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Wireless capsule endoscopy images enhancement via adaptive contrast diffusion

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ABSTRACT

Wireless capsule endoscopy (WCE) has been widely applied to diagnose diseases in human digestive tract due to its advantage that it can directly view the entire small intestine for the first time. However, many WCE images are rather dark, which challenge to analysis and diagnosis exerted by a clinician. To overcome this shortcoming so as to assist physicians, especially computer aided detection, we propose an adaptive contrast diffusion to enhance WCE images. Based on local analysis of WCE images, we put forward a new idea of contrast diffusion. Then, we employ contrast diffusion to enhance WCE images with an adaptive choice of the conductance parameter, which plays an important role in diffusion. Extensive experiments demonstrate that this new method exhibits promising performance of enhancement for WCE images, leading into a better visualization as well as an improved classification performance of WCE images using computerized methods.

1. Introduction

Gastrointestinal (GI) tract related diseases, such as stomach and colon cancers and ulcerative colitis, are now great threats to human's health. According to statistics of the Hong Kong Cancer Registry in 2007 [1], the number of bowel cancer cases in Hong Kong ranked the second of all cancer cases and it was approaching the highest. Different diseases in the GI tract can be prevented and cured through early detection. Traditional detection methods such as endoscopy, ultrasound, and CT scan show great values in diagnosing diseases of the digest tract, however, they may have different drawbacks such as invasiveness, unclearness and so on. In May of 2000, a short paper in Nature [2] introduced a new form of endoscopy, i.e., wireless capsule endoscopy (WCE). This novel endoscopy, first developed by Given Imaging corporation in Israel, almost revolutionize diagnosis methodology for the digestive tract because this small device can directly view the entire small intestine without pain, sedation, or air insufflation, and these breakthroughs make it rapidly used in most hospitals.

As demonstrated in Fig. 1 WCE is a pill-shaped device which consists of a short-focal-length CMOS camera, light source, battery and radio transmitter. When a WCE is swallowed by a patient after about 12 h fast, this miniature device propelled by peristalsis of GI tract begins to work and record images at 2 frames per second while moving forward along the GI tract. At the same time, images are sent out wirelessly to a data recorder attached to the waist. The whole process costs about 8 h, then all the image data are downloaded into a computer, finally physicians could inspect the whole video and analyze different diseases in the GI tract. It must be pointed out that diagnosis process is very time-consuming because of a large amount of video (about 50,000 practically useful images per inspection), so the diagnosis is not a real-time process in fact, and this situation paves a potential way for off-line post processing and computer aided detection. WCE was cleared for marketing through approval of the U.S. Food and Drug Administration (FDA) in 2001. Up to now, WCE has been used to detect the following diseases [3–6]: small intestinal blooding, Crohn's disease, ulcer, tumors, vascular lesions and colon cancers. It has also been reported by Given Imaging that over 1,000,000 patients worldwide have enjoyed the benefits of this small device.

Although clinical findings of WCE are encouraging, there still remains much room for improvement for this small device [7]. Olympus has been investigating a new generation of WCE such as self-propel capsule endoscopy [8] to reduce the image acquisition time. Another problem with the present WCE is the image's quality. Qualities of WCE images are not ideal due to the following reasons. First, in order to reduce the communication bandwidth and save power, WCE images are not very clear due to a high compression ratio [9]. Secondly, though CMOS image sensor has advantages of low power consumption and superior integration, the image quality it produced is not as good as that of CCD imagers [10]. Furthermore, the resolution of WCE image is only $256 * 256$ due to volume

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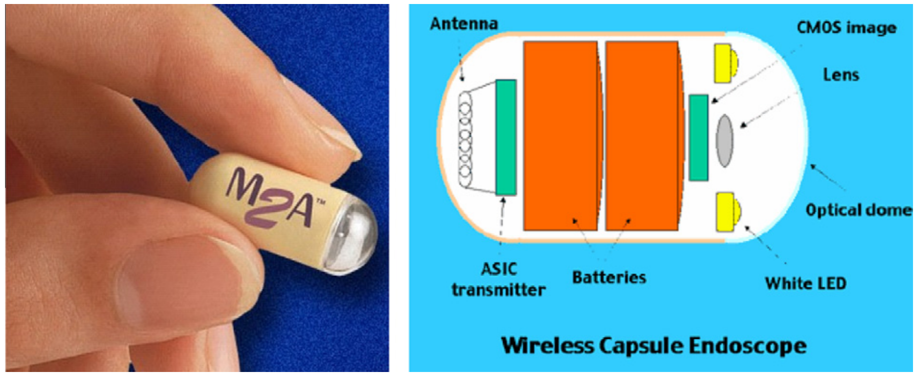
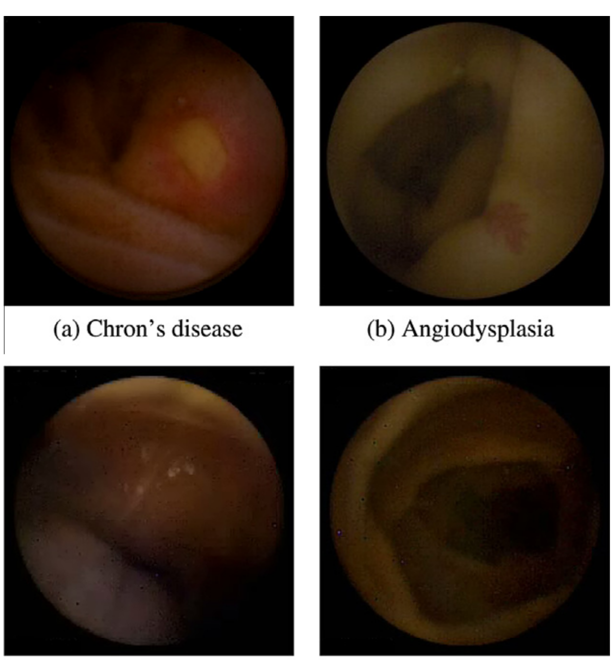


Fig. 1. Wireless capsule endoscopy and its components.

limitation of this little capsule, especially power limitation, whereas traditional endoscopy has a superior performance on this aspect since no power limitation exists. Moreover, bad imaging conditions such as low illumination and complex circumstances in the GI tract will further degenerate qualities of these images. Finally, the short-focal-length image camera can only view a limited distance, which means effects of depth are not ideal. Fig. 2 illustrates some WCE images which contain abnormal regions or are suspected of diseases.

From the illustrated WCE images, we can see that these images are rather dark, sometimes it is even difficult to review contents of the image. Physicians also reflect that images of WCE are not clear enough to see status of mucosa of the digestive tract compared with traditional endoscopies [11]. This situation also challenges to computer aided detection (CAD) because features of diseases might be too vague. To mitigate this situation and facilitate detection of diseases, especially CAD system, it is necessary to enhance these images.

The aim of image enhancement is to improve visibility of dark images while suppressing noise, and considerable interest has been devoted to image enhancement. Histogram-based methods [12,13] are classical approaches to increase visibility of dark images, however, they tend to produce a washed-out appearance,



(a) Chron's disease (b) Angiodysplasia

(c) Suspect of tumor (d) Almost invisible

Fig. 2. Examples of WCE images.

amplified noise or other artifacts. For applications in medical imaging field, perturbations are not desired by physicians at all. Filtering-based methods [14,15], another classical method to enhance images, act mainly as a useful tool to reduce image noise. However, they are incapable of boosting the visibility of images. Besides, neither of these two kinds of methods could preserve local details, which may be important to medical image understanding and diagnosis, so their applications to medical images are limited. The seminal work of anisotropic diffusion proposed by Perona and Malik [16] has an elegant behavior of preserving details efficiently while smoothing noise. Due to this reason, this method has drawn a lot of attention since it was proposed. You et al. discussed thoroughly behaviors of the anisotropic diffusion [17]; extension of anisotropic diffusion to multi-valued image has also been investigated in [18,19]; Weickert [20] proposed a novel coherence enhancement filter which enhances coherence of lines and flow-like textures in images. A new method of enhancing and denoising image with complex diffusion was proposed in [21] by Gilboa et al. The idea of anisotropic diffusion has also been applied successfully to medical images such as ultrasound images [22] and MRI images [23]. Taking into account needs of diagnosis such as no perturbations, preserving details and properties of WCE images, we choose anisotropic diffusion as the mathematical background to fulfill the goal of enhancement.

In order to enhance WCE images for the purpose of facilitating CAD and diagnosis of physicians, we put forward an adaptive contrast anisotropic diffusion in this paper. This new method exploits the local property of WCE images and behaviors of anisotropic diffusion, leading to details enhancement without noise amplification. Experiments show that this new method demonstrates better performances of enhancement than some conventional methods so as to assist diagnosis especially CAD.

The outline of this paper is organized as follows. In the next section the mathematical background of this paper, i.e., anisotropic diffusion, will be briefly reviewed. A new concept of contrast will be presented in Section 3 together with adaptive contrast diffusion and its extension to color space. Section 4 provides experimental validation of the proposed methodology. Finally, conclusions are drawn in Section 5.

2. Anisotropic diffusion

Witkin [24] first found that convolution of a signal with Gaussians at each scale was equivalent to solving a heat diffusion equation with the signal as an initial value. With regard to an image I_0, this process can be described with a partial differential equation:

$$\frac{\partial I(x,y,t)}{\partial t} = g\Delta I(x,y,t) \tag{1}$$

where g is the diffusion conductance constant, and Δ is the Laplacian operator, the original image I_0 is taken as the initial state of the differential equation in (2). Because edges at low scales will be distorted, Perona and Malik [16] proposed a great improvement to this model:

$$\frac{\partial I(x,y,t)}{\partial t} = div[g(\|\nabla I\|)\nabla I] \tag{2}$$

where ∇ is the gradient operator. A desirable characteristic of the conductance function is that it will encourage intra-region smoothing, while inhibit inter-region smoothing. Two functions with the above quality are defined:

$$g(\|\nabla I\|) = \exp\left\{-\left(\frac{\|\nabla I\|}{\alpha}\right)^2\right\} \text{or} g(\|\nabla I\|) = \frac{1}{1+(\|\nabla I\|/\alpha)^2} \tag{3}$$

where α is the conductance parameter that influences the diffusion process. The original diffusion proposed by Perona and Malik is a diffusion process which smooth considerably contents of an image within edges while preserve edges.From the above analysis, we can see that accurate estimation of the edge is crucial to successful diffusion. However, in WCE images, edges are difficult to estimate accurately due to their complicated background. Furthermore, many WCE images are rather dark, so we should try to enhance them. In addition, the parameter α controls behaviors of the diffusion [16], i.e., it determines whether the region in an image will be smoothed or not. This leads into a high dependence of its choice. The original paper proposed a method of choosing this parameter via manually adjustment or using a noise estimator described by Canny. However, both methods are not convenient enough in fact. To solve the above problems and enhance WCE images, we propose an adaptive contrast diffusion approach in the next section.

3. Adaptive contrast diffusion

3.1. Contrast diffusion

In order to get a contrast description of one point in an image, we resort to local analysis of an image by using Hessian matrix. Hessian matrix of one point in a gray image under a given scale σ is:

$$\mathbf{H}_\sigma(x,y) = \begin{bmatrix} I_{xx} & I_{xy} \\ I_{xy} & I_{yy} \end{bmatrix} \tag{4}$$

where I_{xx}, I_{yy}, I_{xy} are the second-order derivative of the image along direction of x, y, xy respectively. Here σ is implicitly contained in the calculation of second-order derivatives. We assume that Hessian matrix of one point has two eigenvalues: $\lambda_1(x,y)$ and $\lambda_2(x,y)$. Considering the fact that intensity variation in background of an image is rather weak, we may conclude that differential values of such regions are small, which result in small eigenvalues. On the other hand, in regions where there is rather apparent intensity variations compared with background, we may draw an opposite conclusion.

Based on the above discussion, we establish a new concept of contrast as follows:

$$c(x,y) = \lambda_1^2(x,y) + \lambda_2^2(x,y) \tag{5}$$

It characterizes intensity variations from the standpoint of Hessian matrix eigenvalues. Applying this concept to the whole image, we can get the image's corresponding contrast space. Employing this contrast space, we change the original anisotropic diffusion into:

$$\frac{\partial c(x,y,t)}{\partial} = div[g(c)\nabla]c] = g\nabla c + \nabla g \cdot \nabla c \tag{6}$$

where $g(c)$ is alike to (3):

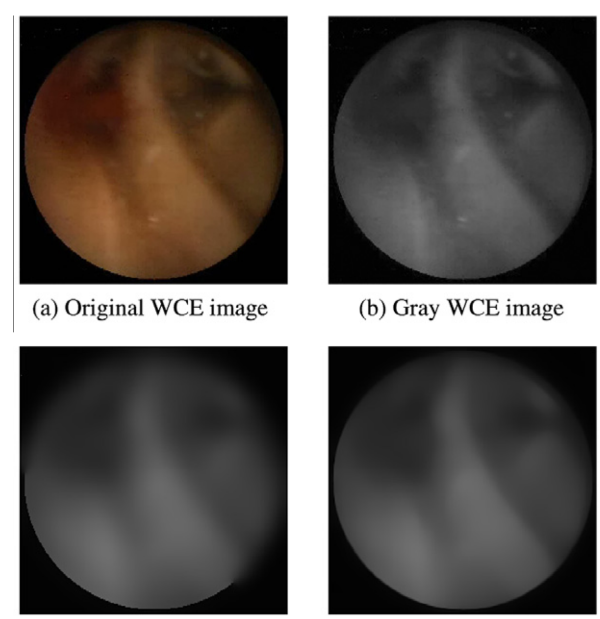
$$g(c)\frac{1}{1+(\|\ c\ \|/k)^2} \tag{7}$$

Here, the contrast parameter k has a similar role to the parameter α in the original anisotropic diffusion, i.e., it determines behavior of the diffusion according to the value of contrast in the region. After diffusing in the contrast space, the diffused result is transformed back to image space by normalization as illustrated below:

$$I = \frac{c - c_{\min}}{c_{\max} - c_{\min}} \times 255 \tag{8}$$

Fig. 3 demonstrates one set of enhancement results for a rather dark WCE image. Figs. 3a and b show the original WCE image and its gray form, respectively. Fig. 3c is the enhancement result for Fig. 3b obtained using gradient based diffusion, i.e., PM diffusion. Fig. 3d illustrates the enhancement for Fig. 3b guided by the smaller eigenvalue of the Hessian matrix [25], which aims to diffuse an image along the edge directions. From Fig. 3c and d it can be observed that both of these two approaches can smooth the image content, but they are incapable of enhancing details as a matter of fact. As such, it is great desired that details of a WCE image be enhanced without noise amplification. To improve details in a WCE image, we choose to use the sum of the squared eigenvalue as shown in (5) for each pixel during the diffusion process, which may enhance the details in a WCE image.

Compared to the original anisotropic diffusion, the contrast diffusion for WCE images is more suitable here due to the following reasons. The second-order derivative in Hessian matrix is more apt to extract the intensity variations than the first-order derivative of gradient because the second-order derivative of lines and textures, which are common in images, may produce large second-order derivative but may not generate large first-order derivative [25]. Moreover, since the final goal of our research is to implement CAD for abnormal WCE images, we hope to boost the difference between normal region and abnormal region in a WCE image. Second-order derivative of Hessian matrix may work better than first-order derivative on this aspect due to the first reason. In addition, the advantage of applying PM diffusion on the contrast space is that it may achieve the goal of enhancing details of a WCE image without noise amplification since we keep the original property of smoothing in the proposed diffusion. The scheme in [25] is not chosen neither for the contrast space because feature



(a) Original WCE image (b) Gray WCE image

(c) PM enhancement for (b) (d) Enhancement for (b) by [25]

Fig. 3. Enhancement using PM and Hessian diffusion.

direction in a WCE image is not important here taking into account the specified imaging process for a WCE. A WCE itself suffers from an unstable motion which may contain rotation during its working procedure in the digestive tract. It means that the feature direction in a WCE image may not be significant for diagnosis or computerized detection any more. Hence, it is expected that PM diffusion on the contrast image would be enough to provide a better enhancement result which might be beneficial to diagnosis or computerized detection. The experimental results in Section 4 will validate this point.

3.2. Adaptive parameter choice

Generally speaking, a large k leads to smoothness while a little k leads to sharpness in one region of an image. A fixed k during the diffusion process can simplify the implementation; however, it may cause problems if the value of k is not suitable, i.e., the region we want to enhance will be smoothed instead if the value of k is too high. On the other hand, if the value of k is too low, it will cause enhancement where there is much noise. In addition, a too low k will lead to diffusion's weak effects, which result in too many iterations. In this case the parameter should be equilibrated. Moreover, different images have different suitable values of k. Therefore, a natural approach to solve the above problem is to make this parameter adaptive. Some papers have addressed choice of this parameter [26,27], but they still needed to set an initial value. To make the parameter choice completely automatic, we design it as a function of contrast defined above:

$$k(x,y) = 1/\sqrt{\lambda_1^2(x,y) + \lambda_2^2(x,y)} \tag{9}$$

Considering the fact that we are more interested in regions containing abnormal parts in WCE images, we hope to achieve enhancement in such regions. On the other hand, in a region where the contrast is low we hope to achieve smoothing since it is more likely to be the background, i.e., the conductance parameter should be low in regions where the contrast is high and be high in regions where the contrast is low. And (9) can meet such requirements relatively well.

3.3. Extension to color space

All the above discussions are concerned with gray image, because WCE images are color images, we extend the proposed approach to color space in this part. One natural method of extending scalar-valued diffusion to color image is to diffuse three color channels independently, however, it may cause color edge distortion because diffusion in each channel separately may have different local diffusivity. To solve such a problem, the authors in [18,19,23] proposed methods of diffusing different channels simultaneously to deal with color images so as to retain edges efficiently. We adopted one strategy similar to the scheme in [23] to cope with WCE images.

Based on the diffusion model (6), we extend it to RGB color space as follows:

$$\frac{\partial c_i(x,y,t)}{\partial t} = div[g(\phi)\nabla c_i] \tag{10}$$

where $\phi = \sum c_i$ and $i = R, G, B$, and choice of the conductance parameter in $g(\phi)$ changes correspondingly into

$$k(x,y) = 1\sqrt{m_1^2(x,y) + m_2^2(x,y)} \tag{11}$$

where $m_1(x,y)$ and $m_2(x,y)$ are eigenvalues of the vector-formed Hessian matrix of one point in a color image as shown below:

$$H_\sigma(x,y) = \begin{bmatrix} \sum_{i=R,G,B} I_{xx}^i & \sum_{i=R,G,B} I_{xy}^i \\ \sum_{i=R,G,B} I_{xy}^i & \sum_{i=R,G,B} I_{yy}^i \end{bmatrix} \tag{12}$$

By combing Hessian matrix from different color channels, the proposed contrast diffusion can achieve the goal of diffusing simultaneously.

4. Experimental results

It should be noted that quantitative measurement of color image enhancement effects is very difficult. Moreover, there is no universal measure specifying both objective and subjective validity of a color image enhancement method. As such, we first demonstrate the results in a subjective means. In addition, to verify enhancement effects of the proposed algorithm in an objective approach and illustrate assistance of the proposed method for CAD, we conduct classification experiments to show that enhanced WCE images can lead to a higher classification performance of WCE image.

4.1. Subjective evaluation

The scale parameter σ used to get Hessian matrix of an image was set to 1 in all our experiments. Fortunately we found that performance of the proposed algorithm is not sensitive to this parameter. Concerning the iteration number, we manually tried 20, 40, 60, 80, 100, and chose the best result from these five choices as the final enhancement image. Generally speaking, the quality of the image results increases as the number of iteration goes up, but tends to degenerate when the iteration continues to grow after it reaches some threshold. It should be admitted that this is not convenient, and it is a venue of future research to find a suitable convergence criterion for our specific problem and the relationship between the iteration and the image quality. We carried out our experiments by comparing the proposed algorithm with contrast limited adaptive histogram equalization (CLAHE) [12] and multiscale retinex color restoration (MSRCR) [28], which are two classical methods to enhance images. Furthermore, we compared the proposed scheme with two up-to-date diffusion based approaches, i.e., Weikert's coherence filter (CF) [20] and the complex diffusion (CD) proposed by Gilbola in 2004 [21]. The performance of the proposed method has been extensively tested, however, only a representative subset of the experimental results are reported here due to space limitation, and more results can be found in our report [29].

Fig. 4 illustrates one set of comparison experiment. Fig. 4a is an original WCE image, Figs. 4b, c, d and e show results of CLAHE, MSRCR, CF and CD, respectively. Fig. 4f presents result of the proposed method, which is obtained after 20 iterations. It can be observed that CLAHE shows some degree of enhancement, however, our interested region (the yellow region on the mucosa, which represents a sign of Chron's disease) in the WCE image is still not clear or obvious. MSRCR can improve the visibility of WCE image to some extent; however, it tends to over-enhance the whole image, so we can notice some degree of color distortion. CF approach enhances the flow-structure along edges in a WCE image without enhancement of the interested region, and CD mainly smoothes a WCE image. The proposed method leads into a better visualization of the region of interest while avoid over-enhancement.

Figs. 5–7 demonstrate another three comparison experiments. It can be also observed that the details in the results of the proposed algorithm look clearer than the other four algorithms.

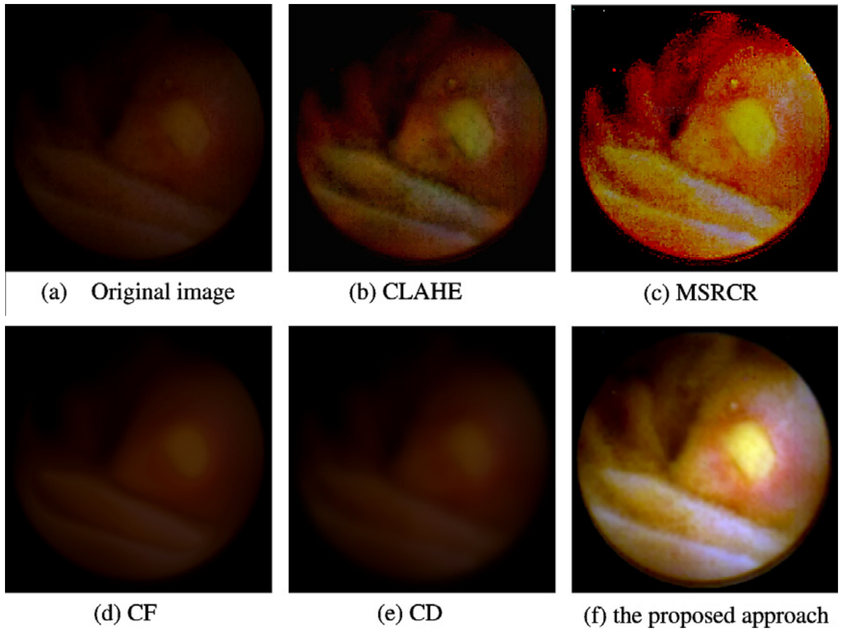


Fig. 4. Comparison of different algorithms.

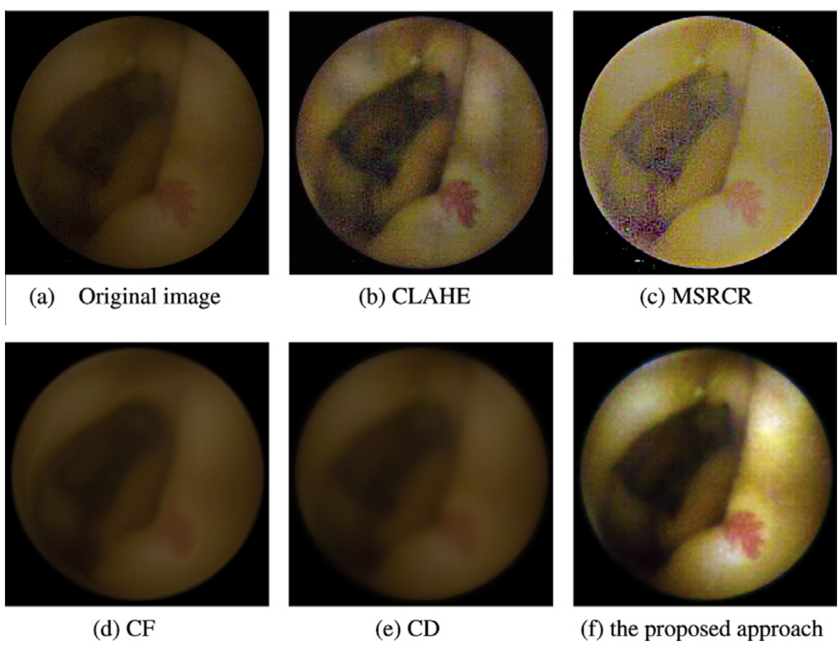


Fig. 5. Enhancement results of different algorithms on one WCE image.

4.2. Objective evaluation through classification

To further verify performance of the proposed algorithm objectively, especially for the final goal of our project, i.e., CAD, we employ classification to test performance of the results in assisting detection using computerized approach. Six statistical features (standard deviation, skew, kurtosis, entropy, energy, and mean) are extracted from each channel's histogram of a WCE image [30]. Six channels (RGB, HSV) result in 36 features for one WCE image, and these features are used as inputs for a classical multilayer perceptron (MLP) neural network (NN), which has also been used to analyze colon status from endoscopic images [31]. The advanced classifiers such as support vector machine are not used here because their superior performance might mask the feature enhancement effects that we hope to verify.

A GI expert chose 400 representative WCE images (200 normal cases and 200 abnormal cases) in our experiments. We first applied the above five algorithms to get enhanced images, providing the data to extract features for training and testing of the MLP NN. The MLP NN was experimentally configured as 10 hidden nodes and 2 output nodes, and it was trained with Levenberg-Marquardt algorithm. In our experiment, we took advantage of 5 folder cross-validation to test performances of classification.

We use sensitivity, specificity and accuracy to measure performances of classification, which are widely used in medical decision domain. The definitions of them are given in (13)–(15). The original

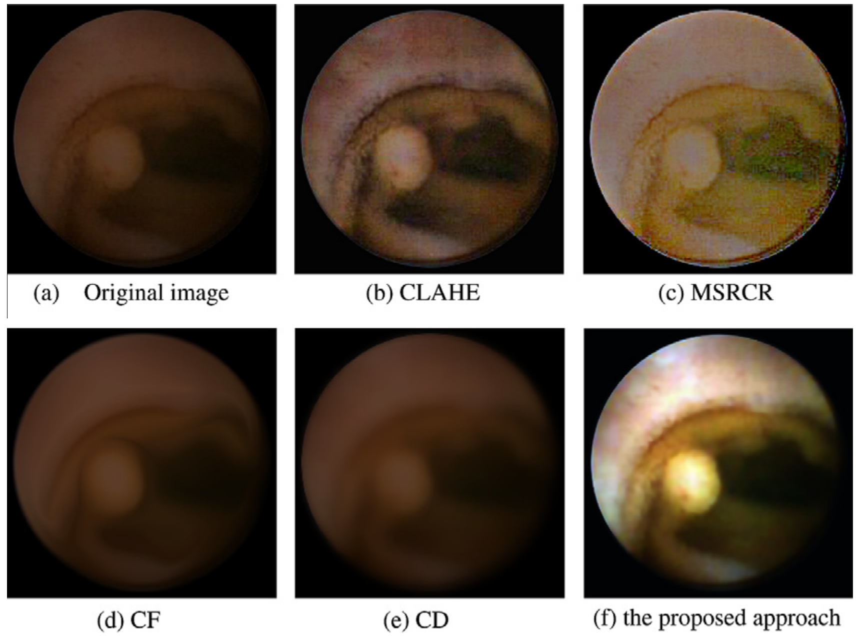


Fig. 6. Enhancement results of different algorithms on another WCE image.

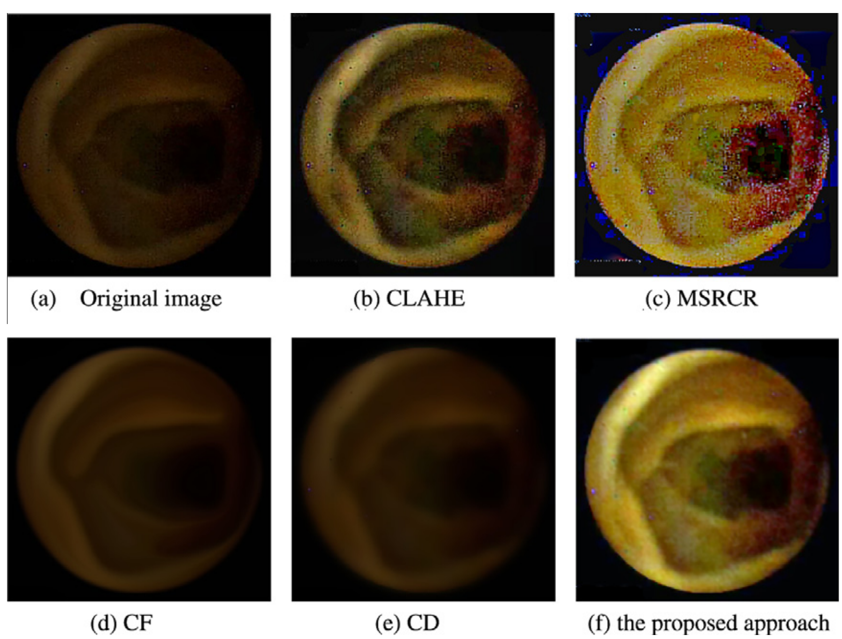


Fig. 7. Comparison results of different algorithms on another WCE image

WCE images are manually labeled to provide the ground truth. The image containing abnormal region is labeled as a positive sample; otherwise, it is labeled as a negative sample. The average classification performance of original WCE images and respective enhanced images is listed in Table 1. From this table, we can note that WCE images processed by the proposed algorithm appear to provide more useful information for discrimination of normal WCE images and abnormal ones and produce better classification performance than the other four algorithms. Hence, the enhancement scheme will probably benefit CAD. It should be admitted that accuracy, sensitivity and specificity of classification for the proposed scheme are still not high enough, and this motivates us to investigate new feature extraction methods based on the enhancement pictures in the future.

Table 1
Average classification performance of the data processed by different algorithms.

	Original	CLAHE	CF	CD	MSRCR	Proposed
Accuracy (%)	36.5	52.0	46.5	42.5	48.5	71.5
Sensitivity (%)	34.0	48.0	43.5	39.0	47.5	69.5
Specificity (%)	39.0	56.0	49.5	46.0	49.5	73.5

$$Sensitivity = \frac{Number\ of\ correct\ positive\ predictions}{Number\ of\ positives} \tag{13}$$

$$Specificity = \frac{Number\ of\ correct\ negative\ predictions}{Number\ of\ negatives} \tag{14}$$

$$Accuracy = \frac{Number\ of\ correct\ predictions}{Number\ of\ samples} \tag{15}$$

5. Conclusions

WCE images show great clinical values in diagnosis of diseases in human digestive tract due to its breakthrough. However, many images it produced are rather dark and noisy, which may cause troubles to diagnosis of physicians especially to CAD. To solve these problems and assist diagnosis of physicians as well as CAD, we have presented an adaptive contrast diffusion method to enhance WCE images.

Based on eigenvalues of Hessian matrix of a WCE image, we have advanced a new concept of contrast. Employing this definition, we then presented an adaptive contrast diffusion method to enhance WCE images. Compared to traditional anisotropic diffusion, this new method can describe variations of WCE images better and avoid a tedious choice of the conductance parameter. Comprehensively experimental results demonstrate that the proposed method may provide better visualization of WCE images so as to assist diagnosis process by comparing it to some traditional enhancement methods. The proposed scheme has also achieved objective improvement in terms of classification performance of WCE images using MLP NN. Novel color or textural features based on the enhanced WCE images will be investigated in the future for automatic detection of abnormal WCE images. Moreover, suitable convergence criterion will also be studied so as to make the contrast diffusion totally automatic as well as the relationship between the iteration and the image quality. One possible solution is to use the L_2 distance between the initial image and the enhanced image as the convergence criterion. When the distance reaches a chosen value ε, the diffusion process will stop automatically.

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