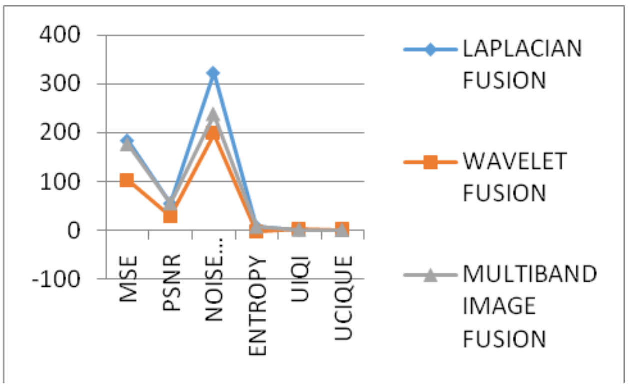


Fig. 10 Comparative study of three methods for image (b)

The above chart for fig (b) shows that metrics are evaluated for all three fusion methods: interpolation fusion, wavelet fusion, and multiband image fusion, with MSE valves in the range of 280dB for descriptor, 100dB for wavelet, and 285dB for multiband, PSNR valves in the range of 0-80dB, noise density valves in the range of 320dB for laplacian, 220dB for multi UIQI valves have an entropy range of 0-0.8 dB, while UCIQUE valves have an entropy range of 0-0.5 dB.

7. Conclusion

Different fusion techniques and input photos for the fusion process are presented in this. The picture is made up of three components: chromatic, brightness, and saliency, each of which preserves various aspects of the image. Preprocessed versions of deteriorated photographs are also used as input images, which recovers and enhances the visual parameters of underwater images to a higher extent. In comparison to the original input image, these input images after fusion provide better image quality. The image is sharper and more informative because to the usage of Laplacian fusion, Wavelet fusion, and Multiband unmixing fusion. For fusing multiband pictures, a new approach based on spectral unmixing is presented. Instead than approximation decoupling two data terms to solve the related picture issue, an approach to directly minimise the associated objective function has been devised. The ultimate numerical results and abundances were alternately updated in this procedure. The suggested approach of Multiband image fusion has a superior entropy value of the fused picture than existing methods, according to numerical updates. In the future, the algorithm might be extended to include videos, and the approaches could be merged to meet the needs of the application.

REFERENCES

[1] Codruta Orniana Ancuti, Cosmin Ancuti, Tom Haber and Philippe Bekaert "Fusion-based restoration of the underwater images", 2018 IEEE International Conference on Image Processing

[2] Cosmin Ancuti, Codruta Orniana Ancuti, Tom Haber and Philippe Bekaert "Enhancing Underwater Images and Videos by Fusion",2017

[3] Z. Wang and A. Bovik, "A universal image quality index," IEEE Signal Processing Letters, vol. 9, pp. 81–84, 2018.

[4] Naveen Kumar and ManinderKaur "Wavelet Transform based Reconstruction of Image from Multi-Scenes" 2017

[5] Deepak Kumar Sahu1, M.P.Parsai2 "Different Image Fusion Techniques- A critical reveiw" International Journal of Modern Engineering Research (IJMER) Vol. 2, Issue. 5, Sep.-Oct. 2016

[6] Jharna Majumdar, Santhosh Kumar K. L. "A Modified Collaborative Learning Method for Automatic Enhancement of Underwater and Medical Imagery",ANUSANDHANA - Journal of Science, Engineering and Management, Vol-02, Issue-01, June 2016

[7] Atlantis Press, Paris, France "Contrast Enhancement and Optimization for Underwater Images", Proceedings of the 2nd International Conference on Computer Science and Electronics Engineering (ICCSEE 2015)

[8] Frédéric P,Anne-Sophie Capelle-Laizé and Philippe C. Underwater Image Enhancement by Attenuation Inversion with Quaternions [C]//ICASSP, Proc. IEEE, 2018: 1177-1180.

[9] Kashif I,Rosalina A S,Azam O,et al. Underwater Image Enhancement Using an Integrated Colour Model[J]. IAENG Interna- tional Journal of Computer Science, 2017, 32(2): 239- 244.

[10] Hou W,Gray D J,Weidemann A D,et al. Comparison and validation of point spread models for imaging in natural waters[J]. Optics Express, 2018, 16(13): 9958-9965.

[11] ZHANG Kai,JIN Weiqi,QIU Su,et al. Multi-Scale Retinex Enhancement Algorithm on Luminance Channel of Color Underwater Image[J].Infrared Technolgy,2017, 33(11):630-634.

[12] Codruta Orniana Ancuti, Cosmin Ancuti, Philippe Bekaert. Effective Single Image Dehazing by Fusion. IEEE, 2016.

[13] JohnY.Chiang and Ying-Ching Chen. Underwater Image Enhancement by Wavelength Compensation and Dehazin. IEEE Transactions on Processing Image, 2015, 21(4):1756-1769.

[14] W. N. McFarland, “Light In the sea—Correlations with behaviour of fishes and invertebrates,” Amer. Sci. Zoology, vol. 26, no. 2, pp. 389–401, 2016.

[15] Rafael C.Gonzalez, Richard E.Woods.Digital Image Processing (Second Edition) [M]. Beijing: Wu Youshou, 2014. 224-233.

[16] R. Achanta, S. Hemami, F. Estrada, and S. Ssstrunk,“Frequency-tuned salient region detection,”

[17] CVPR, 2017.

[18] Mingming Cheng, Guoxin Zhang, Niloy J Mitra2, et al. Global Contrast based Salient Region Detection. CVPR. 2016:409-416.

[19] P. Burt and T. Adelson, “The laplacian pyramid as a compact image code” IEEE Transactions on Communication, 2013.

[20] Zhangming Yu,Fei Gao. Laplacian Pyramid and Contrast Pyramid Based Image Fusion and Their Performance Comparison [J].2014, 21(10):128-130.

[21] Yang Hung-Yu,Chen Pei-Yin,Huang Chien-Chuan,et al. Underwater Image Enhancement Based on Dark Channel Prior. IEEE Computer Society, 2017:17-21.