Research on Tissue Structure Enhancement Method of Medical Endoscope Images

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Abstract

Background:

In clinical surgery, the quality of endoscopic images is degraded by noise. Noise is mainly caused by blood, illumination changes, specular reflection, smoke, etc., which will significantly reduce the quality of the image in the occluded area. Affect the doctor's judgment, prolong the operation time and increase the operation risk.

Methods:

This paper proposes an improved weighted guided filtering algorithm to enhance endoscopic image tissue. An unsharp mask algorithm and an improved weighted guided filter are used to enhance vessel details and contours in endoscopic images. An overall scheme of endoscopic image processing is proposed, which includes detail enhancement, contrast enhancement, brightness enhancement and highlight area removal.

Results:

Compared with several other algorithms, it is better than other algorithms in maintaining edges and reducing halo, and its effectiveness is proved by experiments. The peak signal-to-noise ratio and structural similarity of endoscopic images obtained by the improved algorithm in this paper are the largest. The foreground-background value Detail Variance-Background Variance has been improved.

Conclusion:

Our algorithm has a stronger ability to suppress noise, and is more able to maintain the structure of the original endoscopic image, which improves the details of tissue blood vessels. This paper can provide guidelines for the development of endoscopy devices.

Background

In minimally invasive surgery, doctors make diagnoses based on endoscopic images. Image quality plays an important role in diagnosis. Common gastrointestinal diseases such as gastric cancer and rectal cancer seriously threaten human health. In particular, rectal cancer ranks second in the cancer list with a high number of patients [1]. White light endoscopy is often used in the diagnosis of rectal cancer, but it cannot clearly show important tissue and vascular features, resulting in misdiagnosis and missed diagnosis. In addition, Moreover, the image's brightness and contrast are made worse by the complex folds and bumps in the stomach organ. Therefore, it is necessary to enhance the endoscope image.

The narrow-band imaging (NBI) [2] technique introduced by the Olympus Corporation of Japan in 2006 can considerably improve the contrast of fine blood vessels. NBI technology can obtain the hierarchical endoscope image and provide excellent contrast of endoscope images. Flexible spectral image color

enhancement (FICE) [3] developed by Fujifinone can simulate pigment endoscopes to reproduce the fine structure of the mucosal surface and the direction of microscopic blood vessels. The Storz professional image enhancement system (SPIES) system [4], launched by Karl Storz in 2016, contains numerous enhancement modes for endoscope images, such as Spectra A, Spectra B, Spectra Clara, and Spectra Chroma.

Numerous enhancement algorithms have been proposed to improve the quality of endoscope images. Retinal vascular enhancement in medical images [5] is achieved by using image processing methods, such as the adaptive histogram equalization method [6], unsharpened mask algorithm [7], morphological method, Hessian matrix method [8], multi-scale filtering method [9–11]. The global histogram equalization [12] and adaptive histogram equalization algorithms [13] are examples of image enhancement algorithms based on the histogram. Image enhancement algorithms based on wavelet analysis mainly include high-frequency wavelet transformation [14] and adaptive filtering [15]. Homomorphic filtering enhancement is typically used in image denoising [16] and dehazing [17]. Okuhata et al. [18] proposed an algorithm based on homomorphic filtering. In this method, images containing brightness layer information are extracted from the original image, and Gamma correction is used to achieve high contrast. Considering noise reduction, Gopi et al. proposed a color image noise reduction method based on dual-density dual-tree complex wavelet transform [19]. Mohammed et al. proposed a “tri-scan” image enhancement algorithm that enhances the tissue surface and vascular characteristics. For the mucosal layer, the image R channel is processed by the adaptive Sigmoid function to enhance the vascular contrast. Finally, tonal transformation is performed to enhance the structural characteristics of microvessels and tissues [20].

The quality of the endoscopic images may be low due to some reasons, so it is particularly important to enhance the endoscopic images. The deficiencies of the endoscopic images are as follows: First, due to the poor image quality of conventional photography, improving the image quality of the endoscope and enhancing image details is critical for accurate diagnosis. Second, the background of some tissues and blood vessels captured by the endoscope is red. The overall image contrast is insufficient, making distinguishing microvessels from the tissue background and finding lesions difficult, thus affecting diagnosis. Third, during the shooting process using the complementary metal oxide semiconductor (CMOS) camera, the endoscopic image may have insufficient brightness because of light source problems or insufficient exposure, affecting the observation of the image. Finally, during the endoscopic image shooting process, the interior of the human tissue is smooth, and some water droplets are present in the tissue, causing specular reflection areas in the endoscopic image.

Therefore, this study proposed an improved weighted guided filtering algorithm for image enhancement. Compared with the traditional guiding filter algorithm, the defect of noise residual can be overcome. The vascular detail and contour of endoscope image were enhanced by image enhancement algorithm. The contrast enhancement of the endoscopic image aims to reduce the red component and enhance the blue and green components, so that the contrast of the background region and the vascular region of the endoscopic image can reach the maximum. The highlight area in endoscope image will cause errors in

the feature point matching process of 3D reconstruction, so the detection and removal of the highlight area is very important. During the shooting process of CMOS camera, the endoscope image may be taken with insufficient brightness due to insufficient light source or exposure. In view of this phenomenon, it is necessary to enhance the image brightness of the endoscope image with insufficient brightness. An adaptive and integrated neighborhood dependent approach for nonlinear enhancement (AINDANE) algorithm [21, 22] was used to enhance the brightness of endoscopic images. Combined with all the above algorithms, an endoscope image processing algorithm is proposed. The algorithm includes detail enhancement, contrast enhancement, brightness enhancement and highlight area removal, which can effectively improve the quality of endoscope image. The overall flow chart of this process is displayed in Fig. 1.

Results

The peak signal-to-noise ratio (PSNR) is used to measure the proportion of noise; image quality is directly proportional to the PSNR size. The similarity of two images can be measured through structural similarity (SSIM), and the similarity of images is proportional to the size of SSIM. The PSNR and SSIM values, calculated by the five algorithms after endoscope image enhancement, are presented in Tables 1 and 2. The proposed endoscope enhancement algorithm can increase the PSNR and SSIM values of the final endoscope image, indicating that the enhanced image has less noise and higher structural similarity. In Table 3 The detail variance–background variance (DV–BV) [23] values of the endoscope image enhanced by the algorithm in this study are higher than those of conventional methods. Finally, a contrast enhancement algorithm was used to train the endoscope image after detail enhancement, and a set of optimal solutions $\alpha = 0.75$, $m = 0.525$, $E = 2.15$, $L = 1.241$ were obtained. Next, the endoscope image with enhanced details was stretched to reduce the red component and enhance the green or blue component of the final endoscope image to ensure the tissue background and blood vessels satisfy the relevant requirements from the visual perspective of human eyes.

Table 1
Peak-signal-to-noise ratio (PSNR) calculation results

Image number	GIF	WGIF	GDGIF	EGIF	Proposed
(1)	20.9569	24.5021	24.7910	26.6537	29.4090
(2)	19.7178	23.6563	24.0289	25.1088	28.4882
(3)	20.0447	23.3038	23.3767	24.6815	28.0150
(4)	29.5328	31.2070	31.8931	33.8716	37.5925
(5)	21.3806	24.7216	25.1418	29.3361	29.9575
(6)	33.3530	36.4773	37.1277	32.8452	42.1757

Table 2
Structural Similarity (SSIM) calculation results.

Image number	GIF	WGIF	GDGIF	EGIF	Proposed
(1)	0.7531	0.8373	0.8444	0.9156	0.9212
(2)	0.7341	0.8368	0.8458	0.8919	0.9214
(3)	0.7241	0.8105	0.8124	0.8808	0.9071
(4)	0.8778	0.9026	0.9138	0.9417	0.9681
(5)	0.7024	0.7771	0.7904	0.9225	0.9304
(6)	0.9478	0.9644	0.9686	0.9450	0.9868

Table 3
Detail Variance - Background Variance (DV-BV)
calculation results.

Image number	Original value	Proposed
(1)	17.1937	26.9770
(2)	22.8585	45.6375
(3)	32.8440	68.8868
(4)	7.8341	10.0505
(5)	12.5660	24.4680
(6)	9.5032	17.3654

Discussion

As displayed in Fig. 7, GIF, WGIF [24], GDGIF [25], EGIF [26] and the proposed algorithm were used to process the original endoscopic images; six endoscopic images were enhanced by the endoscopic image enhancement algorithm. The results of endoscopic image enhancement in Fig. 7 revealed that although GIF and others enhanced the details of blood vessels, image distortion and noise amplification also occurred. This phenomenon was attributed to the low edge maintenance ability of GIF and others. The noise retained by the image was amplified by a sharpening factor of ; the image detail layer was obtained while retaining the noise. The edge retention capabilities of the proposed algorithm were superior to those of the GIF ,WGIF, GDGIF and EGIF. Furthermore, the enhancement algorithm was less noisy and enhanced the details of the endoscopic tissue and blood vessels.

Figure 8 shows that the algorithm in this paper can better maintain the basic structure of the endoscopic image, and enhance the tissue outline and blood vessel details. The brightness and contrast have been

greatly improved, and the highlight removal effect is better, which proves the feasibility of the scheme in this paper.

Conclusion

An image enhancement algorithm was proposed for endoscopic images typically used in minimally invasive surgery. The scheme included algorithm an improved second-weighted guided filtering algorithm; the effectiveness of the algorithm was verified experimentally. The results revealed that the proposed method can maintain the edges and reduce the halo effect and detect and remove highlights. Furthermore, the time complexity did not change considerably compared to conventional methods despite improvement in the endoscopic image quality. The proposed algorithm can be applied to endoscopic image processing as its enhancement effect is superior to those of GIF, WGIF, GDGIF and EGIF algorithms. Therefore, our method has a good clinical application prospect in the advanced image processing of endoscopes.

Methods

Guided filtering

Guided Image Filtering (GIF) is a Filtering algorithm proposed by He Kai-ming, which can be used for stereo matching, Image enhancement, Image fusion, defogging, etc. [27]. It is the fastest edge preserving algorithm, and its complexity is $O(N)$. The following linear relationship exists between the leading image G and the output image Q as follows:

$$q_i = a_k G_i + b_k, \forall i \in w_k$$

1

where w_k is the filter window, with a_k and b_k remaining unchanged.

As the gradient between the texture of the output image and that of the guide image is the same, the equation of $\nabla Q = a \nabla G$ is satisfied. Therefore, guided image filtering (GIF) can preserve edges to a certain extent. Its energy function is defined as follows:

$$E(a_k, b_k) = \sum_{i \in w_k} \left((a_k G_i + b_k - P_i)^2 + \lambda a_k^2 \right)$$

2

where λ is the regularization parameter, whose function is to prevent a_k from becoming too large; P is the input image. Eq. (3) is solved using the least square method as follows:

$$a_k = \frac{\frac{1}{|W|} \sum_{i \in W_k} G_i p_i - \bar{P}_k u_k}{\sigma_k^2 + \lambda}$$

3

$$b_k = \bar{P}_k - a_k u_k$$

4

Weighted guided filtering

However, the regularization coefficient is fixed in the energy function of GIF, and the effect of sharpening the prominent edge while denoising is not good. The λ in GIF is artificial and the differences in image textures between various windows are ignored. Therefore, some researchers proposed Weighted Guided Image Filtering (WGIF) [28]. Therefore, an edge weight factor is introduced in the weighted-GIF (WGIF) algorithm to adaptively adjust regularization parameters as follows:

$$\Gamma_G(i) = \frac{1}{N} \sum_{i'=1}^N \frac{\sigma_{G,1}^2(i) + \epsilon}{\sigma_{G,1}^2(i') + \epsilon}$$

5

where i is the center pixel of the current window, and $\sigma_{G,1}^2(i)$ is the variance of the guiding image G in pixel i in the window. Currently, the window size is 3×3 , and N is the pixel size of the image. Here, ϵ is $(0.001 \times L)^2$ and L is the dynamic range of the input image. For 8-bit images, the value of L is 256, and the value of ϵ is a fixed value of 0.065536. The energy function of Formula (6) can be expressed as follows:

$$E(a_k, b_k) = \sum_{i \in W_k} \left((a_k G_i + b_k - P_i)^2 + \frac{\lambda}{\Gamma_G(i)} a_k^2 \right)$$

6

WGIF outperforms GIF with respect to image sharpening and edge highlighting because of the adjustment of the edge weight factor. Furthermore, the algorithm complexity does not increase in WGIF compared with GIF.

Detail enhancement of endoscopic images

(1) Determine parameter α

In this study, α is defined as the sharpening factor that controls the sharpening degree of the image. However, the factor is sensitive to noise and should be suppressed for controlling α . Considering this factor, the following formula is used to calculate α :

$$\alpha = 8 \times \frac{1}{n} \sum_{i=1}^n I_c$$

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where n is the total number of pixels of grayscale image, I_c is the gray image, and C represents R , G , and B channels of image, respectively.

Endoscope images contain details, such as blood vessel information; therefore, the selected window radius should not be too large. Furthermore, the influence of noise should be considered. Therefore, the window radius in the endoscope image enhancement algorithm is set to 16, and λ is 0.12.

(2) Quadratic improved weighted guided filtering

The original endoscope image typically has some noise, whereas the noise of the weighted guided filtering image is partially reduced. However, some residual noise exists in various frequency bands. A quadratic improved weighted guided filtering algorithm was introduced to suppress the noise to overcome this defect.

First, the original endoscope image was filtered by the improved weighted guided filtering algorithm to obtain the filtered image $P1$, with a window radius of 16 and $\gamma = 0.12$. Next, the original image is considered as the input image and $P1$ as the guide image. The improved weighted guide filtering is performed again.

Endoscopic image contrast enhancement

In this paper, an endoscopic blood vessel contrast enhancement algorithm based on spectral transformation is improved. In order to make the endoscopic image visually distinct, the maximization target of the tonal distance is defined:

$$\max(\|$$

8

Among them, $\{B_{ori}\}, \{V_{ori}\}$ is the background area and the blood vessel area of the original endoscopic image, and $\{B_{en}\}, \{V_{en}\}$ is the background area and the blood vessel area of the endoscopic image after the detail enhancement algorithm.

For the red channel component, the model linearly reduces its information by an attenuation factor of α . For the blue and green channel components, the model wants to improve the overall information,

so it uses a nonlinear function to process the endoscopic image to improve its contrast, the formula is as follows:

$$s = \frac{L}{1 + ((m/r)^E)}$$

9

Among them, can control the degree of translation of the function, can control the slope of the function, represents the input image, and represents the output image.

The method of model parameter training is as follows:

$m=20$ endoscopic images and $n=84$ sets of parameters (each set of parameters are $\{\alpha_j\}, \{L_j\}, \{m_j\}, \{r_j\}$ respectively) are selected for training. The steps of training parameters are as follows:

1). Input the i th image, the image size is 316×258 , if is greater than , end the training, then skip to $S8$, otherwise, execute $S2$.

2). Select the vessel region and background region of the endoscopic image.

3). Enter the i th group of parameters, if is greater than , then skip to $S7$, otherwise go to $S4$.

4). Stretch is performed on each of the 3 channels with the following formula:

$$\left\{ \begin{array}{l} G_i = \frac{L_j}{1 + ((m_j/r_i)^{E_j})} \\ R_i = d_j * R_i \\ B_i = \frac{L_j}{1 + ((m_j/r_i)^{E_j})} \end{array} \right. \text{right.}$$

10

5). Both the original training image and the processed image are in *RGB* space, and now they are converted to CIE space. The conversion formula is as follows:

$$\left\{ \begin{array}{l} X = 2.7690 * R + 1.7518 * G + 1.1300 * B \\ Y = 1.0000 * R + 4.5907 * G + 0.0601 * B \\ Z = 0.0000 * R + 0.0565 * G + 5.5943 * B \end{array} \right. \text{right.}$$

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$$\left\{ \begin{array}{l} x = \frac{X}{X+Y+Z} \\ y = \frac{Y}{X+Y+Z} \end{array} \right. \text{right.}$$

12

6). Calculate the distance $\left\{ \begin{array}{l} B_{en} \\ V_{en} \end{array} \right\}$ between the original image and the blood vessel and the distance $\left\{ \begin{array}{l} B_{ori} \\ V_{ori} \end{array} \right\}$ between the original image and the background of the processed image, then save the ratio of $\left\{ \begin{array}{l} B_{en} \\ V_{en} \end{array} \right\} / \left\{ \begin{array}{l} B_{ori} \\ V_{ori} \end{array} \right\}$ in the array *VecDis*, and jump back to $S3$.

7). According to the maximization objective of formula (12), a set of optimal parameters $\{\alpha_i\}, \{L_i\}, \{m_i\}, \{E_i\}$ of the first image can be obtained, and the optimal parameters of this set are saved in *VecA*, *VecL*, *VecM*, *VecE* respectively, and finally jump back to $S2$.

8). Take the average of VecA,VecL,VecM,VecE respectively, then you will get a set of optimal parameters $\{\alpha_{best}\}, \{L_{best}\}, \{M_{best}\}, \{E_{best}\}$, and finally end the training.

After training on 20 images, the final results are: $\alpha = 0.75, m = 0.525, m = 0.525, E = 2.15, L = 1.241$.

Brightness enhancement of endoscopic images

In the process of CMOS camera shooting, the brightness of the endoscope image may be insufficient due to the problem of light source or insufficient exposure. To solve this problem, it is necessary to enhance the brightness of the endoscope image. Li Tao et al. proposed AINDANE algorithm [29], which can improve the brightness of the image when the color of the endoscope image is dark due to the shooting equipment or the surrounding environment. This function is mainly realized by the module of adaptive brightness enhancement.

First, convert RGB images to grayscale images. The calculation process is expressed as follows:

$$I(x,y) = \frac{76.245I_R(x,y) + 149.685I_G(x,y) + 29.01I_B(x,y)}{255}$$

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Where, $I_R(x,y)$, $I_G(x,y)$ and $I_B(x,y)$ represent the values of channels R and G and at (x,y) respectively, all of which are 8 bits.

Then normalize $I(x,y)$ using the following formula:

$$I_n(x,y) = \frac{I(x,y)}{255}$$

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The calculation process of nonlinear transfer function is expressed as follows:

$$I_n^{\prime} = \frac{I_n^{\{(0.72z+0.25)\}} + (1 - I_n)0.4(1 - z) + I_n^{\{(2 - z)\}}}{2}$$

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This process is called dynamic range compression, where the parameter is related to the histogram of the image:

$$z = \left\{ \begin{array}{l} 0 \\ \frac{L - 50}{100} \end{array} \right. \quad \begin{array}{l} L \leq 50 \\ L > 50 \end{array}$$

$$\left\{ \begin{array}{l} 50 < L \leq 150 \\ L > 150 \end{array} \right. \left\{ \begin{array}{l} \text{enhancement} \\ \text{no enhancement} \end{array} \right.$$

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Where, when the cumulative distribution function value is 0.1, represents its corresponding gray value.

is used as an indicator of the brightness of the image. If the image is really dark ($L < 50$), then the brightness must be much higher; If the image is not so dark ($L \approx 100$), there is less need for brightness enhancement; If the image has sufficient brightness ($L > 150$), no enhancement is required. In this way, it makes the algorithm more adaptive. Figure 2 shows the cumulative distribution function of gray value at gray level .

The transfer function is actually a combination of three simple mathematical functions. In Fig. 3, curve 6($z=0$) is compared with the dotted line (line labeled 1), which actually represents the identity transformation. The first two terms are plotted as curve 2 and line 3 respectively, and their sum is curve 4. Add normalized curves 4 and 5 and divide by 2, then the transfer function shown in curve 6 will be generated. The results show that this transformation greatly increases the brightness of the darker regions and less intensifies the brighter regions.

Figure 4 shows the contrast of brightness enhancement effect. Three original endoscope images with low brightness were enhanced by the algorithm in this paper, and their brightness was greatly improved.

Removal of highlights from endoscopic images

(1) Highlight spot detection

First convert the original image from RGB model to HSV color model. To get absolutely bright areas, they used two thresholds $\{T_s\}$ and $\{T_v\}$ on saturation and lightness, respectively, if the area is a highlight area, as in Eq. (17):

$$\left\{ \begin{array}{l} s(x) < T_s \\ v(x) > T_v \end{array} \right.$$

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However, the disadvantage of this method is that the rapid movement of the endoscope lens causes the misalignment of the color channels, so the detected highlights can appear white or highly saturated Red, Green or Blue.

The blue channel $\{c_G\}$ and the green channel $\{c_B\}$ can be normalized by:

$$\{c_E\} = 0.2989 \cdot \{c_R\} + 0.5870 \cdot \{c_G\} + 0.1140 \cdot \{c_B\}$$

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Then compare 95% of the grayscale intensity of the blue channel $\{c_G\}$ and the green channel $\{c_B\}$ with 95% of the intensity of $\{c_E\}$ respectively, we can get:

$$\{r_{GE}\} = \frac{\{P_{95}\}(\{c_G\})}{\{P_{95}\}(\{c_E\})}, \{r_{BE}\} = \frac{\{P_{95}\}(\{c_B\})}{\{P_{95}\}(\{c_E\})}$$

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If a pixel $\{x_0\}$ is a highlight area, then it satisfies the following formula:

$$\{c_G\}(\{x_0\}) > \{r_{GE}\} \cdot \{T_1\} \vee \{c_B\}(\{x_0\}) > \{r_{BE}\} \cdot \{T_1\} \vee \{c_E\}(\{x_0\}) > \{T_1\}$$

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It then detects the parts of the endoscopic image where the highlights are not too strong. Its essence is to compare each given pixel with a smooth, non-special surface color at the pixel location, which is estimated by local image statistics in the endoscopic image. Contrast intensity, and then set a slightly lower threshold $T_2^{\{rel\}}$ by a method similar to detecting brighter highlight areas. Median filtering is first performed on the RGB three channels of the original image due to its robustness to outliers and edge-preserving properties, followed by filling each detected highlight region to a region within a fixed distance from the region contour. The centroid of the pixel color in, incorporating information about possible highlight locations into the median filter. This region of interest is then isolated by complete separation of the masks obtained by performing two different dilation operations on the masks of possible highlight locations. For the dilation operation, disk-shaped structuring elements with radii of 2 and 4 pixels are used.

By comparing pixel values in the input image and the median filtered image, highlights are found as color outliers. For this comparison, several distance measures and ratios are possible. An example of such a metric is the Euclidean distance or the infinite norm of the difference in *RGB* space. During the evaluation, it was found that the maximum ratio of the three color channel intensities in the original image to the median filtered image yielded the best results. For each pixel position x , this intensity ratio max is calculated as:

$$\{\varepsilon_{\{ \hbox{max} \}}\}(x) = \hbox{max} \left\{ \left\{ \frac{\{c_R(x)\}}{\{c_R\}^{\{ * \}}(x)}, \frac{\{c_G(x)\}}{\{c_G\}^{\{ * \}}(x)}, \frac{\{c_B(x)\}}{\{c_B\}^{\{ * \}}(x)} \right\} \right\}$$

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where $c_R(x)$, $c_G(x)$ and $c_B(x)$ are the intensities of the median filtered red, green and blue components, respectively.

Different color balance and contrast can cause this characteristic to vary greatly from image to image. These changes are compensated for using a contrast factor of τ_i , calculated for the 3 color channels of each given image:

$$\tau_i = \left(\frac{\bar{c}_i + s(c_i)}{\bar{c}_i} \right)^{-1}, i \in \{R, G, B\} \quad (22)$$

Among them, $\bar{c}_i$ is the sample mean of all pixel intensities in the color channel $s(c_i)$, and $s(c_i)$ is the sample standard deviation. Using these coefficients, formula (23) is modified to obtain a contrast-compensated intensity ratio $\tilde{\epsilon}_{\max}(x)$, as follows:

$$\tilde{\epsilon}_{\max}(x) = \max \left\{ \tau_R \cdot \frac{c_R(x)}{c_R^*(x)}, \tau_G \cdot \frac{c_G(x)}{c_G^*(x)}, \tau_B \cdot \frac{c_B(x)}{c_B^*(x)} \right\} \quad (23)$$

If this pixel is a highlight pixel, the formula is as follows:

$$\tilde{\epsilon}_{\max}(x) > T_2^{\{rel\}} \quad (24)$$

The outputs of the first and second modules are connected by logical disjunctions that generate masks. The two modules complement each other well: the first module uses a global threshold, so only very prominent and bright specular highlights can be detected; the second module detects less obvious highlight regions by comparing the relative characteristics of surface colors. Due to the high dynamic range of the image sensor, the second module alone can also achieve good results. However, since the sensor is easily saturated, the relative highlights become less intense, so that no given area of the image is bright, so the first module still allows detection in this case. Figure 5 shows the detection of the highlight area of the endoscope.

(2) Repair of highlight areas

Fill each detected highlight region with pixel color points within the range of the distance profile. Then the gaussian function is used to filter the image, which is similar to the median filtering after the image is filled, and finally a smooth image is obtained.

The binary mask of the highlighted area in the labeled image is converted to a smooth weighted mask. Smoothing is achieved by adding nonlinear attenuation to the contour of the mirror area. The weight of the pixels around the highlight in the weighted template is calculated according to the Euclidean distance from it to the contour of the highlight area:

$$b(d)=\left[\left\{ 1+\exp \left(\left(l_{\text{max}} \right) - \left(l_{\text{min}} \right) \right) \cdot \left(\frac{d}{\left(d_{\text{max}} \right)} \right)^c + \left(l_{\text{min}} \right) \right\} \right]^{-1}, d \in \left[0, d_{\text{max}} \right]$$

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Where, the logical attenuation function from $\{l_{\text{min}}\}$ to $\{l_{\text{max}}\}$ in the window, the distance range of the mapping from 0 to $\{d_{\text{max}}\}$, constant $c=0.7$.

The weighted sum between the integer weighted mask $m(x)$, the original image $c(x)$ and the smooth image $\{c_{\text{sm}}\}(x)$ after Gaussian filtering can obtain the repaired image $\{c_{\text{inp}}\}(x)$. The calculation process is expressed as follows:

$$\{c_{\text{inp}}\}(x)=m(x) \cdot \{c_{\text{sm}}\}(x)+(1 - m(x)) \cdot c(x)$$

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Figure 6 shows the comparison before and after the restoration of the highlight area of the endoscope image. It can be clearly seen from the figure that the highlight area is well repaired after using the algorithm.

Specific steps of endoscope image enhancement algorithm

The image enhancement algorithm is performed in the following steps:

- 1) Categorize the original endoscope image into R , G , and B channels.
- 2) Obtain the base layer image of each channel by using the quadratic improved weighted guided filtering algorithm for the three channels.
- 3) Subtract the corresponding base layer images of R , G , and B of the three channels to obtain the images of the detail layer of the three channels.
- 4) Multiply the detailed layer images of the three channels the coefficients α to obtain the enhanced detail layer images.
- 5) Add the detail layer images of the three enhanced channels and the corresponding base layer images of the three channels. Finally, merge the three channels to obtain the enhanced endoscope image.

Declarations

Author Contributions:

Conceptualization, YP and WS; Methodology and guidance of the project, WS and GZ; Validation, formal analysis and data analysis, WS and GZ; Writing—GZ, JL, EC, YP, WS. All authors read and approved the final manuscript.

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Availability of data and materials

The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

Conflict of interest

The authors declare no conflicts of interest.

Ethical standards

All procedures performed in studies involving human participants were in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Helsinki Declaration and its later amendments or comparable ethical standards.

Human and animal rights

This article does not contain any studies with animals performed by the author.

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Figures

Figure 1

Algorithm flowchart.

Figure 2

CDF cumulative distribution function of gray value.

Figure 3

Non-linear transfer function.

(a) The original image

(b) After brightness enhancement

Figure 4

Comparison of brightness enhancement effects .

Figure 5
Detection of highlight regions in endoscopic images.

(a) Original Highlights

(b) Restored Highlights

Figure 6
Comparison of endoscopic image highlights before and after restoration.

(a) Original Image

(b) GIF algorithm renderings

(c) WGIF algorithm renderings

(d) GDGIF algorithm renderings

(e) EGIF algorithm renderings

(f) Ours algorithm renderings

Figure 7

Endoscopic image enhancement results. (a) Original Image; (b) GIF algorithm renderings; (c)WGIF algorithm renderings; (d) GDGIF algorithm renderings; (e) EGIF algorithm renderings; (f) Ours algorithm renderings.

(a) Original Image

(b) Ours--Enhanced Images

Figure 8

Endoscopic image enhancement results.