Underwater Image Enhancement by Cubic Interpolation and Histogram Distribution Prior

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Abstract

Images captured under water are usually degraded due to the effects of absorption and scattering. Degraded underwater images show some limitations when they are used for display and analysis. For example, underwater images with low contrast and color cast decrease the accuracy rate of underwater object detection and marine biology recognition. To overcome those limitations, a systematic underwater image enhancement method, which includes an underwater image dehazing algorithm and a contrast enhancement algorithm, is proposed. Built on a minimum information loss principle, an effective underwater image dehazing algorithm is proposed to restore the visibility, color, and natural appearance of underwater images. In this project , a novel self-similarity-based method for descattering and super resolution (SR)of underwater images is proposed based on ambient light and transmission map estimation . A simple yet effective contrast enhancement algorithm is proposed based on a kind of histogram distribution prior, which increases the contrast and brightness of underwater images. The proposed method can yield two versions of enhanced output. One version with relatively genuine color and natural appearance is suitable for display. The other version with high contrast and brightness can be used for extracting more valuable information and unveiling more details. MATLAB simulation tool will be used to evaluate existing and proposed system performance

I. INTRODUCTION

The water is a strong attenuator of electroma gneticradiation, so while satellites can map entire planets from spaceusing cameras and laser ranging, underwater vehicles must bewithintens of meters at best for optical sensors to be useful.While mechanical waves do travel well through water, thereare practical tradeoffs between source strength, frequency,and propagation distance. Ship-based sonars use lower frequenciesto reach the bottom, but these longer wavelengthscome at the price of reduced resolution. To map fine-scalefeatures relevant to many practical applications, both opticaland acoustic imaging platforms must operate relatively close tothe seafloor. We are particularly interested in optical imagingbecause it captures the color and texture information usefulfor distinguishing habitats and organisms.

An underwater photograph not only captures the sceneof interest, but is an image of the water column as well.Attenuation of light underwater is caused by absorption, athermodynamic process that varies nonlinearly with wavelength,and by scattering, a mechanical process whereby aphoton’s direction is changed. At increasing depths,ambient light is attenuated to where colors can no longer bedistinguished and eventually to effective darkness. Artificiallight sources must subsequently be used to illuminate thescene, but these sources contribute to scattering and canintroduce beam pattern artifacts in the image. In summary,uncorrected underwater imagery is typically characterized bynon-uniform illumination, reduced contrast, and colors that aresaturated in the green and blue channels.

It is often desirable for an underwaterimage to appear as ifit were taken in air, either for aesthetics or as a pre-processingstep for automated classification. Methods range frompurelypost-processing techniques to novel hardware configurations,and the choice depends heavily on the imaging system, thelocation, and the goals of the photographer.

In this paper, we proposes a super resolution (SR) of underwater images is proposed. To overcome the high-frequency information is lost during descattering. Consequently, we propose a novel high turbidity underwater image SR algorithm. We apply a convex fusion rule for recovering the final HR image. The super-resolved images have a reasonable noise level after descattering and demonstrate visually more pleasing results than conventional approaches.

The organization of the paper is as follows. In Section II, basic concepts along with the underwater imaging proposed in the earlier literatures have been discussed. The proposed methodology is presented in Section III. Thesimulation resultshas been presented in

Section IV. Finally, the paper is concluded in Section V.

II. RELATED WORKS

Hitam, M.S et al. [1] has been worked on "Mixture contrast limited adaptive histogram equalization for underwater image enhancement,". By improving the quality of an underwater image has received substantial attention due to rundown visibility of the image which is caused by physical properties of the water. Here they presented a new technique called hybrid Contrast Limited Adaptive Histogram Equalization (CLAHE) color spaces that specifically developed for underwater image improvement. The technique operates CLAHE on RGB and HSV color spaces and both results are joint together using Euclidean rule. Tentative results show that the future approach considerably improves the visual quality of underwater images by enhancing contrast, as well as dropping noise and artifacts.

Shamsuddin, N et al. [2] developed a technique on "Significance level of image enhancement techniques for underwater images,". Underwater imaging is fairly a demanding in the area of photography specially for low resolution and normal digital camera. There are some problems arise in underwater images such as partial range visibility, low contrast, non identical lighting, blurring, intense artifacts, color diminish and noise. This research concentrated on color diminished. Major application of typical computer vision techniques to marine imaging is mandatory in dealing with the thought problems. Both automatic and manual level methods are used to record the mean values of the stretched histogram.

Ying-Ching Chen et al [3] researched on "Underwater Image Enhancement by Wavelength Compensation and Dehazing,". Where light scattering and color modify are two main sources of alteration for underwater shooting. Light scattering is affected by light event on objects reflected and deflected many times by particles present in the water prior to reaching the camera. This in turn lowers the visibility and contrast of the image captured. Color change corresponds to the unstable degrees of reduction encountered by light traveling in the water with diverse wavelengths, depiction ambient underwater environments conquered by a bluish quality. No obtainable underwater processing techniques can handle light dispersion and color change distortions caused by underwater images, and the probable presence of false lighting concurrently. This literature proposed a novel systematic come up to to improve underwater images by a de-hazing algorithm, to give back the attenuation difference along the broadcast path, and to take the pressure of the possible presence of an false light source into consideration. Previously the deepness map, i.e., distances between the objects and the camera, is expected, the foreground and background within a view are segmented. By managing the effect of artificial light, the haze occurrence and inconsistency in wavelength attenuation along the underwater broadcast path to camera are corrected. Secondly, the water deepness in the image scene is predictable according to the remaining energy ratios of diverse color channels obtainable in the background light.

Jinbo Chen et al [4] proposed "A detection method based on sonar image for underwater pipeline tracker,". The surveillance and inspection of underwater pipelines are carried out by operators who drive a remotely operated underwater vehicle (ROV) with camera mounted on it. Though in extremely turbid water, the camera cannot capture any scene, even with supplementary high-intensity light. In this case the optical detection devices are unable to complete the surveillance task In recent years, forward looking sonar is broadly applied to the underwater examination, which is not subject to the control of light and turbidity. So it is appropriate for the inspection of pipelines. But the active change of ROV by the water flow will show the way to the aim to escape from the sonar image effortlessly. In adding up, the sonar image is with high noise and little contrast. It is difficult for the operator to identify the pipeline from the images. Furthermore, the observation of underwater pipelines is deadly and time unbearable and it is easy to create mistakes due to the exhaustion and interruption of the operator. Then, the study focuses on rising image processing algorithms to distinguish the pipeline repeatedly. By means of the proposed image processing technique, firstly the images are improved using the Gabor filter. And then these images are useful for an edge detector. Lastly the parameters of the pipeline are designed by Hough transform. To decrease the search area, the Kalman filter is explored to forecast the parameters of the pipeline on the next picture. And the research is shown the vision system is on hand to the observation of underwater pipelines.

Iqbal, K et al [5] worked on "Enhancing the low quality images using Unsupervised Colour Correction Method,", The affected underwater images reduced contrast and non-uniform color cast because of the absorption and scattering of light rays in the marine environment. For that they proposed an Unsupervised Colour Correction Method (UCM) for underwater image quality enhancement. UCM is based on color matching, contrast improvement of RGB color model and contrast improvement of HSI color model. Firstly, the color cast is concentrated by equalizing the color values. Secondly, an improvement to a contrast alteration method is useful to increase the Red color by stretching red color histogram towards the utmost , similarly the Blue color is concentrated by stretching the blue histogram to the minimum. Thirdly, the Saturation and Intensity parts of the HSI color model have been useful for contrast correction to enlarge the true color using Saturation and to address the illumination problem through Intensity.

III. PROPOSED METHODOLOGY

Underwater images are degraded due to scatters and absorption, resulting in low contrast and color distortion. In this project, we proposes a super resolution (SR) of underwater images is proposed. The traditional approach of preprocessing the image using an SR method, has the limitation that most of the high-frequency information is lost during descattering. Consequently, we propose a novel high turbidity underwater image SR algorithm. we apply a convex fusion rule for recovering the final HR image. The super-resolved images have a reasonable noise level after descattering and demonstrate visually more pleasing results than conventional approaches.

The principal idea of image super resolution is to reconstruct an HR image using interpolation and reconstruction of LR image patches, learning, and indexing for the best matching patches as the HR map. In this paper, we focus on a single-image SR method. As mentioned in the introduction, according to the source of training data, single-image SR can be summarized to 3 principal categories.

A. External Database-Driven SR

These kind of methods use learning algorithms to study the LR-HR mapping from an existing LR-HR database. There are many learning algorithms for super-resolving LR images, such as nearest neighbor, kernel ridge regression, sparse coding, manifold learning, and CNNs. The principal challenge is how to model the patch space effectively. Instead of studying a global mapping over the entire database, some models attempt to reduce computational complexity by partitioning or pre-clustering the external database. Other approaches such as dimensionality reduction and higher-level features extraction are also used for learning LR-HR mapping.

B. Internal Database-Driven SR

Glasner *et al.* proposed a self-similar patch-based SR algorithm using a natural statics model. Freeman and Fattal determined further that self-similar patches is existed in spatial neighbor patches. Gao *et al.* λrst introduced sparse neighbor embedding for searching self-similar patches. Singh *et al* used the self-similarity ideas for solving noisy image SR.

C. Unified Database-Driven SR

Singh and Ahuja proposed a sub-band texture patterns similarity-based method for SR. Zhu *et al* used optical λow-based patch deformation as a dictionary searching rule. Huang *et al.* proposed a transformed self-exemplars method for single-image SR. Textures can be recovered well through the use of geometric variation.

IV. PROPOSED ALGORITHM

1.Initial
Estimate I` by using NLM to denoise input image Y λ
Estimate transmission tλ and ambient light Aλ from I` using color lines
Descatter I` through an underwater dark channel prior
2. Second round estimation of Iλ
3. Iterate between the estimates for Iλ and B λ until the minimum mean square error (MSE) is reached
While MSE ≥ MSE min
do Estimate I`λ using B` λ (Eq. 1)
Estimate B` λ using I`λ (Eq. 2)
end while

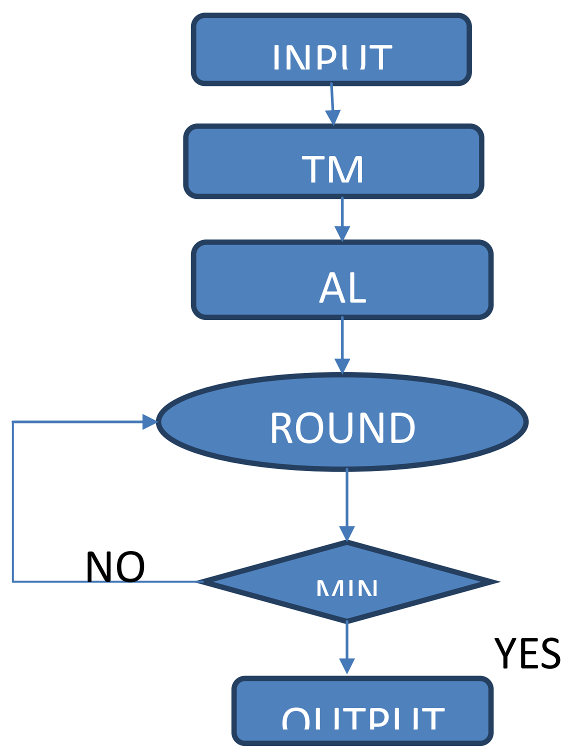

FIG. Proposed Flowchart

Considering that scattering and noise are included in underwater imaging, the observation model is

$$Y_\lambda(x) = DLI_\lambda(x) + n, \lambda \in \{r, g, b\} \quad (1)$$

where $Y\lambda(x)$ is the LR underwater image, $I\lambda(x)$ is the HR underwater image, the matrices D and L represent down sampling and blurring, respectively, and n is the noise generated.

The SR reconstruction problem is to estimate the underlying HR image $I\lambda(x)$ of $Y\lambda(x)$. We assume the noise to be independent and identically distributed (I.I.D.), with variance λ2.

Considering that the HR image $I\lambda(x)$ contains scatters, (1) can be written as

$$Y_\lambda(x) = DL\,(J_\lambda(x)t_\lambda(x)+(1-t_\lambda(x))A_\lambda) + n,\ \lambda \in \{r, g, b\}$$

where $J\lambda(x)$ is the clean image, $t\lambda(x)$ is the transmission map, and $A\lambda$ is the ambient light. Assuming that the ambient light and transmission map are known.

A. Non-local means(NLM)

Non-local means is an algorithm in image processing for image denoising. Unlike "local mean" filters, which take the mean value of a group of pixels surrounding a target pixel to smooth the image, non-local means filtering takes a mean of all pixels in the image, weighted by how similar these pixels are to the target pixel. This results in much greater post-filtering clarity, and less loss of detail in the image compared with local mean algorithms.

If compared with other well-known denoising techniques, non-local means adds "method noise" (i.e. error in the denoising process) which looks more like white noise, which is desirable because it is typically less disturbing in the denoised product.[2] Recently non-local means has been extended to other image processing applications such as deinterlacing[3] and view interpolation.

B. Transmission Map Estimation

The estimation of transmission map is the most important step for foggy scene rendering and consists in image segmentation, initial map estimation based on MRF, and refined map estimation using bilateral filter.

The transmission map describes the portion of the light that is not scattered and reaches the camera. Since the map is a continuous function of depth, it thus reflects the depth information in scene. Koenderinkexperimentally measured the human's ability to infer depth from an image, which shows that people cannot determine the relative depth of two points unless there is some visible and monotonic surface that connects them. Therefore, image segmentation technique is used here for estimating the transmission map and enhancing our knowledge of the image structure. The advantage of this technique is that it can often group large homogeneous regions of the image together while dividing heterogeneous regions into many smaller parts.

Mean-shift (MS) algorithm as a classical image segmentation technique is a robust feature-space analysis approach. It can significantly reduce the number of basic image entities, and due to the good discontinuity preserving filtering characteristic, the salient features of the overall image are retained. Besides, it is particularly important in the partitioning of images, in which only several distinct regions are used in representing different scenes such as sky, mountain, building, lake, and animal, whereas other information within a region is often less important and can be neglected. All these features are very useful for acquiring the relative depth information of scene objects. Thus, MS method is used as the first step to estimate the transmission map.

C. Ambient Light Estimation

The first step applied to the proposed change detection process focuses on correcting the differences in ambient illumination. Variations in global luminance when no other changes occur, are accurately detected with the use of image histograms. A change in the global illumination of an image causes shifting of its histogram towards brighter or darker regions. Therefore, one may expect that, with no content changes present, all pixels of the histogram of the image difference would concentrate in one peak. In practice, the noise effect dictates that the largest percentage of pixels will spread in a region around the histogram peak. The extent of this region depends on noise variance.

In real conditions, the difficulty that a change detection application encounters in luminance normalization is the fact that it needs to perform tracking of ambient luminance variations when both illumination and content changes exist. It is possible that content changes will introduce additional peaks to the histogram of the image difference. In such cases, plain peak detection does not suffice.

It is based on the assumption that there's no content change that occupies more than half of the image plane and causes homogeneous change of brightness to its entire extent at the same time. This assumption is valid in most cases and fails in the exceptional case of large objects with homogeneous luminance covering regions of also homogeneous luminance. The noise influence dictates that a large percentage of the image difference pixels will be strongly concentrated to a region around the peak of the histogram with index that lies close to the luminance offset. Therefore, one may take advantage of the fact that the peak corresponding to the luminance offset will be characterized by larger pixel concentration compared to peaks caused by content changes. Consequently, instead of the amplitude of a specific peak of the dress the issues of light temperature change and a problem of unequal change of ambient.

The proposed technique in the present the histogram, the amount of pixels concentrated to its neighbourhood is considered a reliable criterion for luminance difference detection. The aforementioned process can also be used to ad white balance readjustment. These scenarios represent minance between the colour channels, therefore they constitute a problem of a similar nature. In order to cope with such changes, it is enough to apply the luminance correction technique on each colour channel of the image difference independently.

V. RESULT AND DISCUSSIONS

Matlab tool has been used to evaluate performance of our proposed algorithm figure shows coreesponding ouputs and psnr improvement

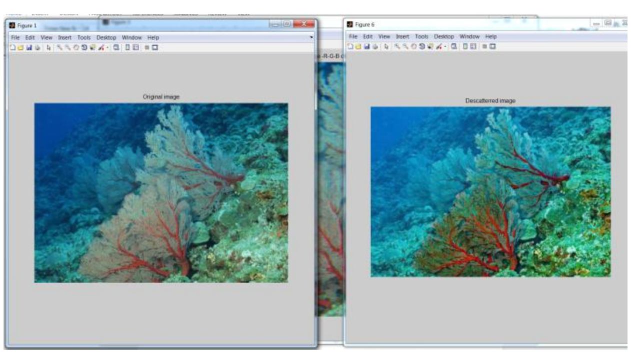

Fig output image

Table psnr comparison

s.no	Dataset image	psnr
1	ANCUTI3	27
2	ANCUTI1	27
3	REEF1	20.5

VI. CONCLUSION

In this project, we presented SR method for recovering distorted images in high turbid water. We have overcome the noise or artifacts in high resolved scattered images. The HR image of scattered and descattered images is obtained using a self-similarity SR algorithm. Then, a proposed convex fusion rule is applied to recover the final HR image. The super-resolved images have a reasonable noise level after descattering and demonstrate visually more pleasing results than images obtained using conventional approaches.Furthermore, numerical metrics demonstrated that the proposed algorithm shows consistent image improvement, with significant improvement for the edges

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