Research on the method of underwater image enhancement

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Abstract. A multi-angle image enhancement method based on underwater imaging was proposed to solve the problems of color bias, geometric distortion and low contrast of the observed object in the complex and changeable underwater environment. Firstly, the gray world algorithm is used to preprocess the underwater image. Then an image optimization denoising algorithm based on K-SVD dictionary learning is used to keep the structure and texture information of the original image. Finally, combining with the underwater optical imaging model, the blue-green channel enhancement algorithm is used to realize the underwater imaging defog processing, which makes the restored image closer to the reality. The results show that this method can solve the problems of noise interference, fuzzy underwater image and low contrast.

Keywords-component: image enhancement; Grayscale world algorithm; Sparse representation denoising; Blue-green channel.

1. Introduction

The twenty-first century is the century of the ocean. Only by going to the ocean, exploring the ocean and developing the ocean rationally can we remain in an invincible position in the tide of The Times. As an effective carrier of visual information, underwater image plays an irreplaceable role in the process of ocean exploration. In terms of ecological environment research, underwater images can be used to observe changes in Marine geology and geomorphology, understand changes in Marine environment, measure the concentration of pollutants in seawater, and count Marine organisms for protection. In the field of ocean engineering, underwater image can be used to detect the aging degree of underwater dock. In military, underwater image can be used to detect and identify submarines and underwater gliders, which plays an important role in anti-submarine and anti-ship.

At present, the processing methods used to enhance or restore underwater images can be roughly divided into non-physical model image enhancement and physical model-based image restoration. Image enhancement method based on the physical model through a simple image processing means to improve the quality of underwater image, by adjusting the image pixel values to improve visual quality, the method adopts the method of adjustment of image pixel values directly improve image quality and does not consider the physical process of underwater image degradation, belong to the category of image enhancement. Retinex Theory [1] is a theory based on color constancy first proposed by Land in the 1970s. This theory is based on three hypotheses ;(1) the real world has five colors, and the colors seen by human beings are the result of the interaction between light and objects; (2) Each color is composed...
of three primary colors: red, green and blue; (3) The three primary colors determine the color of each unit area. Retinex algorithm can be adaptive to different types of image enhancement, than the traditional single image enhancement algorithm has better adaptability, because of the traditional image enhancement algorithms can only one kind of feature, whereas the Retinex enhancement algorithm could in dynamic range compression and detail enhancement and color correction achieve good balance effect, therefore, Retinex theory has been widely developed and applied.

In this paper, we preprocessed the underwater image based on the underwater optical imaging model and the grayscale world algorithm, and carried out color correction based on the diagonal theory of Von Kries. Some parameters were approximately estimated based on the prior knowledge, assumptions or underwater optical properties, and then the image effect was obtained by solving the model. Secondly, the sparse representation image denoising based on K-SVD algorithm is used to obtain a more accurate image. Finally put forward a kind of underwater image restoration algorithm based on red dark channel prior, estimated by red dark channel prior theory of underwater image dark channel prior, based on the channel transmission rate and improve the image contrast, the linear relationship between the optical transfer function better balance color, contrast and saturation of the image and visual scene more close to natural scene images.

2. Underwater image enhancement algorithm

2.1. Underwater optical imaging model

Among many underwater optical imaging models, the underwater optical imaging model designed by Jaff-McGlamery et al. [2-3] is the most classic. This model proposes that the total amount of light received by the camera consists of three parts: 1) the unscattered light reflected by the target object (the direct component); 2) Small Angle scattered light (forward scattering component) is reflected from the target object; 3) The scattered light (backscattered component) reflected from a non-target object but still captured by the camera.

![Fig. 1 Underwater optical imaging model](image_url)

(1) The direct component refers to the light directly reflected from the target object to the imaging plane, during which there is no scattering effect of light. This imaging image contains real, clear and reliable target object information. The mathematical formula is as follows:

$$E_d = J * t$$

In this formula, $E_d$ is the direct component, $J$ represents the real information of the object, and $t$ represents the light transmittance, which reflects the comprehensive attenuation degree of the light on the direct light path.

(2) Forward scattering component refers to the light that reaches the imaging plane after the reflected light of the target object is scattered at a small Angle. The magnitude can be obtained by the convolution of the direct component and the point spread function. The mathematical formula is as follows:

$$E_f = E_d \otimes g = (Jt) \otimes g$$
In the formula, \( \mathbf{E}_f \) is the direct component, \( g \) is the point spread function, and its value is related to the transmission distance of light.

(3) Backscattering component, which represents the light that reaches the camera after scattering from fine particles in the water without reflecting from the target object. The mathematical formula is as follows:

\[
\mathbf{E}_b = \mathbf{A}(1-t)
\]  

In the above equation, \( \mathbf{E}_b \) represents the backscattering component, and \( \mathbf{A} \) represents the sum of the illumination intensity of the underwater environment. To sum up, the total amount of light reaching the imaging plane, i.e. the observed image, can be represented by the above components as follows:

\[
\mathbf{E} = \mathbf{E}_d + \mathbf{E}_f + \mathbf{E}_b = \mathbf{Jt} + (\mathbf{Jt}) \otimes g + \mathbf{A}(1-t)
\]

For the imaging process of underwater environment, the forward scattering makes the details of the image blurred, while the back scattering makes the overall color of the image distorted and the contrast decreased. Backscattering has a greater influence on underwater image imaging, so the influence of forward scattering can be ignored in the process of subsequent research. Therefore, the above underwater optical imaging model can be simplified as:

\[
\mathbf{I} = \mathbf{J} \times t + \mathbf{A} \times (1-t)
\]

In the formula, \( \mathbf{I} \) is the underwater image observed, representing the total amount of light received by the imaging plane; In the underwater image enhancement algorithm based on the physical model, the images of ambient light intensity \( \mathbf{A} \) and transmittance \( t \) are approximated by the observation images \( \mathbf{I} \), and then the restored images \( \mathbf{J} \) with color balance and high contrast are obtained according to the above imaging models.

2.2. Image preprocessing: grayscale world algorithm

Grayscale world algorithm is based on the "grayscale world hypothesis", which believes that in the objective world, the color changes of objects and their surrounding environment are random and independently related. In the physical sense, the grayscale world algorithm assumes that the mean value of the average reflection of light from the natural scene is a fixed value on the whole, and this fixed value is approximately gray. The ultimate goal of the grayscale world algorithm is to estimate \( \hat{\mathbf{E}} \) and then conduct color correction according to the diagonal theory of Von Kries [4].

\[
\hat{\mathbf{E}} = \int \mathbf{S}_k(\lambda) \mathbf{E}(\lambda) \frac{d\lambda}{dx}
\]

If there \( \mathbf{S}_k(\lambda) \) and \( \mathbf{E}(\lambda) \) are no further assumption, the algorithm will fail. The grayscale world algorithm assumes that the average reflectance coefficient in the scene is a gray value, i.e.

\[
\int R(x, \lambda) dx = k
\]

Where, \( k \) is a constant value, and there are usually two ways to get the value:

1. Set \( k \) as a fixed value directly, and take half of the maximum value of each channel, that is \( k = 128 \);

2. Let \( k = (\overline{R} + \overline{G} + \overline{B}) / 3 \), \( \overline{R} \), \( \overline{G} \), \( \overline{B} \) and represent the average values of red, green and blue channels respectively. Here we use the second method, which \( \hat{\mathbf{E}} \) can be estimated by calculating the average value of the three channels.
\[ \int_{1}^{x} \frac{1}{dx} = \int_{1}^{x} \frac{S_{i}(\lambda)E(\lambda)R(x,\lambda)}{dx} \]

\[ = \int_{1}^{x} \frac{R(x,\lambda)dx}{dx} \times \int_{1}^{x} S_{i}(\lambda)E(\lambda) \]

\[ = k \int_{1}^{x} S_{i}(\lambda)E(\lambda) \]

\[ = k \hat{E} \]  

Specific calculation steps:

1. Calculate the average value of the three channels of \( R, G, B \) the image (\( \bar{R}, \bar{G}, \bar{B} \))

\[ \bar{R} = \frac{1}{N} \sum_{i=1}^{N} R_{i} \quad \bar{G} = \frac{1}{N} \sum_{i=1}^{N} G_{i} \quad \bar{B} = \frac{1}{N} \sum_{i=1}^{N} B_{i} \]  

Where, \( N \) is the total number of pixels of the image, and, \( R_{i}, G_{i}, B_{i} \) are the values of the red, green and blue components of the \( i \) pixel before correction. The average gray value of the image

\[ \text{Grey} = \frac{\bar{R} + \bar{G} + \bar{B}}{3} \]  

2. Gain coefficients of channels \( R, G, B \) are

\[ k_{r} = \frac{\text{Grey}}{R} \quad k_{g} = \frac{\text{Grey}}{G} \quad k_{b} = \frac{\text{Grey}}{B} \]  

According to Von Kries diagonal model, \( C \) for each pixel in the image, adjust its \( R, G, B \) component so that,

\[ \begin{align*}
C(R') &= C(R) \cdot k_{r} \\
C(G') &= C(G) \cdot k_{g} \\
C(B') &= C(B) \cdot k_{b}
\end{align*} \]  

\( k_{r}, k_{g}, k_{b} \) are the gain coefficients of the \( R, G, B \) three channels respectively, and \( R', G', B' \) are the corrected values of the three components of red, green and blue respectively.

3. Adjust each pixel \( R', G', B' \), and of the image to the display range \([0,255]\). For example, for a 24-bit true color map, let \( \text{MAX}_{val} \) be the maximum of all \( R, G, B \), and three components in the image, and let

\[ \text{factor} = \frac{\text{MAX}_{val}}{255} \]

If \( \text{factor} > 1 \), then for each pixel in the image \( C \), and \( R', G', B' \) components are readjusted so that

\[ \begin{align*}
C(R') &= \frac{C(R')}{\text{factor}} \\
C(G') &= \frac{C(G')}{\text{factor}} \\
C(B') &= \frac{C(B')}{\text{factor}}
\end{align*} \]
3. Underwater image denoising

3.1. Sparse representation image denoising based on K-SVD algorithm

K-SVD algorithm [5-6] introduces a strategy to train atoms for signal content, so as to obtain a super-complete dictionary that can realize signal sparse representation based on adaptive signal content. This algorithm mainly includes two structures: the first is the sparse coding stage; Then the dictionary update stage; In the K-SVD algorithm, the minimization is carried out iteratively. First, the dictionary $D$ is fixed to find the sparse matrix $X$. This stage is called the sparse coding stage, and the residuals are:

$$\|Y - DX\|_F^2 = \sum_{i=1}^{N} \|y_i - Dx_i\|_2^2$$ (15)

Transform to the following model:

$$\min_X \{\sum_{i=1}^{N} \|y_i - Dx_i\| \} \Rightarrow \|x_i\|_0 \leq T_0$$ (16)

Each of these signals $y_i$ is made up of a number of atoms in the dictionary $D$, and no more atoms are used to represent each sample $T_0$. After the sparse coding task is completed, the dictionary update stage is carried out. The dictionary updating process is the process of updating atoms and their sparse vectors. In the model, it is assumed that the columns other than atoms $d_k^T$ are fixed in $X$ the dictionary $D$, and only atoms $d_k^T$ and their corresponding sparse vectors $x_k^T$ (represented by the $k$-th row of $X$) are considered. Then the residualities can be further rewritten as:

$$\|Y - DX\|_F^2 = \|Y - \sum_{j=1}^{K} d_j^T x_j^T\|_F^2$$

$$= \| (Y - \sum_{j\neq k} d_j^T x_j^T) - d_k^T x_k^T \|_F^2$$

$$= \| E_k - d_k x_k^T \|_F^2$$ (17)

It can be seen from the above equation that the equation decomposes two multiplied matrices $DX$ into the sum of $K$ matrices with rank 1. It's assumed that this $K-1$ term $\sum_{j\neq k} d_j x_j^T$ is fixed, and this term $d_k x_k^T$ is left to be solved; At the same time, the above equation is divided into two parts. One part is the residual term $E_k$, which represents the residuals generated when atoms $d_k$ is used to represent the samples from $N$ the samples. The other part is the rank 1 matrix $d_k x_k^T$.

We define $w_k$ as a set of coordinates -- the label of the position of the non-zero term of the corresponding vector $x_k^T(i)$ when the signal $y_{ki}$ is represented by atom $d_k$. The mathematical formula is denoted as:

$$\omega_k = \{i \mid 1 < i < K, x_k^T(i) \neq 0\}$$ (18)

Define the size of matrix $\Omega_k$ to be $N \times |\omega_k|$, where its elements are 1 in the $(\omega_k(i), i)$ position and 0 in the other positions. The matrix $x_k^T$ is multiplied by the matrix $\Omega_k$, denoted as $x_k^R = x_k^T \cdot \Omega_k$, and $x_k^R$ is the row vector contracted by discarding the zero terms in $x_k^T$, thus making the length of vector $x_k^R$ is $|\omega_k|$. You multiply the matrix $Y$ times the matrix $\Omega_k$, $Y_k = Y \Omega_k$, $Y_k^R$ is the matrix...
n × |ω_k|, and again, you have \( E_k^R = E_k \Omega_k \), the magnitude of \( E_k^R \) is \( n \times |ω_k| \), and it takes into account the residuals that are generated when atom \( d_k \) represents the signal.

By using matrices \( \Omega_k \), the dictionary space and vectors \( x_k^R \) are reduced by removing vectors that do not contribute to the dictionary \( D \). The above equation is equivalent to:

\[
\begin{align*}
\| E_k \Omega_k - d_k x_k^R \|_p^2 &= \| E_k^R - d_k x_k^R \|_p^2 \\
(19)
\end{align*}
\]

We can apply the SVD decomposition theorem directly to matrices \( E_k^R \). Let’s do the SVD decomposition of \( E_k^R \) and call it \( E_k^R = U \Delta V^T \). We take the first column \( U \) of the orthogonal matrix as the updated atom \( d_k \), and multiply the maximum singular value of the matrix \( \Delta \) by the first column of \( V \) as the updated sparse vector \( x_k^R \).

Fig. 3 Sparse denoising effect of underwater image

3.2. Evaluation criteria for image quality

After image denoising processing, it is necessary to determine the denoising effect of the image, which can be evaluated by objective evaluation criteria. It mainly includes three evaluation criteria: The first is the Mean Squared Error (MSE) criterion, the second is the Peak Signal Noise Ratio (PSNR) criterion and the third is the Structural Similarity (SSIM) criterion.

1) Mean square error

The calculation of mean square error is simple and intuitive, and the image quality is evaluated by pixel error. Its model is as follows:

\[
MSE = \frac{1}{MN} \sum_{i=0}^{M} \sum_{j=0}^{N} (f_{ij} - \hat{f}_{ij})^2
\]

(20)

The method calculates the mean square value of the pixel difference between the clear image and the contaminated image, and then determines the distortion degree of the contaminated image.

2) Peak signal-to-noise ratio

In image processing, PSNR is the most commonly used objective evaluation standard of image denoising quality. PSNR is the ratio of signal maximum power to noise power, and its calculation formula is as follows:

\[
PSNR = 10 \times \log \frac{L^*}{MSE} \]

(21)

The digital image pixel is regarded as a discrete pixel, so it is generally set as \( L = 255 \).

3) Structural similarity

MSE and PSNR are simple to calculate and have clear meaning, but they are not related to people's subjective evaluation. Structural similarity is a better and more adequate evaluation standard than them. Considering the sensitivity of human visual features to the change of image information, a new evaluation model is established. The evaluation criteria for structural similarity (SSIM) are composed of brightness contrast, contrast contrast and structure contrast, and the following SSIM evaluation indexes are obtained:

\[
SSIM(x, y) = [o(x, y)]^\alpha \times [p(x, y)]^\beta \times [q(x, y)]^\gamma
\]

(22)
Brightness:

\[ o(x, y) = \frac{2u_x u_y + C_1}{u_x^2 + u_y^2 + C_1} \]  

(23)

Contrast:

\[ p(x, y) = \frac{2\sigma_x \sigma_y + C_2}{\sigma_x^2 + \sigma_y^2 + C_2} \]  

(24)

Structural similarity:

\[ q(x, y) = \frac{\sigma_{xy} + C_3}{\sigma_x \sigma_y + C_3} \]  

(25)

Here, \( u_x \) and \( u_y \) are respectively the gray mean of the image \( x \) and \( y \); \( \sigma_x \) and \( \sigma_y \) are the variance of images \( x \); \( \sigma_{xy} \) is the covariance of \( x \) and \( y \); \( \alpha \), \( \beta \) and \( \gamma \) in general are set as 1; \( C_1 \), \( C_2 \) and \( C_3 \) are constants that are both greater than and near zero, preventing the denominator from being zero. Normal, \( SSIM \) smaller, represents more efficient image processing.

4. Underwater image restoration based on blue-green channel enhancement algorithm

In the process of underwater image imaging, due to the absorption of light by water and the scattering of fine particles, the observed underwater image presents low contrast and color distortion and other degradation states. The research methods of underwater image enhancement are mainly divided into two kinds: physical model and non-physical model. In the research method of image enhancement based on physical model, Wen et al. directly applied the foggy image model to underwater imaging, and only the blue-green channel was used to calculate the dark channel of the image to realize the deblurring and color correction of the underwater image.

4.1. Dark channel prior theory

In order to achieve fog removal, He Kaiming et al. [7] proposed a Dark Channel Prior (DCP) enhancement algorithm for aerosol images through a large number of experimental statistical analysis. The algorithm points out that for fog-free images in atmospheric environment, except for the local areas of most fog-free images, there is always a certain color channel with extremely low gray value in the dark channel images corresponding to color images. The dark channel image can be obtained by minimum filtering of the minimum image, which can be expressed by the following mathematical formula:

\[ J_{\text{dark}}(x) = \min_{\Omega}(\min_{\mathbb{R}^3}(J(x))) \]  

(27)

In the above formula (2), \( J_{\text{dark}}(x) \) is the dark channel image \( J \) corresponding to the clear image without fog, \( x \) represents the pixel coordinates of the image, \( \Omega \) represents the local window area, and \( r, g, b \) represents the red, green and blue color components respectively. Formula (1) and Formula (2), the calculation formula of dark channel can be expressed as follows:

\[ \min_{\Omega}(\min(I(x))) = 0 \]  

(28)

Based on the above dark channel prior theory, the optical imaging model is transformed as follows:

\[ \frac{I_s(x)}{A_c} = \frac{J_s(x)(x)}{A_c} + (1 - t(x)) \]  

(29)
Secondly, two minimum filtering operations as shown in Equation (3) are performed on both sides of Equation (4), and the results are as follows:

\[
\min_{\Omega} (\min_{c} \left( \frac{I_c(x)}{A_c} \right) ) = \min_{\Omega} (\min_{c} (\frac{I_c(x) t(x)}{A_c} + (1 - t(x))) )
\]  

(30)

(4) Substituting Equation (3) into Equation (5), the projection rate image can be obtained as follows:

\[
t(x) = 1 - \min_{\Omega} (\min_{c} \left( \frac{I_c(x)}{A_c} \right) )
\]  

(31)

Finally, the intensity of atmospheric light \(A\) is estimated, and the optical imaging model is solved in reverse to obtain the enhanced image with high contrast and relatively clear.

4.2. Underwater image restoration based on blue-green channel enhancement algorithm

When the light travels in the underwater environment, the attenuation rate of the red light in the three channels is the largest, while the attenuation rate of the blue and green light components is similar to that in the atmospheric environment. An underwater image enhancement method based on blue-green channel enhancement algorithm is proposed according to its physical characteristics and the above dark channel prior theory. Firstly, dark channel prior operation is carried out on the blue-green channel in the underwater color image to obtain the transmittance image:

\[
\{ \Omega \times I_{gb} \} = \min_{\Omega} (\min_{c} (\frac{I_c(x)}{A_c}))
\]  

(32)

Secondly, according to the different attenuation rates of the three channels in the underwater environment, the ambient light intensity value corresponding to each channel is calculated according to the maximum difference channel, as shown in Equation 9. The maximum difference channel is determined by the difference of each color component, as follows:

\[
D(x) = \max_{\Omega, c} I_c(x) - \max_{\Omega, c \in \{g, b\}} I_c(x)
\]  

(33)

\[
A_c = \text{avg}_x (I_c (\text{arg min}_c D(x))), c \in \{g, b\}
\]  

(34)

After the transmittance image and ambient light intensity corresponding to the underwater image are obtained by the above formula (7) and (9), the enhanced blue-green channel image \(G_r\) can be obtained by the reverse solution operation of the optical imaging model. Then, through comprehensive analysis with the original red channel \(R\), the red channel is compensated by applying the gray world idea that the average color of the object in the ideal image is gray:

\[
(avg R_r + avg G_r + avg B_r) / 3 = 0.5
\]  

(35)

\[
R_r = R_r^* \frac{avg R_r}{avg R}
\]

In the above formula, \(avg R_r\), \(avg G_r\), \(avg B_r\) respectively represent the average pixel value corresponding to the enhanced three-channel image, and are the red component after color correction.

Finally, in order to solve the problem of uneven brightness of the restored image, the following operation is performed on the brightness component \(V\) in HSV color space to obtain the adaptive illumination compensation map \(s(x)\). \n
\[
s(x) = GF \left[ \frac{V_r(x) V_j(x) + \lambda V_r^2(x)}{V_j^2(x) + \lambda V_r^2(x)} \right]
\]  

(36)

In Formula 12, \(V_j(x)\) represents the brightness component after color correction; \(V_r(x)\) is the brightness component corresponding to the original underwater image; \(GF \) stands for guided filtering operation to improve the clarity of image details; Take \(\lambda = 0.3\) in the simulation experiment. After the adaptive illumination compensation map is obtained, the following operations can be carried out in
combination with the color-corrected underwater image, and finally the enhanced image with uniform brightness, high contrast and balanced color can be obtained.

\[ \text{Output} = J_c(x) \times s(x) \] (37)

**Fig. 4** Enhanced color compensation effect of blue-green channels

5. **Specific steps of this algorithm**

1) The gray world algorithm is used for image preprocessing of the underwater image, and the average value \((\bar{R}, \bar{G}, \bar{B})\) and gain coefficient \(k_r, k_g, k_b\) of three channels of image \(R, G, B\) are obtained. The ultimate goal is to estimate \(\hat{E}\) and then correct the color according to Von Kries' diagonal theory.

2) According to the known image information, image denoising model is established, the design is based on K - SVD algorithm the sparse representation of image denoising, image noise filtering, restore the real effect of the original image of high quality image, to content the atomic strategy training to introduce signal, so as to realize based on adaptive signal content can realize signal sparse representation over complete dictionary.

3) Underwater image restoration, using formula 27 to carry out minimum filtering with minimum value image to get dark channel image.

4) Transform the optical imaging model according to Formula 29, and get the image transmittance \(t(x)\). Finally, estimate the atmospheric light intensity \(A\), and reverse solve the optical imaging model to get the enhanced image with high contrast and relatively clear.

5) In order to solve the problem of uneven brightness of the restored image, Equation 36 is used to operate the brightness component \(V\) to obtain the adaptive illumination compensation graph \(s(x)\).

6) Operate with the color-corrected underwater image through Equation 37, and finally get the enhanced image with uniform brightness, high contrast and balanced color.

6. **Experimental results and evaluation**

Order to prove the rationality and effectiveness of the algorithm in this paper, the algorithm in literature [8-10] was compared with the algorithm in this paper under the same environment. The experimental operating environment in this paper is Windows Professional 64-bit, the processor is Intel Core i5-8300H, the memory is 8GB, the version of the simulation software MATLAB is R2013A, and in formula 36, \(\lambda = 0.3\) is taken.

In this paper, image quality evaluation criteria are used to compare the processing effects of the four algorithms. Information entropy represents the amount of information carried in the image; Average gradient reflects the abrupt change degree of image detail edge, which is used to describe the sharpness of image and the change of texture features. The larger the value is the clearer the image will be. The table 1 and 2 shows the objective quality evaluation statistics of the above images under different algorithms. It can be seen that the algorithm in this paper is higher than other algorithms in information entropy and average gradient, which can enhance the underwater image well and achieve a good visual effect.
Table 1. Average gradient comparison

|          | original picture | literature [8] | literature [9] | literature [10] | Algorithm in this section |
|----------|------------------|----------------|----------------|------------------|---------------------------|
| Fig.1    | 0.1440           | 0.3255         | 0.3031         | 0.4383           | **0.4573**                |
| Fig.2    | 0.0569           | 0.1407         | 0.1686         | 0.1787           | **0.1928**                |
| Fig.3    | 0.4240           | 0.6710         | 0.6750         | **1.127**        | 1.014                     |
| Fig.4    | 0.0436           | 0.2606         | 0.1903         | 0.1476           | **0.3968**                |
| Fig.5    | 0.1947           | 0.2765         | 0.2908         | 0.3530           | **0.4127**                |

Table 2. Information entropy comparison

|          | original picture | literature [8] | literature [9] | literature [10] | Algorithm in this section |
|----------|------------------|----------------|----------------|------------------|---------------------------|
| Fig.1    | 7.1721           | 7.3766         | 7.3122         | 7.2411           | **7.7868**                |
| Fig.2    | 6.6821           | 6.8324         | 7.1319         | 7.0109           | **7.2908**                |
| Fig.3    | 7.1262           | 7.1118         | 7.3674         | 7.4022           | **7.6195**                |
| Fig.4    | 5.6829           | 5.3427         | 6.4232         | 6.9168           | **7.1544**                |
| Fig.5    | 7.3416           | 6.9322         | 7.3330         | **7.6090**       | 7.4466                    |

(a)Original image (b) Reference 8 (c) Reference 9 (d) Reference 10 (e) Algorithm in this section

Fig. 5 Comparison effect of underwater image enhancement algorithm

7. Conclusion
In view of the underwater imaging environment is complex, underwater image fuzzy, low contrast and color distortion, this paper first USES the algorithm of underwater image grayscale world of image preprocessing, and then the sparse representation based on K - SVD algorithm for image denoising, finally based on the blue green channel enhancement algorithm for underwater image restoration, access to effectively improve the quality of underwater image, Get clearer underwater images. By comparing with other algorithms, it can be concluded that the algorithm in this paper can enhance the underwater image better, and its performance is better than other algorithms.

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References
[1] Jobson D J, Rahman Z, Woodell G A. Properties and performance of a center/surround retinex[J]. IEEE transactions on image processing, 1997, 6(3): 451-462.
[2] Mcglamery B L .A Computer Model For Underwater Camera Systems [J].Proc Spie, 1979, 208(208).
[3] Jaffe J S .Computer modeling and the design of optimal underwater imaging systems [J]. IEEE
Journal of Oceanic Engineering, 1990, 15(2):P.101-111.

[4] ZHU Gui-dong, SHEN Li, WANG Jinjue. A colour correction method based on the regionspecific von-Kries adaptation[J]. Computer Engineering & Science, 2007, 29(2): 50-52. Zhu Guidong, Shen Li, Wang Jinjue. Color Correction Method Based on Von-Kries Color Adaptation [J]. Computer Engineering and Science, 2007, 29(2):50-52.

[5] Kumar A., Omair Ahmad M., Swamy M. N. S. Image denoising via overlapping group sparsity using orthogonal moments as similarity measure [J]. International Transactions, 2019, 85(2): 293-304.

[6] Lebrun M., Leclaire A. An implementation and detailed analysis of the K-SVD image denoising algorithm [J]. Image Processing On Line, 2012, 2012(2): 96-133.

[7] He K, Sun J, Tang X. Single image haze removal using dark channel prior [C]// Computer Vision and Pattern Recognition, 2009. CVPR 2009. IEEE Conference on. IEEE, 2009: 1956-1963.

[8] Carlevaris-Bianco N, Mohan A, Eustice R M. Initial results in underwater single image dehazing [C]// Oceans. IEEE, 2010: 1-8.

[9] Li C, Quo J, Pang Y, et al. Single underwater image restoration by blue-green channels dehazing and red channel correction[C]// IEEE International Conference on Acoustics, Speech and Signal Processing. IEEE, 2016: 1731-1735.

[10] Wen Z, Lambert A, Fraser D, et al. Bispectral analysis and recovery of images distorted by moving water surface[J]. Applied optics, 2010, 49(33): 6376-6384.