WIRELESS CAPSULE ENDOSCOPY IMAGES ENHANCEMENT BASED ON ADAPTIVE ANISOTROPIC DIFFUSION

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ABSTRACT

Wireless capsule endoscopy (WCE) is a new innovative solution for gastrointestinal disease detection. The image quality of WCE is not satisfactory for medical applications since some of them are dark and low-contrast. The WCE image enhancement is a challenge task, mainly because the diversity of the WCE images of different people and the need to preserve the local fine details of WCE images. Hence, it is difficult to apply the traditional image enhancement methods based on global information to WCE image enhancement. In this paper, motivated by the capability of the anisotropic diffusion method in preserving local fine details, a new adaptive contrast anisotropic diffusion method has been developed to enhance WCE images, where the Hessian matrix is used to obtain better representation of the contrast information of WCE images meanwhile the diffusion parameter of the diffusion coefficient function is automatically determined according to the local characteristic. Experimental results have demonstrated the effectiveness of the proposed image enhancement method.

Index Terms— wireless capsule endoscopy, anisotropic diffusion, adaptive, image enhancement, local characteristic

1. INTRODUCTION

In the past year, digestive system cancer has been the second cancer-related killer in U.S.A. and caused 61,950 death[1]. Early detection and treatment of gastrointestinal disease are very important. Wireless Capsule Endoscopy (WCE) was invented in year 2000 and put in use in 2001 [2]. When a patient swallows a WCE, it will be propelled by peristalsis though the entire gastrointestinal tract, while it records and sends the captured images to a device attached to the patient wirelessly. The main advantages of WCE are that patients can avoid cross infection and suffer no pain. WCE solution brings big benefits to elder and weak patients.

The whole examination process of WCE will last for 8 hours and produce about 5,000-10,000 images per person. However, the images taken by WCE system are not as distinct as those taken by traditional endoscopy due to the following reasons. Firstly, due to the volume restriction of the WCE, the battery capacity is limited. Hence, some images are not taken under sufficient illumination. Secondly, the camera used in WCE is low-focal-length camera which may produce blurring images. Thirdly, complicated circumstance of gastrointestinal tract and moving imaging method also lead to a poor image quality. Fourthly, the image-data must be compressed in high ratio before transmission outside. As a result, the image enhancement is highly demanded in WCE medical applications. There are many famous image enhancement methods. Histogram equalization and its derived methods [3, 4] are common approaches to enhance low-luminosity and low-contrast images, which are effective and fast. Filter based methods [5] and transform domain based methods [6] are also useful in image enhancement. However, research shows that the WCE images have rather smooth and low-contrast properties. Experimental results showed that, the methods mentioned above don't have desired effect in preserving local fine details in the enhancement process which are important for medical diagnosis. In 1990, anisotropic diffusion, also called Perona–Malik diffusion, was proposed, which is a technique aiming at reducing image noise without removing significant parts of the image content, typically edges, lines or other details [7]. Anisotropic diffusion has been widely used in medical image enhancement and other image processing applications [8, 9].

In this paper, motivated by the favorite properties of the anisotropic diffusion, we put forward a new adaptive contrast anisotropic diffusion method for WCE image enhancement by exploring the local characteristics of WCE images. Referring to [10], we took the advantage of the property of Hessian matrix to obtain better representation of the contrast information of WCE images. The experimental results validated the effectiveness of the proposed method.

2. IMAGE ENHANCEMENT USING ANISOTROPIC DIFFUSION

The anisotropic diffusion proposed by Perona and Malik is based on the following equation:

$$\begin{cases} \partial I(x,y,t)/\partial t = div\left[c(x,y,t)\times\nabla I(x,y,t)\right] \\ I(x,y,t=0) = I_0(x,y) \end{cases} \tag{1}$$

where x, y is the abscissa and ordinate of the point in image respectively, t is the diffusion time. $I(x,y,t)$ is the gray level of point (x,y) at time t, and $I_0(x,y)$ is the original gray level; *div* and ∇ are the divergence and gradient operators, respectively; $c(x,y,t)$ is the diffusion coefficient function controlling the diffusion rate and is usually chosen as a function of the image gradient to preserve edges in the image**.** Anisotropic diffusion is a continuous process in which the value of each pixel of the image is diffused to its neighborhood pixels. Each pixel adds its neighbors' diffused value to form a new current value iteratively.

From (1), we can see that accurate measurement of gradient information of the image is crucial to the edge preserving during the anisotropic diffusion process. But in WCE images, the edges are rather weak and the gradients are difficult to estimate accurately. To achieve better performance, Li and Meng proposed a contrast description of the original image using Hessian matrix [10] to stress the gradient information. Suppose $\boldsymbol{I}$ is a grayscale image, its Hessian matrix at (x,y) under scale σ is defined as:

$$\boldsymbol{H}_\sigma = \begin{bmatrix} I_{xx} & I_{xy} \\ I_{xy} & I_{yy} \end{bmatrix} \tag{2}$$

where I_{xx}, I_{yy}, I_{xy} are the second-order derivative of the image along direction x, y, xy respectively. The second-order derivative is more sensitive to edges than the first-order derivative, so it is more appropriate to detect details in low contrast image like WCE images. Since the Hessian matrix is a 2×2 matrix, it has two eigenvalues λ_1 and λ_2 and they are proportional to the intensity variations of the image. Hence, the flat image region corresponds to small eigenvalue and the image region including edges and more details will yield larger eigenvalue. Based on above observations, a contrast description of $\boldsymbol{I}$ at scale σ is as

$$I_c(x,y) = \sqrt{\lambda_1(x,y)^2 + \lambda_2(x,y)^2}\,\big|_\sigma \tag{3}$$

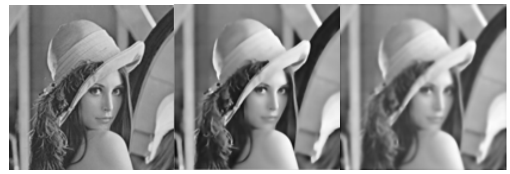
Following the definition given in (1), the anisotropic diffusion of $\boldsymbol{I}_c$ can be formulated as the following:

$$\begin{cases} \partial I_c(x,y,t)/\partial t = div\left[c(x,y,t)\times\nabla I_c(x,y,t)\right] \\ I_c(x,y,t=0) = I_{c0}(x,y) \end{cases} \tag{4}$$

Assume we get a resultant image $\boldsymbol{D}$ after the anisotropic diffusion, then we will normalize it to get the enhanced image using the following equation:

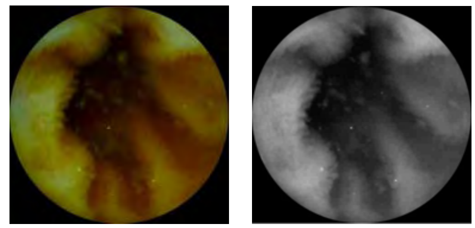
$$I_{result}(x,y) = \frac{D(x,y) - \min(D(x,y))}{\max(D(x,y)) - \min(D(x,y))}\times 255 \tag{5}$$

Discussions: the image enhancement technique based on anisotropic diffusion using (1) or (4) significantly depends on the choice of the diffusion coefficient function $c(x,y,t)$. In



(a) (b) (c)

Fig. 1. Anisotropic diffusion with different parameter k: (a) original image (b) k=10, iteration=30 (c) k=30, iteration=30



(a) (b)

Fig. 2. (a) WCE image; (b) its gray scale image

order to achieve smoothness in non-edge regions and preserving edges and local details in inter-edges regions, the function $c(x,y,t)$ should have the following properties: for the-non-edge or flat regions, $c(x,y,t)$ should be of large value; for the inter-edge and rich detail regions, $c(x,y,t)$ should be of small value. Two famous functions for the diffusion coefficient are shown below

$$c(x) = 1/\left(1 + (x/k)^2\right) \tag{6}$$

and

$$c(x) = \exp\left[-(x/k)^2\right] \tag{7}$$

where k is an edge sensitivity controlling parameter and is usually chosen experimentally or as a function of the image local properties. Therefore, the selection of k is very crucial to the quality of the enhanced image $\boldsymbol{I}_{result}$. Experimental results illustrated that the larger k leads to the smoother image and the smaller k leads to a sharper image. One example is shown in Fig. 1.

Careful evaluation shows that the low-contrast regions in the WCE image contain less medical information. Conversely, the high-contrast regions contain much more medical information, which is important to diagnose and should be preserved. Therefore, it is desired that the large k is selected for the low-contrast regions and small one for the high-contrast regions.

3. SELECTION OF DIFFUSION THRESHOLD PARAMETER BASED ON IMAGE LOCAL DETAILS

As we discussed in Section 2, the parameter k in diffusion coefficient function plays a key role. Obviously, it is optimal to select k according to its local information and it should be big where the local contrast is low and be small where the local contrast is high. Bearing this idea, let's define a data-related parameter

$$k(x,y) = K_0 / \left(L_{dd}(x,y)\right) \tag{8}$$

where K_0 is a constant. L_{dd} is a local detail descriptor, which should meet the following requirements: For the flat regions of the image, the L_{dd} should be small. For the high contrast regions, the L_{dd} should be of large value. With the definition in (8), the formulation of the local descriptor L_{dd} is a key. In this paper, we proposed to use the local complexity (LC) termed as L_c and the local variance (LV) named as L_v to jointly form L_{dd}. Essentially, L_c and L_v measure the local image entropy and dynamic variation, respectively.

Intuitively, flat regions have poor uncertainty and less information, on the contrary, edges and fine details tend to have massive uncertainty and information. Image entropy proposed by Pun in 1980 can appropriately describe the uncertainty of an image [11]. Considering an image region centered at (x, y) with a fixed m×n window, the image local entropy can be defined as

$$L_e(x,y) = -\sum_{j=0}^{L-1} P_j \log P_j \tag{9}$$

where $$P_j = n_j / (m \times n) \tag{10}$$

where L is the gray levels, n_j is the number of pixels of the level j. From (9), it is clear to see that the local entropy is a good local uncertainty descriptor, but it suffers from high computation complexity. Aiming at reducing the complexity, an alternative approach is adopted [12]:

$$L_c(x,y) = \sum_{k=0}^{L-1} \mathrm{sgn}(k) \tag{11}$$

where k is the gray levels of the image between 0 and L-1.

Simulation studies showed that either $L_e(x,y)$ given in (9) or $L_c(x,y)$ given in (11) is not good enough to represent the local descriptor required in (8). This is because $L_e(x,y)$ and $L_c(x,y)$ are only able to measure the overall uncertainty of the region, but cannot measure the dynamic change in the region. It is well-known that the data variance is an appropriate measure of the image gray level spread range. Thus, the gray level local variance of the image region centered at (x, y) with a fixed m×n window is defined as:

$$L_v(x,y) = \frac{1}{m \times n} \sum_{i=1}^{m} \sum_{j=1}^{n} \left(f(x,y) - m_f \right)^2 \tag{12}$$

where m_f is the mean gray level of the pixels in the $m \times n$ neighborhood window. Taking both local complexity and local variance into consideration, the proposed local detail descriptor L_{dd} can be formulated as follows:

$$L_{dd}(x,y) = L_c(x,y) \times \left(\log\left(L_v(x,y) \right) \right)^2 \tag{13}$$

The reasons for formulating L_{dd} in (13) are as follows: For low-contrast regions, since $L_c(x,y)$ and $L_v(x,y)$ are small, then $L_{dd}(x,y)$ is small as a consequence. In high-contrast regions, since $L_c(x,y)$ and $L_v(x,y)$ are large and $L_{dd}(x,y)$ is large as well. It is noted that $L_v(x,y)$ in (12) is sensitive to noise and any impulsive noise may lead to a large $L_v(x,y)$. But $L_c(x,y)$ in (11) is much robust to impulsive-like noise. Therefore, for noise regions, $L_c(x,y)$ is small which makes $L_{dd}(x,y)$ smaller than high-contrast regions. It is noted that the log operator in (13) is able to eliminate the effect of impulsive-like noise in some measure. Generally, the variation of $L_c(x,y)$ is much smaller than that of $L_v(x,y)$. For example, for a WCE image shown in Fig. 2, the $L_c(x,y)$ ranges from 2 to 84 but $L_v(x,y)$ ranges from 1.13 to 3150, meanwhile the $(\log(L_v(x,y)))^2$ is in the range of [0.15, 64.89] which nearly matches the variation range of $L_c(x,y)$. In conclusion, L_{dd} proposed in (13) is able to distinguish high-contrast regions from low-contrast regions and alleviate the adverse impact of the impulsive-like noise.

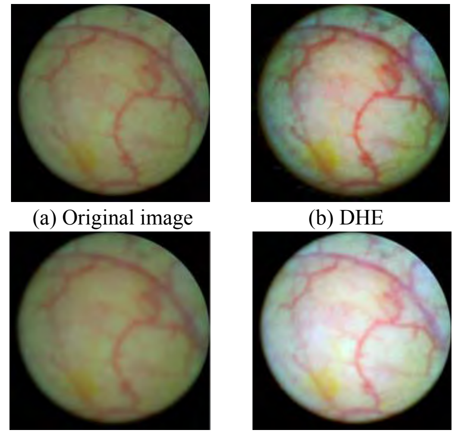
Extensive experiments have been carried out with real WCE images to validate the formulation of the proposed local detail descriptor L_{dd} in (13). It is confident to conclude that L_{dd} given in (13) is able to appropriately descript the local details of WCE images and meanwhile is robust to noise.

4. EXPERIMENTAL RESULTS

In order to evaluate the performance of the proposed image enhancement algorithm, we conducted several experiments. The WCE images used are from Shenzhen JiFu Technology Ltd., which were captured data from trial patients. The size of the WCE images is 480×480. Since the captured WCE images are RGB color images, therefore, we directly applied the proposed image enhancement method on R, G, B images respectively then merged them to the enhanced color WCE images. We compared the results of the proposed image enhancement algorithm with the anisotropic diffusion method (ADM) [7] and the Dynamic Histogram Equalization (DHE) image enhancement algorithm [3].

For ADM method and our proposed method, (6) is taken as the diffusion coefficient function concerning its low computing complexity. For ADM method, parameter k in (6) is set to 10. For our proposed method, the parameter K_0 in (8) is also set to be 10. Local window size used in (11) is set to 11×11. The results are obtained after 30 iterations of diffusion. Iteration time is also a key factor to the result. It is noted that with the increase of the iterations, the enhanced images tend to converge to the best result and then start to degenerate. Hence, 30 iteration is an empirical choice after the comparison with 10, 20 40, and 50 iterations. The optimal choice of the iteration is also our future research content. It is noted that it is difficult to evaluate the performance of a color image enhancement algorithm objectively. According to our knowledge, there is no authoritative quantitative measurement. So we will estimate the proposed approach in a subjective way. Due to the paper length limitation, we only present three sets of the experimental results here.

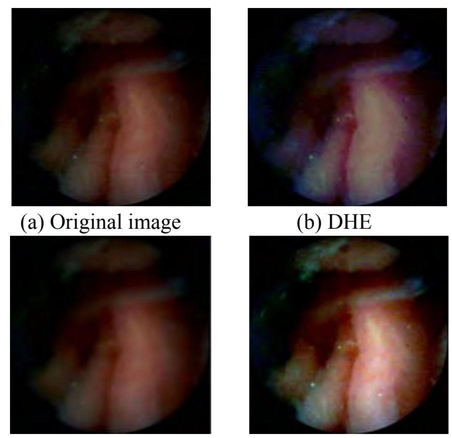
Fig. 3 demonstrated a set of experimental results. Fig. 3 (a) is the original WCE image of some vessels. Fig. 3 (b) to Fig. 3 (d) shows the enhanced WCE image by DHE algorithm, the anisotropic diffusion method (ADM), and our proposed method, respectively. As we can see, the original image is blurred slightly. Some of the edges of this WCE image are too weak to detect. The ADM algorithm failed to enhance the image and produced an even more blurred image. The DHE algorithm produced acceptable result but magnified some noise. In the image enhanced by our proposed method, we can clearly see the vessels without noise amplification. Fig. 4 gives another set of experimental results, where the original WCE image in Fig. 4 (a) is much dark compared with the one in Fig. 3 (a). Our proposed algorithm produced a clear result even in the dark regions reflecting image details clearly, which is shown in Fig. 4 (d). Result produced by the ADM algorithm shown in Fig. 4 (c) is also inferior to the original image. Result from DHE algorithm is also dark, and caused chrominance change as we can see in Fig. 4 (b). In Fig. 5 (a), the original image is suspect of jejunum erosion disease. The result from DHE algorithm produced some chrominance change in the abnormal region as shown in Fig. 5 (b). Our proposed approach enhanced the image properly, as shown in Fig. 5 (d), especially at the abnormal region where much more image details can be viewed for more accurate judgment. From the experimental results illustrated, we can conclude that our proposed method has the ability to effectively enhance the color WCE images.



(a) Original image (b) DHE

(c) Anisotropic diffusion (d) Proposed approach

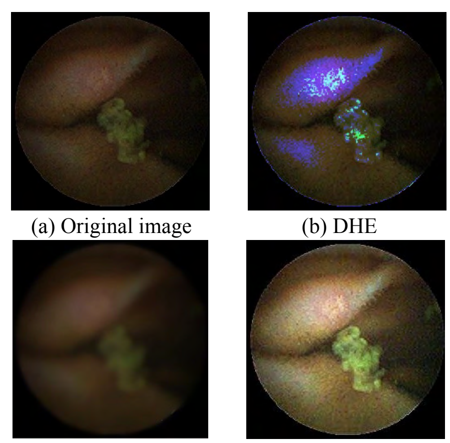
Fig. 3. Enhancement result of different approaches



(a) Original image (b) DHE

(c) Anisotropic diffusion (d) Proposed approach

Fig. 4. Enhancement result of different approaches



(a) Original image (b) DHE

(c) Anisotropic diffusion (d) Proposed approach

Fig. 5. Enhancement result of different approaches

5. CONCLUSION

This paper works on the WCE images enhancement technique. With the analysis of the local characteristic of WCE images, we proposed an efficient image enhancement method based on the anisotropic diffusion technique. A new approach of automatically selecting the parameter of the diffusion coefficient based on the local information of the WCE image has been developed. Extensive simulations with the real WCE images show that the proposed image enhancement method is able to effectively enhance various WCE images with the good preservation of the local details. Future study will focus on reducing the computational complexity of the proposed approach and automatic nidus detection based on the enhanced images.

ACKNOWLEDGMENT

This work is partially supported by the funded project of the Shenzhen Government and the collaboration research project funded by Shenzhen JiFu Technology Ltd. and the authors would thank Shenzhen JiFu Technology Ltd. for providing us the WCE testing images.

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