Curvature Anisotropic Gaussian Filter for MRI brain Images enhancement and edge preserving

Shaima Abd El-Kader, Mohamed Morse, Mohy Eldin A. Abo-Elsoud, and Rasheed MokhtarEl-Awady

Nile academy, Mansoura.Egypt,

Summary

Magnetic Resonance Imaging (MRI) brain images often suffer from low contrast and noise, especially in brain imaging. This noise hampers further tasks such as segmentation of the important features and classification of brain tumor. As a result, the visual quality gets deteriorated and perfect diagnosis of the disease becomes difficult. During the acquisition process of (MRI), irregular bias is imposed in the intensity values of the pixels. These biases follow the Gaussian Noise distribution model and act as a constraint to the effective medical diagnosis. We are interested in Partial Differential Equations (PDE) in order to smooth MRI brain image in an anisotropic manner. The Anisotropic Diffusion filter (ADF) approach is limited to preserve the structural integrity of MRI brain image at only low noise levels. This paper proposes (CADF) algorithm aimed to improve the estimation of the diffusion constant to facilitate better edge detection and preservation of details. We demonstrated how the diffusion tensor computed in an anatomically enhanced MRI brain image coordinate by (CADF).This framework facilitates radiologist to assess brain tissue change and guide them to evaluate MRI brain image of having brain tumor Simulation trials have been conducted at different Gaussian noise variances and performance has been evaluated on the basis of Peak Signal- Noise Ratio (PSNR) and Structural Similarity (SS). The proposed algorithm has shown stable value of evaluation parameters at higher noise variances. Also, the preservation of details has improved as compared to the Curvature Anisotropic Diffusion Filter. Finally, we illustrate the efficiency of our generic curvature-preserving approach. Experimental results show that the new method can achieve better denoising results in a variety of MRI brain images, and the new approach shows superior performance on edge and curvature preserving edges and texture image.

Keywords:

MRI; T1;T2;Anisotropic Smoothing; Diffusion PDE's, Tensor valued Geometry; Denoising; ADF; SSIM;CADF; PDE component ;SS

1. Introduction

The degradation of an image is usually unavoidable during its acquisition and transmission. It is necessary to apply an efficient denosing technique to compensate for image corruption. Denoising algorithm performance mainly depends on a suitable representation to describe the original image information. Image noise removal remains a challenge since it introduces artifacts and causes blurring. One of the major concerns in image denoising methods is their edge preservation capability .The existing denoising methods can be parted into two groups: (1) Sparse representation; (2) Smoothing denosing . The former regards that the signal can be sparse decomposition, and the construction of a sparse dictionary is one of the key problems. The latter views noise as local oscillation signal which can be removed by smoothing method. As the sparse decomposition method generates larger time consumption comparatively, this paper focuses on the research of smoothing denoising method

Among a variety of the develop denoising techniques, partial differential equation(PDE) have been widely used over the past few decades, due to its great advantage that it can preserve image edges while reducing noise .

Local denoising methods carry out certain weighted averaging operations on the intensity values of a local neighborhood of the pixel under consideration, and have developed fast in the last 20 years, which has been applied to many fields of computer vision successfully. But in recent years, the anisotropic diffusion filter and its advancing gradually became the hot research topic in medical image denoising. These methods perform some kind of edge preserving Nonlinear PDE based method is introduced by the pioneering work in [3], which used scalar-valued decreasing function to control the process of smoothing. In facts, this model is isotropic denoising method. The most representative of anisotropic PDE denoising methods are tensor-driven method such as divergence-based PDE first presented by Weichert in work [4], which replaces the scalar-valued function in [3] by a matrix-valued diffusion tensor that describes the direction of smoothing, computed from the so-called structure tensor. Subsequently, a tensor-driven trace-based PDE model for color image was introduced in [2], which replaces the divergence operator of divergence-based PDE in [4] by the trace operator. Meanwhile a link between [3] and [4] was made in the work.

The recent years have seen the emergence of MRI as a powerful diagnostic technique for the detailed visualization of the internal structures of the human body[9]. However, the image quality of the obtained MRI is constrained by the presence of large amount of noise introduced during the acquisition process. This noise,

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usually modeled as Gaussian noise [5]-[6], introduces irregular intensity bias in the pixel values, thereby hampering the performance of the various image post-processing modules such as enhancement [17], segmentation [7] and classification [8]-[9]. Thus, removal of this unwanted noise becomes a fundamental process in the medical image processing. Over the years, various denoising approaches [10] based on linear smoothen in have been developed for the suppression of the noise. However, these approaches eliminated the noise at the expense of the fine details and tissue edges which were lost due to blurring. This lead to the development of edge preserving ADF approach introduced by Perona and Malik and was based on the scale space concept introduced. This approach overcame the limitations of the linear smoothening approaches, such as blurring and loss of details, by suppressing the noise while respecting the tissue edges and small structures present within the image. Gerig et al. in their work utilized this technique for noise suppression in MRI. Further improvements in the denoising ability of the ADF approach were carried out. An analysis on the behavior of the denoising mechanism of ADF was performed. This was utilized by Black et al. for the development of a robust ADF filter which incorporated the robust statistics in the AD filter. A fourth order partial differential equation based denoising approach was developed which utilized the concept of signal dependent noise characteristics in MRI. The application of AD filter was extended for spatially varying noise levels in MRI in the work carried out by Samsonov and Johnson. Recently, an extension of the ADF filter based on the estimation of noise level has been developed [13]. The disadvantage of isotropic diffusion The disadvantage of isotropic diffusion is that it is symmetric and orientation insensitive, leading into blurred edges. Perona and Malik (PM) [13] developed an anisotropic diffusion process as a nonlinear image noise removal method, which analogized heat diffusion to adaptively remove the noise of the images. The main idea of anisotropic diffusion is that it encourages intra-region smoothing and discourages inter-region at the edges [14].The decision on local smoothing is based on diffusion. As the trace based PDE can't preserve the curvature structure very well, a refreshing curvature-preserving PDE filtering model was suggested in [3], which has better performance on curvature preserving and was implemented by averaging of different Gaussian-pondered Line Integral convolutions along the integral curves of vector field that obtained from projecting the square root of diffusion tensor into different orientations.

We propose an improved version of ADF called CADF model, which adopted weighted strategy to design adaptively weight coefficients for PDEs under different vector field. In this paper we proposed a new implement version of the former model. In other words, we implemented the Anisotropic Curvature filter denoising.

In this paper, MRI brain images have been removing of film artifact then denoising as pre-processing step. In the remaining part of the paper, Section II details the anisotropic diffusion filter (ADF) process and the proposed filtering algorithm curvature anisotropic filter (CADF) is used also as filter, Section III presents the simulation results and their subsequent discussions and Section IV includes the conclusion part. The rest of the paper is organized as follows. The section presents the MRI brain image contrast and the noise characteristics of MRI and the various denoising and contrast enhancement techniques. The section 2 explains the design methodology. The section 3 presents (ADF) and (CDF) for denoising .The section 4 presents the performance validation and simulation results. Finally, the conclusions and future work are provided in the last section.

2. Methodology

The proposed enhancement approach can be viewed as a three stage process as seen on fig 1.Then adding different variance of Gaussian noise as seen on fig 2.to test two method of denoising.

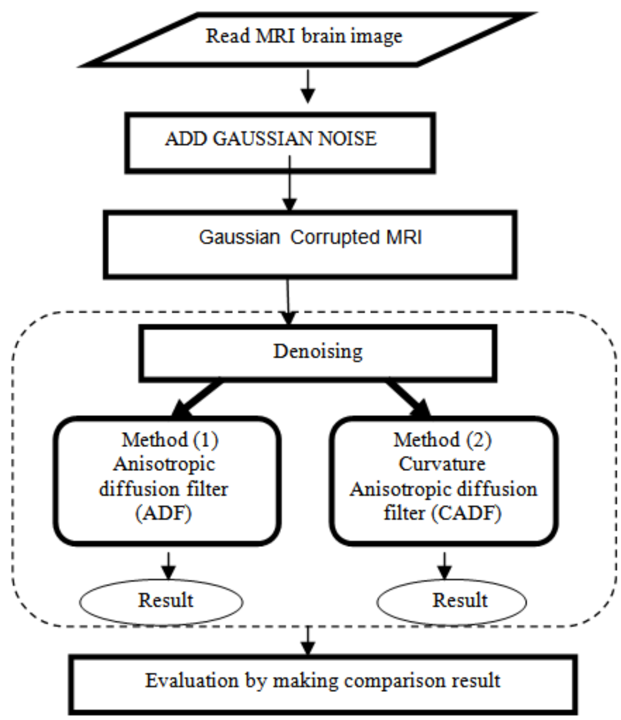

Fig.1 proposed algorithm

Preprocessing is the basic step in any noise reduction image processing. The first stage deals with preprocessing by using ADF ,then CADF as it produces better preprocessing with less blurring of edges. The advantage of CADF is that, it is not affected by individual noise spikes, eliminates Gaussian noise quite well, and it does not blur edges of brain image much and can be applied iteratively The first stage after reading MRI brain image we add Gaussian noise, then to increases the visibility of fine details and helps to clearly distinguish between the gray matter, white matter and CSF we using denoising method. The first stage handles the denoising by using (ADF) and using (CADF) as it preserves fine structures and reduces correlated noises. This proposed approach increases the image contrast and also adapts to the homogeneous and non-homogeneous Gaussian noise

3. Preprocessing step

Pre-processing is mainly used to enhance the contrast of MRI, removal of noise and isolating objects of interest in the image. MRI brain images have been removing of film artifact then denoising as pre-processing step. In the remaining part of the paper, Section II details the anisotropic diffusion filter (ADF) process and the proposed filtering algorithm curvature anisotropic filter (CADF) is used also as filter.

3.1 Removal of film artifacts and add Gaussian noise

First, the MRI brain image consists of film artifacts or label on the MRI such as patient name. film artifacts that are removed using tracking algorithm .Here, starting from the first row and first column, the intensity value of the pixels are analyzed and the threshold value of the film artifacts are found The threshold value, greater than that of the threshold value is removed from MRI. The high intensity values of film artifacts are removed from MRI brain image and adding Gaussian noise as shown in fig 2.

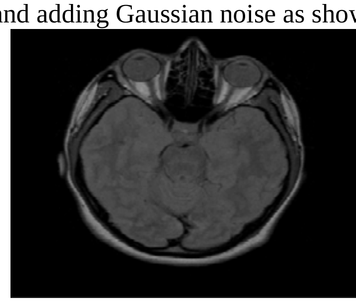

Fig.2 Input MRI image after adding noise

3.2 Anisotropic Diffusion Filter (ADF)

ADF is a widely used filtering algorithm for the biomedical images specifically MRI. It is a filtering technique aimed at the noise suppression without the removal of the significant parts of the image content, typically the edges and boundaries. This technique incorporates the non-linear and space-variant transformation of the original MRI, so as to produce a family of parameterized images. These parameterized images are depicted as the convolution between the original MRI and the isotropic Gaussian filter and are termed as the mask images of the original MRI. The basic ADF equation as described by [15] is:

$$It = c\ (x, y, t)\ \Delta I + \nabla c \nabla I \qquad (1)$$

where: t is the time parameter, I is the original image, I is the filtered image, ΔI , ∇I are the gradient and the laplacian of the image respectively and c(x, y, t)is the diffusion constant This Eq. 1 can be further reduced to:

$$It = c\ (x,y,t)\ \Delta I \qquad (2)$$

The diffusion constant c(x, y, t) is the primary edge stopping parameter which controls the filtering process and leads to the edge preservation. The value of the diffusion constant can be calculated by:

$$c(x,y,t) = g(\nabla I) \qquad (3)$$

Where: g (∇I)is the conduction coefficient function and is represented by:

$$g\ (\nabla I) = e(-(\| \nabla I \| /k)2 \quad) \ (4)$$

$$g\ (\nabla I) = \frac{1}{1 + (\| \nabla I \| / k)2} \qquad (5)$$

Where: k is the gradient modulus constant and $\| \nabla I \|$ is the parameterized image or the decomposed mask images. Equation (4) is used when high contrast is preferred over low contrast and (5) is used when wider regions are preferred over smaller regions. It can be observed from (3) that the value of the diffusion constant is dependent on the conduction coefficient. Further, the conduction coefficient depends on the parameterized images or the mask images. Therefore, these mask images play a crucial role in the estimation of the diffusion constant. In case of an MRI corrupted with the additive Gaussian noise, the decomposed mask images of that MRI will also contain biased pixel intensity values due to the noise. This will lead to an incorrect estimation of the diffusion constant, thereby, leading to degradation in the performance of the ADF, as seen on fig 3.In this paper, CADF approach has been proposed in order to remove this limitation

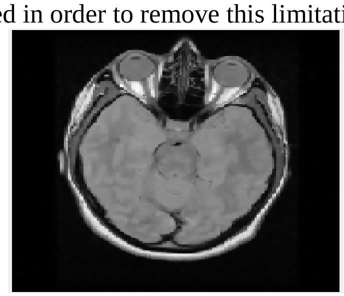

Fig.3 Output of Anisotropic diffusion filter

3.3 Diffusion tensor

In this paper our aim is to study inside the brain tissues changes its orientation tissue structures orientation or homogeneity .Structure tensor provides the useful indication of local perceptual orientation of brain tissue on MRI. Often the edges are quite noisy causing the gradient to fluctuate considerably, both in magnitude as well as in direction. In order to ignore the less important features of the MRI brain image, anisotropic diffusion tensor is adopted to facilitate the better estimate of the perceptual significant orientation of the edge direction in order to pickup the changes occurred in the temporal brain image in time line. We adopt the diffusion tensor construction as described by [15]. Diffusion tensor D is constructed, as in

$$c(x,y,t) = \frac{1}{\sqrt{l2\ Norm(i_s^\delta, i_\varphi^\delta)}} \begin{bmatrix} c1(i_s^\delta) + c2\left(i_s^{\delta^2}\right) & (c2-c1) i_s^\delta i_\varphi^\delta \\ (c2-c1) i_s^\delta i_\varphi^\delta & c1\left(i_s^{\delta^2}\right) + c2\left(i_s^{\delta^2}\right) \end{bmatrix} \quad (6)$$

Where Σ denotes the image observed at scale σ, c1 is conductivity in the direction of gradient and c2 is the conductivity along the isophote. As described by [15] we set the diffusion along the edge to be equal to the isotropic diffusion in the Perona and Malik diffusion [16] and set the conductivity across the edge to be one fifth of the conductivity along the edge. However this comes after running number of experiments until the linear structure of the brain tissues are visible in the mammogram. Having the diffusion tensor in equation (6), we compute their eigenvalues λ1 - λ2 and their associated eigenvectors [17]. From equation (6) we then calculate the coherence of diffusion tensor to evaluate the quantification of orientation in MRI brain tissue.

3.4 Curvature anisotropic diffusion tensor (CADF)

In order to improve the performance of anisotropic diffusion tensor so as to extract noticeable and significant orientation of brain tissue, we adopt a curvature anisotropic diffusion on an image using a modified curvature diffusion equation (MCDE) [17]. MCDE does not exhibit the edge enhancing properties of classic anisotropic diffusion, but instead consider image as a manifold defined by graph of function embedded in some Euclidian space. Mean curvature motion of these graphs is considered as an underlying model for diffusion. This facilitates the natural geometric way to treat the image in order to extract their anatomical structural information. Equation (7) show mean curvature described by [17] was adopted to evolve an Image during diffusion,

$$I_t(S,\varphi) = \frac{I_{ss}(1 + I_\varphi I_\varphi) - I_S I_\varphi I_{s\varphi} + I_\varphi I_\varphi (1 + I_s I_s)}{2(1 + I_S I_S + I_\varphi I_\varphi)^{1.5}} \quad (7)$$

The difference between ADF and the CDAF is that the anisotropic diffusion filter does not have the edge enhancing properties, as shown in fig 4.

Fig.4 Output of Curvature Anisotropic diffusion filter

Parameters:

1. Time Step - this parameter refers to the time step involved in solving the partial differential equation in the algorithm. For 2D, the typical value to use is 0.125. In general, for n-dimensional images,
2. Number Of Iterations - this specifies the number of iterations that the solver must perform before returning a solution image. More the number of iterations, more smooth the image would be. A typical number for the number of iteration is 5, increasing the number of iterations linearly increases the computation time.
3. Conductance - this parameter controls conductance, which in turn controls the sensitivity of the algorithm in preserving the edges. If the value of the conductance is low, the algorithm preserves the image features to a larger extent. If the value of the conductance is high, the algorithm smooths (or diffuses) the features in the image. A typical value of conductance that can be used is 3, but in general it will depend on the type of image and the number of iterations.

Below, we give the images obtained by applying the CADF on the MRI brain image in figure (1), show the image obtained by using parameters suggested above (conductance =4, iterations =4, and time step = 0.135). The result obtained shows considerable noise removal, and also preserves the edges quite well.

4. Simulation Result and Discussion

4.1 Datasets

Experiments have been conducted on real MR datasets to compare two denoising methods. The simulated datasets of brain MRI are obtained from, http://www.mans.Edu.EG/Facmed/Radiology. The data set consists of T1weighted Axial, T2weighted Axial and PD images of 181 x 217 x 181 voxels. In order to validate the results, the ground truth image from the Mansoura hospital database are corrupted with different level of Gaussian noise from 3% to 12%.. In the clinical data sets, the images acquired using Philips Medical Systems 1.5T

Scanner were obtained from http://www.osirix viewer.com/datasets. Here, the images are acquired using spin echo (SE) sequences with long repetition time (TR) and short echo time (TE).The results are validated on T1 weighted Axial MR images of normal brain with TR = 449 ms, TE = 10 ms, 5 mm thickness and 512 x 512 resolution.

4.2-Validation Strategies

There are two criteria that are used widely to measure image quality- the visibility of artifacts and the preservation of edge details. It is usually measured by visual inspection. Here the performance of the approach is measured using different measures:

1) *Mean Square Error (MSE)*
2) *Root Mean Square Error (RMSE)*
3) *Peak Signal to Noise Ratio (PSNR)*
4) *Structural similarity index (SSIM)*

The MSE quantifies the strength of error signal and is calculated according to the formula, Noise Ratio (PSNR) in dB is given by the formula,

$$PSNR = 10log_{10}\left(\frac{Max^2}{MSE}\right) \quad (8)$$

Where MAX is the maximum possible pixel value of the image. Higher the PSNR, the better the denoising algorithm is. The Structural Similarity (SSIM) index (Zhou Wang et al, 2004) is a method for measuring the similarity between the original and the denoised images. It is based on the idea that the human visual system is highly adapted to the structural information from visual scenes. Apart from the structural changes, image quality is also affected by luminance and contrast, which must be also accounted for better quality analysis. The SSIM works as follows: let x and y be two non negative images, where as one has perfect quality. It can be defined as:

$$SSIM(x,y) = \frac{(2\mu_x\mu_y + c_1)(2\sigma_{xy} + c_2)}{(\mu_x{}^2 + \mu_y{}^2 + c_1)(\mu_x{}^2 + \mu_y{}^2 + c_1)} \quad (9)$$

Where C1 and C2 are the regularization constants to avoid instability when .Its values are given as and where K1,K2 <<1 is a small constant regularization parameter and L is the dynamic range of the pixel values. µx and µy are the estimated mean intensity and σx and σy are the standard deviations, respectively. The SSIM index shows how well the structures are preserved in the resultant image. It quantifies the subjective image quality better than MSE or PSNR.SSIM can be viewed as a quality measure of one of the images being compared, provided the other image is regarded as of perfect quality. As opposed to the RMSE, this index accounts for the similarity between image structures and not between grey levels. It is in the range of 0 for worst quality and 1 for images shown in figure 1 identical to ground-truth The SNR value for CDAF is 30.3166 and the SNR value for ADF is 27.7755 when noise ratio is 15.

This section deals with the application of the proposed filtering algorithm on a sample MRI, evaluation of its validity for noise suppression and comparison with ADF approach [2. The experimental simulations were carried out using
MATLAB (R2012a) on a computer with 2.30 GHz core-i3processor. For the simulation, a sample MRI, corrupted with synthetic Gaussian noise of different noise variance values, has been subjected to the proposed algorithm.
The performance evaluation of the filtered MRI was carried out at different noise variances: 5, 12, 13, 18 and the obtained values of PSNR and SSIM have been enlisted under Table I. The noisy MRI and its corresponding filtered MRI have been illustrated in Table (1) for the purpose of visual assessment.

Table 1: Comparison of the ADF algorithm and CADF

ADF		Proposed Technique CADF		Noise ratio
PSNR	SSIM	PSNR	SSIM	
35.131	0.721	37.728	0.931	5
31.09	0.510	34.713	0.631	12
28.13	0.421	32.11	0.41	13
25.7	0.311	27.231	0.31	18

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