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Underwater Image Enhancement using Colour Restoration based on YCbCr Colour Model

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Abstract

In this study, improvement of underwater images via colour re-correction was performed by designing a new method that uses colour restoration based on the integrated colour model with Rayleigh distribution (CRBICMRD). The proposed method was utilised for colour restoration in an image in the RGB model and for colour transformation in YCbCr space, where it processed the Y component. The integrated colour model with Rayleigh distribution was applied. Quantitative analyses indicated that the proposed method outperformed the multi-scale retinex algorithm with colour restoration, unsupervised colour correction method and Rayleigh stretching and averaging image planes by calculating no-reference-image quality assessments. Results indicated that CRBICMRD performed considerably better than the other methods in enhancing underwater images.

Keywords — underwater image processing, image colour restoration, integrated colour model, Rayleigh distribution

1. INTRODUCTION

Image enhancement algorithms are used to increase visibility by increasing contrast or removing distortions in images, such as colour cast. Underwater image enhancement is an important field because of its many applications. Images taken underwater have visible degradation due to light attenuation and scattering effects. When light changes its path whilst travelling in water, scattering occurs due to dissolved chemical compounds, water molecules and suspended particles. Recently, several algorithms are proposed to deal with underwater image enhancement. In [1, 2, 3], the scene depth was derived by the dark channel prior, which was proposed to remove hazy in natural terrestrial images by calculating the amount of spatially homogeneous haze using the darkest channel in the scene. Some algorithms use a prior that exploits the strong difference in attenuation amongst three image colour channels to estimate the depth of the scene and then use the depth map to reduce the effect of water [4]. Eustice et al. [5] proposed an extension method for the MATLAB image processing toolbox. In the current study, we focus on the first extension to apply contrast limited adaptive histogram specification as a pre-processing step. In the previous study, the researchers confirmed that the Rayleigh distribution is ideal for representing underwater images. Many methods, such as in [6], suggested that global histogram equalisation is unsuitable when illumination in an image is unequal and local methods are needed. Previous authors proposed a method of histogram clipping and then equalised contrast by division method. In [7], the integrated colour model (ICM) and the unsupervised colour correction method (UCM) were proposed. In this previous study, the output image in the RGB colour model was stretched over the entire dynamic range. An important algorithm used to improve lighting and contrast is multi-scale retinex (MSR) [8], which was utilised to improve underwater images. Some algorithms have been redeveloped on the basis of trapping and Raleigh function [9] as Rayleigh stretching and averaging image planes (RSAIP). Thus, in the current work, the CRBICMRD algorithm is used to enhance underwater images that are captured in different depths.

2. IMAGE ENHANCEMENT OPERATIONS USING THE PROPOSED METHOD

We propose input colour image \( C(x,y,i), i = 1, 2, 3 \) (red, green, blue) components and perform image colour restoration. Firstly, the mean value and standard deviation in red, green and blue (RGB) channels are calculated. Secondly, the maximum and minimum of each channel in the underwater image are calculated.

\[
\begin{align*}
C_{\text{max},i} &= C_{\text{mean},i} + \alpha \cdot C_{\text{std},i} \\
C_{\text{min},i} &= C_{\text{mean},i} - \alpha \cdot C_{\text{std},i}
\end{align*}
\]

where \( \alpha \) is a scaling factor.
where \( i \in \{R, G, B\} \); \( c_{\text{mean},i} \) and \( c_{\text{std},i} \) are the mean value and standard deviation in the \( c \) channel; \( \kappa \) is a parameter to control the image dynamic; and \( c_{\text{max},i} \) and \( c_{\text{min},i} \) are the maximum and minimum of the \( i \) channel, respectively. The colour-restored image is obtained by

\[
c_{r,i} = \frac{c_{i - c_{\text{min},i}}}{c_{\text{max},i - c_{\text{min},i}}} \times 255.
\]

In treating on a light component, we convert colour image \( c_{r,i} \) from RGB to YCbCr space and estimate \( Y \) components and \( \text{CbCr} \). The transformation is given by the following equation.

\[
y = 0.298r + 0.587g + 0.114b
\]

\[
cb = -0.147r - 0.2880g + 0.3438b
\]

\[
cr = 0.6149r + 0.514g - 0.100b
\]

C from RGB is converted to YCbCr space, and \( Y \) and \( \text{CbCr} \) components are estimated. The best enhancement is conducted by applying the integrated colour model with Rayleigh distribution on the \( Y \) component to obtain \( Y_R \). The grey distribution of histograms in the original image usually falls within a specific range of grey value because the concentrated focus of the repetitive histogram is not fully distributed across the entire density level. Thus, the image contrast is increased by extending the histogram to the image layer. Effectiveness is distributed outside the frequency range, which extends the pixels over the full range of the grey level. This condition limits the intensity to 5% of the maximum and minimum during operation. These limits are applied to reduce the effects of improved and luxurious areas in the image. The extended histogram is provided by

\[
Y_S = (Y - Y_{\text{min}})(\frac{Y_{\text{max}} - Y_{\text{min}}}{Y_{\text{max}} - Y_{\text{min}}}),
\]

where \( Y_S \) and \( Y \) are the output and input pixels, respectively. \( Y_{\text{max}} \), \( Y_{\text{min}} \) and \( O_{\text{max}} \), \( O_{\text{min}} \) are the maximum and minimum values for the grey number of outputs and input images, respectively. In the histogram, the pixel distribution follows the Riley distribution, which is similar to the bell-shaped distribution in which most of the pixels are centred in the grey scale. The upper and lower sides of the intensity of the histogram have the lowest number of pixels. The distributions of a probability function and a cumulative function are given in the Riley distribution by Equations (6) and (7), respectively. In these equations, \( x \) refers to the input pixel and the 0.4 distribution parameter for the Rayleigh distribution. This value is set in accordance with the default value and was used in [10, 11]. In this method, the value is used for all types of underwater images by using

\[
\text{PDF}_\text{Rayleigh} = \left(\frac{2}{\Omega} \right) e^{(-x^2/2\Omega^2)} \text{for } x \geq 0, \quad \Omega > 0 \quad (6)
\]

\[
\text{CDF}_\text{Rayleigh} = \int_0^x \frac{2}{\Omega} e^{(-x^2/2\Omega^2)} \ dx = 1 - e^{(-x^2/2\Omega^2)} \quad \text{for } x \in (0, \infty) \quad (7)
\]

Equation (5) is integrated into Equation (6) to obtain the equation of stretched Rayleigh distribution. The result of the integration is shown in

\[
Y_R = \frac{[Y_S]}{\Omega^2} e^{-\frac{[Y_S]^2 + \text{min}}{2\Omega^2}}.
\]

For excellent enhancement, we compute average component \( Y_p \) for \( (Y_R, Y) \). We also convert the image from YCbCr to RGB space. The transform is given by

\[
r = y_p \cdot 1.401cr
\]

\[
g = y_p - 0.394cb - 0.580cr
\]

\[
b = y_p \cdot 2.032cb
\]

The summary of the algorithm is presented in Figure (1).

3. QUANTITATIVE ANALYSIS

Quantitative analysis is performed to evaluate the resultant image. The quantitative evaluation is only used to support the visual observation. In this study, a quantitative evaluation is conducted depending on entropy average gradient and natural image quality evaluator (NIQE).
1. Entropy Value

Entropy, which refers to the abundance of image information that measures the image information content, is interpreted as the average uncertainty of the information source. In an image, entropy is the corresponding states of intensity level that individual pixels can adopt. It is calculated as the summation of the products of outcome probability multiplied by the log of the inverse of outcome probability \[12\].

\[
H(x) = \sum_{x=0}^{L} p(x) \log_2 p(x) \tag{10}
\]

2. Average Gradient

Average gradient shows the fine contrast, texture characteristics and clarity of an image. The above-mentioned value of average gradient indicates that the image has many intensity levels and is clear \[13\]. The average gradient can be defined as follows:

\[
\mathcal{G}^2 = \frac{1}{(M-1)(N-1)} \sum_{i=1}^{M-1} \sum_{j=1}^{N-1} \sqrt{\mathcal{G}^2_x f(x,y) + \mathcal{G}^2_y f(x,y)} \tag{11}
\]

where \(\mathcal{G}^2_x f(i,j)\) and \(\mathcal{G}^2_y f(i,j)\) are the gradients on the row and column directions, respectively. \(M\) and \(N\) are the numbers of the row and column of the enhanced image, respectively.

3. Natural Image Quality Evaluator (NIQE)

NIQE is a no-reference photograph quality assessment version that fully utilises measurable deviations from statistical regularities discovered in a natural photograph without knowledge on human-rated distorted photographs. NIQE assesses picture greatness without information on expected distortions or human reviews. NIQE is based on the construction of a quality-aware collection of statistical features based on a simple and successful space domain natural scene statistic (NSS) model. These features are derived from a corpus of natural, undistorted images. NIQE is applied by computing 36 identical feature patches of the same size \(p \times p\) from the image to be quality analysed. Then, they are fitted with the multivariate Gaussian (MVG) model, and the MVG fit is compared with the natural MVG model. In the implementation of NIQE, the patch size is set to 96 \(\times\) 96 as implemented by the authors in their studies. However, stable performance across patch sizes ranges from 32 \(\times\) 32 to 160 \(\times\) 160. Thus, the quality of an image, \(D\), is expressed as the distance between the quality-aware NSS feature model and the MVG fit to the features extracted from the distorted image.
where $\mathbf{v}_1, \mathbf{v}_2$ and $\Sigma_1, \Sigma_2$ are the mean vectors and covariance matrices of the natural MVG model and the MVG model of the distorted image, respectively. A low value of NIQE indicates excellent image quality [14].

IV. RESULTS AND DISCUSSION

Four methods (UCM, RSAIP, MSRCR and the proposed method) are implemented and tested. Simulation experiments are conducted on five popular test images by using MATLAB software to simulate the proposed method based on the integrated colour model with Rayleigh distribution and the association of different methods. The results can help determine the advantages of these methods. Figures 2, 3, 4 and 5 illustrate the restoration images for groups b, c, d and e, respectively. These figures show that the best algorithm is the proposed method because it enhances lightness and contrast. Table 1 shows the comparative values of entropy, average gradient and NIQE for the images shown in Figures 2, 3, 4 and 5. Figure 2 shows that the quantitative performance of the proposed method is better than that of the other methods in terms of entropy. Figure 3 indicates that the proposed method is the best in terms of entropy. Figure 4 shows that the proposed method is the best in terms of entropy and average gradient. Figure 5 reveals that the proposed method is the best in terms of NIQE and entropy. The proposed method is thus a suitable technique for enhancing underwater images.
Fig (3): (a) Original second image, image enhancement by (b) UCM, (c) RSAIP, (d) MSRCR and (e) Proposed Method.

Fig (4): (a) Original third image, image enhancement by (b) UCM, (c) RSAIP, (d) MSRCR and (e) Proposed Method.
Fig (5): (a) Original forth image, image enhancement by (b) UCM, (c) RSAIP (d) MSRCR and (e) Proposed Method.

Table (1) Quantitative results of Entropy, NIQE, Average Gradient.

| Images | Method  | Entropy | AG   | NIQE  |
|--------|---------|---------|------|-------|
| Fig (2)| UCM     | 7.1081  | 46.7855 | 3.5577 |
|        | RSAIP   | 6.1258  | 46.5162 | 3.0007 |
|        | MSRCR   | 7.0747  | 67.4605 | 3.8673 |
|        | Proposed| 7.3227  | 45.4325 | 3.4795 |
| Fig (3)| UCM     | 6.9460  | 9.8518  | 5.6543 |
|        | RSAIP   | 6.0859  | 11.6049 | 5.3848 |
|        | MSRCR   | 5.8149  | 8.9711  | 5.8479 |
|        | Proposed| 7.0201  | 9.6657  | 5.7175 |
| Fig (4)| UCM     | 7.0418  | 19.2810 | 3.6091 |
|        | RSAIP   | 6.2906  | 19.6536 | 3.0090 |
|        | MSRCR   | 6.1431  | 16.8146 | 3.5940 |
|        | Proposed| 7.1200  | 19.9521 | 3.5784 |
| Fig (5)| UCM     | 7.3955  | 16.8531 | 3.3281 |
|        | RSAIP   | 7.1341  | 17.4385 | 3.6454 |
|        | MSRCR   | 7.1923  | 22.7195 | 2.9715 |
|        | Proposed| 7.5123  | 16.7162 | 2.1532 |
4. CONCLUSIONS

The proposed algorithm is flexible and simple and successfully retrieves missing details by processing colour components. The MSRCR algorithm does not improve colours well. UCM and RSAIP fail to improve the lightness of the colour images. The proposed method improves lightness and contrast in underwater images of poor visibility and provides better visual representation than the other methods (UCM, RSAIP and MSRCR).

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