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PARTICLE SWARM OPTIMIZATION BASED TOTAL VARIATION FILTER FOR IMAGE DENOISING

[1]JANSI S., [2]SUBASHINI P.
[1]Research Scholar., Department of Computer Science, Avinashilingam University, Coimbatore.
[2]Professor., Department of Computer Science, Avinashilingam University, Coimbatore.
E-mail: [1]jansi.sm@gmail.com, [2]mail.p.subashini@gmail.com

ABSTRACT

Denoising of images is an important task in Magnetic Resonance (MR) image processing and image analysis, and it plays a significant role in modern applications in different fields, including medical imaging and computer vision. While many algorithms have been proposed for the purpose of image denoising, the problem of noise image suppression remains an open challenge, because noise removal introduces artifacts and causes blurring of the images. In this paper, Non Local Means, Anisotropic Diffusion, Bilateral, and Total Variation methods are used to reduce the image artifacts and noise in MRI images. Finally, PSO is implemented to find the optimal value of the regularization parameter of total variation method. The experimental results are obtained to show the performance of the proposed method. The proposed methods are compared and evaluated based on the error rate and their quality of the image.

Keywords: *Medical Image Processing, Image denoising, MRI brain images, Filtering techniques, Regularization parameter, Particle Swarm Optimization.*

1. INTRODUCTION

Medical Image Processing is a technique and process used to create images of the human body for clinical purposes or medical science. The medical image processing application enables quantitative analysis and visualization of medical images of many modalities such as PET, MRI, CT and Ultrasound. It is very important to get precise images to help exact observations for the given application [1]. The medical images are corrupted by different types of noises such as Rician noise and Additive White Gaussian Noise. Since the noise is related to high frequencies, it is difficult to remove without important features of the images.

Denoising is a technique used to remove noise in images and used as a preprocessing step in many medical image processes and analysis tasks such as registration or segmentation to reduce the Additive White Gaussian noise arising due to the acquisition process [2]. The denoising of MR images is an important problem that has been frequently discussed by researchers. The noise in MR images is removed by using proper filters. Popularly available denoising filters for MRI are Non-local Means, Anisotropic, Bilateral and Total Variation filter.

In this paper, total variation filter is applied to MR images to remove the noise. In total variation filter the regularization parameter (λ) makes the image become smoothed. For choosing the optimized value of the regularization parameter, the Particle Swarm Optimization algorithm is implemented in a total variation filter.

PSO is a heuristic global optimization method. It is developed from swarm intelligence and is based on the research of bird and fish movement behavior. The PSO algorithm is easy to implement and has been successfully applied to solve a wide range of optimization problems [3] in medical image processing.

The rest of this paper is organized as follows: In section 2, the overview of methodologies and technical details of image denoising methods are described. In section 3, the experimental results and discussions are done. Finally, conclusions are given in section 4.

2. METHODOLOGY

2.1 Non Local Means Filter

Non-Local Means (NLM) algorithm is based on the natural redundancy of information in images to remove noise [4]. The non-local means filter averages all observed pixels to recover a single

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pixel. The weight of each pixel is calculated by depending the distance between its intensity gray level vector and that of the target pixel [5]. The NLM filter is a neighborhood filter which achieves denoising by averaging similar image pixels according to their intensity similarity.

The key idea of the non-local means filter is that a given noisy image $f:\Omega\subset R^2\mapsto R$ is filtered by

$$u(x)=\int w_f(x,y)f(y)d_y \qquad (1)$$

where $u:\Omega\mapsto R$ is the denoised image and $w_f:\Omega\times\Omega\mapsto R^+$ is a normalized weight function written as

$$w_f(x,y)\Leftrightarrow\frac{e^{-\frac{d^2f(x,y)}{h^2}}}{\int e^{-\frac{d^2f(x,y)}{h^2}d^y}},\ for\ d^2f(x,y)\Leftrightarrow\left\|f_x-f_y\right\|^2G\sigma \qquad (2)$$

where eqn (2) is the differences of f_x and f_y, weighted against a Gaussian window G_σ with standard deviation σ. The map $d_f(x,y)$ measures the different patches of f centered in x and y. If two patches are similar, then the corresponding weight $w_f(x,y)$ will be higher. Otherwise if the patches are dissimilar, the weight $w_f(x,y)$ will be small (but positive) [6]. Dimensions of the similarity between two patches are defined as σ and the parameter h regulates how strict or relaxed to consider the patches similarly. Finally, the result of the non-local means filter has several (similar) patch used to reconstruct another one.

2.2 Anisotropic Diffusion Filter

Anisotropic filter is non-optimal for MR images with spatially varying noise levels of such sensitivity-encoded data and intensity inhomogeneity corrected images [7]. Persona and Malik formulate the anisotropic diffusion filter as a diffusion process that encourages intraregion smoothing while inhibiting interregion smoothing [8]. Mathematically, the process is defined as follows:

$$\frac{\partial}{\partial t}I(\bar{x},t)=\Delta\cdot\left(c(\bar{x},t)\Delta I(\bar{x},t)\right) \qquad (3)$$

In this case, $I(\bar{x},t)$ is the MR image, $\bar{x}$ refers to the image axes and t refers to the iteration step. $c(\bar{x},t)$ is the diffusion function and is a monotonically decreasing function of the image gradient magnitude.

$$c(\bar{x},t)=f\left(\left|\Delta I(\bar{x},t)\right|\right) \qquad (4)$$

It allows for locally adaptive diffusion strengths, edges are selectively smoothed or enhanced based on the evaluation of the diffusion function.

2.3 Bilateral Filter

The bilateral filter is an edge-preserving and noise reducing smoothing filter which is developed by Tomasi and Manduchi. This filtering technique is achieved by the combinations of two Gaussian filters: one filter works with partial domain and the other one works with intensity domain [9]. The intensity value of each pixel in an image is replaced by a weighted average of intensity values from nearby pixels. The weight is mainly based on the Gaussian distribution. The output of the bilateral filter is

$$I_s=\frac{1}{k(s)}\sum_{p\in\Omega}f(p-s)g(I_p-I_s)I_p, \qquad (5)$$

where $k(s)$ is a normalization term.

$$k(s)=\sum_{p\in\Omega}f(p-s)g(I_p-I_s) \qquad (6)$$

Here, the eqn (5), (6) uses a Gaussian for f in the spatial domain and a Gaussian for g in the intensity domain. Therefore, the value of the pixel s is spatial domain, and that has a similar intensity. This is easy to extend to color images, and any metric g on pixels can be used [10].

One of the main advantages of the bilateral filter is that it smoothes the areas where the pixels are similar. This allows us to leave relatively unaffected edges in the image.

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2.4 Proposed Total Variation Filter

Total Variation filter is a technique that was initially developed for Additive White Gaussian Noise by Rudin, Osher, and Fatemi for image denoising in 1992. The total variation regularization method is one of the most popular and successful methodologies for image denoising. In this method, the energy model is composed by the types of two terms: one is regularization term and another one is fidelity term. The regularization term plays a critical role in achieving the right amount of noise removal and the fidelity term plays an important role in preserving edges. The total variation is defined as the following variation model:

$$\min_u \left\{ \int_\Omega |\Delta u| d\Omega + \frac{1}{2\lambda} \int_\Omega (u - f)^2 \, d\Omega \right\} \quad (7)$$

where Ω is the image domain, f is the observed image function which is assumed to be corrupted by additive white gaussian noise, and u is the sought solution. The parameter λ is used to control the amount of smoothing in u. In the proposed method, the best value of the regularization parameter (λ) is estimated and optimized by using Particle Swarm Optimization.

PSO is an efficient search and optimization technique [11] based on the movement and intelligence of swarms. It is developed by 1995 by James Kennedy and Russell Eberhart. This algorithm is based on a swarm of particles flying through the search space [12]. The position of each particle represents a potential solution to the optimization problem. In order to apply the PSO parameters such as representation of the initial population, representation of position and velocity strategies, fitness function identification and the limitation should be considered first.

The proposed method is best suited for denoising the MR images. The regularization parameter (λ) is a positive value specifying the fidelity weight which controls the amount of denoising. The parameter, may be tuned the large value of lambda, it removes a number of noises at the same time the image become smoothed. The regularization parameter is not estimated using standard estimators. If the value of the parameter is zero ($\lambda = 0$) the estimated solution is highly affected by noise that is, as same as the input image and if ($\lambda = 1$), the estimated solution is going to be smooth. So the regularization parameter plays a critical role in the denoising process.

3 RESULTS AND DISCUSSIONS

In order to measure the performance of the algorithm, metrics such as PSNR, RMSE and SSIM are to be calculated.

PSNR is formulized as the ratio of peak signal power to average noise power

$$PSNR(db) = 10\log_{10}\left(\frac{D^2 MN}{\sum_{i,j} (x(i,j) - y(i,j))} \right) \quad (8)$$

for $0 \le i \le M-1 and 0 \le j \le N-1$, where D is the maximum peak-to-peak swing of the signal (255 for 8-bit images). Assume that the noise $x(i,j) - y(i,j)$ is uncorrelated with the signal.

RMSE is often used to measure the difference between values predicted by a model or an estimator and the values actually observed. It has a good measure of accuracy [13]. These individual differences are also called residuals.

$$RMSE\left(\hat{\theta}\right) = \sqrt{MSE\left(\hat{\theta}\right)} = \sqrt{E((\hat{\theta} - \theta)^2)} \quad (9)$$

The RMSE of an estimator $\hat{\theta}$ with respect to the estimated value θ is defined as the square root of the mean square error.

Structural Similarity Index Metric is a method for measuring the similarity between two images. It is calculated on various windows of an image. This metric is designed to improve the methods like PSNR and MSE. The measure between two windows x and y of common size $N \times N$ is [14]: MN=size of the original image and filtered image.

$$SSIM(x,y) = \frac{(2\mu_x\mu_y + c_1)(2\sigma_{xy} + c_2)}{(\mu_x^2 + \mu_y^2 + c_1)(\sigma_x^2 + \sigma_y^2 + c_2)} \quad (10)$$

where,

μ_x - the average of x;

μ_y - the average of y;

σ_x^2 - the variance of x;

σ_y^2 - the variance of y;

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σ_{xy} - the covariance of x and y

In order to evaluate the image quality this formula is applied.

Figure 1 shows the resultant images obtained by various denoising methods which reduces the image artifacts and noise in MRI brain images. Table 1 shows the performance metrics obtained from various denoising methods. From table 1 it is observed that the PSNR value for total variation is higher when compared to other methods. Hence, the total variation method would be the best method to reduce the noise and preserving sharp edges. The error rate of RMSE is reduced and SSIM value is higher than other methods. The total variation method must be cautious about the value of the regularization parameter, if the value of the parameter $\lambda = 0$, the estimated solution is highly affected by noise, that is, as same as the input image and if $\lambda = 1$, the estimated solution is going to be smooth. Here, the PSO is used to estimate the regularization parameter value ranges between **0.0136 to 0.0203**, and it also aspires to eliminate the blurring effect by choosing the optimal value for regularization. The proposed method gives the best performance of the method shown in table 1.

4 CONCLUSION

This paper has presented a comparison of various denoising methods by measuring their performance using evaluation metrics. Here, the total variation using PSO is proposed for image denoising. In the proposed system, the total variation method is best suited for denoising the MR brain images and the PSO algorithm is used for computing an optimal value of the regularization parameter. The regularization parameter may be tuned the lambda value, and also used to control the amount of smoothing. From the experimental results, it is inferred that only the proposed method gave the significant improvement not only in noise suppression but also in edge preservation. The proposed PSO method yields higher PSNR values when compared with other methods used in this paper.

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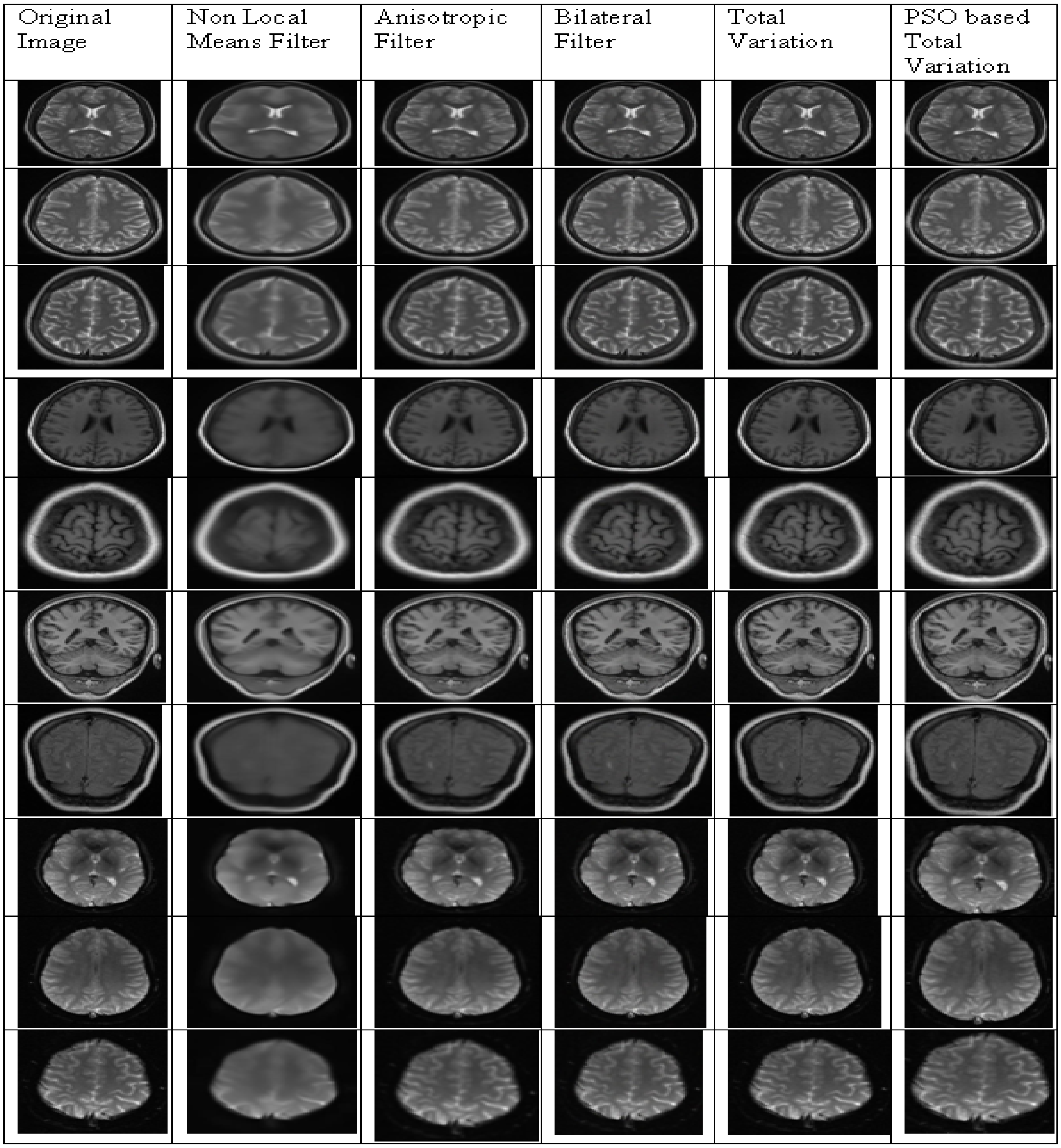

Figure1: Resultant Image of Various Denoising Method

Table1: Performance Measurements for Proposed Method

Methods	**PSNR**	**RMSE**	**SSIM**
Non Local Means Filter	22.75789	9.94876	0.48942
Anisotropic Filter	24.70934	9.9216	0.74072
Bilateral Filter	27.73612	6.78906	0.80826
Total Variation	29.35175	6.38414	0.87724
PSO based Total Variation	**32.0451**	**5.56058**	**0.95278**