VISUALLY AUGMENTED AND COLOUR-CONSISTENT UNDERWATER IMAGE RESTORATION USING RETINAL MECHANISMS

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ABSTRACT:

Since the light is absorbed and scattered while traveling in water, color distortion, under-exposure and fuzz are three major problems of underwater imaging. In this project, a novel retinex-based enhancing approach is proposed to enhance single underwater image. The proposed approach has mainly three steps to solve the problems mentioned above. First, a simple but effective color correction strategy is adopted to address the color distortion. Second, a variational framework for retinex is proposed to decompose the reflectance and the illumination, which represent the detail and brightness respectively, from single underwater image. An effective alternating direction optimization strategy is adopted to solve the proposed model. Third, the reflectance and the illumination are enhanced by different strategies to address the under-exposure and fuzz problem. The final enhanced image is obtained by combining use the enhanced reflectance and illumination.

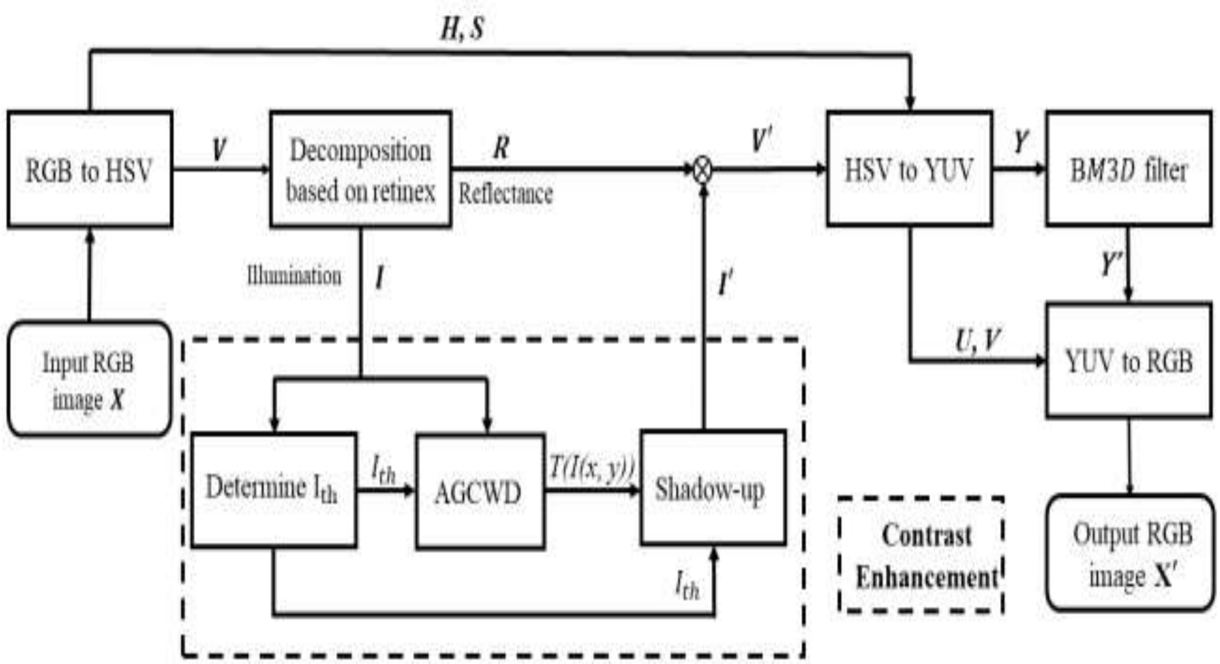
INTRODUCTION:

UNDERWATER images often suffer from noise, color distortion and low contrast, because light is attenuated when it propagates through water. These problems increase the difficulty of various tasks such as automatic fish and plankton detection and recognition. Therefore, many methods have been proposed to recover or enhance the degraded underwater images. The noise reduction methods for underwater images could be roughly classified as wavelet-based and filter-based [2], [3]. Some algorithms consider the forward and backward scattering components for removing the noise and improving the global contrast [4]. The operation of color correction aims to reduce the strong color cast that typically exists in underwater images [5], [6]. Many strategies aim for a visually pleasing result, but without the capability of realizing color constancy (CC) that is required for robust color-vision based applications. A measurement of available visibility would serve to inform the driver that the vehicle speed is not adapted or could even limit the speed automatically depending on speci_c momentary conditions. We have sought to build such a system through use of an onboard camera. The onboard nature of the application however does not allow us from generating, at any point in time, a reference image. Furthermore, by using just a single camera, the depth view of the scene of each image is unknown. Given that we are not actually performing temporal monitoring within the scene, the elements at our disposal for developing the method are restricted, due to the nature of the application context, to the presence of road and sky in the image. The solution proposed herein is able to overcome these obstacles to a large extent. A preprocessing procedure, by means of region growing, enables locating the most pertinent objects in the image for subsequent application of the newly-developed method. The success of this preprocessing step provides direct information on the level of compatibility between the processed image and the set of Koschmieder's Law hypotheses. Our method then makes it possible to recover not only the various parameters of the Koschmieder's Law, but by the same occasion the visibility distance as well. Use of visual sensing techniques to detect low visibility conditions may have a number of advantages when combined with other methods, such as satellite based remote sensing, as data can be collected and processed in real or near real time.

LITERATURE SURVEY:

In [4] C. Busch and E. Debers introduced an approach to determine the visibility range under foggy weather conditions from images of stationary traffic management systems. Aftera manual masking of the road they performed a wavelet based contrast measurement. The image line, upon which no contrast higher than 5% appears, defines the visibility range in the camera image. From the known camera configuration relative to the road a transformation from image to world coordinates was done. In the range from 300 to 1000m the proposed system outputs a visibility range in 50m steps, in the range of less than 300 m in 10 m steps. Even if this system was designed for a stationary use it is interesting in our field of application, as with existing image processing techniques, like an appropriate lane and object detection, it could be applicable for the use in vehicles. In [18] D. Pomerleau introduced a system to estimate the visibility range through the use of a camera mounted inside a vehicle. His system is generic and aims to cover all possible situations of low visibility caused by dazzling, rain, snow or fog. The visibility range is thereby estimated by the attenuation of the contrast along similar road features like lane markings, banquet or even oil stripes. Initially a trapezoid region containing the road ahead is extracted and warped to the bird-eye-view. Then by shifting the rows of the image on this warped view a straight road profile is obtained. The horizontal intensity profile of this image is analyzed at different image rows and from the difference in intensity peaks of the upper and lower rows the contrast attenuation is estimated. This contrast change usually happens around road features like lane markings. In [11] Hautière et al. proposed a method for fog detection form images captured by a camera mounted inside vehicles. It is based on Duntley's law for the contrast attenuation C = C0ekd [15]. Here, C is the perceived contrast at the distance d from an object with the intrinsic contrast of C0 and k is the extinction coefficient that characterizes the visibility conditions.

PROPOSED TECHNIQUE:



Block diagram of the proposed method.

RETINEX THEORY:

Retinex theory is based on the relation, S = R · L, where original image S is the product of illumination L and reflectance R. When the information of only one surround is used for the conversion of each pixel, its approach is called Single-Scale Retinex (SSR) [6]. In SSR, halo artifacts occur unnaturally in the boundary of regions with large gradient values. To solve this problem, Multi-Scale Retinex (MSR) [7] was proposed. However, since a logarithmic transformation is used, MSR still causes a problem that the results do not stabilize due to the influence of noise in dark areas. Simultaneous reflection & illumination estimation (SRIE) [8] and weighted variation model (WVM) [1] are also Retinexbased methods. These methods have a good performance for images without noise, but some strange areas are generated in strong noise environments. Therefore, many outstanding methods [2], [9], [10] have been proposed to improve the quality of images, and preserve more details.

WEIGHTED VIBRATIONAL METHOD:
In this process, a weighted variational model for simultaneously estimating reflectance and illumination is presented. First, by analyzing the characteristic of the logarithmic transformation, we show that the logarithmic transformation is not proper to be directly used as regularization terms. Then, based on the previous analysis, a weighted variational model is introduced for better prior representation and an alternating minimization scheme is adopted to solve the proposed model. Unlike existing variational methods using complex techniques, such as nonlocal techniques [35] and dictionary learning techniques [3], the proposed model can achieve significant improvement by simply weighting the widely used regularization terms. Compared with classical variational models, the proposed model can preserve the estimated reflectance with more details. Moreover, the proposed model can suppress noise to some extent. An alternating minimization scheme is adopted to solve the proposed model. Experimental results demonstrate the effectiveness of the proposed model with its algorithm. Compared with other variational methods, the proposed method yields comparable or better results on both subjective and objective assessments. The physical model of light reflection can be simply described as S = R·L, where S is the observed image, R is the reflectance of the image within the range (0, 1], and L is the illumination within the range (0, ∞). The dot "·" denotes pixel-wise multiplication and all images are vectorized. It follows that S ≤ L. The goal is to estimate the reflectance R and the illumination L from the observed image S. To this end, most variational methods first transform S = R · L into the logarithmic domain, s = r + l, where s = log(S), r = log(R) and l = log(L). Using this logarithmic transformation, the first variational algorithm for this decomposition was proposed in [11]. This approach only models the illumination l and then estimates the reflectance R by exp(s − l) in post-processing. Another variational method [26] considers both illumination and reflectance in the objective function, which is arguably more appropriate. However, the directly estimated reflectance images are typically too smooth and loose much of the desired edges and texture details. In [26], the authors abandon the directly estimated reflectance and instead use exp(s − l). Our goal is to develop an objective function that outputs a usable illumination and reflectance. To this end, we observe that conventional methods use an objective function along the following lines:

$$E(\mathbf{r},\mathbf{l}) = \|\mathbf{l}+\mathbf{r}-\mathbf{s}\|_2^2 + \lambda_1\|\nabla \mathbf{l}\|_2^2 + \lambda_2\|\nabla \mathbf{r}\|_1 \quad s.t.\ \mathbf{r} \le 0 \ \text{and}\ \mathbf{s} \le \mathbf{l}. \tag{1}$$

In this objective function, the logarithmic illumination l uses a squared penalty to enforce spatial smoothness and the logarithmic reflectance r is encouraged to be piece-wise constant using L1-norm.

IMAGE ENHANCEMENT:
The histogram equalization (HE) [11] is one of the most popular algorithms for contrast enhancement [12] and various extended versions of HE have been proposed [5], [13]–[17]. Contrast enhancement using adaptive gamma correction with weighting distribution (AGCWD) [5] aims to prevent overenhancement and under-enhancement caused by using adaptive gamma correction and a modified probability distribution. However, the over-enhancement and the loss of contrast in bright areas are still caused under the use of these histogrambased methods. Some noise hidden in the darkness is also amplified. Because of such a situation, a number of histogrambased contrast enhancement methods have been proposed to prevent the noise amplification. In the methods, a shrinkage function is used for preventing the noise

amplification. Low light image enhancement based on two-step noise suppression (LLIE) [4] uses both noise level function (NLF) and just noticeable difference (JND) for contrast enhancement with noise suppression. Although this method can reduce some noise, it does not preserve details in bright areas as with histogram-based methods. Another way for enhancing images is to use a multi-exposure image fusion method by using photos with different exposures

AGCWD (ADAPTIVE GAMMA CORRECTION WEIGHTED DISTRIBUTION):

As we know that Power-law transformation (PLT) [2] method, in which main drawback is to give the value of gamma manually for image enhancement. This problem solved by the Adaptive gamma correction weighted distribution method. In which the value of gamma is find out automatically with the help of weighted distribution function. Gamma correction techniques make up a family of general HM (Histogram Modification) techniques obtained simply by using a varying adaptive parameter ΄Y (Gamma). The simple form of the transform-based gamma correction is derived by

T(l) = lmax (l / lmax) ΄Y (1)

Where lmax is maximum intensity of the input. The intensity l of each pixel in the input image is transformed as T (l) after utilize the Eq. (1). When the contrast is directly or manually modified by gamma correction then different images will results the same changes in intensity as a result of the fixed parameter. So this problem can be solved by probability density of each intensity level in a digital image can be calculated. As we know that density function of image will be different. So, intensity of each image will be different. The probability density function (pdf) can be approximated by

Pdf (l) = n1 / (MN) (2)

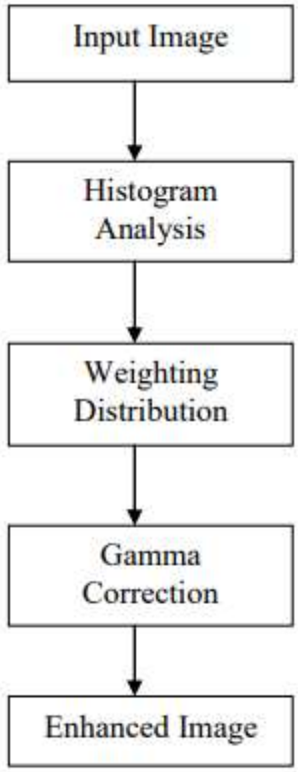
Where n1 is the number of pixels that have intensity l and MN is total number of pixels in the image. The cumulative distribution function (cdf) is based on pdf, and is formulated as:

Cdf (l) = ∑ pdf (k). (3)

After the cdf of the digital image is obtained from Eq. (3) traditional Histogram Equalization (THE) directly uses cdf as

T (l) = cdf (l) lmax. (4)

The flow chart of proposed adaptive gamma correction as given below:



Above figure shows the flowchart of proposed AGCWD [3] method. Digital image used as input. After that the next step is histogram analysis in which RSWHE method is used. In the third step weighted distribution function, the fluctuant phenomenon cab be smoothed, thus reducing the over-enhancement of the gamma correction. And last enhanced image is at the output. The proposed adaptive gamma correction (AGC) is formulated as follows:

$$T\ (l) = l_{max}(l / l_{max})^{Y} = l_{max}(l / l_{max})^{1 -\ cdf\ (l).}$$

The weighted distribution (WD) function is formulated as:

$$Pdf_w\ (l) = pdf_{max} \left(\frac{Pdf(l)\ -\ pdf_{min}}{Pdf_{max}\ -\ pdf_{min}} \right)^{\alpha}$$

Where α is adjusted parameter, in which we give the value of alpha manually. Experimentally we set to 0.5 value of alpha. So, we optimize this alpha parameter in the propose method in next section with the help of RSWHE method. pdfmax is the maximum pdf of the statistical histogram, and pdfmin is the minimum pdf. The modified cdf is approximated by

$$Cdf_w\ (l) = \sum_{l=0}^{l_{max}} pdf_w\ (l)\ \ / \sum pdf_w$$

Where the sum of pdfw is calculated as follows:

$$\sum pdf_w = \sum_{l=0}^{lmax} pdf_w\ (l).$$

Finally the gamma parameter based on cdf of Equation (5) is modified as follows:
΄Y = 1 – cdfw (l). (8)
So, as we can see the upper equations of AGCWD that provides us Adaptive Gamma Correction and enhanced the dimmed and aerial images.

SHADOWUP FUNCTION:

Shadow up function , which consists of a nonlinear part and a linear part, is given by

$$I'(x,y) = \begin{cases} T(I(x,y)) & \text{, if } I(x,y) < I_{th} \\ I(x,y) & \text{, otherwise} \end{cases},$$

where I(x, y) ∈ [0, 255] is the intensity of illumination layer at a coordinate (x, y), T(I(x, y)) is a monotonically increasing function, and Ith is an upper limit of the nonlinear part for avoiding over enhancement in bright areas. Contrast is enhanced only when I(x, y) is less than the threshold value Ith, according to (1). To determine a proper threshold value Ith for illumination layer, we take into account the luminance distribution of the illumination layer. Let it be H = {(x, y) : Ith < I(x, y) < Imax}, where Ith is the th percentile of luminance I(x, y) of the input image, and Imax is the maximum of I(x, y). The threshold value Ith is calculated as follows:

$$I_{th} = 255 - \frac{1}{|H|} \sum_{(x,y)\in H} I(x,y).$$

A threshold value Ith for a bright image becomes smaller than for a darker image. AGCWD is a method to design a function T(I(x, y)). However, AGCWD usually causes a noise amplification problem, because it does not consider the influence of noise included in images [4]. To overcome this problem, both the Retinex theory and Ith are applied to AGCWD in this paper.

DEOISING FILTER:

Image de-noising has a great tradition in the research field of signal processing because of its fundamental role in many applications. In particular, block-matching and 3D filtering (BM3D) [22] is one of the most successful advances. In this paper, BM3D is used as one of noise suppression techniques. Our purpose is not only to enhance contrast with noise suppression, but also to preserve details in bright regions based on Retinex theory. Block-matching and 3D filtering (BM3D) is a 3-D block-matching algorithm used primarily for noise reduction in images.

GROUPING

Image fragments are grouped together based on similarity, but unlike standard k-means clustering and such cluster analysis methods, the image fragments are not necessarily disjoint. This block-matching algorithm is less computationally demanding and is useful later on in the aggregation step. Fragments do however have the same size. A fragment is grouped if its dissimilarity with a reference fragment falls below a specified threshold. This grouping technique is called block-matching, it is typically used to group similar groups across different frames of a digital video, BM3D on the other hand may group macroblocks within a single frame. All image fragments in a group are then stacked to form 3D cylinder-like shapes. The BM3D algorithm has been extended (IDD-BM3D) to perform decoupled deblurring and denoising using the Nash equilibrium balance of the two objective functions.[2]

RSULT:

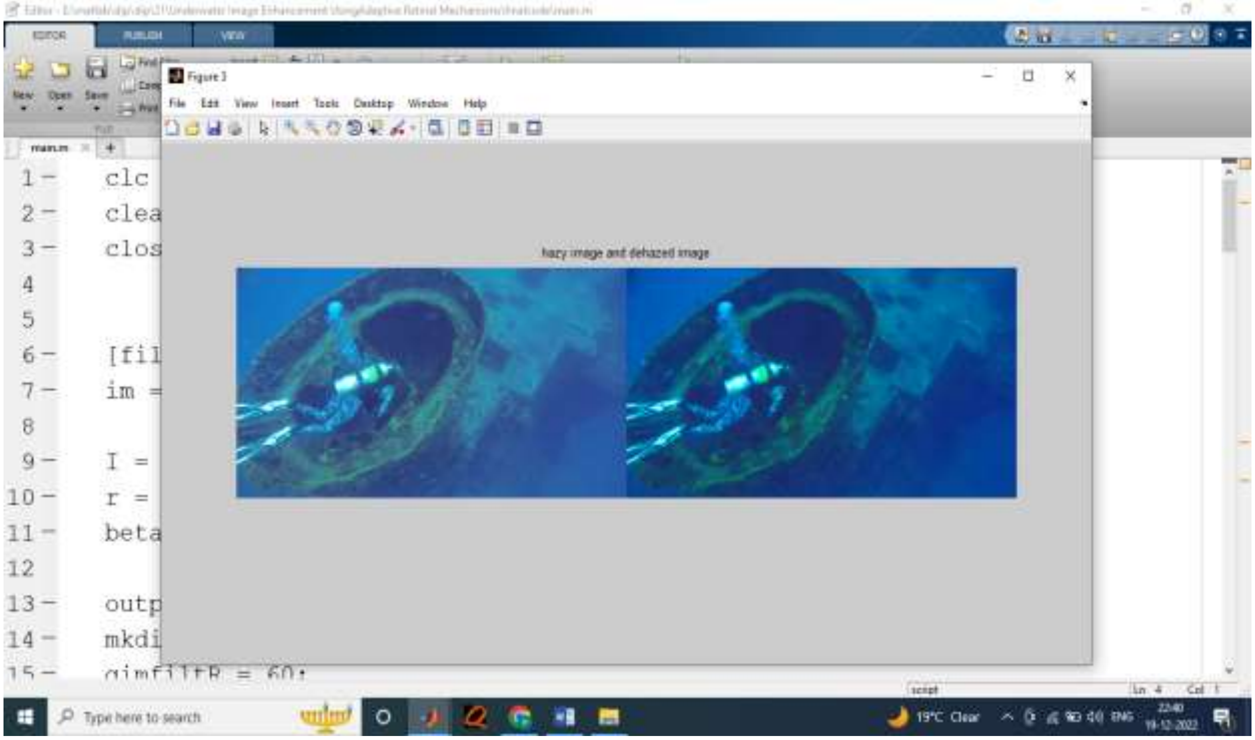


Fig: Input image1, output image1 before and after restoration

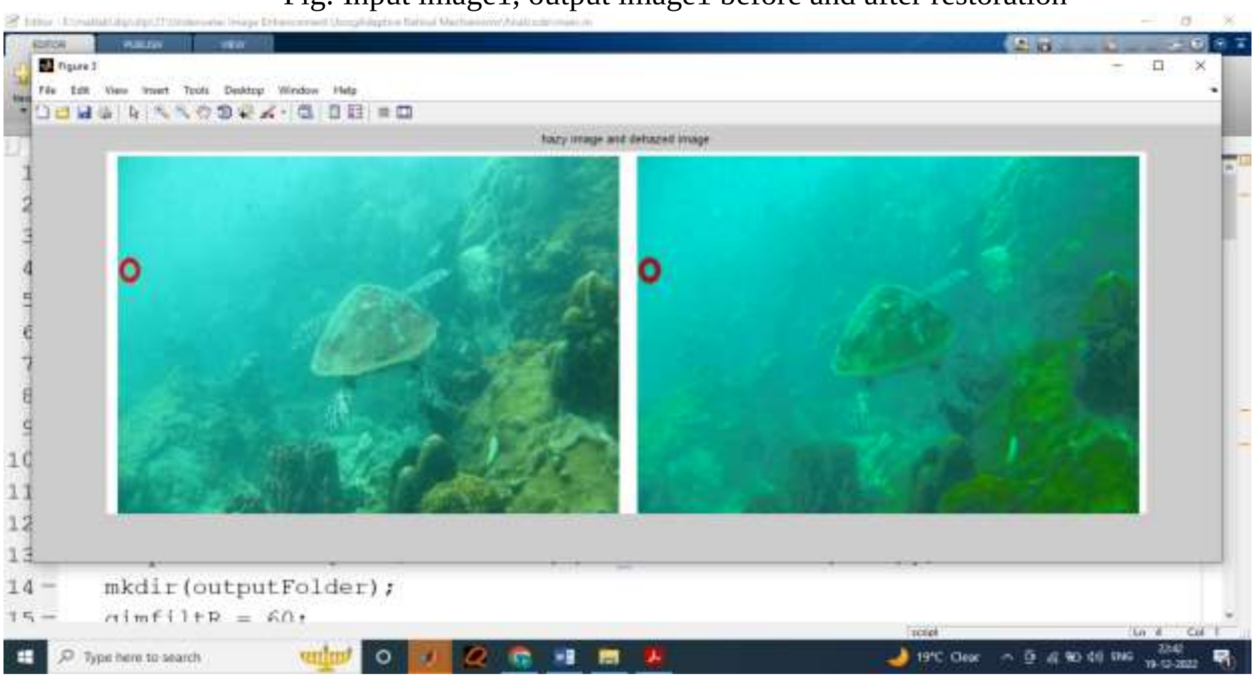


Fig: Input image2,output image2 before and after restoration

CONCLUSION:

In this paper, we propose and evaluate a visibility estimation framework using multiple image datasets captured by visual systems that provides contextual information that can be used to complement current fog prediction systems. We have assessed the potential of a range efficient methods to classify images on the basis of visibility. From these results, and based on the training sets provided, the Joint Histogram method provides the highest classification accuracy, closely followed by....These initial results will be used to further develop an offshore fog detection platform based on image analysis methods.

FUTURE SCOPE:

So in near future, the problem of uneven illumination of the digital fog removal has to be sorted out. To enhance the visibility of image caused by atmosphere suspended particles like dust, haze and fog which causes failure in image processing such as video surveillance systems, obstacle detection systems, outdoor object recognition systems and intelligent transportation systems. And visibility restoration techniques should be developed to run under various weather conditions.

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