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UNDERWATER IMAGE FUSION FOR ENHANCEMENT

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ABSTRACT

Human incapability in diving within the deep ocean for an extended time has increased the challenges of underwater analysis. A new single image enhancement approach based on image fusion strategy is introduced in this paper. The method first applies the white balance and image sharpening technique to the original image respectively, then taking these two adapted versions of the original image as inputs that are weighted by specific maps as gradient magnitude form and jet mapping. We obtain the enhanced results by computing the weight sum of the two inputs in a per-pixel fashion using three image fusion strategies such as Laplacian fusion, Wavelet transform based image fusion and Multiband image fusion based on spectral unmixing. These methods on their own have unique features which deconvolates the pixels with both the input images, that are evaluated through six numerical metrics as MSE, PSNR, noise density, entropy, UIQI and UCIQE. The three resulting fusion problems are convex and are solved efficiently using the alternating direction method of pixel multipliers. Experiments are conducted for both satellite real images and semi-real images. The proposed unmixing-based fusion scheme improves both the abundance and end member estimation compared with the state-of-the-art joint laplacian fusion and wavelet algorithms.

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. Actually, underwater scenes are generally veiled by the light interaction with the medium: absorption and scattering of the light induce poor contrast, low luminosity and restricted visibility. And turbider the water is, greater the proportion of scattering part is. Before any analysis or understanding it has to be pre-processed and the data acquired under the sea often suffer of large 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

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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 the background information and related algorithms are introduced briefly .The rest of this paper is organized as follows. In section 2, we give the literature survey for underwater images and outline of the algorithm is presented in Section 3. In section 4 the proposed method is illustrates in detail. And the simulation results show in section 5.

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. The proposed method is provided with more accurate BL and depth estimation. First, BL is chosen from blurry regions in an underwater image. Then, the depth map and the TMs are achieved based on the BL to restore scene radiance.

Blurriness is an important measure of depth. Depth is not estimated by using image blurriness alone, both image blurriness and light absorption are also considered. Blurriness BL is determined from candidate BLs estimated from blurry regions. The most comprehensive underwater image restoration techniques are then used. By considering BL, depth estimation based on light absorption can handle artificial lighting. Water absorbs more light as the light rays travel through longer distance in the water. Artificial lighting is occasionally used to provide sufficient light for taking underwater images and videos. Artificial lighting in an underwater image forms a bright foreground. The light arising from an artificial lighting source is reflected by foreground objects. It travels less far in the water and is less absorbed and scattered. Artificially illuminated bright foreground pixels is less improved by a restoration method than background pixels. If the BL of an underwater image with dim artificial lighting, the restoration using the depth map derived by the red channel map would regard those bright pixels as being close and not over-compensate their color. When BL is bright, the red light from the background pixels would attenuate more than that of the foreground pixels, which could be correctly interpreted as scene depth. The proposed method can create better restoration and enhancement results in different underwater color tones and lighting conditions compared to other underwater image restoration methods.

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. 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

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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. First, a reduced-order model of the coupled fluid vehicle (CFV) system is developed. The inability to observe fluid motion motivates a fluid compensation control (FCC) approach that compensates for the hydrodynamic loads synthesized from surface measurements. Tracker, a regulator, and a fluid compensator are in the FCC. A condition is provided that guarantees vehicle stability. The tradeoff between regulation and fluid compensation is also examined. A numerical example of an elliptically shaped vehicle illustrates the results.

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:

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

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.

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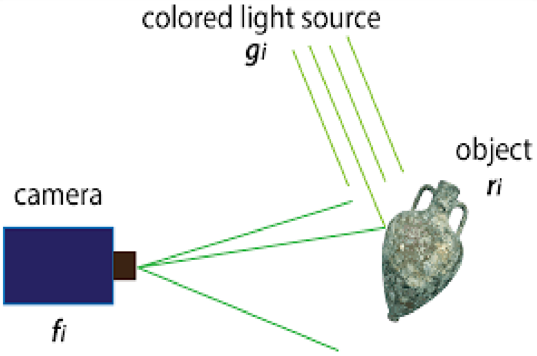

Fig. 1 Process of image capturing

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 β being the medium attenuation coefficient due to the scattering while d represents the distance between the observer and the considered surface. The direct attenuation term J(x) T(x) describes the decay of scene radiance in the water and the second part B(1-T(x)) is the background light formed by multi-scattering . These will cause the color deviation, we use white as a benchmark and restore color offset. And then enhance the contrast, increasing the performance of the details. Such a hypothesis is the theoretically able to achieve our desired results.

4. Image Fusion techniques

The image fusion process is outlined as gathering all the important information from multiple images and their inclusion into fewer images, usually a single one. This single image is new information and accurate than any single source image, and it has all the necessary information. The purpose of image fusion is not only to reduce the amount of data but also to construct images that are more appropriate and understandable for the human and machine perception. In computer vision, Multisensor Image fusion is the process of combining relevant information from two or more images into a single image. The ensuing image will be additional informative than any of the input images.

In remote sensing applications, the increasing availability of space borne sensors gives a motivation for different image fusion algorithms. A number of situations in image processing require high spatial and high spectral resolution in a single image. Most of the available equipment is not capable of providing such information convincingly. The integration of different information sources are enabled in Image fusion techniques. The fused image has complementary spatial and spectral resolution characteristics. However, the normal image fusion techniques will distort the spectral information of the multispectral data whereas merging.

The major three types of fusion are

1. Wavelet transform
2. Laplacian fusion

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3. Multiband image fusion

4.1 Wavelet Transform Based Image Fusion

In wavelet image fusion scheme, the source images are decomposed into approximation and detailed coefficients at required level using DWT. In the usual wavelet based fusion, once the imagery is decomposed via wavelet transform a composite multi-scale representation is built by a selection of the salient wavelet coefficients. The selections are often based on choosing the maximum of the absolute values or an area based maximum energy. An inverse discrete wavelet transform on the composite wavelet representation is the final stage. The fused image could be obtained by taking the inverse discrete wavelet transform (IDWT) as shown in figure. The fusion rule used simply averages the approximation coefficients and picks the detailed coefficient in each sub band with the largest Magnitude.

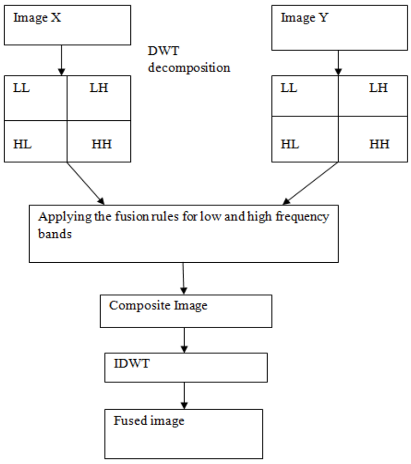

Fig. 2 Wavelet transform based fusion algorithm

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. Band pass copies can be obtained by calculating the difference between low pass images at successive levels of a Gaussian pyramid. A strength measure is used to decide from which source what pixels contribute at each specific sample location. Take the average of the two pyramids corresponding to each level and add them. Simple average of two low resolution images at each level is the resulting image. Decoding of an image is done by expanding, then summing all the levels of the fused pyramid which is obtained by simple averaging. 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.

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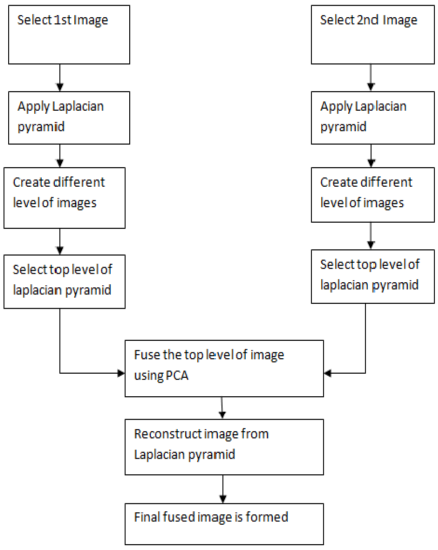

Fig. 3 Laplacian Fusion algorithm

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 resulting sub problems are convex and are solved efficiently using the alternating direction method of multipliers. This optimization drawback is attacked with an alternating optimization strategy. Simulation results shows that the abundance and end member estimation are improved in the proposed unmixing-based fusion scheme when compared with the state-of-the-art joint fusion and unmixing algorithms. For both synthetic and semi-real data experiments are conducted.

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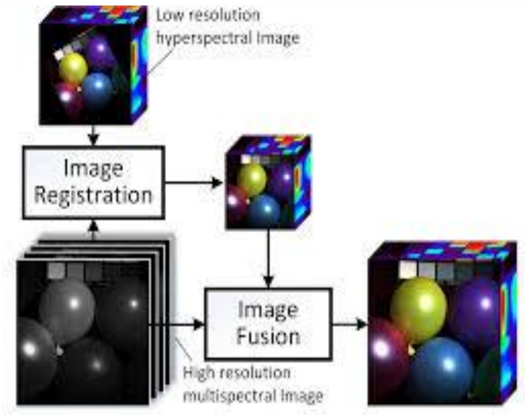

Fig. 4 Multiband image Fusion algorithm

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. The original image is processed by using two inputs. First the image is processed and white balance is completed. Then the weights are applied to this image followed by fusion of these resulting weighted images. In the same way image is processed by the second input. The two resultant images are undergone for fusion and the enhanced image is obtained. The below flowchart describes the range of the image processing to be done in order to furnish the required image enhancement for the vision of clearance in the quality of the image .This provides a secure and not hardware involved based project .

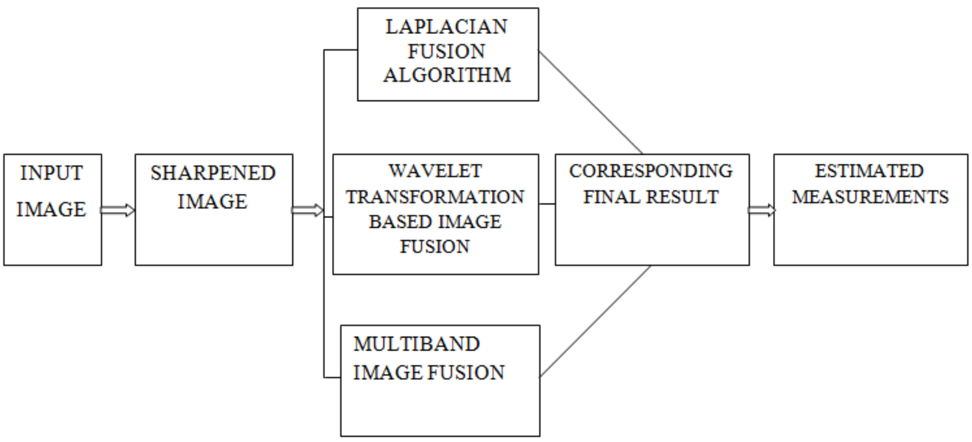

Fig. 5 Proposed Methodology

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

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application fields like medical imaging, foggy images, etc. This paper discusses different techniques for pixel level image fusion and their performance evaluation parameters. 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. This is due to the fact that the optical density of haze varies across the image and affects the values differently at each pixel. Practically, the limitation of the general contrast enhancement operators (e.g. gamma correction, histogram equalization, white balance) is due to the fact that these techniques perform (constantly) the same operation across the entire image. In order to overcome this limitation, we introduce three measures (fusion methods). These maps are designed in a per-pixel fashion to better define the spatial relations of degraded regions. Our fusion methods balance the contribution of each input and ensure that regions with high contrast or more saliency from a derived input, receive higher values. The luminance weight map measures the visibility of each pixel and assigns high values to regions with good visibility and small values to the rest. Since hazy images present low saturation, an effective way to measure this property is to evaluate the loss of colorfulness. This weight is processed based on the RGB color channel information. We make use of the well-known property that more saturated colors yield higher values in one or two of the color channels.

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. This paper discusses different techniques for pixel level image fusion and their performance evaluation parameters.

Depending upon the use of the given application, some users may wish a fusion outcome that would show more color details, some may desire more analysis or mapping; while some may want improved accuracy of application; and some others may wish for a visually beautiful and appealing fused color image, solely for visualization purposes. 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. Table provides the associated quantitative evaluation, using three recent metrics: PCQI, UCIQE, and UIQM. While PCQI is a general-purpose image contrast metric, the UCIQE and UIQM metrics are dedicated to underwater image assessment. UCIQE metric was designed specifically to quantify the non uniform color cast, blurring, and low-contrast that characterize underwater images, while UIQM addresses three important underwater image quality criterions: colorfulness, sharpness and contrast.

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6. Results and Discussions

To illustrate the performance of our method, we use two test images, shown in Fig.6. Comparing the image quality for three enhancement methods, it is obvious that the proposed method can effectively enhance the underwater image. The first group is the contrastive experiments with the literature, this method reduce scattering of water and increase true characteristic of underwater objects by MSR calculations for luminance channel of color underwater image. Comparison results are shown in Fig .7. Seen by the group of comparison images in Fig .7, whether the degree of bright color or the display of details, our result is more satisfactory.

The literature employs deconvolution, and we compute the weight sum of the two inputs in a per-pixel fashion, computational efficiency is more efficient. The literature empolys underwater image enhancement based on dark channel prior. The method firstly use the median filter to estimate depth map, then combine the black channel to build the scene image, finally they employ the color enhancement. However, this method exist estimation error. And it will result in the deviation of the color fidelity. Through the Fig (b) we can see that the color fidelity can be maximize saved under the premise of enhancing the underwater image. The water depth in the image scene is estimated according to the residual energy ratios of different color channels existing in the background light in the literature. There must be exist estimation error.

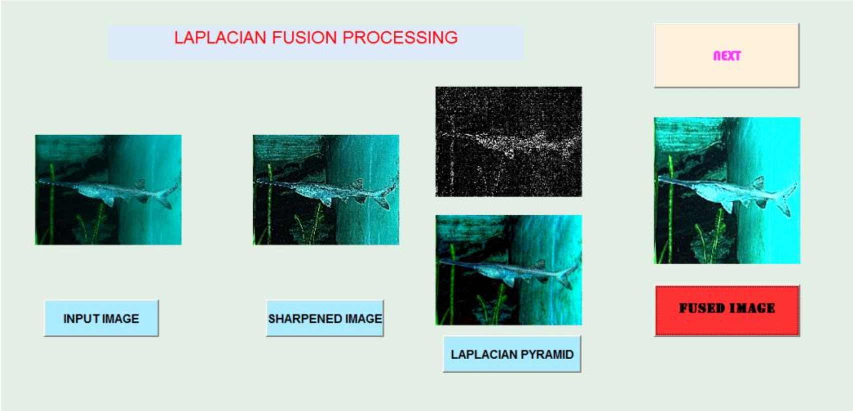
Through the Fig (b) we can see that the results of this paper demonstrate more realistic colors and sharper details. Overall, our algorithm can highlight details, without causing color distortion. And various contrastive experiments verify the effectiveness of our algorithm. The results obtained are better visual effects. In addition, the proposed algorithm has a distinct advantage in computational efficiency. Besides, this method requires less computing resource and is well suitable for implementing on the surveillance and underwater navigation in real time. Even thought the method performs generally well, as the previous methods, a limitation of this algorithm is when the images are characterized by non-homogenous medium in the water.

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

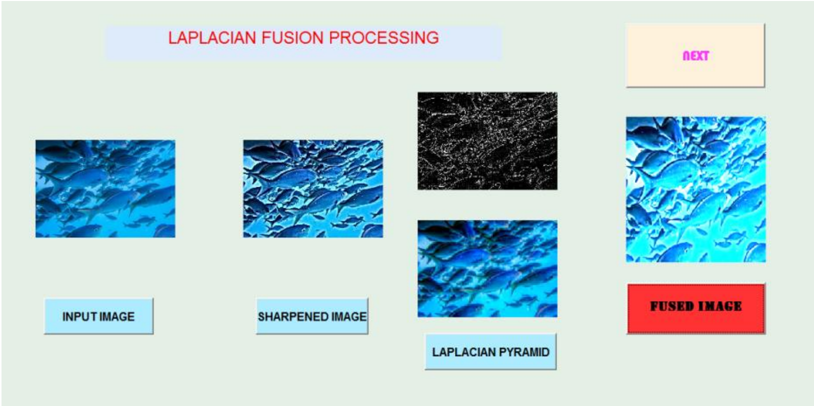
(a) (b)

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.



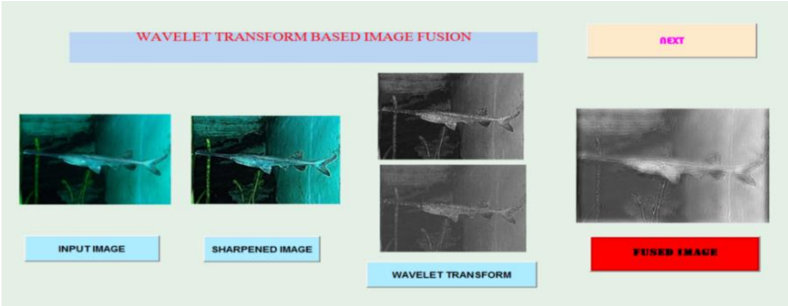
(a)



(b)

Fig. 7 Laplacian Fusion Processing of Input Images

In wavelet image fusion scheme, the source images are decomposed into approximation and detailed coefficients at required level using DWT as depicted in Fig.8. In multiband fused image, a multiband image fusion algorithm based on unsupervised spectral unmixing for combining a high-spatial–low-spectral-resolution image and a low-spatial– high-spectral-resolution image. Fig.9 illustrates the simulation results obtained from multiband image fusion method.



(a)

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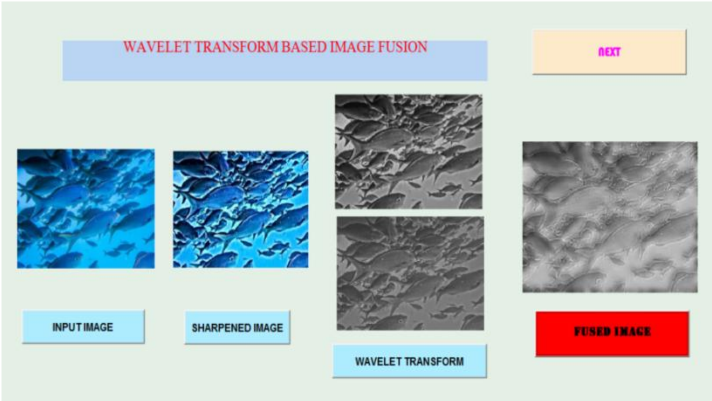
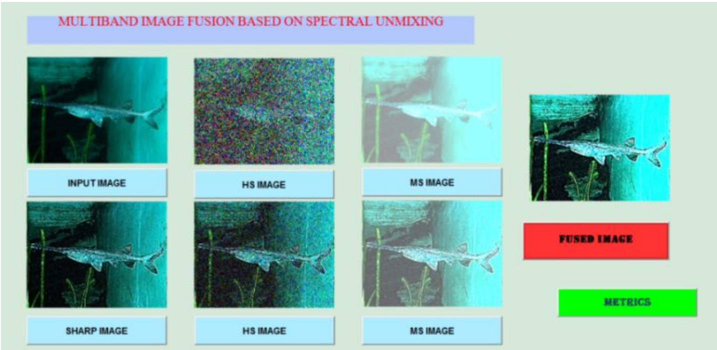


(b)

Fig. 8 Wavelet Transform Based Image Fusion of Input Images



(a)

(b)

Fig. 9 Multiband Image Fusion Based On Spectral Unmixing

The evaluation metrics are given as MSE –Mean Square Estimation, PSNR-Peak Signal to Noise Ratio, NOISE DENSITY, ENTROPY, UIQI-Universal Image Quality Index and UCIQE-Underwater Color Image Quality Evaluation. For the image Fig (a) the metrics are given in Table 1.

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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

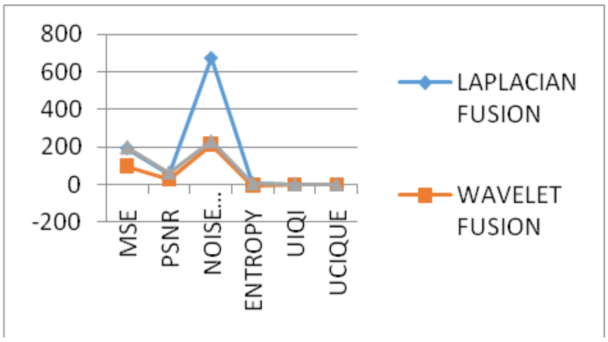

Fig. 10. Comparative study of three methods for image (a)

It is inferred from the above chart that metrics are evaluated MSE valves are in the range of 200dB for multiband image fusion, 190dB for laplacian fusion, 100dB for wavelet fusion on comparison with the three fusion methods, 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, 180dB for wavelet fusion, Entropy ranges are 0- 30 dB, UIQI valves are in the range of 0- 10 dB and UCIQUE valves are in the range of 0-10 dB these values are evaluated for all the three fusion methods as laplacian fusion, wavelet fusion and multiband image fusion. 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

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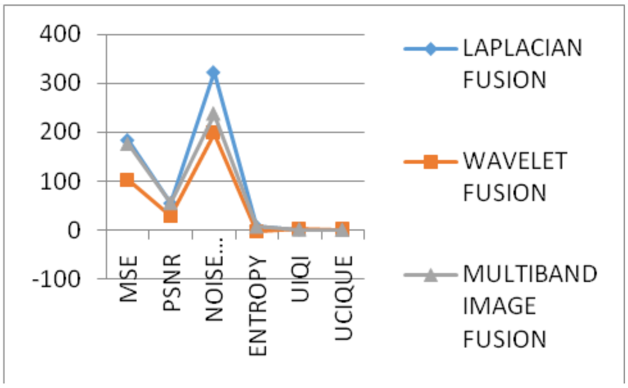

Fig. 10 Comparative study of three methods for image (b)

It is inferred from the above chart for the fig (b) that metrics are evaluated for all the three fusion methods as laplacian fusion, wavelet fusion and multiband image fusion as MSE valves are in the range of 280dB for laplacian,100 dB for wavelet and 285 dB for multiband, PSNR valves are in the range of 0-80 dB, noise density valves are in the range of 320 dB for laplacian,220dB for multiband and 190 dB for wavelet, Entropy ranges are 0- 15 dB, UIQI valves are in the range of 0-0.8 dB and UCIQUE valves are in the range of 0-0.5 dB.

7. Conclusion

In this a different fusion strategies are presented and input images for fusion process. The image consists of chromatic, luminance, and saliency which preserve different specific information from the image. Also as input images are the preprocessed version of degraded images, which restores and improves the underwater images visual parameter to greater extent. These input images after fusion gives improved image quality as compared to the original input image. Laplacian fusion, Wavelet fusion and Multiband unmixing fusion used here gives clearer and informative image. New algorithm based on spectral unmixing is proposed for fusing multiband images. Instead of solving the associated image problem approximately by decoupling two data terms, an algorithm to directly minimize the associated objective function has been designed. In this algorithm, the end numerical results and abundances were updated alternatively. The numerical updates evidenced for the proposed method as Multiband image fusion has the entropy value of the fused image is better than other methods. For future work algorithm can be extended for videos, we can also merge the methods as per the requirement of application.

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