MRI DENOISING AND ENHANCEMENT BASED ON OPTIMIZED SINGLE-STAGE PRINCIPLE COMPONENT ANALYSIS

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ABSTRACT

Magnetic resonance (MR) images are normally corrupted by Rician noise which may mask the fine details in the image and decreases its resolution. This makes the feature extraction complicated which results in unreliable data analysis. Therefore denoising methods have been applied to improve the image quality. In this study, we propose an optimized single stage principal component analysis (OSPCA) to balance between noise reduction and information preservation. Principal component analysis highlights the data similarities and differences in a better way, which helps in separating noise and edges. Denoising is performed efficiently when the noise and edges are separated. The performance metrics Mean Square Error (MSE), Structural similarity index (SSIM), and Edge Preservation Index (EPI) shows the ability of the proposed method in denoising and preserving information.

KEYWORDS: *Magnetic resonance imaging, Principal Component Analysis, Denoising, Information preservation.*

I. INTRODUCTION

The quantity of data acquired in Dynamic Contrast Enhancement Magnetic Resonance Imaging (DCE-MRI) is huge. The interpretation of such huge data is a complex task for the radiologist. To obtain high temporal resolution and to cover a three-dimensional volume over time, short acquisition times are used, resulting in low signal-to-noise ratio (SNR). The accurate detection and characterization of small lesions may be crucial [1] because of the poor signal-to-noise ratio. The data is corrupted by hardware -induced noise, geometric distortions, and motion artifacts. So the image data should be improved to get good SNR without loss of information. A good denoising algorithm which attenuates noise and preserve the fine structural details, with minimum artifacts is essential. Conventional low-pass filters with pixel averaging, can improve the SNR, but they decrease the spatial resolution. The traditional approach like anisotropic diffusion [2] reduces image noise by considering a scale space. It is used to suppress the Rician noise. Anisotropic diffusion filter combined with the Wiener filter [3] has been used for MRI denoising which spatially averages pixels according to their correlation structure. This anisotropic diffusion served well for denoising but fine structures are preserved only to a limited extend. The nonlocal means filter (NLM) has been applied for MRI denoising with feature preservation [4,5]. It is based on an estimation of the restored pixel value by weighted averaging within an image over a large portion of the pixels.. To preserve the edges, weights are computed by comparing the patches instead of single point. Wavelets have become an efficient tool in various applications for denoising and data analysis. Wavelet domain denoising of MR images has produced many algorithms [6, 7]. PCA-based scheme was proposed for image denoising by using a moving window to calculate the local statistics, from which the local PCA transformation matrix was estimated [8]. A 3D wavelet transform (3DWT)-based bilateral filtering for Rician noise removal was proposed [9]. The delineating capability of 3D WT was used to represent the noisy coefficients. Bilateral filtering of the approximation coefficients in a modified neighborhood improved the denoising efficiency with edge preservation. Complex denoising of MR images using wavelets was proposed by Zaroubi and Goelman [10]. Wavelet has been used for MRI denoising in combination with Radon transform, which estimates noise variance in different scales [11]. Optimal Multicomponent Nonlocal Means PCA (OMNL-PCA) [12] filter reduce noise in the images by using information of the spatial domain as well as in the inter component domain. Unbiased nonlocal means filter (UNLM) [13] reduces noise on a set of diffusion weighted images It exploits not only the spatial redundancy, but the redundancy in similar gradient directions as well. It takes into account the N closest gradient directions to the direction being processed.

The organization of the paper is as follows. In Section II of this paper, the proposed method for MRI denoising is presented in detail. Section III describes the principal component analysis followed by local pixel grouping in section IV. Section V describes the edge enhancement. The evaluation results by the MSE, SSIM, and EPI are discussed in Section VI followed by the conclusions in Section VII.

II. OPTIMIZED SINGLE-STAGE PRINCIPAL COMPONENT ANALYSIS (OSPCA)

In the proposed OSPCA approach, the noisy MRI breast images are taken as input. The first step of OSPCA is local pixel grouping (LPG). In this, pixels are grouped based on characteristics similarity. A pixel and its nearest neighbors are modeled as a vector variable. The training samples of this variable are chosen by grouping the pixels with similar local structures corresponding to the underlying local window. After grouping the pixels, Principal component analysis transform was used for denoising. Due to shrinkage in the PCA domain, the edges are not well preserved even after the local statistics of the variables are accurately calculated. Hence an edge enhancement algorithm was applied in order to preserve and enhance the edges. Fig. 1 shows the block diagram of the proposed algorithm OSPCA.

III. PRINCIPLE COMPONENT ANALYSIS

PCA is a classical de-correlation technique in statistical signal processing used mainly in pattern recognition and dimensionality reduction [14]. By transforming the original dataset into PCA domain, the noise and trivial information can be removed by preserving the most significant principal components. $Y = [y1\ y2\ y3 \ldots .\ ym]$T an m-component vector variable and denoted by

$$Y = \begin{bmatrix} y11 & y12 \ldots\ldots & y1n \\ ym1 & ym2 \ldots .. & ymn \end{bmatrix} \tag{1}$$

the sample matrix of y, where yij j=1,2,…..,n, are the discrete samples of variable y_i , i=1,2,….,m. The i_{th} row of sample matrix Y, denoted by $Y = [y_i^1\ \ y_i^2\ \ y_i^3 \ldots \ldots .\ y_i^n]$ is called the sample vector of y_i. The mean value of Yi is calculated as

$$\mu = \frac{1}{n}\sum_{j=1}^{n} yi(j) \tag{2}$$

And the sample vector Yi is centralized matrix of Y is

$$\bar{yi} = [\overline{y_i^1}\ \ \overline{y_i^2} \ldots\ldots\ldots\ \overline{y_i^n}] \tag{3}$$

Where $\overline{y_i^1} = y_i^j - \mu i$. Accordingly the centralized matrix of Y is

$$\bar{y} = [\overline{y_1^T}\ \ \overline{y_2^T} \ldots\ldots\ldots\ \overline{y_m^T}] \tag{4}$$

Finally the co-variance matrix of the centralized dataset is calculated as

$$\Omega = \frac{1}{N}\overline{YY} \quad (5)$$

The goal of PCA is to find an orthonormal transformation matrix P to de-correlate $\overline{y}$,. i.e. $=PY$ so that the co-variance matrix of the Z is diagonal. Since the covariance matrix Ω is symmetrical, it can be written as

$$\Omega = \Phi\Lambda\Phi^T \quad (6)$$

Where $\Phi = [\Phi_1\ \Phi_2 \dots \dots \dots \Phi_m]$ is the mXm ortho normal eigenvector matrix and $\Lambda = diag\{y_1\ y_2 \dots \dots \dots y_m\}$ is the diagonal eigen value matrix with $y_1 \geq y_2 \geq \cdots \dots \geq y_m$. The terms $\Phi_1\ \Phi_2 \dots \dots \dots \Phi_m$ and $y_1\ y_2 \dots \dots \dots y_m$ are the eigenvectors and eigen values of Ω.

In PCA, the energy of a signal will concentrate on a small subset of the PCA transformed dataset, while the energy of noise will evenly spread over the whole dataset i.e. it fully de-correlates the original dataset $\overline{y}$, separating signal from noise.

Assuming that the original image I is white additive which is corrupted by the Rician noise v, i.e. $I_v = I + v$, where I_v is the observed noisy image.

An image pixel is described by two quantities, the spatial location and its intensity, while the image local structure is represented as a set of neighboring pixels at different intensity levels. The edge structures convey its, edge preservation semantic information of an image which is highly desired in image denoising. In this paper we model a pixel and its nearest neighbours as a vector variable and perform noise reduction on the vector instead of the single pixel.

To denoise an underlying pixel, KxK window is centered on it and is denoted by y =[y1 ….ym]**T** , m=K2,the vector containing all the components within the window. The observed image is corrupted by noise.

IV. LOCAL PIXEL GROUPING (LPG)

LPG procedure is applied in order to group the pixels with similar characteristics for the purpose of denoising. For grouping purpose L x L training window is taken. and a K x K variable moving window is taken which moves over the training window . Among the techniques for local pixel grouping we selected block matching because it is simple and more suitable. In $\mathbf{I_v}$ which is the corrupted image there are $(L-K+1)^2$ possible training blocks within L x L training window.

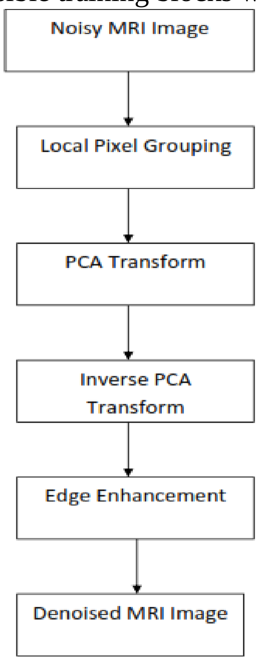


Figure 1. Proposed Methodology OSPCA

V. Edge Enhancement Algorithm

Fig.2 shows the block diagram of the edge enhancement algorithm. The edge information has to be enhanced while the noisy pixels are to be attenuated. To accomplish this we adopt two gain parameters namely G1 and G2. The first gain parameter is used to enhance the edge information while the other gain parameter is used to attenuate the noise. These gain parameters are applied based on selecting an arbitrary pixel value such that, the pixel values below the arbitrary pixel selected are assumed to be the edge pixels and the pixels above the arbitrary pixel value are noisy pixels. The arbitrary pixel in this context is selected by taking minimum and maximum pixel value in the high-pass filtered image and taking the average of both.

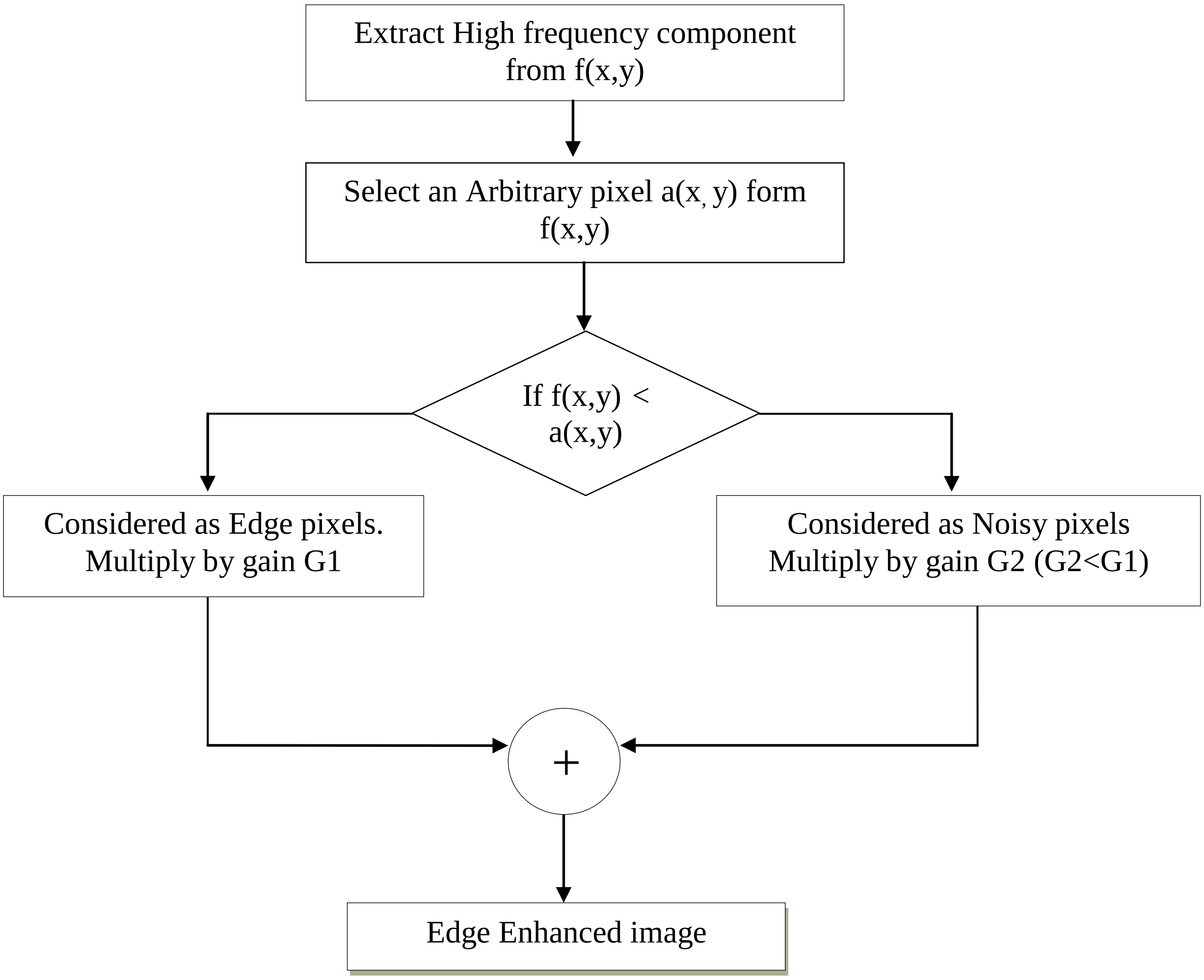


Figure 2. Edge Enhancement Algorithm

VI. Experimental Results and Discussion

In this section the performance of the proposed approach is evaluated on DCE MRI breast images downloaded from the National Cancer Institute USA(www. Cancer imaging archive.net). The dataset consists of T_1 weighted and T_2 weighted images. For our experimental purpose we used only T_2 weighted images. The Rician noise of 3% was added to the image. The algorithm OSPCA was implemented in MATLAB-7 and applied to the noisy image. The efficiency of the proposed denoising method OSPCA was compared quantitatively and qualitatively with the existing techniques, like Optimal Multicomponent Nonlocal Means PCA (OMNL-PCA) and unbiased nonlocal means filter (UNLM). For quantitative assessment the mean squared error (MSE) [15], Structural Similarity index

(SSIM) [16], and Edge Preservation Index (EPI) [17] were calculated. Table.1 and Fig.3 shows the results. The results reveal that, our approach is performing better in preserving edges and removing noise.

6.1 Mean Square Error (MSE)

MSE quantifies the deviation of estimated values from the true value.

$$MSE = \frac{1}{mn}\sum_{i=0}^{m-1}\sum_{j=0}^{n-1}\| I(i,j) - K(i,j)\|^2 \tag{7}$$

6.2. Structural Similarity Index Measure (SSIM)

The Structural Similarity Index Measure (SSIM) is used to measure the similarity between two images. The SSIM index is a measurement of image quality based on an initial uncompressed or distortion-free image as reference. SSIM is designed to improve on traditional methods like peak signal-to-noise ratio (PSNR) and mean squared error (MSE), which have proved to be inconsistent with human eye perception. The greater value of SSIM denotes the better image quality.

$$\mathrm{SSIM}(x,y) = \frac{(2\mu_y\mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_2)} \tag{8}$$

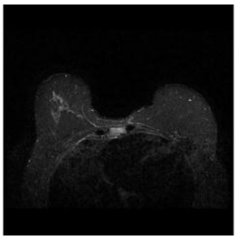
μ_x :- The average of x.
μ_y :- The average of x.
σ_x^2 and σ_y^2 :- variance of x and y.
σ_{xy} :- The covariance of x and y .
C_1 and C_2 :- Two variables to stabilize the division with weak denominator.

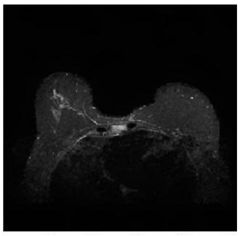
6.3. Edge Preservation Index (EPI)

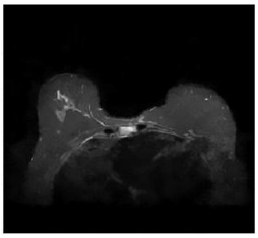
The edge preservation index is defined as follows:

$$\mathrm{EPI} = \frac{\sum(|I_p(i,j) - I_p(i+1,j)| + |I_p(i,j) - I_p(i,j+1)|)}{\sum(|I_o(i,j) - I_o(i+1,j)| + |I_o(i,j) - I_o(i,j+1)|)} \tag{8}$$

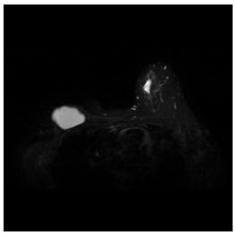
Where I_o (i, j) is an original image pixel intensity value for the pixel location (x, y), I_p (i, j) is the processed image pixel intensity value for the pixel location (x, y). The greater value of EPI gives a much better indication of image quality.


Original image


OMNLM_PCA


UNLMS Filter


Proposed Method OSPCA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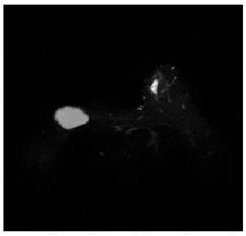
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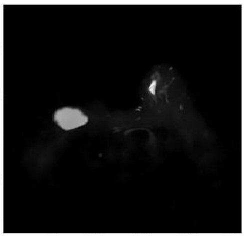
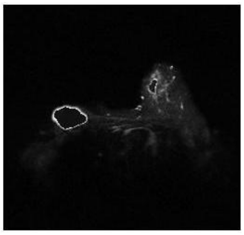
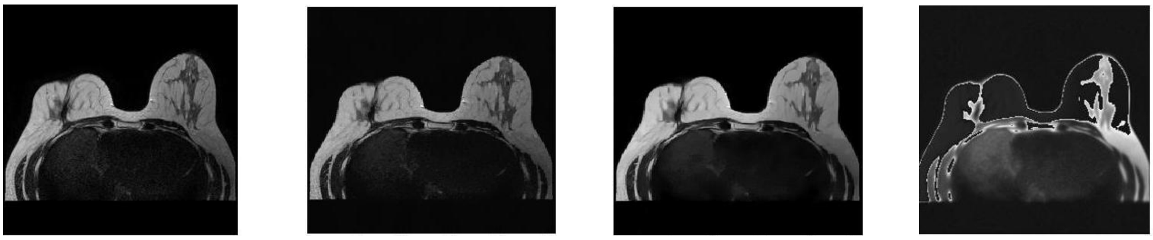

UNLMS Filter


Proposed Method OSPCA



Original image OMNLM_PCA UNLMS Filter Proposed Method OSPCA

Figure. 1. The denoising results of 3 MRI images by different Techniques

Table 1. MSE, SSIM, and EPI results of the denoised images for noise level of 3%

IMAGES	METRICS	OMNLM_PCA	UNLMS	PROPOSED METHOD-OSPCA
MRI Breast Image 1	MSE	63.61	27.17	2.8453
	SSIM	0.6904	0.6985	0.908
	EPI	0.7801	0.7467	0.9213
MRI Breast Image 2	MSE	67.38	80.91	2.2556
	SSIM	0.2872	0.5971	0.2891
	EPI	0.6392	0.6978	0.9032
MRI Breast Image 3	MSE	26.55	7.9326	2.9319
	SSIM	0.5778	0.9292	0.5471
	EPI	0.7215	0.6819	0.9162

V. CONCLUSIONS

In this paper, we have presented a method to improve the signal to noise ratio in MRI breast images.The proposed method Optimized Single-Stage Principal component analysis (OSPCA) presents a spatially adaptive image denoising method. This method is using single stage principal component analysis, which can protect the image from over blurring. While denoising, the local image structures have to be preserved. So blocks with similar pixels are gathered using local pixel grouping (LPG). Then the image is transformed in PCA domain. Shrinking technique is applied on the PCA transformed coefficients to preserve the image fine structures while smoothing noise. The quantitative performance metrics MSE, SSIM and EPI values are showing better performance when compared with the existing methods OMNLM_PCA and UNLM. The proposed method can improve the accuracy of breast cancer diagnosis and detection, especially in the case of subtle tumor.

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