# Underwater Image Restoration Using UICCS Method in Matlab

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*Abstract*— **Due to absorption and scattering of underwater the images obtained suffers an information loss. The study of underwater is very important to find the unfound many algorithms have been derived to enhance an underwater image but no method gives a clear vision of human eye. Many methods found suffers a disadvantage that the clarity reduces as the depth of the water increases this is due to the fading of colours in underwater. To solve this problem, we get into a non-reference underwater image enhancement method the UICCS method. The three main attributes of an image are its colour contrast and sharpness. In this method we modify the attributes of the image step by step to attain a clear image. The results of this experiment demonstrate clearly that this method produces an output image with a high information the measures are applied to underwater images to show their importance in practical application. This project solves this problem my a simple and easy methodology with changing the three main attributes of an image thus enhancing the information of the image.**

*Index Terms*— **Absorption, Scattering, Clarity, Enhancement, Algorithms, Underwater image, Human eye, Attributes, methodology.**

## I. INTRODUCTION

Image processing is the field of signal processing where both the input and output signals are images. Images can be thought of as two-dimensional signals via matrix representation, and image processing can be understood as applying standard one dimensional signal processing techniques to two-dimensional signals. Image processing is a very important subject, and finds applications in such fields as photography, satellite imaging, medical imaging, and image compression, just to name a few. In the past, image processing was largely done using analog devices. However, as computers have become more powerful, processing shifted toward the digital domain. Like one-dimensional digital signal processing, digital image processing overcomes traditional analog "problems" such as noise, distortion during processing, inflexibility of system to change, and difficulty of implementation. The image processing technique we will be implementing will be uiccs. As the board we have does not support a direct connection for the input image, we will use MATLAB to output the image as a matrix and store it in the data memory of the DSP. To do this, we will use the parallel port connection to get our input data into the board. The DSP will then do the processing and write the output data in the program memory. We extract the output data and go back to MATLAB to analyse the results there exist many constraints in underwater imaging.

First, due to the medium, scattering always causes a blurring effect in underwater photography; this rarely occurs in land photography. Second, wavelength absorption usually causes a colour reduction in the captured images, which rarely occurs in air. Third, except for electronic noise, the sediments in the water also affect high dimensional imaging. Another problem occurs because artificial lighting is widely used for underwater photography, and this non-uniform lightingcauses vignetting in captured images. Furthermore, the flickering affects always exist in sunshine day. This will cause the captured imageswith strong highlights intheshallow ocean. Consequently, underwater images have specific characteristics that need to be taken into account during gathering and processing. Common issues with underwater images, such as light attenuation, scattering, non-uniform lighting, shadows, colour shading, suspended particles, or the abundance of marine life, can be overcome via underwater optical image processing.

The volume scattering function describes the angular distribution of light scattered by the suspension of particles in a direction at a given wavelength. Scatters redirect the angle of the photon path; absorption removes the photons from the light path. Absorption in pure water indicates that blue wavelengths are more sensitive to absorption than red wavelengths. However, in phytoplankton water, red wavelengths are not terminated more than blue wavelengths. Therefore, it is difficult to measure absorption rates in practice. On the other hand, the wavelength absorption is relayed on the geographic location of the seawater. Different salinity of seawater has different wavelength absorption coefficients.

Underwater vehicles are used to survey the ocean floor, much often with acoustic sensors for their capability of remote sensing. Optical sensors have been introduced into these vehicles and the use of video is well integrated by the underwater community for short range operations. However, these vehicles are usually remotely operated by human operators: the automated processing and analysis of video data is only emerging and first suffers from a poor quality of the images due to specific propagation properties of the light in the water. Underwater cameras are widely used to observe the sea floor. They are usually included in autonomous underwater vehicles (AUVs), unmanned underwater vehicles (UUVs), and in situ ocean sensor networks. Despite being an important sensor for monitoring underwater scenes, there exist many issues with recent underwater camera sensors. Because of light's transportation characteristics in water and the biological activity at the sea floor, the acquired underwater images often suffer from scatters and large amounts of noise.

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Over the last five years, many methods have been proposed to overcome traditional underwater imaging problems. This paper aims to review the state-of-the-art techniques in underwater image processing by highlighting the contributions and challenges presented in over 40 papers. We present an overview of various underwater image-processing approaches, such as underwater image de-scattering, underwater image colour restoration, and underwater image quality assessments.

## II. LITERATURE SURVEY

Asurvey was done among different proposed methods to obtain a clear vision about the problems stated. Most existing no reference image quality metrics were developed for measuring the grayscale image quality of jpeg-2000 coded images which losses information due to blurring and ringing the widely used quality metrics for grayscale images are contrast or edge sharpness. measuring the perceived quality of image is extremely difficult because of human vision is highly no linear for different colours. Recently there have been many software based approaches to underwater imaging. depending on the outcome of the results we can divide these to two different methods reference method and non-reference method. Reference method uses a reference image with a raw image to find the information where the non-reference method analyses the size, pixel ratio histogram qualities of the image there are many proposals for nonphysical methods.

Galdran at el. proposed a method to solve the scattering ad noise problem simultaneously and proposed a viable kernel size de-scattering method after de scattering some halos and artefacts remain in the image a light attenuation inversion after processing the rgb colour space contraction using quaternions. An underwater image quality assessment is also important to measure the performance of different underwater image processing methods the major disadvantage is that histogram equalization to address non uniform lighting and haze. In many cases local histogram equalization to address non-uniform lighting and haze in many cases local histogram equalization does not perform well in very darkness

Lu et al [1] proposed a single image dehazing method using depth map refinement. The improved bilateral filtering can smooth the depth map, while there are some residual noises exist on the image. As a light absorption method Torres-mendez et al proposed a Markov random filed mrf learning method to estimate the related colour value of each pixel of hyper spectral imaging and mathematical stability model to compare the attenuation coefficients using depth map.

Zuiderveld et al [2]. proposed contrast limited adaptive histogram equalization (CLAHE) to adjust the target region according to an interpolation between the histograms of neighbouring regions. However, non-uniform light remains on the processed image, because it operates on local regions instead of entire image. Inspired by HDR imaging, in high turbid water, the espouse fusion method cannot remove the scatter well.

Liu et al [3] measured the PSF and MTF of seawater in the laboratory by means of the image transmission theory and used Wiener filters to restore the blurred underwater images. The degradation function is measured in a water tank. An experiment is constructed with a slit 4 image and a light source. In a first step, one dimensional light intensity distribution of the slit images at different water path lengths is obtained. The one dimensional PSF of sea water can be obtained by the deconvolution operation. According to the property of the circle symmetry of the PSF of seawater, the 2-dimensional PSF can be calculated by mathematical method. In a similar way, MTFs are derived.

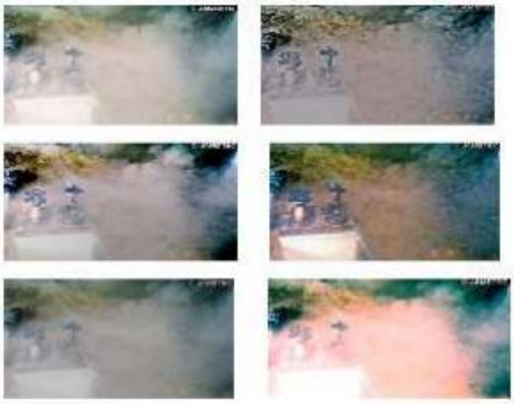

Fig 1 enhancement of underwater image by dehazing method

Garcia et al [4]in this paper, we presented a comprehensive review of underwater image processing. We divided the underwater image processing methods into two categories according to their imaging types. The state-of-the-art approaches of the two classes were discussed and analysed in detail. For software- based underwater image processing, wavelength compensation approach, e.g. physical model, non- physical model and colour reconstruction approach are discussed. Finally, the quality assessment methods and future trends are summarized. One of the leading methods refers to bcc estimation which was developed by the

Cifuentes et al[6] used as a frame work eco estimate physiological factors concerning the carrying capacities in monte hermoso beach this frame work estimates the maximum number of people that an area can support considering Its physical and management conditions as mentioned above three levels of carrying capacities are mentioned physical carrying capacity pcc real carrying capacity rcc and effective carrying capacity 5 pcc considers the maximum limit of visitors in space during a specific time rcc is maximum limit of visitors in the space during a specific time rcc is the maximum number of visitors that can support based on rcc and management capacity PCC=A/Au * Tf Where a is the size of the study area Au represents the area availability and Transfer function is the number of times that a person is able to visit the area in a day A in fact may vary widely according to tidal conditions in the study reportedly here we consider the worst case scenario that is area in high tide .the occupancy criteria were based on the model established by normacubana which considers three possible situation high, medium, low occupancy with space for each visitor of 5, 10,or 25m respectively .

## III. EXISTING METHODOLGY

*Under water degradation:*The absorption and scattering of light in influence the overall performance of the underwater imaging system including absorption and scattering by phytoplankton, absorption by coloured dissolved organic matter (CDOM) and finally, light scattering by total suspended matter. Forward scattering (randomly deviated light on its way from an object to the camera) generally leads to blurring of the image features On the other hand, backward scattering (the fraction of the light reflected by the water towards the camera before it actually reaches the objects in the scene) generally limits the image contrast, generating a characteristic veil that superimposes itself on the image and hides the scene. Floating particles (marine snow) increase the absorption and scattering effects as a result of different absorption spectra, the reflection of colours will vary between different water types depending on the contribution from the different Inside Optical Parameters (IOP). The concentration of IOP and the distance to the object of interest are therefore important factors when evaluating image quality,the visibility range can be increased with artificial lighting but these sources not only suffer from some scattering and absorption

*De scattering technique:*De-scattering[4] recently, there have been many software-based approaches to underwater imaging. Depending on the outcome of the results, we can divide these approaches into two methods Wavelength compensation (sediment scattering) and colour reconstruction (light absorption). To solve the scattering problem, many researchers have proposed both physical model-based methods and non-physical model-based methods. Traditional physical model-based methods are as follows Then, they employed guided filtering to refine the depth map and obtain clear images. This method can achieve real-time processing a wavelength compensation and scattering method for underwater image restoration. It is the first time to consider the wavelength absorption in the imaging model. This method is used to find some flickers exist in captured underwater images and proposed a corresponding robust ambient light estimation method and underwater median dark channel prior for de-scattering.

Fig 2 Experimental Results of Traditional Physical Model based Methods.

Underwater Image Colour Restoration:As a light absorption recovering method Torres-Mendez et al. proposed a Markov Random Field (MRF) learning method to estimate the related colour value of each pixel. Alhen et al [3] developed a hyper spectral imaging and mathematical stability model to compute the attenuation coefficients using the depth map. A light attenuation inversion after processing the RGB COLOUR space contraction using quaternions. Lu et al. modelled the spectral response function of a camera as a function of the wavelength of the light to recover the contrast of the COLOUR the experimental result is shown in Figure 6. In this method, the artificial vignetting has also been solved.

Fig 3 experimental results of underwater image colour restoration

*Anisotropic regularization of the Perona–Malik process:*In[5] the interior of a segment the nonlinear isotropic diffusion equation behaves almost like the linear diffusion filter but at edges diffusion is inhibited. Therefore, noise at edges cannot be eliminated successfully by this process. To overcome this problem, a desirable method should prefer diffusion along edges to diffusion perpendicular to them. Anisotropic models do not only take into account the modulus of the edge detector $\nabla u\sigma$, but also its direction. To this end, we construct the orthonormal system of eigenvectors v1, v2 of the diffusion tensor D such that they reflect the estimated edge structure: v1 k $\nabla u\sigma$, v2 $\perp\nabla u\sigma$. In order to prefer smoothing along the 8 edge to smoothing across it, Weickert proposed to choose the corresponding eigenvalues $\lambda1$ and $\lambda2$ as $\lambda1(\nabla u\sigma) := g(|\nabla u\sigma|\ 2\ )$, $\lambda2(\nabla u\sigma) := 1$. Section.

Hence, this model behaves really anisotropic. If we let the regularization parameter $\sigma$ tend to 0, we end up with the isotropic Perona–Malik process. Another anisotropic model which can be regarded as a regularization of an isotropic nonlinear diffusion filter has been described in Anisotropic models for smoothing one-dimensional objects A second motivation for introducing anisotropy into diffusion processes arises from the wish to process one-dimensional features such as line-like structures. To this end, Cottet and Germaine constructed a diffusion tensor with eigenvectors as in (1.47) and corresponding eigenvalues $\lambda1(\nabla u\sigma) := 0$, (1.50) $\lambda2(\nabla u\sigma) := \eta|\nabla u\sigma|\ 2\ 1 + (|\nabla u\sigma|/\sigma)\ 2\ (\eta > 0)$. (1.51) This is a process diffusing solely perpendicular to $\nabla u\sigma$. For $\sigma \to 0$, we observe that $\nabla u$ becomes an eigenvector of D with corresponding eigenvalue 0. Therefore, the process stops completely. In this sense, it is not intended as an anisotropic regularization of the Perona–Malik equation.

*Background Subtraction:*Background subtraction removes a low-frequency 2D background from each slab of an image using the rolling-ball method. The method involves considering the 2-D grayscale image as a 3-D surface, where height is given by pixel intensity. The surface mapped by the centre of a ball as it rolls over the 3-D surface identifies a smoother background surface (after adjusting its height by the ball radius) which ignores features which are narrower than the ball's radius. These narrow features are left after subtraction of the background. If the 'Light Background' option is not checked (implying a dark background,) then the ball rolls along the underside of the 3-D surface and positive-going narrow features are left in the image after subtraction. If 'Light Background' is enabled the ball would roll along the upper side of the 3-D surface and negative going narrow features are left in the image.

## IV. PROPOSED METHODOLOGY

By analysis of all the underwater image restoration methods the major methods deal with the adjustment of the parameters like the contrast, the brightness, sharpness etc. so we have proposed a technique where we only modify the chrominance and saturation values of the three main parameters hence obtaining a clear image with good information to achieve this the image characteristics must be studied like the pixel ratio of the image the size of the image the noise that the image suffers etc.

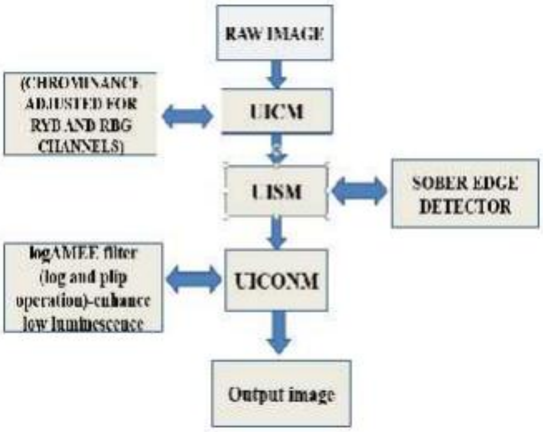


Fig 4 Flow chart of UICCS method

Researches shows that colourfulness can be represented effectively with functions of image statistical values. Practically, users have the flexibility to choose which colour spaces and which order statistical values to use, as well as the design of the fusion functions and the weighting coefficients. As mentioned before, the HVS captures colours in the opponent colour plane the overall colourfulness metric used for measuring underwater colourfulness is demonstrated in UICM. The linear combination coefficients are obtained by linear regression. It is seen that the coefficient for the mean term is negative and the coefficient for the variance is positive, which confirm the analysis of the mathematical meaning of the two terms. Table I shows the sensitivity of the UICM for an underwater image in suffers from severe 10 green colour casting problem. . The UICM assigns a greater colourfulness measure value for the enhanced image. The results show that with image statistical values, the UICM successfully measures the colourfulness attribute for underwater images.

Sharpness is the attribute related to the preservation of fine details and edges. For images captured under the water, severe blurring occurs due to the forward scattering. This blurring effect causes degradation of image sharpness. To measure the sharpness on edges, the Sobeledge detector is first applied on each RGB colour component. The resultant edge map is then multiplied with the original image to get the grayscale edge map. By doing this, only the pixels on the edges from the original underwater image are preserved. It is known that the enhancement measure estimation (EME) measure is suitable for images with uniform background and shown no periodic patterns. Accordingly, the EME measure is used to measure the sharpness of edges. The de scattering algorithm in aims to remove the scattering effect of water. Contrast has been shown to correspond to underwater visual performance such as stereoscopic acuity. For underwater images, contrast degradation is usually caused by backwardscattering. In this paper, the contrast is measured by applying the log AMEE measure on the intensity image as shown in where an image is divided into blocks, and are the PLIP operations introduces the entropy-like operation to the traditional Again measure of enhancement by entropy (AMEE), which is formulated as the average Michaelson contrast in image local regions. The PLIP operations, which provide the nonlinear representations that are consistent with human visual perceptions, are also used in the logAMEE formulation. It has been demonstrated that underwater images can be modelled linear superposition of absorbed and scattered components. Besides, it is known that the absorption and scattering effects cause colour, sharpness, and contrast degradation. Therefore, it is reasonable to use the linear superposition model for generating the overall underwater image quality measure as well.

The selections of these parameters are application dependent. For example, for underwater image colour-correction applications, more weights should be applied to the UICM, while in enhancing underwater image visibilities, the contrast term UIConM and the sharpness term UISM are more significant. If two of the parameters are zero, the quality measure UICCS reverts to an underwater image attribute measure. For general applications, the combination coefficients are obtained using multiple linear regression (MLR). The fusion-based enhancement algorithm effectively removes the background casting The UICM assigns a greater colourfulness measure value for the enhanced image.

From the above flowchart we understand that the input image is obtained from the source and hence contrast is adjusted by changing the values of the chrominance of red yellow green and red yellow blue channels because red image suffers a decrease in contrast as the depth of the image increases due to its low wavelength followed by yellow and green. The next part moves towards the sober edge detector the sharpening of the images represents the sharpening of the edges depending upon the quality and pixel ratio the sober edge detector is selected here one can an also use other models of edge detectors to find and enhance the image. The last step is the enhancement of the contrast where the contrast is modified using logamee filter logamee filter is selected considering for the change in the properties of the red green blue and red green yellow channels. The main aim of sober edge detector is to enhance the luminance of the image. Hence these three images which are separated into different blocks are reunited together.

## V. SOFTWARE IMPLEMENTATION

*Matlab coding:*

```
a = gpuArray(imread('123.png'));
figure imshow(I)
b = imadjust(a);
figure imshow(b)
title ('colourful Image');
c = imadjust (b, [0.3 0.7], []);
figure imshow(c)
d=imcontrast(c)
```

```
imshow(d)
title ('contrast Image');
e=imsharpen(d,'Radius')
imshow(e)
title ('Sharpened Image');
edge Threshold = 0.4;
amount = 0.5;
e = local contrast ( amount)
inshow(e)
title ('final Image'); 13
```

## VI. SIMULATION AND RESULT

The above coding represents the conversion for the raw image to enhanced image recovering 80 percent of information the input coordinates of the functions can be also changed to get a better output. Depending upon the pixel ratio the intensity luminescence chrominance the values to the predefines function can be varied and different forms of output can be obtained for different kinds of input raw image

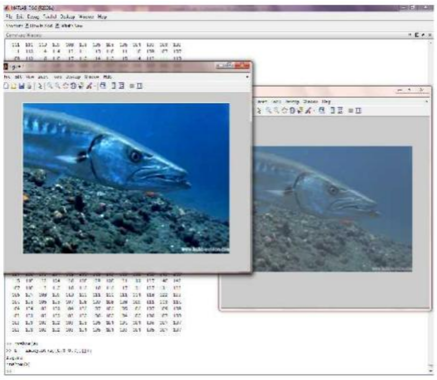

Fig 5 Simulink model for image conversion using matlab

The above image shows the simulation of underwater image processing by matlab coding. The above raw image is converted into various images by changing the values of the input function. The below images represent the output for differentimage processing functions of the matlab.The measures are also important in the design of underwater image processing algorithms, which can be used in monitoring sea life, accessing geologicaland biological environment information, as well as port and security inspection.

Fig 6 Raw image to clear image by contrast adjustments

Fig 7 Raw image to clear image by histogram adjustments

Fig 8 Raw image to clear image by colour adjustments

The low visibility and strong colour casting bring difficulties for the underwater searching and inspection. There have been lots of attempts to enhance the visibility of single degraded underwater colour images, such as defogging based algorithms contrast stretching methods and the newest image fusion enhancement. Images processing of such methods suffer a serious disadvantage that the depth and lighting setup affects the quality of the image

## VI. CONCLUSION

In this paper, a new no reference underwater image quality measure UICCS was presented. The UICCS comprises a colourfulness measure (UICM), a sharpness measure (UISM), and a contrast measure (UIConM). Each attribute measure can be used separately for specific underwater image processing tasks. Several properties, such as luminance and contrast masking, the colour perception property, and relative contrast sensitivity, are incorporated in the formulations of the measures. Therefore, comparing with other quality measures used in existing underwater image processing algorithms, the UICCS has stronger correlation with human visual perception, and it effectively measures the underwater image quality in a complete and comprehensive means. This method is a simple method which gives 70 percent of information from the raw image only by adjustments of colour, sharpness and contrast. A first-of-kind underwater colour image quality evaluation metric is proposed.

## VII. RESULT

The results indicate that the proposed metric has fast processing time, which makes it applicable for real-time image processing. It is able to successfully predict the relative distortion with similar scenes and the difference between enhancement results. It also shows better correlation with subjective evaluation. The proposed approach is promising in terms of both computational efficiency and practical reliability for real-time applications and most importantly it is a meaningful structural model to realize effective underwater colour image quality evaluation for different applications.

## REFERENCES

[1] [1] M. Yang and Z. Ji, "Underwater COLOUR image enhancement based on quaternion and fuzzy morphological sieves," Chin. J. Sci. Instrum. , vol. 33, no. 7, pp. 1601–1605, September 2012.

[2] [2] M. Yang and C.-L. Gong, "Underwater image restoration by turbulence model based on image quality evaluation," Int. J. Advancements Comput. Technol., vol. 4, no. 15, pp. 38–46, December 2012.

[3] [3] M. Yang and Z. Ji, "Quaternion COLOUR morphological filters for underwater images," Adv. Sci. Lett., vol. 7, no. 5, pp. 557–560, November 2013.

[4] [4] R. Schettini and S. Corchs, "Underwater image processing: State of the art of restoration and image enhancement methods," EURASIP J. Adv. Signal Process., vol. 2010, p. 14, Jan. 2010.

[5] [5] R. A. Pramunendar, G. F. Shidik, C. Supriyanto, P. N. Andono, and M. Hariadi, “Auto level COLOUR correction for underwater image matching optimization,” Int. J. Comput. Sci. Netw. Secur., vol. 13, no. 1, pp. 18–23, may 2014.
[6] [6] Z. Wang, A. C. Bovik, H. R. Sheikh, and E. P. Simoncelli, “Image quality assessment: From error visibility to structural similarity,” IEEE Trans. Image Process., vol. 13, no. 4, pp. 600–612, Apr. 2004.
[7] [7] C. Gao, K. Panetta, and S. Agaian, “A new COLOUR contrast enhancement algorithm for robotic Applications,” in Proc. IEEE Conf. Technol. Practical Robot Appl. (TePRA), pp. 42–47 Apr, 2012.
[8] [8] Y. Wang, Q. Chen, and B. Zhang, “Image enhancement based on equal area dualistic subimage histogram equalization method,” IEEE Trans. Consum. Electron., vol. 45, no. 1, pp. 68– 75, Feb. 2013.
[9] [9] M. Kim and M. Chung, “Recursively separated and weighted histogram equalization for brightness preservation and contrast enhancement,” IEEE Trans. Consum. Electron., vol. 54, no. 3, pp. 1389–1397, Aug. 2014.
[10] [10] S.-D. Chen and A. R. Ramli, “Minimum mean brightness error bi-histogram equalization in contrast enhancement,” IEEE Trans. Consum. Electron., vol. 49, no. 4, pp. 1310–1319, Nov. 2014.