Segmentation Assisted Isotropic Diffusion

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Abstract—*Images are often corrupted by noise during the acquisition process. Image denoising is an important image processing task. Denoising aims at eliminating noise while trying to preserve important signal features such as texture and edges. The proposed scheme is based on segmentation of an image with isotropic diffusion. Isotropic diffusion is a process, where diffusion is same in every direction. This diffusion process is a linear and space-invariant transformation of the original image. Anisotropic diffusion is a technique aims at reducing image noise without removing significant parts of the image content, mainly edges, lines or other details that are important for representation of the image. Anisotropic diffusion is a process that creates a scale space, where an image generates a parameterized family of successively blurred images formed by convolving the image with 2D isotropic Gaussian filter, where the width of the filter increases with the parameter. The proposed method is evaluated and compare with anisotropic diffusion*.

Keywords-**Anisotropic Diffusion, Segmentation, Isotropic Diffusion, Scale Space.**

I. INTRODUCTION

Scale-space is a theory for multi-scale signal representation for handling image structures at different scales, by representing an image as a parameterized family of smoothed images with size of the smoothing kernel used for suppressing fine-scale structures. The main type of scale space is the linear scale space, being possible to derive from a small set of scale-space axioms. It generates coarser resolution images by convolving the original image with a Gaussian kernel. Image segmentation is the process of partitioning a digital image into multiple segments. Segmentation could be used for object recognition, boundary estimation in motion, image compression, editing, or image database look-up. It is the process of assigning a label to every pixel in an image such that pixels with the same label share similar properties. The simplest method of image segmentation is called the thresholding method. Connected components labeling scans an image and groups pixels into components based on pixel connectivity, i.e. all pixels in a connected component share similar pixel intensity values. Once groups are determined, each pixel is labeled with a gray level or a color depending on the component it was assigned to.

Gaussian filtering is used to blur images and remove noise and detail. The Gaussian filter works by using the 2D distribution as a point- spread function (PSF). This is achieved by convolving the 2D Gaussian distribution function with the image, this transformation is also known as the Weierstrass transform.

II. LITERATURE SURVEY

Some work has been done in the area of Scale space representation of images by witnik [1] is the 1-dimensional signal is first expanded into a 2-dimensional scale-space image, by convolving with Gaussian's over a continuum of sizes. This continuous surface is collapsed into a discrete structure, using the connectivity of extremely points tracked scale space appears which is a concise but complete qualitative description of the signal at all scales of observation. Perona and Malik suggested a new definition through Anisotropic Diffusion (AD), a non-linear partial differential equation-based diffusion process [2]. The diffusion coefficient is chosen as to encourage intra region smoothing rather than inter region smoothing. It is shown that the 'no new maxima should be generated at coarse scales' property of conventional scale space is preserved. As for the behavior of the continuous form of AD, research proving the ill posedness of the diffusion equation and developing new well-posed equations or regularizing methods [3] J.Weickert, in his paper gives an overview of scale-space and image enhancement techniques which are based on parabolic partial differential equations in divergence form. In the nonlinear setting this filter class allows to integrate a-priori knowledge into the evolution [4].In [5,6] a semi-implicit scheme for very small time steps leads to poor efficiency. Based on a discrete nonlinear diffusion scale-space framework we present semi-implicit schemes which are stable for all time steps. These novel schemes use an additive operator splitting (AOS), which guarantees equal treatment of all coordinate axes. while in [7] a different discrete implementation was proposed in order to obtain better isotropy. In contrast to acquisition-based noise reduction methods a post process based on anisotropic diffusion is proposed.

In [8] a time- dependent numerical scheme suggested that the gradient threshold gradually decreasing with time, which is significant to preserve edge and boundary features. The stopping time is dependent on an iterative SNR measure, so as to avoid the excessive smoothing problem. In [9] a modified method that considers also the variance of the brightness levels in a local neighborhood around each pixel. Since the fine details in the neighborhood of the image generally have larger gray-level variance than the noisy background, the proposed diffusion model incorporates both local gradient and gray-level variance to preserve edges and fine details while effectively removing noise. A defect embedded in a low-contrast surface image is extremely difficult to detect, because the intensity difference between the unevenly illuminated background and the defective region is hardly observable and no clear edges are present between the defect and its surroundings described in [10]. In [11,12] anew conductance functions are proposed. The purpose is to give an analysis of the anisotropic diffusion (AD) and propose adaptive nonlinear filtering based on a judicious choice of the conductance function (CF) and the edginess threshold. In [13] how the parameter adapts itself to the denoising of the filtered image after every iteration, preserving all the edges above a decreasing threshold using gradient threshold parameter shown. In [14], a stabilized, insensitive to the number of iterations process was introduced. The new Brent-NCP parameter choice method, the proposed denoising algorithm chooses the regularization parameters automatically. This makes it more adaptive and efficient.

III. Anisotropic Diffusion

3.1. Overview of the process : Anisotropic diffusion resembles the process that creates a scale space, where an image generates a parameterized family of successively more and more blurred images based on a diffusion process.

The basic equation of anisotropic diffusion equation as presented in is

$\partial I(x,y,t)\ \partial t$ =div[g(|$(x,\ y,t)$|)$\nabla I(x,\ y,t)$] (3.1.1)

where t is the time parameter, I(x,y,0) is the original image, $\nabla I(x,\ y,t)$ is the gradient of the version of the image at time t and g(.) is the so-called conductance function. This function is chosen to satisfy limx-0 g(x)=1, so that the diffusion is maximal within uniform regions, and limx-1 g(x)=0, so that the diffusion is stopped across edges. Two such functions proposed by Perona and Malik were

$$g_{1(x)} = \exp[-\left(\frac{x}{k}\right)^2] \qquad (3.1.2)$$

And

$$g_{2(x)} = \frac{1}{1+(\frac{x}{k})^2} \qquad (3.1.3)$$

where K is the gradient magnitude threshold parameter that controls the rate of the diffusion and serves as a soft threshold between the image gradients that are attributed to noise and those attributed to edges. Black et al. in [18], through an interpretation of AD in terms of robust statistics, defined a different conductance function, called Tukey's biweight function.

$$g_3(x) = \frac{1}{2}[1-\left(\frac{x}{s}\right)^2]^2 \qquad x\leq s \qquad (3.1.4)$$

Where s=k√2

The flow function Ø defined as

$$Ø(x) = g(x)x \qquad (3.1.5)$$

represents the sum of the brightness flow that is generated. The maximum flow is generated at locations where |∇I|=k

Perona and Malik discretized their anisotropic diffusion equation to

$$I_{t+1}(s)=I_t(s)+\frac{\lambda}{|ns|}\sum_{p\in ns} g_k(|\nabla I_{s,p}|)|\nabla I_{s,p|} \qquad (3.1.6)$$

where I is a discretely sampled image, s denotes the pixel position in the discrete 2-D grid, t denotes the iteration step, g is the conductance function and K is the gradient threshold parameter. Constant & determines the rate of diffusion and Ns represents the spatial 4- pixel neighborhood of pixel s: Ns={N,S,E,W}, where N, S, E and W are the North, South, East and West neighbors of pixel s, respectively. Consequently, |Ns| is equal to 4 (except for the image borders). The symbol ∇ which in the continuous form is used for the gradient operator, now represents a scalar defined as the difference between neighbouring pixels in each direction:

$$\nabla I_{s,p|}= I_t(p)- I_t(s), \quad p\in ns=\{N,S,E,W\} \qquad (3.1.7)$$

As mentioned by Perona and Malik, this scheme is not the exact discretization of the continuous equation, with more numerically consistent methods.

The parameters in Anisotropic Diffusion According to Perona and Malik is , the g1 conductance function favours high-contrast edges over low-contrast ones, while the g2 function favours wide regions over smaller ones. The g3 function, according to Black et al., yields sharper edges improving considerably the experimental results of the filtering, since the diffusion process converges faster. The basic AD scheme has a good edge-preserving behavior after choosing the right conductance function, but is incapable of denoising efficiently images with high levels of noise. This problem lies in the fact that the image gradient is not a reliable measure since it is susceptible to noise. A response to this problem is to replace term g(|$\nabla I(x,\ y,t)$|) in (1) with g(|$\nabla(G\sigma * I(x,\ y,t))$|) where G$\sigma$ is a Gaussian filter of scale σ. This means that the local gradients that are the argument of the conductance function are now computed using a smoothed version of the image in every iteration. In order to estimate automatically scale s of the Gaussian filter according to the level of the Gaussian noise within an image, a sliding window of size between 25*25 and 64*64 pixels is used so that the most uniform block of pixels within the image is detected. The uniformity measure used is the standard deviation of the pixels within each block. Finally, the standard deviation of the most uniform block is considered to be the scale s of the Gaussian filter. From the value of s the size of the smoothing Gaussian filter is then determined.

The estimation of the gradient threshold parameter plays a major role in the diffusion process, since it defines the threshold between the image gradients that are attributed to noise and those attributed to true edges. Some methods that have been proposed in order to estimate the gradient threshold parameter are the following:

1. Perona and Malik in suggested the use of the ‘‘noise estimator’’ described by Canny , where a histogram of the absolute values of the gradient throughout the image is computed and S is set equal to the 90% value of its integral in every iteration.

2. Black et al. defined S $=\sigma e\sqrt{5} = 1.4826MAD(\nabla I)$, where MAD denotes the median absolute variation and is defined as MAD = median(|∇I −median(∇I|).

Since AD filtering is an iterative process, it is highly sensitive to the number of iterations. The choice of the stopping time T is crucial, since overestimating it may result in blurring the true edges, while underestimating it may leave unfiltered noise artifacts. Choosing the optimal conductance function and gradient thresholding parameters leads to higher PSNR values. However, PSNR is always maximized in a specific iteration, which is the time when the process should ideally be terminated. Therefore, the optimal stopping time T should be estimated using only the statistics of each filtered version of the noisy image.

IV. Existing System

Denoising aims at eliminating this measurement noise while trying to preserve important signal features such as texture and edges. Mainly anisotropic diffusion is a technique aiming at reducing image noise without removing significant parts of the image content, typically edges, lines or other details that are important for the interpretation of the image. Anisotropic diffusion filtering is highly dependent on some crucial parameters, such as the conductance function, the gradient threshold parameter and the stopping time of the iterative process. An automatic stopping criterion takes into consideration the quality of the preserved edges as opposed to just the level of smoothing achieved. Overestimating one of the parameters may lead to an over smoothed blurry result, while underestimating it may leave the noise in the image unfiltered. The cost of parameters which are considered in anisotropic diffusion is very high.AD filtering is an iterative process, it is highly sensitive to the number of iterations. Here number of iterations yields high cost and the stopping criteria depends on number of iterations. So, we proposed a method which is not sensitive to number of iterations. Then we came with segmentation with isotropic diffusion.

V. Proposed System

We deal with the isotropic diffusion which is linear scale space invariant transformation of the original image along with the segmentation. This is also a technique aims at reducing image noise without removing significant parts of the image content, typically edges, lines or other details that are important for the interpretation of the image but in different approach using Segmentation. This method is compared with anisotropic diffusion in time and accuracy. The steps of the proposed method are the following:

1. The original image I is first added with white gaussian noise of mean and variance 8 and then computed the global threshold level to convert intensity image into binary image. This conversion of gray to binary image is done by using otsu’s method. In Otsu's method we exhaustively search for the threshold that minimizes the intra-class variance (the variance within the class), defined as a weighted sum of variances of the two classes:

$$\sigma^2\omega(t) = \omega o(t)\sigma o^2(t) + \omega 1(t)\sigma 1^2(t) \qquad (5.1)$$

Weights $\omega o$and $\omega 1$are the probabilities of the two classes separated by a threshold t and $\sigma o^2$and$\sigma 1^2$are variances of these two classes. The class probability ωo, $1(t)$is computed from the L histograms:

$$\omega o(t)=\sum_{i=0}^{t-1} p(i) \qquad (5.2)$$

$$\omega 1(t)=\sum_{i=t}^{L-1} p(i) \qquad (5.3)$$

Otsu shows that minimizing the intra-class variance is the same as maximizing inter-class variance:

$$\sigma_b^2= \omega o(t)\ \omega 1(t)[\mu_0(t)-\mu_1(t)]^2 \qquad (5.4)$$

which is expressed in terms of class probabilities ω and class means μ.

while the class mean $\mu_{0,1,T}$ is:

$$\mu_0(t)=\sum_{i=0}^{t-1} ip(i)/\omega_0 \qquad (5.5)$$

$$\mu_1(t) = \sum_{i=t}^{L-1} ip(i)/\omega_1 \qquad (5.6)$$

$$\mu_T=\sum_{i=t}^{L-1} ip(i) \qquad (5.7)$$

2. Then find the connected components from the binary image with desired connectivity and converted the rgb to gray image using luminosity method. The luminosity method is a more sophisticated version of the average method. It also averages the values, but it forms a weighted average to account for human perception. We’re more sensitive to green than other

colors, so green is weighted most heavily. The formula for luminosity is 0.21 R + 0.72 G + 0.07 B.

3. Then provides the Gaussian low pass filter and convolve the extracted component image with the kernals of Gaussian operator.

fspecial creates Gaussian filters using

$$h_g(n_1,n_2)=e^{\frac{-(n1^2+n2^2)}{2\sigma^2}} \qquad (4.2.8)$$

$$h(n_1,n_2)=\frac{h_g(n_1,n_2)}{\sum_{n1}\sum_{n2} h_g} \qquad (4.2.9)$$

conv2 uses a straightforward formal implementation of the two-dimensional convolution equation in spatial form. If a and b are functions of two discrete variables, n1 and n2, then the formula for the two-dimensional convolution of a and b is

$$c(n_1,n_2)=\sum_{k1=-\infty} a(k_1,k_2)b(n_1-k_1,n_2-k_2) \qquad (4.2.10)$$

In practice however, conv2 computes the convolution for finite intervals.

4. Convolve the other part of the image which is not extracted and add both smoothed images.

5. Keep the resulted image back into the binary image using ind2sub which is I1and then subtract the I1 from the original image. Ind2sub uses tall arrays algorithm.

Tall arrays can be used in a variety of ways from a single system running an application that has access to large amounts of data. This manages the data manipulation and program distribution. Tall arrays are columnar data with rows of elements like a database table or spreadsheet. Support includes mathematical and statistical operations, as well as data manipulation operations.

6. We will perform the same procedure for all connected components and then compares with Anisotropic diffusion images.

VI. Experimental Results

Here are some implemented results of proposed algorithm based on segmentation technique followed by diffusion. This technique is further implementable on different standard images such as MRI imges.

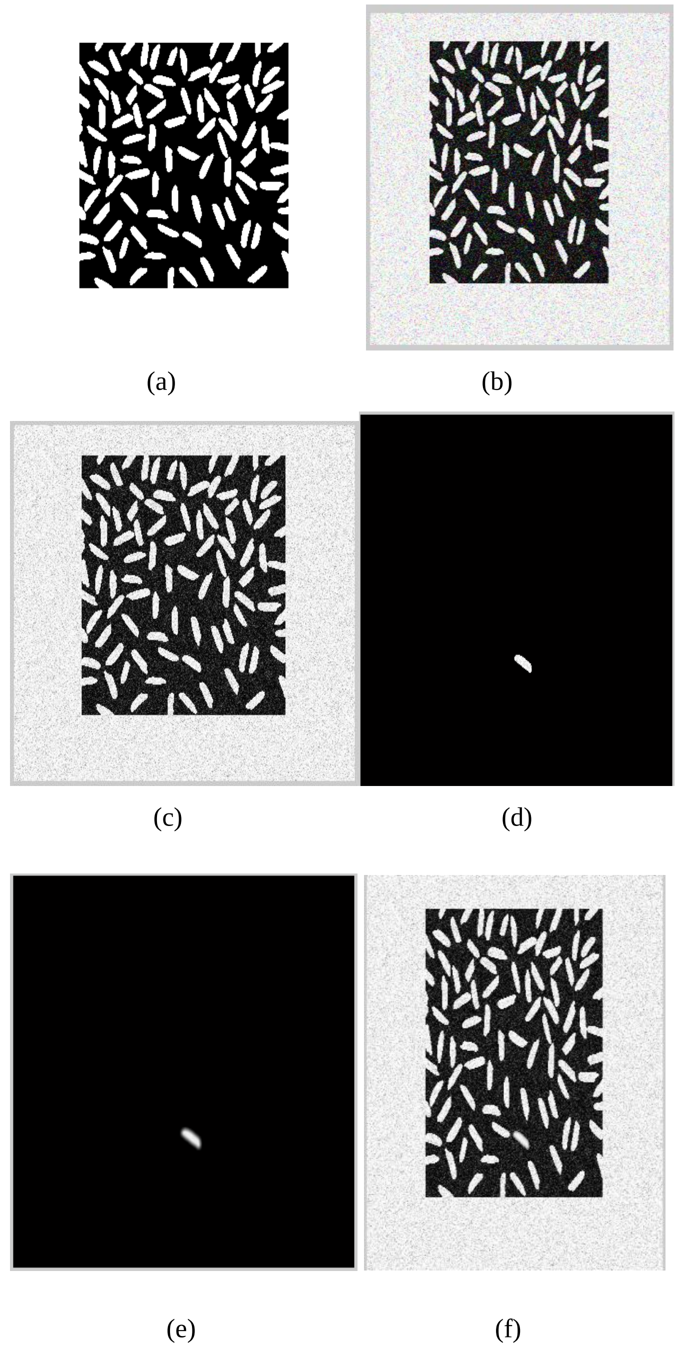

Fig 5.1 (a) original image.(b) image with added Gaussian noise.(c) global threshold applied to convert image to gray.(d) segmented grain image.(e) convolved image with Gaussian filter.(f) segmented image placed to original image.

VII. Future Work And Conclusion

In this paper we have studied about segmentation technique in combination with isotropic diffusion which is a different approach applied with diffusion. We used Otsu's method to determine threshold that minimizes the intra-class. The proposed scheme costs less than Anisotropic diffusion in terms of time. Anisotropic diffusion generates a parameterized family of successively more and more blurred images based on number of iterations which incurs high cost. The most difficult images to improve with AD and SAID are those with many details and texture. In future we deal with anisotropic diffusion along with different parameters and compare them with proposed method. This method is also applied on medical MRI images.

VIII. References

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