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Optimization of Gradient Threshold Parameter in Feature Preserving Anisotropic Diffusion for Image Denoising

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Abstract: Image denoising emphasizes on noise removal while preserving meaningful details such as blurred thin edges and low contrast fine features. In this work, feature preservation anisotropic diffusion is proposed which not only removes noise but also has the capability of preserving fine details even of low contrast in the denoised image. This type of filtering technique is also highly dependent on some crucial parameters of filtering such as conductance function, gradient threshold parameter and stopping time. This paper also focuses on the optimization of gradient threshold parameter. The alternative options for the parameters of anisotropic diffusion at each stage of the algorithm are examined, evaluated and the best choice is selected. Experimental results evaluated on standard test images have shown that the proposed anisotropic diffusion gives better results in terms of subjective and objective measure in respect to other compared diffusion techniques.

Keywords: Image denoising, anisotropic diffusion, feature preservation, conductance function, gradient threshold parameter, noise variance, edge detection

I. Introduction

Images are often corrupted by noise during the acquisition and transmission process leading to significant degradation of image quality for the human interpretation and post processing tasks. Image denoising is often used for pre-processing of images so that subsequent image analysis is more reliable. Besides noise removing capability another important requirement for image denoising procedure is that true image structures such as edges should be preserved in the denoised image. Starting with the pioneering work of Perona-Malik[1] diffusion based partial differential equations (PDEs) are widely used in image noise removal and edge detection. The impressive results of the anisotropic diffusion techniques are mainly attributed to the introduction of anisotropic smoothing and iterative diffusion for the processing of each image pixel. Unlike conventional spatial filtering techniques that do not respect region boundaries or small structures, anisotropic diffusion techniques can simultaneously eliminate noise and preserve or even enhance edges.Perona-Malik has given a new definition of scale-space through an anisotropic diffusion(PMAD),these diffusion technique have been extensively used for image smoothing[7,17-18],image segmentation[27,28,30], edge detection[5,18] and image enhancement[19,21,23].The anisotropic diffusion have been widely used in various applications such as biomedical imaging[21-24],astronomical imaging[25,26] and forensic imaging[31]. The PMAD technique has been extensively used for general image denoising in terms of preferring intra-region smoothing to inter-region diffusion since it emerged. However, the classic P-M anisotropic diffusion along with its revised versions [1-3, 7], solely makes use of spatial gradient as a discontinuity measure. It lacks the adaptivity to local contextual features, thus resulting in fine feature loss and the edge blurring. In this paper, in order to retain fine details while removing noise, local gray level variance is added to anisotropic diffusion model. However this filtering technique can successfully smooth noise while preserving the region boundaries and small structures within the image as long as some of its crucial parameters are determined or estimated correctly. Overestimating any of the parameters may lead to an over smoothed blurry result while underestimating may leave the noise unfiltered in the denoised image. The organization of the paper is as follows: Section 2 gives the overview of the Perona-Malik anisotropic diffusion model.

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The implemented feature preservation anisotropic diffusion model technique is also discussed in this section. Section 3 discusses the issues regarding choice of the conductance function and gradient threshold parameters in order to come up with the optimal automatic discrete scheme. Section 4 presents the denoising algorithm and discussion of results using a set of test images. The paper is concluded in section 5.

II. LITERATURE SURVEY

The success of the discrete implementation of PMAD technique depends upon the accuracy of the selected values of the parameters. The choice of diffusion function is important in controlling smoothing and even enhancement of edges. The choice of diffusion function studied in [1-3] depends on the image content as (2) favours high contrast edges over low and (3) favours wide regions. The diffusion coefficient given in [3] yields shaper edges. The gradient threshold parameter also plays an important role in removing noise. The automatic selection of this parameter has been studied in [12-14]. In [3], the attention was drawn mostly to the discrete implementation of the scheme and the experimental results of the new conductance functions that were proposed. The automatic estimation of the methods parameter is also studied in [19]. Several conductance function can be used differentiating considerably the filtered results as shown in [18], It is necessary to define and scale the appropriate parameter in a way that the edges remain the sharpest possible. The gradient threshold parameter of the AD filtering technique also needs adaptation to the denoising needs of the filtered image. The value of the parameter selected should be such that all the edges are preserved above a decreasing threshold. Among the histogram based thresholding algorithms for image segmentation [32-37] mentioned in earlier research works suggested using the valleys of the histogram, while some advocated the choice of the median. Otsu developed a thresholding method maximizing the between-class variance. Tsai proposed a choice of the threshold at which resulting binary images have identical first three moments. Various other methods estimating the threshold parameter were proposed using statistical characteristics of the image [12-14] and the morphological operator. Perona-Malik in [1] suggested the use of the noise estimator described by canny, where a histogram of the absolute values of the gradient is computed and the parameter is set to 90% values of its integral in every iteration, black et al. defined $K = \sigma_e \sqrt{5} = 1.4826\, MAD(\nabla I)$ where MAD denotes the median absolute deviation. Voci et al. [12] used the p-norm of the image to estimate gradient and in the other work used morphological operators to estimate image gradient threshold. These methods are compared in the current work and a statistical method which estimates two gradient threshold parameters base on knee algorithm [14] that yield robust filtering results are implemented in this work.

III. ANISOTROPIC DIFFUSION

A. Overview of the Perona-Malik anisotropic diffusion

It is an algorithm that generalizes Gaussian filtering used to reduce additive Gaussian noise, to make it adaptive to local image gradient, so that edges are preserved. The basic idea behind the Perona-Malik anisotropic diffusion is to evolve from an original image I(x, y), a family of increasingly smoothed images I(x, y, t), based on the following partial differential equation []:

$$\frac{\partial I(x,y,t)}{\partial t} = div[g(||\nabla I(x,y,t)||).\nabla I(x,y,t)] \qquad (1)$$

Where div(.) is the divergence operator and ∇ is the gradient operator. g(.) is the diffusivity function so that its minimum value g(.)=0 corresponds to no diffusion across edges and its maximum value g(.)=1 corresponds to maximum diffusion within uniform regions.Two such diffusivity functions proposed by perona-malik were:

$$g_1(x) = \exp[-(\frac{x}{K})^2] \qquad (2)$$

$$g_2(x) = \{1 + (\frac{||\nabla I(x,y,t)||}{K})^2 \}^{-1} \quad (3)$$

Here K is the gradient threshold parameter that controls the rate of diffusion. The image gradient values above the K value which are mainly attributed to edges are preserved while the values below K which are attributed to noise are smoothed away. One more diffusivity function given by Black et al. called tukey's biweight function defined as:

$$g_3\,(x) = \{\tfrac{1}{2}(1 - \tfrac{x}{S})^2\}\ x \leq S \ and\ 0, otherwise \quad (4)$$

Where $S = K\sqrt{2}$

The choice of diffusivity function depends on the efficiency of diffused image as in (2) (Gaussian function), the conductivity privileges edges with high contrast over edges with low contrast and in the (3), the conductivity privileges large regions over smaller ones. In any case, the above conductivity definitions tell us that for ||∇I||>k edges are preserved (that means the diffusion effect is small), and for ||∇I||>k, the diffusion coefficient has a high amplitude and then the smoothing effect is stronger. In other words is a contrast parameter because regions in which ||∇I||>k are considered as edges and the diffusion process has a low effect. The continuous anisotropic diffusion of (1) can be discretely implemented by:

$$I(x,y,t+1) = I(x,y,t) + \frac{1}{4}\sum_{i=1}^{4}[g(||(\nabla I_i\ \ (x,y,t))|| * \nabla I(x,y,t)] \quad (5)$$

Where $\nabla I(x,y,t)$, i=1, 2, 3, 4 represents the gradient of four neighbours in the north, south, east and west directions respectively.

B. Parameter optimization for gradient threshold

The basic P-M model has a good edge preserving behaviour but is incapable of efficiently denoising images with high level of noise content. It is due to the unreliability of the image gradient since it is itself susceptible to noise. This problem can be solved by replacing the term $g(||(\nabla I(x,y,t)||)$ in (1) with $g(||G_\sigma * (\nabla I(x,y,t)||)$, where G_σ is a Gaussian filter of scale σ. It means that the argument of the diffusivity function can be computed by using a smoothed version of the image in every iteration. The parameter σ can be computed by taking the standard deviation of sliding window of size 11×11 so that most uniform block of pixels within the image is detected. The experimental results in the subsequent section shows that local gradients values obtained from a smoothed version of image can successfully reduce artefacts in the denoised image as comparison to the basic PMAD method. The gradient threshold parameter plays very important role important role in the diffusion process. It defines a threshold between the image gradient that are attributed to noise and those attributed to true edges. In the P-M model, for every pixel in the image there are four difference values which are defined as the difference between the brightness values of each of the 4 neighbours in the 4 pixel neighbourhood. This gives the idea of using four different threshold parameter each one estimated using the respective difference along the four directions. However in the given entire image, the absolute values of the north and south differences are almost same while the same happens true in the case of east and west differences. Therefore two different gradient threshold parameters are estimated each for the north-south (K_{NS}) and east-west (K_{EW}) directions respectively. This changes the discrete anisotropic diffusion of (5) to:

$$I(s,t+1) = I(s,t)\ + \frac{1}{4}[(\sum_{p\in N,S} g\big(G_\sigma *\ \ \nabla I_{s,p}\big)\nabla I_{s,p} + \sum_{p\in E,W} g\big(G_\sigma * \nabla I_{s,p}\big)\nabla I_{s,p})w(s,t)] \quad (5)$$

By estimating two gradient threshold parameters, it is expected to get better experimental results. Since the extent of smoothing is not same in both directions but depends on the strength of the differences in both direction. This estimation is more prompt for the images where the edges are oriented more towards one of the two directions. The stronger difference in any one direction lead to estimation of higher K values in that direction. In order to estimate the two gradient thresholds parameter K_{NS} and $K_{EW,}$ the knee algorithm [14] is employed. The knee algorithm, which is the histogram based method, is used to estimate the threshold between two populations in histogram with one peak and one long tail. In the case taken in this paper, the population that has a long tail is that due to edges while the steeper

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distribution attributes to differences due to noise. One way to identify a meaningful threshold in such a case is to fit with straight lines the descending part of the peak and long tail, and select as threshold the coordinates where the two lines meet. The process can be repeated to refine the estimate of the threshold. A detailed description of knee algorithm is given in [14].The process is illustrated fig 1, where y denotes the histogram of the gradient values and x denotes the gradient threshold values. The abscissa of the point of intersection of the two lines is the estimate of the value of the threshold parameter.

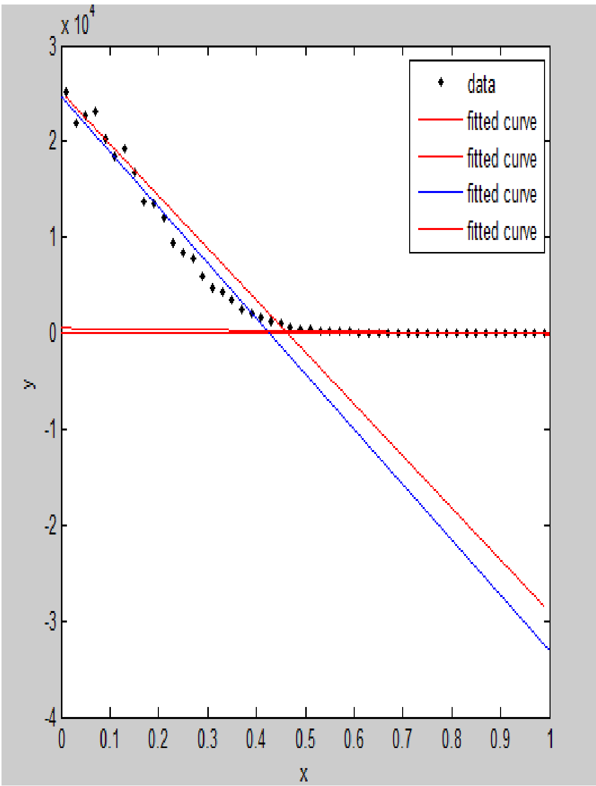

Fig.1. Threshold identification using knee algorithm for a histogram with one peak and a long tail

IV. PROPOSED DENOISING ALGORITHM

In the context of P-M anisotropic diffusion, this work is focused to retain the intrinsic features (i.e. edges and textures) in an image as much as possible while reducing the noise content in it. This is achieved by assigning proper weights to the diffusivity functions as well as by accurate estimation of gradient threshold parameters in the P-M model of anisotropic diffusion. The idea of weighted diffusivity function is implemented by taking the local gray level variance to identify contextual discontinuities from the image. The local gray level variance is calculated by:

$$\hat{\sigma}_I\,(x,y) = \frac{1}{D^2-1}\sum_{i,j=-\frac{D-1}{2}}^{\frac{D-1}{2}}[I(x+i,y+j)-m_I(x,y)]^2 \qquad (6)$$

Where D is the size of sliding window and $m_I(x,y)$ is the local mean. The local gray level variance more effectively characterizes the local features of the image in comparison to gradient magnitude. It is observed that region containing edges or textures will have higher variance than more homogenous regions and as degree of homogeneity increases the

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local gray level variance $\hat{\sigma}_I{}^2$ approaches to noise variance σ_N^2. With this observation, the weight function $w(x,y,t)$ is constructed by incorporating both $\hat{\sigma}_I(x,y,t)$ and $\hat{\sigma}_N(x,y,t)$ at iteration t.

$$w(x,y,t) = \exp\left\{-\frac{1}{\beta}\left[\left(\frac{\hat{\sigma}_I(x,y,t)}{\hat{\sigma}_N(x,y,t)}\right)^{\rho} - 1\right]\right\} \qquad (7)$$

Where β and ρ are parameters that control the steepness and sensitivity of the weight function. The extreme values of weight function are such that:

$$\lim_{\hat{\sigma}_I(x,y,t)\to\infty} w(x,y,t) = 0 \ \ and \ \lim_{\hat{\sigma}_I(x,y,t)\to\hat{\sigma}_N(x,y,t)} w(x,y,t) = 1$$

i.e. in homogenous regions the diffusion continues while in heterogeneous region (edges or textures), the diffusion stops.

The main steps of the diffusion algorithm are as follows:

Initialize- input a noisy image and set the parameters β, ρ and T (maximum number of iterations). The initial values are given in section 4.
Step.1 Estimate the noise variance as mentioned in section 2.2 and perform Gaussian smoothing of the noisy image by defining a filter of size 3×3 and the estimated noise variance as a parameter.
Step.2 Estimate the two gradient threshold parameters K_{NS} and K_{EW} by using the knee algorithm [14] as described in the section 2.2.
Step.3 Estimate the local gray level variance for each pixel value as defined in (6) and calculate the values of weight according to (7).
Step.4 Perform the diffusion process according to (5).
Step.5 Increment number of iteration parameter t and continue the process until maximum number of iteration T is met.

V. EXPERIMENTAL RESULTS

In this section, the performance of the proposed denoising algorithm is evaluated and the results are compared with those obtained with the P-M anisotropic diffusion [1], context adaptive anisotropic diffusion [20], detail and edge preserving anisotropic diffusion [11]. All the above methods require the noise variance of the noisy image and also some initial value of the gradient threshold parameter. None of the four methods including our proposed method require a priori knowledge of the characteristics or the structure of the original noise free image. The maximum number of iteration is required to be known in advance by all the methods including the proposed one. In order to evaluate the denoised results, two different quality measures is used between the filtered image and the original noise free image. The peak signal to noise ratio (PSNR) is simple to calculate but is not always in accordance with the human judgment of quality. So, the structural similarity index (SSIM) that is closer to human visual system is used as well. A detailed study of various other quality measure is found in [38].The proposed diffusion algorithm is tested for all the image sizes ranging between 256×256 and 512×512 pixels. The test images are shown in Fig. 2. The test images are corrupted with Gaussian white noise of standard deviation 20 and their denoised performance is compared with other diffusion filtering methods PM [1],CA [20] and detail[11] and the results are tabulated in Table 1. In the implementation of the proposed method, the diffusivity function given in (3) is chosen and the parameters β=4,ρ=1/3,D=11 and maximum number of iterations T=9 are set. The denoised results for the noisy Lena image are shown in Fig.3.for visual comparison. In order to evaluate the denoised image, peak signal-to-noise ratio (PSNR) and corresponding structural similarity index measure (SSIM) are taken in to account. The proposed algorithm is implemented in MATLAB 7.11 2010(b) version. For both quality measures, the larger values indicate a better effect in noise removal and feature preservation, respectively. By analysing the results in Table 1, it is found that the proposed algorithm provides best denoising performance in comparison to other diffusion methods in terms of both PSNR and SSIM. The PSNR improvement of approximately more than 1dB can be observed for all the images as shown in Table1.

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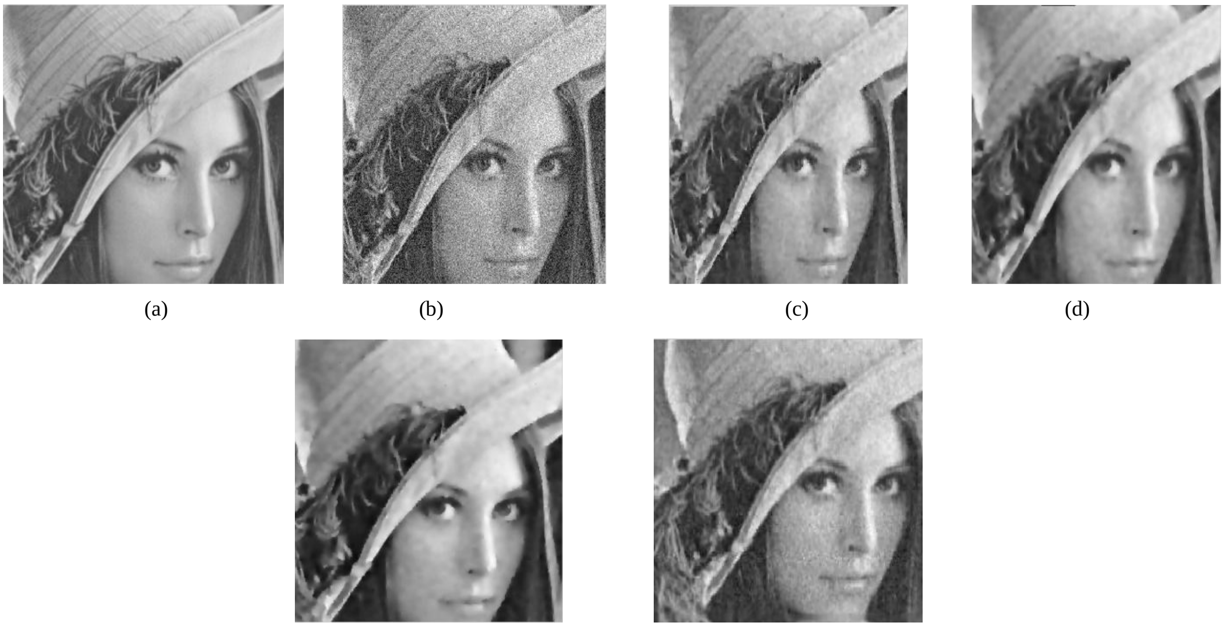

(a) (b) (c) (d)

(e) (f)

Fig.2. Visual Comparison of the denoising results from various filtering methods: (a) original Lena image (b) Noisy Lena image (c) proposed diffusion filtering (d) Context adaptive diffusion filtering (e) P-M diffusion filtering (f) detail preserving diffusion filtering

Table1.
PSNR and SSIM values of four anisotropic diffusion algorithms for the test images

Image	PSNR(dB)/SSIM			
	Proposed	**PM**	**CA**	**Detail**
Lena	32.15/0.8572	31/0.8428	31.28/0.8507	29.9/0.7769
House	31.07/0.8312	30.57/0.8289	30.6/0.8299	27.1/0.7566
Girl	31.8/0.8095	30.62/0.8000	30.8/0.8057	28.7/0.7641
Cameraman	28.9/0.8225	27.9/0.8060	28.4/0.8189	25.18/0.7142
Boat	29.51/0.7653	28.34/0.7478	28.6/0.7507	26.13/0.7069
Barbara	26.79/0.8241	25.61/0.8144	26.12/0.8217	23.32/0.7877
Man	29.64/0.7815	28.68/0.7672	28.92/0.7697	26.89/0.7407
Goldhill	28.12/0.7215	26.61/0.6693	26.9/0.6766	25.3/0.6470

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(a) (b) (c) (d)

(e) (f) (g) (h)

Fig.3. Test Images used in the experiment

All the test images are corrupted with same noise standard deviation of value 20. In the experiments performed and results tabulated, PSNR is calculated MATLAB function and the implementation of SSIM is taken from [39].

VII. CONCLUSION

In this work, all the steps of P-M anisotropic diffusion filtering is carefully studied and come up with a efficient feature preservation diffusion method along with an optimal estimation of gradient threshold parameter. The incorporation of contextual information in diffusivity function by computing local variance and noise variance of noisy image improves the denoising performance effectively. In addition to it, by estimating two gradient threshold parameters rather than one as used in the P-M anisotropic model, also improves the adaptability of the proposed diffusion filter. It is observed that estimation of one gradient threshold parameter over smoothes the image since the extent of smoothing is same in all directions irrespective of the strength of the gradient values. Therefore, this algorithm leads to better edge preservation in the denoised image. The proposed denoising algorithm is applied to a set eight noisy images and both subjective and objective have demonstrated the effectiveness of it in comparison to other anisotropic diffusion methods.

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