RESEARCH ARTICLE

Method of Image Block Denoising Based on Adaptive Total Variation

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Abstract:

To overcome the shortcomings of traditional total variation (TV) denoising algorithm that is sensitive to noise and easy to blur, we propose an algorithm of image block denoising based on adaptive total variation for the cell image denoising. This algorithm uses image block method to segment cell image into flat region and edged region, then adaptively select the isotropic 2-norm total variation image denoising model for flat region or the anisotropic 1-norm one for edged region according to the local gray mean grads. To solve the border processing problem of blocked image, we just copy the neighboring pixels to fill the image border. Experimental results showed that, when adding Gaussian noise of 0 mean and variance of 0.01 to the blurred image, the method of image block denoising based on adaptive total variation can increase the Peak Signal-to-noise Ratio (PSNR) of the noise image by 10.72dB. Compared with the traditional denoising algorithms, our algorithm can not only preserve more texture details of the edge region, but also efficiently suppress the noise of the flat region, making it more suitable for biomedical cell image denoising.

Keywords **—Total variation, image denoising, image block, border processing, gray mean grads.**

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I. INTRODUCTION

The biomedical images acquired with digital X-ray photograph digital X-ray photograph, X-CT, magnetic resonance imaging (MRI) and other imaging methods are generally vulnerable to noise due to environmental interference, which will seriously affect image analysis and processing [1] [2]. Thus the image denosing is of great important to improve the quality of these images for further analysis and information extraction [3] [4].

The traditional methods of image denoising, such as Fourier transform and wavelet denoising in the frequency domain processing [5], and median filtering and Wiener filtering in the spatial domain processing [6], are not suitable for processing the biomedical images because of it removing some edge details of image which should be preserved in the processing of biomedical images. Take median filtering for an example [7], though it can effectively suppress the impulse noise and salt-and-pepper noise of cell images, it can also be possible to remove the nucleus. Therefore, these methods are generally not applicable to biomedical image processing.

In recent years, the image denoising method based on variation has attracted extensive attention for its relative good performance in denoising and edge preserving. In 1992, Rudin,Osher et al. [8] proposed an anisotropic diffusion 1-norm total variation (TV) denoising model. This model can preserve edges while denoising images. But sometimes it may mistake the noises in flat areas for edges and bring these "false edges" to the restored image. Different from 1-norm total variation (TV) denoising model, the classical variation denoising model which is usually based on the 2-norm isotropic diffusion variation algorithm [9], can effectively remove the image noise, but it will probably make the edge details blurred. The advantages and disadvantages of these two models are complementary, so using either one of them alone for biomedical image denoising cannot yield a desired result. Later on, Bing Song [10] proposed a generalized TV denoising model based on norm $L^{1+p}, 0<p<1$; Zhang Hongying [11] proposed a model which can adaptively select norms L^{1+p} according to the characteristics of each pixel; In addition, HouYuqing et al. [12] also proposed an adaptive model which can adjust its smooth measurement according to local gradient. These denoising models effectively reduced the staircase effect and showed a good performance in denoising.

In this paper, basing on the adaptive total variation denoising model, the advantages and disadvantages of the two different variation denoising models are analyzed at first. Then, an algorithm combining the advantages of these two models was proposed, which should be applicable to the denoising of cell images with the image blocking method based on the local gray mean grads and copying neighboring pixels to fill the edges to deal with the noise sensitivity and edge blurring defect of the traditional total variation denoising algorithm. Finally, by comparing peak signal-to-noise ratio (PSNR) and local variance, this algorithm was tested and proved to be more suitable for preserving the edge details of cell images and for suppressing the noise in flat areas.

II. TOTAL VARIATION IMAGE DENOISING ALGORITHM

Noises in biomedical image are primarily of two types: the additive noise and the multiplicative noise. We mainly consider the additive noise in the paper, whose model can be defined as:

$$f(x,y) = u(x,y) + n(x,y) \tag{1}$$

Where $f(x,y)$ denotes the noisy image observed, $u(x,y)$ the unknown original image, and $n(x,y)$ the additive noise.

The problem of the traditional total variation (TV) denoising is about minimizing the following energy function [8]:

$$\min_u J(u) = \int_\Omega \| \nabla u \| dxdy + \frac{\lambda}{2} \int_\Omega | u - f |^2 dxdy \tag{2}$$

Where Ω denotes image regions, and the second term on the right side of the equation, named as Fidelity Term, controls the difference between original image u and observed image f. $\lambda>0$ is the regularization parameter, exerting important balance effect between the Regularization Term and the Fidelity Term. The higher the λ is, the closer the u is to the observed image f, and the weaker the smoothing is on local details, and thus the denoising quality is not good; Oppositely, the smaller the λ is, the stronger the smoothing is on both the detail and noise. The first term on the right side of the equation is the Regularization Term of TV model. Discrete $TV(u)$ can be expressed as [9]:

$$TV(u) = \sum_{i,j=1}^{n} \| D_{ij} u \| \tag{3}$$

Where $u \in R^{n\times n}$ denotes a $n\times n$ gray image, $\|\cdot\|$ is the Frobenius norm, and $D_{ij}u \in R^2$ denotes the first-order finite difference of gray intensity u_{ij} of pixel (i,j) in horizontal and vertical directions. When $\|D_{ij}u\|$ takes 2-norm, it is the isotropic discrete total variation; when $\|D_{ij}u\|$ takes 1-norm, it is the anisotropic discrete total variation.

To solve equation (2), we introduce the method proposed by Wang et al. (similar to the solution of anisotropic discrete total variation), which utilizes the alternating direction method (ADM) raised by Min Tao et al., to transform the original problem into a subproblem, and eventually solve the original problem through solving the subproblem via alternate iteration.

An auxiliary variable $w_{ij} = ((w_h)_{ij}, (w_v)_{ij})^T \in R^2$ is introduced to replace the horizontal and vertical first order finite differences of $D_{ij}u$. To ensure that w_{ij} is close enough to $D_{ij}u$, we add a penalty term, thus the new denoising model is [14]:

$$\min_{w,u} \sum_{i,j=1}^{n} \| w_{ij} \| + \frac{\beta}{2} \sum_{i,j=1}^{n} \| D_{ij}u - w_{ij} \|^2 + \frac{\lambda}{2} \| u - f \|^2, \; i,j \in \{1,2,\cdots,n\} \tag{4}$$

Where β is the parameter of penalty term. When β tends to infinity, equation (4) converges to equation (2). The model above can be transformed into two subproblems, namely optimizing the w and optimizing the u, i.e.:

$$w\text{-}subproblem: \min_{w} \sum_{i,j=1}^{n} \left(\| w_{ij} \| + \frac{\beta}{2} \| D_{ij}u - w_{ij} \|^2 \right) \quad (5.1)$$

$$u\text{-}subproblem: \min_{u} \frac{\beta}{2} \sum_{i,j=1}^{n} \| D_{ij}u - w_{ij} \|^2 + \frac{\lambda}{2} \| u - f \|^2 \quad (5.2)$$

The optimum solution of w-subproblem in ADM algorithm can be obtained through application of the two-dimensional contraction operator method [15]; the solution of u-subproblem can be worked out via Fourier transformation or cosine transform [9][13].

To solve the dilemma mentioned in paragraph 3 about the isotropic 2-norm (short for *TV2* algorithm) and the anisotropic 1-norm (TV1 algorithm), Bing Song [10] raised a generalized TV denoising model based on L^{1+p}, $0<p<1$ norms. His model could availably prevent false edges and preserve edge details, however it was sensitive to the selection of p, hence it was far from being adaptive. For these reasons, and we propose an algorithm of image block denoising based on adaptive total variation (*BTV* algorithm).

III. ADAPTIVE TOTAL VARIATION IMAGE DENOISING

A. *Image block*

Processing a large image (e.g. pictures with over 10 million pixels) as a whole is energy, time and memory consuming, and at most times it is unnecessary. Considering the special case of biomedical image processing, common biological cell images retains only a few texture details; in addition, researchers care more about the cellular morphology in such images, hence the regions covering cells are of great study value and the rests are often the less important. So, in this paper we name the regions covering cells as edged region, and the rests as flat region. To divide the two different regions adaptively, we partition the image into blocks and utilize gray mean grads (GMG) as judging threshold parameters.

$$\begin{cases} \bar{g}_k \ge a\bar{G}, & B_k \text{ is edged region} \\ \bar{g}_k < a\bar{G}, & B_k \text{ is flat region} \end{cases}, k=1,2...K; \quad (6)$$

Where $\bar{G}$ is gray mean grad (GMG) and defined as:

$$\bar{G} = \frac{1}{(M-1)(N-1)} \sum_{i=1}^{M-1} \sum_{j=1}^{N-1} \sqrt{\frac{[f(i+1,j)-f(i,j)]^2 + [f(i,j+1)-f(i,j)]^2}{2}} \quad (7)$$

In (6), parameter a is used to adjust the threshold parameter $\bar{G}$, $\bar{g}_k$ is the local GMG of B_k of the block. For gray images, the gradient of regions including edge information is always higher than that of flat region. When local GMG of block $\bar{g}_k \ge \bar{G}$, the block is deemed as edged region, for which the anisotropic 1-norm of the total variation image denoising model, which has better preservation of edge, should be used. When local GMG of block $\bar{g}_k < \bar{G}$, the block is flat region, for which the isotropic 2-norm of the total variation image denoising model, which has better denoising effect, should be used.

Size of blocks of image should be determined based on different conditions. If the block size is too big, the block number would be too few to yield the expected processing effect, oppositely if the block size is too small, the block number would be too many, that will cause augmentation of computation burden and the so-called "block effect" which leads to severe jumping of gray level in edged regions.

B. *Border Processing*

Border of images should be particularly taken into consideration during image filtering or denoising to prevent from meaningless pixels or application error. Traditional border processing mainly applies methods of shrinking processing range and boundary fill. In the method of shrinking processing range, the border of 1 pixel width around image f is neglected; while in the method of boundary fill, the border of image f is replaced by a constant value. All such methods can ensure that the processing will not exceed the border of image f, but gradient will always occur on the border.

In the finite-difference calculation proposed by *Wang* et.al [9], 0 is used to fill the excess part of image border without effectively processing the border, leading to severely irregular gray levels of the border parts. Fig.1(c) shows the enlarged lower border of Fig. 1(a). From Fig. 1(c) we can see that the irregular gray levels present on the border. Hence border processing must be taken into consideration during the process of image block to prevent jumping of gray level on border areas of the image blocks. As shown in 1(b), gray level jumping presents in border areas of blocks. To solve it, we copy the neighboring pixels to fill the image border so as to preserve the smoothness, as shown in Fig.1 (d).

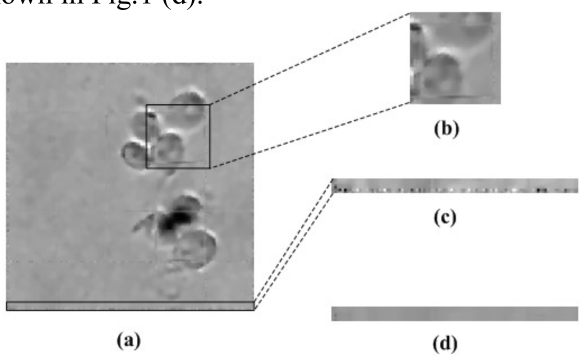

Fig. 1Image border processing

IV. EXPERIMENT PROCESS AND ANALYSIS

The object of the study is cell image. We capture several gray images of nasopharynx cancer cell using optical microscope, from which we pick out a representative one as original image (Fig. 2(a), 250×250 pixels), and introduce a Gaussian noise with mean value 0 and variance 0.01 (Fig. 2(b)). The size of one image block is set as 50×50 pixels. To verify the feasibility of our algorithm, we implement the process in Matlab 2010b, which can be summarized as follows:

*1.**Input** : f, u and $\beta>0$;*
*2.**Image blocking:** $f=\{B_k\}, k=1,2\ldots K$;*
*3.**If :** $\bar{g}_k > a\bar{G}$*
    TV is isotropic;
Else
    TV is anisotropic;
*4.**While** k=1:K,and "not converged";*
    $f=B_k$;
    Compute w-subproblem;
    Compute u-subproblem;
End do

We employ peak signal to noise ratio (PSNR) as the denoising effect assessment function, which is defined as:

$$PSNR = 10\log_{10}\frac{255^2}{\frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}[u(i,j)-f(i,j)]^2}(dB) \quad (8)$$

In general, the higher the PSNR value, the better the denoising quality. However PSNR cannot reflect the quality of edged regions; in particular, when edged region of the image to be assessed and that of the original image slightly move during processing, obvious difference would present. In essence, such slight moves exert no influence on the whole visual effect of the image. Hence, we introduce the average value of local variance (ALV) as auxiliary index for denoising effect assessment [17]. The local variance of the kth image block window D is defined as:

$$\sigma_k^2 = \frac{1}{N}\sum_{(i,j)\in D}(f(i,j)-\mu(i,j))^2 \quad (9)$$

Where μ is the average gray value of window *D*:

$$\mu = \frac{1}{N}\sum_{(i,j)\in D} f(i,j) \quad (10)$$

Where *N* denotes the pixel size of window *D*, *f(i, j)* is the gray value of image *f* at pixels *(i, j)*. Then the ALV of window *D* can be expressed as:

$$\bar{\sigma}^2 = \frac{1}{K}\sum_{k=1}^{K}\sigma_k^2 \quad (11)$$

To calculate, we define the size of window *D* used to set local variance and average gray value be equal to that of image block B_k, i.e., $D=B_k$. ALV can in fact reflect the noise level of an image. Lower ALV means lower noise of image and better denoising quality of the processing.

Fig. 2(c) shows the image after being processed using the algorithm of image block denoising based on adaptive total variation. Fig. 2(d), 2(e) and 2(f) show the images being processed using TV1, TV2 and Wiener filter algorithm respectively. Table 1 presents their corresponding PSNR and ALV. The curves in Fig. 3 illustrate the change of ALV with the number of iteration after being processed under the algorithm of image block denoising based on adaptive total variation (BTV), TV1 and TV2 respectively.

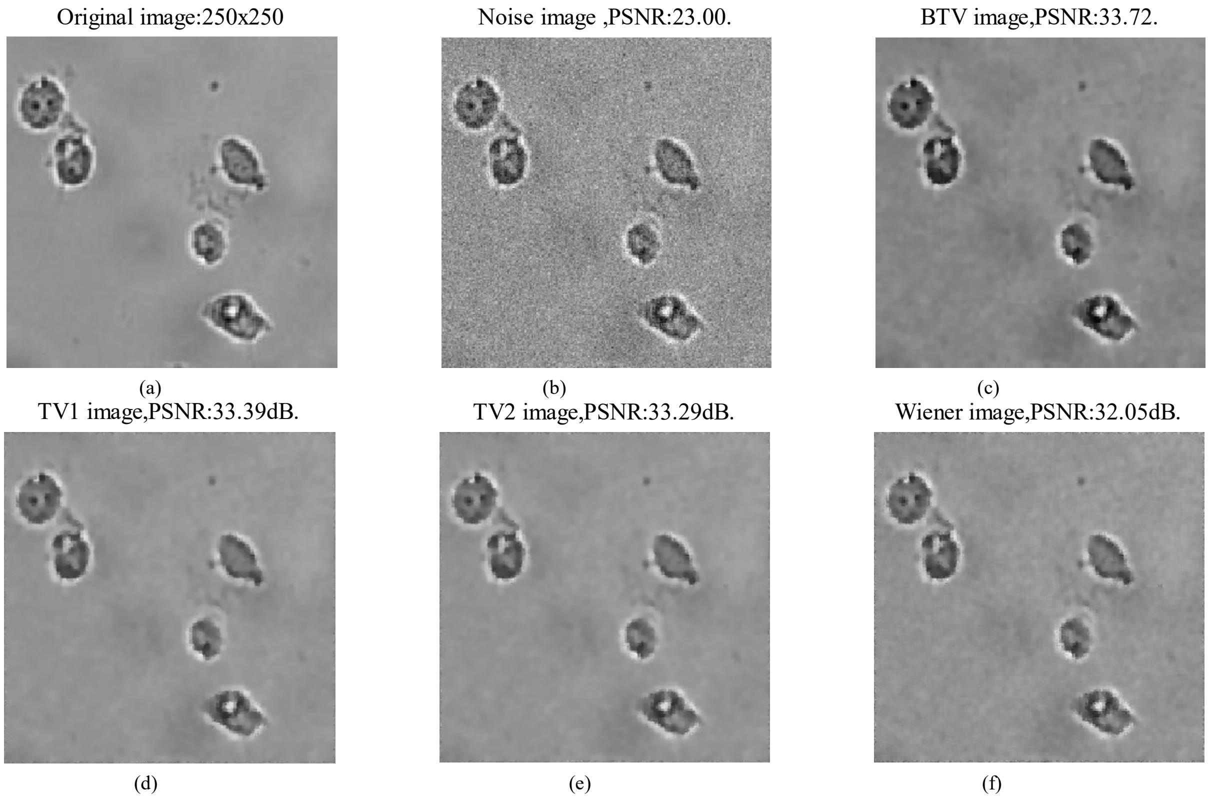

Fig. 2 Denoising quality of the four algorithms

From Fig. 3 it can be found that at the beginning of iteration, the BTV ALV result is higher than that of TV1 and TV2, while at the stage of convergence, the local variance of BTV is obviously lower than that of TV1 and TV2 due to BTV's effective process on border in each iteration. Meanwhile we can see from Fig. 2 and Table I that the image denoised by classic Wiener Filter has the lowest PSNR and the highest ALV, indicating that Wiener Filter may not be suitable for cell image denoising. Also we can find that the denoising effect of TV1 algorithm and TV2 algorithm almost be same to each other from Table I, though the isotropic diffusion which blurs the edged region makes TV2 algorithm weaker than TV1 algorithm in terms of denoising quality. Finally, comparing the PSNR of the BTV algorithm in Table I, it is not hard to see that the denoising algorithm we proposed is better than other algorithms attributed to that our BTV algorithm not only combines the merits of both TV1 and TV2, but also improved border processing.

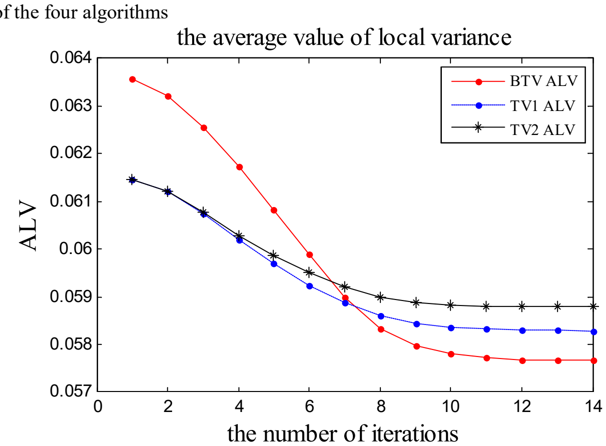

Fig.3 Change curves of ALV with number of iteration

TABLE I
PSNR AND ALV OF THE FOUR ALGORITHMS

Image(Size:250×250)	PSNR(dB)	ALV
Fig2(b) Noise Image	23.00	0.0959
Fig2(c) BTV Image	33.72	0.0577
Fig2(d) TV1 Image	33.39	0.0583
Fig2(e) TV2 Image	33.29	0.0588
Fig2(f) Wiener Image	32.05	0.0618

V. CONCLUSIONS

Combining the merits of the two traditional total variation denoising models, namely TV1 and TV2, We propose an algorithm of image block denoising suitable for cell image processing based on adaptive total variation. The algorithm uses image block method to segment the cell images into flat region and edged region, and adaptively choose denoising models in accordance with local gray mean grads. To prevent from meaningless pixel and application error during border processing, we copy the neighboring pixels to fill the image border so as to overcome the shortage of border processing occurred in traditional total variation algorithm. The result of experiments show that, when adding Gaussian noise of 0 mean and variance of 0.01 to the blurred image, the method of BTV (our method) can increase the Peak Signal-to-noise Ratio (PSNR) of the noise image by 10.72dB and effectively solve the defects lying in the traditional total variation denoising algorithm that is sensitive to noise and easy to blur. Compared with traditional denoising algorithms, namely TV1, TV2 and Wiener filter, our algorithm not only protects the texture details of cell images' edge regions better, but also efficiently suppresses the noise of flat regions.

ACKNOWLEDGMENT

This work is supported in part by Strategic Emerging Industries Project of Guangdong Province (No.2011912027).

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