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Adaptive Enhancement of Robot Vision Image on the basis of Multi-Scale Filter

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To improve the image quality effectively, increase the mean square error value, information entropy and average gradient, an adaptive enhancement method for robot vision images is proposed based on multi-scale filters. An HSV color space model is built in order to: enhance the brightness and saturation components of the image; smooth the robot vision image through the total variation model and remove the noise in the image. The compressed sensing reconstruction algorithm is used to reconstruct the robot vision image and to improve the real-time and rapid processing of the image. The multi-scale filter obtained by the combination of the multi-scale Gaussian filter (MGF) and the high-pass filter (HPF) improves the adaptive processing of the robot vision image, and enhances the image by adjusting the weight of each filter. The experimental results show that the proposed method has a higher mean square error value, information entropy and average gradient, better image visual effect, and the enhanced image has sharp details and moderate color.

Keywords: multi-scale filter; image enhancement; HSV color model; compressed sensing; mean square error; average gradient

1. INTRODUCTION

An intelligent robot system is a comprehensive system with multiple functions which can integrate environmental perception, make decisions, and control and perform multiple tasks [1]. Robots rely mainly on the vision system for environmental perception. Robot vision is not complicated [2]. It uses visual sensors to obtain a two-dimensional image of a three-dimensional scene, and then processes and analyzes the collected images through a computer. The external environment data is converted into symbolic representations and, with the help of these images, valuable information can be extracted to control the intelligent activities of the robot according to specific tasks [3]. Current robot vision images are affected by various interference factors, so the user's actual requirements will be hard to meet. Therefore, for practical reasons, it is important to improve the image obtained by robot vision [4].

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Huang et al. [5] suggested a low-exposure image enhancement (LIE) method based on a progressive dual network (PDN) model comprising an image denoising module and an image enhancement module. The construction of each module is based on the notion of progression, taking account the change in image brightness from dark to light, and the image recovery process from coarse to fine, so that the enhanced results are closer to the real image. To train a better network, a bidirectional constraint loss function is constructed, which makes the network learning result approach the real data from the positive and negative directions of the image degradation model, and achieves a dynamic balance. To verify the effectiveness of the proposed method, results are compared with those obtained by several mainstream methods from both subjective and objective aspects. The experimental results obtained by this method are closer to the actual images; however, the mean square error value of this method is small. By means of MDARNet, Jiang et al. [6] proposed a low-light image enhancement method, and introduced a dense convolution module as well as an attention mechanism module to improve image enhancement performance. First, MDARNet adopts three kinds of scale convolution kernels, two-dimensional ones and one-dimensional ones, to extract features from images, and applies the pixel attention module to carry out targeted learning of multi-scale feature maps. Second, a skip connection structure is designed for feature extraction to maximize the use of image features. In the final step, the pixel attention module and the channel attention module are used to simultaneously carry out both weight learning and illumination estimation on the extracted feature maps. According to experimental results, the proposed method can improve the brightness, contrast and color of low-illumination images effectively, but its information entropy and average gradient are small, and the enhanced image has a local blur problem. Yuan et al. [7] proposed an infrared image enhancement (IIE) method based on the atmospheric scattering model. First, the infrared image was inverted, and the atmospheric scattering model is introduced to describe its degradation mechanism. Then, the image is divided into a series of sub-blocks by using the quadtree decomposition technique, and the corresponding sub-block-based model factor estimation strategy is applied to recover the scene object. Finally, combined with the guided total variation model and a correction algorithm on the basis of the Retinex model, the visual effect of the enhanced image is further strengthened. According to experimental results, the algorithm has good robustness and certain advantages in terms of effective information gain, but the image enhancement is not good since details are lost.

To effectively improve the image quality, an adaptive enhancement method based on multi-scale filters is proposed for robot vision images. The major contributions of this method are:

(1) The HSV color space model. On the one hand, the model eliminates the relationship between the color information in the image and the luminance component. On the other hand, it can ensure that the saturation and hue components approximate human visual perception.

(2) A new compressive sensing reconstruction algorithm suitable for robot vision image reconstruction, which can avoid the problem of discarding a large amount of sampled data during the compression process.

(3) The use of multi-scale filters to enhance the processing of robot vision images. By adjusting the weight of each filter, the enhancement of the texture area can be reduced as much as possible while the enhancement of the flat area can be minimized.

(4) Compared with traditional methods, the proposed approach increases the mean square error, with the highest value being 27.457. The proposed method has a larger information entropy, with the highest value being33.489; Moreover, the edge of the image processed by the proposed method remains more complete, there is less loss of detail, and the subjective vision is better. The enhanced image does not have the problem of local blur; hence, the image enhancement achieved with the proposed method.

2. ROBOT VISION IMAGE PREPROCESSING

2.1 HSV Color Model Construction

Color images are generally represented by RGB models in computers, and robot vision images are no exception. However, if the contrast enhancement of three color components -R, G, and B- is performed separately, since the operations are performed independently, it cannot be guaranteed. The linear transformation coefficients happen to be the same, so the hue cannot be preserved. A great deal of testing has proven that the HSV color space is a better choice for color image enhancement [8]. Therefore, in this paper, as the first step, the image is transformed from RGB space into HSV space [9]. This model has three parts: hue (H), saturation (S) and brightness (V). This model is closer to the human perception of color. The importance of this model is that: 1) it eliminates the relationship between brightness components and color information in the image; and 2) the saturation and hue components closely approximate human visual perception.

The HSV color model is generally represented by an inverted hexagonal pyramid. As shown in Figure 1, the pure color without black is on a color plane on the bottom surface of the hexagonal pyramid. The V value is a straight line which passes through the center of the base of the pyramid, and is perpendicular to the base. The V value is 0 (black), and the V value at the bottom is 1 (white); the H value of any color point P accords with the angle between the vector pointing to this point and the red, with $-180^\circ \sim 180^\circ$ or $0^\circ \sim 360^\circ$ measurement; S is in proportion to the length of the vector pointing to the point. The longer it is, the more saturated it is. Its value is within 0 to 1.

As shown in Figure 1, on the base of the hexagonal pyramid, the diagonal tangent to the vertex of the center point is used to obtain the longitudinal section of the triangle, and the right half of the triangle is taken to obtain an isosceles triangle, as shown in Figure 1(b). The two right-angled sides of this isosceles triangle represent the luminance component and the saturation component, respectively, and the saturation on the hypotenuse is 1. The hue inside the triangle is exactly the same; only the saturation and lightness are changing. It can be seen from the triangle that when the V value decreases, it is equivalent to adding an appropriate amount of black component to this color amount and appropriately reducing its saturation. When the V value is constant, reducing the saturation of the color is equivalent to adding a white component.

If the histogram equalization of V component is directly carried out, some areas with only small fluctuations of gray value in the original image will become large, stiff contrast. To further enhance the brightness, in order to not only emphasize the image details, but also to not make the small fluctuation area become large contrast, this paper adopts the local enhancement method and uses the mean and variance characteristics of the neighborhood pixels of each pixel in the image. The proposed brightness component enhancement formula is shown in Formula (1):

$$V_s = \int_{x_i}^{x_j} \exp\left\{-\frac{1}{2}(X_i - X_j)\right\} \times \sigma_i \tag{1}$$

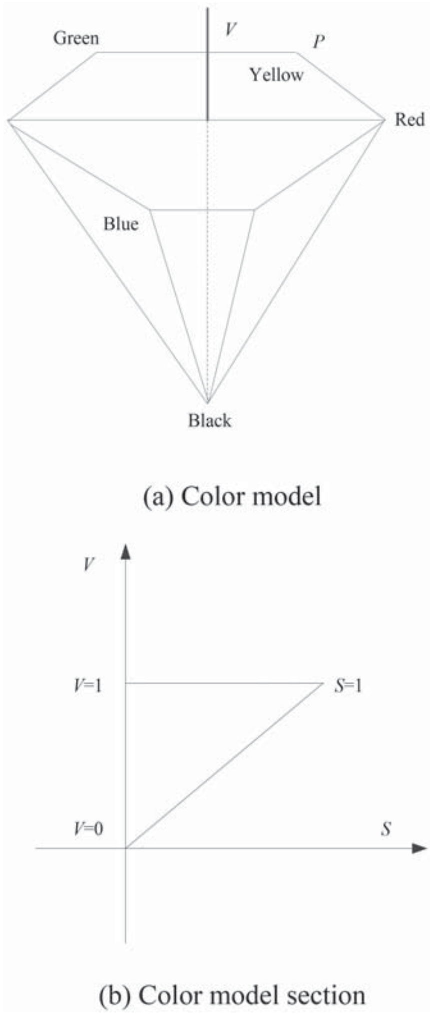

Figure 1 Schematic diagram of the HSV model.

In the formula, σ_i indicates the neighborhood size of the pixel point; X_i and X_j represent the brightness value of the original image pixel point and the brightness value of the pixel point after enhancement, respectively, and the expressions of the two are:

$$X_i = p_i(x|x_i)dx \tag{2}$$

$$X_j = p_j(x|x_j)dx \tag{3}$$

In the formula, p_i and p_j both represent the mean value of the pixels in the pixel field.

In the HSV color space, although the enhancement of the luminance component does not change the color content of the original image, the enhanced image looks somewhat different in color. This is because the enhancement of the luminance makes people feel different about saturation. Therefore, to be more suitable for human visual characteristics, it is necessary to enhance the saturation component after the luminance component has been enhanced. In this paper, the method of the correlation coefficient between the saturation component and the luminance component is used to make the saturation component change with the change of the luminance component. To do this, Formula (4) is used:

$$S_v = 1 - \frac{\mu_i |x_i(t) - x_j(t)|}{x_i(t) + x_j(t) + |x_i(t) - x_j(t)} \tag{4}$$

In the formula, $x_i(t)$ and $x_j(t)$ represent the average brightness and saturation of the pixel neighborhood, respectively; μ_i indicates the saturation variance, and its expression is:

$$\mu_i = \sqrt{\sum_{k=1}^{n} w_k |x_{ik} - x_{jk}|^2} \tag{5}$$

In the formula, n indicates the number of pixels; k indicates the proportionality constant; w_k indicates the correlation coefficient between brightness and saturation; x_{ik} and x_{jk} both represent the area with gentle grayscale changes.

2.2 Robot Vision Image Denoising

In terms of image processing, denoising is a basic problem, and traditional denoising methods inevitably remove some detailed features of the image [10]. By means of the designed HSV color model, the robot vision image is further denoised, which can retain the image features effectively while suppressing the noise.

The noise model of the image is:

$$Y_0(x, y) = Y(x, y) + F(x, y) \tag{6}$$

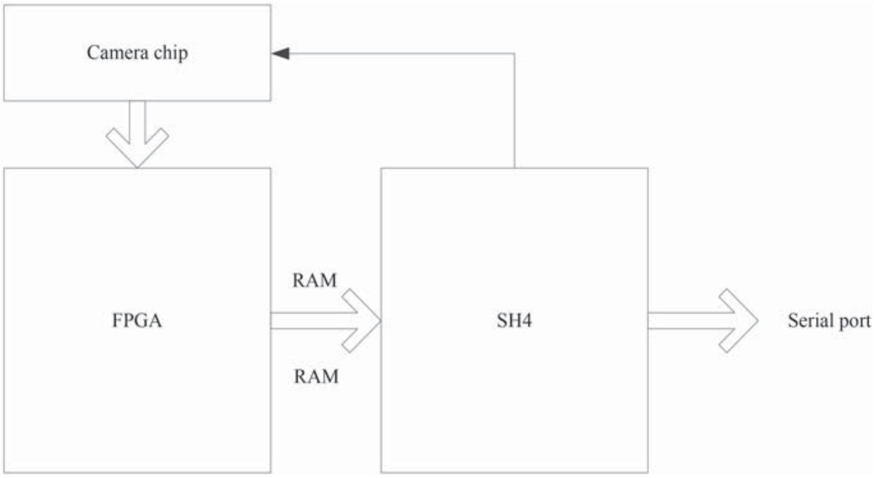

Figure 2 Schematic diagram of robot visual image acquisition.

In the formula, $Y(x,\ y)$ indicates an unknown image; $Y_0(x,\ y)$ indicates a known noisy observation image; $F(x,\ y)$ indicates an additional Gaussian white noise with a mean of 0 and a variance of θ^2. Recovering $Y(x,\ y)$ from $Y_0(x,\ y)$ involves solving the following minimization model:

$$\min D(y) = \partial \times |y - y_0|^2 + E(y) \tag{7}$$

In the formula, ∂ indicates the regularization parameter; the second term on the right side of the equation is called the approximation term, which controls the difference between the image y and the observation map y_0; the third term is the regularization term, whose role is to reduce oscillation, punish discontinuity and smooth the image; $E(y)$ is the scale parameter, which plays a significant balancing role in the regularization term and the approximation term. The larger $E(y)$ is, the closer y is to the observation image y_0, the weaker the local features of the image are, and the corresponding denoising effect is not ideal; the smaller $E(y)$ is, the stronger the details and noise of the image are. In image denoising, the classical total variation model is used, and its energy form is:

$$\min D(y) = \int_\infty |\Delta y| dxdy + \partial \int_\infty |y - y_0|^2 \tag{8}$$

Using the gradient descent method, the Euler Lagrange equation of Formula (8) is obtained as:

$$\begin{cases} y_i = \left(\frac{\Delta y}{|\Delta y|}\right) + \partial(y_0 - y) \\ y(a, b, 0) = y_0 \end{cases} \tag{9}$$

In the formula, $i > 0$; $(a, b) \in \Omega$.

The total variation model does not have the ability of back diffusion, so the processed image is blurred and the edges cannot be sharpened, resulting in the loss of some important details. Therefore, based on the total variational model, a nonlinear weighted variational model is designed, which can better separate the structure and texture.

The regularization term in the nonlinear weighted variational model is:

$$Q(y) = U(y) = \int_\infty |\Delta y| dxdy \tag{10}$$

When finding the minimum value, a large amount of smoothing is achieved regardless of whether the gradient is small or large (such as edges), thereby smoothing out important information and blurring the image.

To address this, the weight function $H(\Delta y)$ is added to the regular term, which is a differentiable function $= \leq H(x) \leq 1$, which satisfies $H(0) = 1$, $g(x) = 0$ and $\log_{10} H(x) - 0$. Therefore, where the gradient is large, $H(\Delta y)$ is smaller, thereby reducing the smoothness and protecting the edges better. Where the gradient is small, $H(\Delta y)$ is larger, thereby achieving strong smoothing and removing noise from robot vision images.

2.3 Robot Vision Image Reconstruction

Due to the huge amount of image data collected by the image acquisition device in the adaptive enhancement processing of the robot visual image, Figure 2 is the schematic diagram of the robot visual image acquisition, the processing complexity is very high, and it cannot meet the real-time and rapidity requirements. Moreover, these data often need to be transmitted and stored. To reduce the cost, this problem is often solved by compression, but a large amount of sampled data is discarded during the compression process, resulting in a huge amount of waste [11,12]. To fundamentally solve the above problems, some researchers have applied traditional compressive-sensing reconstruction algorithms [13]. However, these compressive sensing reconstruction algorithms have several defects when applied to the problem of robot visual image reconstruction. A new compressive sensing reconstruction algorithm suitable for robot vision image reconstruction is proposed [14].

The general working of the image block compressed sensing theory is as follows. First, divide the image Y into m blocks of size 5×5, whose pixels are $I_a \times I + b$, and the vector feature of the t-th block image signal is recorded $y_t = 1, 2, \ldots, m$; Then use the same perceptual matrix ψ_A to observe each sub-image y_i, and the length of the obtained observation vector z_i is L_A, denoted as $z_i = \psi_A y_i$. Here, the observation matrix ψ_A uses a random measurement Gaussian matrix, and M observations can be obtained through the Gaussian matrix observation, $M = m \times M_A$. For the whole image, the total perceptual matrix ψ is a block diagonal matrix with ψ_A in each diagonal element:

$$\psi = \begin{bmatrix} \psi_A & \\ & \psi_A \end{bmatrix} \tag{11}$$

It can be seen that the observation process of the block compressed sensing theory does not need to store the total sensing matrix ψ, but needs to store only each small matrix block ψ_A. When the block standard A is relatively small, the required storage amount is also small, and the sampling calculation speed is greatly improved. For image reconstruction based on block compressed sensing theory, signal observation and image reconstruction operations are performed on each sub-image individually, and the l_1-norm optimization model is used here:

$$\phi_i = \arg \sqrt{\|y - y_i\|_{l_1}} \tag{12}$$

in:

$$y_i = \Psi_A z_i \tag{13}$$

In the formula, Ψ is the transformation matrix. Use the TV model optimization principle to transform Formula (12):

$$\phi_i = \arg \sqrt{\min \|y - y_i\|_{TV}} \tag{14}$$

Reconstructing each sub-image block separately, that is, each y_i can be restored with high probability, and finally each reconstructed y_i is merged into a whole image.

Given the above explanation, the image reconstruction algorithm based on the block compressive sensing theory calculates each sub-image block separately, which reduces the amount of calculation significantly, and the real-time performance of the image processing is good. However, the block compressive sensing method also has shortcomings, one of which is that the reduction in the amount of calculation is at the expense of the quality of the rebuilt image. In other words, after the image blocks have been calculated separately, the quality of the combined reconstructed image is degraded. It is also not conducive to the actual processing of robot vision. Therefore, the next step will be to adaptively enhance the robot vision image.

3. ADAPTIVE ENHANCEMENT OF ROBOT VISION IMAGE

According to the above analysis, through image denoising and reconstruction, the noise interference in the image is removed, and the image processing efficiency is improved. To further improve the image quality, the robot vision image adaptive enhancement is performed [15, 16].

By comparing the distortion costs of different regions in the robot vision image, it can be found that there are some abnormal pixels. That is, there may be some pixels with high distortion cost in the region with complex texture, while there may be some pixels with low distortion cost in the flat region. Affected by these abnormal pixels, these flat regions may be over-enhanced in the process. To solve the influence of outliers on the robot vision image, an image enhancement algorithm based on multi-scale filters is proposed in this study. To solve the problem caused by abnormal pixels, an intuitive approach is to deal with the image noise in different regions respectively. The noise in complex texture regions should be enhanced and the noise in flat regions should be suppressed. To solve this problem, multi-scale filters obtained by the combination of MGF and HPF is proposed [17]. By adjusting the weight of each filter, it can enhance the texture region can be enhanced the enhancement of the flat region can be reduced as much as possible.

The MGF contains multiple Gaussian filters of different scales. Firstly, the whole image is convoluted with three different Gaussian filters to obtain three filtered smooth images:

$$\begin{cases} F_1 = S_1 \otimes Y \\ F_2 = S_2 \otimes Y \\ F_3 = S_3 \otimes Y \end{cases} \tag{15}$$

In the formula, the symbol $\otimes$ indicates the convolution operation; S_1, S_2 and S_3 respectively represent three Gaussian filters of different sizes; F_1, F_2 and F_3 respectively indicate the smooth image generated from filtering the carrier image Y. To obtain sharpened details at different scales, the three smooth images are converted into Formula (16).

$$\begin{cases} B_1 = Y - F_1 \\ B_2 = F_1 - F_2 \\ B_3 = F_2 - F_3 \end{cases} \tag{16}$$

In the formula, B_1, B_2, and B_3 indicate the details of images of different sizes, respectively, and the global detail of carrier image Y consists of the weighted sum of three image details B_1, B_2, and B_3:

$$B = \frac{(1 - \eta_1)\mathrm{sgn}(B_1)}{(B_1 + B_2 + B_3)(\eta_1 + \eta_2 + \eta_3)} \tag{17}$$

In the formula: η_1, η_2 and η_3 represent the weights of different sharpening details respectively; sgn ( ) indicates the sign function, when $B_1 > 0$, the function returns 1, when $B_1 < 0$, the function returns -1, otherwise it is 0.

To obtain as much detailed texture as possible, the image is enhanced using both an MGF and an HPF. Taking advantage of the fact that the noise in the flat area is more sensitive to the small-scale filter, the weight of the small-scale filter is reduced in order to strengthen the texture area and reduce the noise enhancement in the flat area. Therefore, an adaptive enhancement method for robot vision images on the basis of multi-scale filters is designed [18]. The method consists of two parts: image enhancement and distortion cost calculation. The algorithm flow is shown below:

(1) Use a MGF to strengthen the carrier image Y to obtain the enhanced part E_y;

(2) Use a HPF to sharpen the carrier image y to obtain a sharpened part R_y;

(3) The final enhanced image Y' is obtained by the weighted sum of the two enhanced parts E_y and R_y:

$$Y' = \delta E_y + (1+\delta) R_y + Y \tag{18}$$

In the formula, δ indicates the weight.

(4) Calculate the distortion cost J of the enhanced image Y' with the help of the distortion function;

(5) According to the diffusion principle, the mean filter is used to smooth the distortion cost J, and obtain the smoothed distortion cost J';

(6) According to the distortion cost J', the STC coding method is used to realize the adaptive enhancement of robot vision images [19, 20].

4. EXPERIMENTAL STUDIES

To verify the performance of the multi-scale filter-based adaptive enhancement method for robot vision images, the experiments compare the performance differences between the proposed method and the LIE method on the basis of the PDN model and the low-light image enhancement method on the basis of MDARNet. To ensure the comparison fairness, the consistency of the experimental conditions is guaranteed during the experiment.

4.1 Experimental Environment and Dataset Settings

Select the image, which is in the Bossbase1.01 image database, as the experimental object, and select the image with the size of 512×512 in the database as the test image. To test the correctness of the adaptive enhancement method of robot vision image based on multi-scale filters, the experimental analysis is carried out in the environment where the simulation software is MATLABR2009a.

4.2 Image Enhancement Quality Evaluation Index

The correct evaluation of image quality is a very important but difficult topic to research. The image quality is directly related to the subsequent image interpretation, analysis, measurement and effective use. To explore the capabilities of various methods used for image enhancement, the three most commonly used image quality evaluation standards are applied as experimental indicators to determine the image enhancement effects of different methods.

(1) Mean square error

The mean square error shows the dispersion of image pixel gray level related to the average gray level. It can also be used to determine the extent of image contrast. The larger the value, the more uniform is the gray distribution in the image; the higher the image contrast, the better is the image quality. The mean square error can be calculated with Formula (19):

$$Fitness = \frac{1}{w_1 w_2}\sum_{a=1}^{w_1}\sum_{b=1}^{w_2} c^2(a,b) - \left[\frac{1}{w_1 w_2}\sum_{a=1}^{w_1}\sum_{b=1}^{w_2} c(a,b)\right]^2 \tag{19}$$

In the formula, $c(a, b)$ indicates the grayscale of the image at pixel (a, b); w_1 and w_2 show the image width and image height, respectively.

(2) Information entropy

Entropy is a measure indicating the image information richness from the perspective of information theory. In accordance with Shannon's information theory principle, the entropy of an image is defined as:

$$P(y) = -\sum_{i=0}^{L=1} \overline{\omega}_k |\overline{\omega}_k \times g| \tag{20}$$

In the formula, L indicates the maximum gray level of image Y; $\overline{\omega}_k$ indicates the number of pixels with gray value of k in image Y.

The information entropy has the following characteristics: when the pixels in the image are uniformly distributed at each gray level, that is, when the frequency of occurrence of each gray level is $\overline{\omega}_k = 1/L$, then $P(Y)$ has the maximum value. At this time, the image information is the most abundant and the gray level distribution is the most uniform, has the most layers; when all pixels in the image have a certain gray level only and no other gray levels, $P(Y)$ has the minimum value of 0, and the image has no information at this time. When the gray level of the image decreases, the entropy also decreases.

(3) Average gradient

The average gradient refers to the extent of reflecting the subtle contrast of the image. Generally, the larger the average gradient, the clearer the image and the better the contrast. The calculation formula is:

$$\alpha = \frac{1}{(w_1-1)(w_2-1)} \times \sum_{i=1}^{w_1-1}\sum_{j=1}^{w_2-1} \frac{c(a,b)+c^2(a,b)}{2} \tag{21}$$

4.3 Experimental Results

(1) Comparison of mean square error

The proposed method, the LIE method on the basis of the PDN model, and the low-illumination image enhancement method on the basis of MDARNet are used to enhance the image. The comparison results of the mean square errors of different methods are shown in Table 1.

The data in Table 1 show that the mean square error of the proposed method is relatively large, the highest value is 27.457, and the lowest value is 21.369. The mean square error of the PDN model and the MDARNet method is lower than that of the proposed method. The highest values were 19.564 and 18.562, respectively. In sum, the proposed method can alleviate the problem of image information loss to a certain extent, the gray distribution of the image is more uniform, the image contrast is greater, and the image quality is better.

Table 1 Comparison results of mean square error of different methods.

Pattern	Mean squared error		
	The proposed method	Progressive dual network model	MDARNet
1	24.256	19.564	15.257
2	23.478	18.472	18.562
3	21.369	17.639	16.367
4	27.457	19.002	17.426
5	25.581	18.563	15.010

Table 2 Comparison of information entropy results for different methods.

Pattern	Information entropy		
	The proposed method	Progressive dual network model	MDARNet
1	31.254	24.568	19.852
2	30.663	24.147	21.236
3	33.489	23.635	24.159
4	29.637	28.634	24.357
5	32.321	22.463	25.028

Table 3 Comparisonofaverage gradient results for different methods.

Pattern	Average gradient		
	The proposed method	Progressive dual network model	MDARNet
1	0.899	0.523	0.725
2	0.856	0.574	0.746
3	0.912	0.634	0.637
4	1.023	0.702	0.694
5	0.157	0.693	0.703

(2) Information entropy comparison

The above methods are used for image enhancement, and the information entropy comparison results of different methods are presented in Table 2.

The data in Table 2 show that the information entropy of the proposed method is larger, the highest value is 33.489, and the lowest value is 29.637. The information entropy of the PDN model and the MDARNet method is lower than that of the proposed method, and the highest value of the two is 28.634 and 25.028 respectively. Hence, it can be concluded that the proposed method can make the gray levels of the pixels in the image more uniformly distributed and the image information is richer, as well as the layers are the most.

(3) Average gradient

The image enhancement effects of the proposed method, the PDN model and the MDARNet method are compared, and the average gradient comparison results of different methods are presented in Table 3.

As shown in Table 3, on the average gradient, the proposed method achieves the maximum value, it can be seen that it has a good performance in maintaining image details, and the image clarity is higher; while the PDN model and the MDARNet method are in the average gradient index. The results obtained are quite different from those of the proposed method, indicating that the image enhancement effect of the PDN model and the MDARNet method is not so good as that of the proposed method.

A comprehensive analysis of the experimental indicators above indicate that the proposed method has the best comprehensive performance, and it has obvious advantages in terms of preservation of information and details, gray distribution, contrast, and information richness of images.

(4) Comparison of image enhancement visual effects

To further verify the image enhancement effect of the proposed method, the visual images collected by the robot are selected as the research object arbitrarily in the experimental data set, and the enhancement process is carried out. The results are shown in Figure 3.

Figure 3 clearly shows that the proposed method can produce more complete image edges. Compared with the PDN model and the MDARNet method, there is less loss of detail and the subjective vision is better. The enhanced image has no local blur problem and the edge information and texture features are preserved. Therefore, the proposed method significantly improves image quality, exhibits relatively better performance, and is more suitable for robot vision image processing. This is because the proposed method applies a non-linear weighted variational algorithm based on the total variation. This results in an image that has more smoothing in the flat area and less smoothing at the edges, which reduces both the influence of noise and the complexity of denoising the image. According to experimental results, the image processing effect of the proposed method is better.

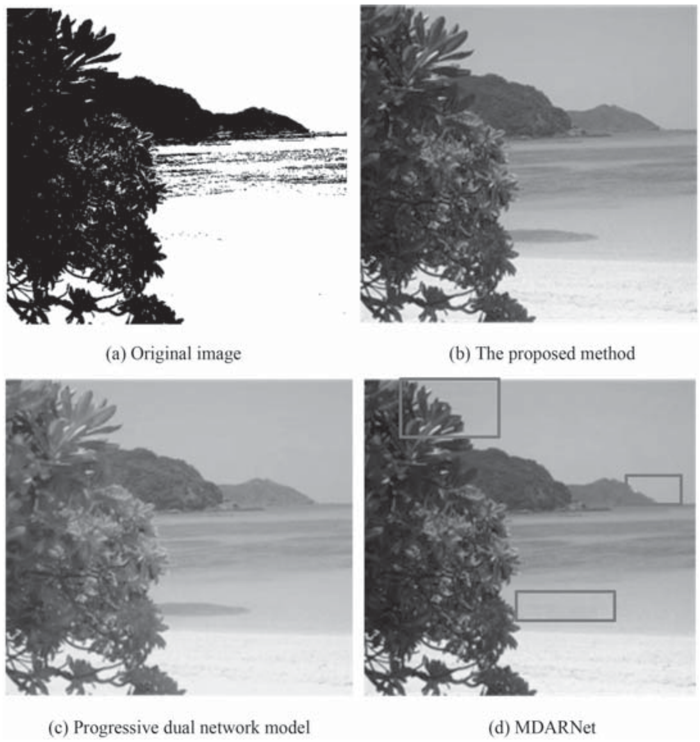

Figure 3 Comparison of image enhancement visual effects.

5. CONCLUSION

To address the problem of low mean square error value, information entropy and average gradient in the image enhancement process present in traditional methods, and poor visual image effect, an adaptive enhancement method of robot vision image based on multi-scale filters is proposed. The main innovations contributed by this method are:

(1) The HSV color space model established in this paper enhances the brightness and saturation components of the image and eliminates the connection between the brightness component and the color information in the image.

(2) The traditional compressed sensing reconstruction algorithm is improved, which can avoid the problem of having to discard a large amount of sampled data during the compression process, thereby reducing the cost of image processing.

(3) Multi-scale filter enhancement is used to process robot vision images, and image enhancement is achieved by adjusting the weight of each filter.

(4) According to experimental results, the proposed method has a large mean square error, with the highest value being 27.457; it also has a larger information entropy, with the highest value being 33.489; moreover, the image edge processed by the proposed method remains more complete, there is less loss of detail, the subjective vision is better, and the enhanced image does not have the problem of local blur, which validates the image enhancement effect obtained by the proposed method.

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