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De-noising of Dynamic Contrast Enhanced MR Images

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ABSTRACT: *This paper explores de-noising based on Adaptive nonlocal means filter for Dynamic Contrast Enhanced MR Images. This algorithm utilizes singular value decomposition and K-means clustering for the efficient block classification of noisy image. Then a local window is adjusted adaptively for matching with the local property of a block and a rotated matching algorithm that aligns with the dominant orientation is used for similarity matching. Empirical evaluation on the performance of the proposed filter relative to other de-noising methods-simple Gaussian filtering, bilateral filtering, anisotropic filtering, non-local means filter and dynamic non-local means filter are also presented. The results of quantitative evaluation based on signal to noise ratio (SNR) and peak signal to noise ratio (PSNR) is made with the proposed algorithm and the other conventional filtering methods.*

Keywords: *De-noising, dynamic contrast-enhanced (DCE) magnetic resonance imaging, nonlocal means, and adaptive non local means.*

I. INTRODUCTION

Conventional Contrast Enhanced MR Imaging shows a single snapshot of the tumor growth after the administration of contrast agent, even though it provides anatomical information but it lacks functional information. Dynamic Contrast Enhanced MR Image relies on taking fast sequences of images before, during and after the administration of contrast agent. Normally gadolinium (Gd) DTPA is used as the contrast agent. It is commonly used to enhance the contrast between the normal and the pathologic tissue. The images obtained before the contrast agent administration is called pre-contrast image, and after is called post –contrast image. The cancerous tissue will be supported by many blood vessels, and the contrast agent gets diffused in the vascular medium. If the tissue analyzed is pathologic, the post-contrast image shows an enhancement. The pharmacokinetics is used for the detection and characterization of tumors. During DCE MRI the tumors demonstrate rapid, intense enhancement followed by a relatively rapid washout compared to normal tissue. DCE MRI is analogous to a movie and has already emerged as a valuable biomarker in both research and clinical studies. DCE MRI has many clinical applications. It is used for the initial diagnosis and staging of tumors. It is also used as a biomarker for monitoring the response to conventional chemotherapy for various types of cancer such as breast, prostrate, colon and gynecologic malignancies.

The analysis and interpretation of DCE MRI by the clinician is very difficult. The complexity of the task is due to the acquisition of large amount of data and the task is further get complicated by the addition of noise. The different noises in MRI are hardware induced noise, physical distortions, intensity non-uniformities and due to patient movement during the image acquisition time. For the faithful detection and characterization if tumor, the image data should have high signal to noise ratio. A fair de-noising algorithm should attenuates the noise present in the image, while maintaining the enhancement pattern and also the de-noising should not lead to the introduction of other artifacts.

Nonlocal means filtering exploits the spatial correlation in the entire image for the removal of noise. In this filter the image pixels are replaced by the weighted average of the other pixels whose neighborhood has similar geometrical configurations. As the image pixels are strongly correlated and the noise is independently and identically distributed, averaging these pixels results in the cancellation of noise and yield a pixel whose value is similar to the original value.

In this paper, Adaptive non local means filter based de-noising is presented. Here the matching and the filter parameters are improved depending on the local structure of the pixel. The filtering method is compared with other de-noising methods such as Gaussian filter, bilateral filtering, anisotropic diffusion filtering, nonlocal means and dynamic nonlocal means filtering.

The results of the proposed filter is compared with the results of other conventional filters on the basis of signal to noise ratio and peak signal to noise ratio.

II. DE-NOISING OF MR IMAGES

The presence of noise in the MR image may affect the performance of different post processing techniques applied to MR data such as segmentation, registration, classification etc. Noise in MR data follows Rician distribution. Unlike Gaussian distribution, Rician distribution is signal dependent and is very difficult to remove without losing the diagnostically important details. For low SNR, the Rician distribution can be approximated to Rayleigh distribution and for high SNR, the Rician distribution can be approximated to Gaussian distribution. This can be accomplished only if, $\frac{A}{\sigma}>3$, where a is the mean signal strength and the mean signal strength and σ is the standard deviation of the noise.

An effective de-noising method should remove the noise without using the diagnostically important details needed for the clinician. This can be accomplished by either increasing the image resolution without increasing the effect of noise or having a better signal to noise ratio for a given image resolution.

Various de-noising techniques are proposed including the anisotropic diffusion filtering, nonlocal means, dynamic nonlocal means. Several of them are described below including the simple Gaussian low pass filter and bilateral filter.

1) Simple Gaussian Filter

It is one of the simplest methods used for image de-noising. It is a smoothing filter, which performs de-noising at the expense of blurring the fine details and sharp edges. Since the fine details of MRI are very much important in case of clinical applications, the Gaussian filter is seldom used for MRI de-noising. The amount of filtering is directly proportional to the standard deviation of Gaussian kernel.

2) Bilateral Filter

It is a non-linear filter, which has wide applications in image processing. As the name suggests, it is a combination of two filters, one is a function of spatial distance and other is a function of intensity difference. In discrete case, the bilateral filter can be defined as follows. Given an image, f, the filtered value of the image at the position x is defined by

$$h(x)=\frac{\sum_{\varepsilon} f(\varepsilon).\, c(\varepsilon,x).\, S(f(\varepsilon),f(x))}{\sum_{\varepsilon} c(\varepsilon,x).\, S(f(\varepsilon),f(x))}$$

where c(ε,x) measures the distance between the neighborhood center, x, and the nearby pixel, ε,; and S(f(ε),f(x)) measures the intensity similarity between the neighborhood center, x, and a nearby pixel, ε.
An important case of the bilateral filter is when both similarity measures are Gaussians. In this case, c(ε,x) is defined

$$c(\varepsilon,x)=e^{\frac{1}{2(\|\varepsilon-x\|/\sigma_d)^2}}$$

And S(f(ε),f(x)) as

$$S(f(\varepsilon),f(x))=e^{\frac{1}{2(\|f(\varepsilon)-f(x)\|/\sigma_r)^2}}$$

where σ_d the spatial is spread and σ_r is the photometric spread.

The bilateral filter performs better than a linear filter such as Gaussian filter and preserves the fine details and sharp edges of the image and removes significant amount of noise and can be used for de-noising MRI data.

3) Anisotropic Diffusion Filter

This type of filtering diffuses the higher pixel intensities to lower pixel intensities based on a threshold. In short, it is a process of balancing concentration changes. Here, the image intensity is viewed as concentration and noise as concentration inhomogeneties. These inhomogeneties are smoothened by diffusion. Thus the image area get blurred where the gradient magnitude is small but diffuses little over the areas where the gradient is large

4) Nonlocal Means

The nonlocal means use the redundancy of information in an image. This redundancy is usually seen in natural images because they usually contain textured and smooth regions. The discrete version of the algorithm can be described as follows. Let I be the discrete grid of pixels (voxels), and v= {v(i) |i ϵ I} be a noisy image. The estimated de-noised value is computed as the weighted average of the image pixels

$$NL(v)(i)=\sum_{j\epsilon I} w(i,j)v(j)$$

Where the weight values {w(i,j)} depend on the similarity between the pixel i and j and satisfy the conditions 0≤w(i,j)≤1 and $\sum_j w(i,j)=1$.

The definition of the weights {w(i,j)} relies on the definition of a neighborhood system on I and of a distance measure between two neighborhoods or similarity windows. A neighborhood system on I is a family N= $\{N_i\}_{i\in i}$ of subsets of I such that for all i ϵ I

i) i ϵ N_i

ii) j ϵ N_j

The subset N_i is called the neighborhood or the similarity window of i_i. Let the restriction of v to the neighborhood N_i be denoted by v(N_i) , where

$$v(N_i)=\{v(j)\vee j\in N_i\}$$

The Gaussian weighted Euclidian distance between two similarity-windows is defined

$$S(V_1,V_2)=\|V_1-V_2\|_{2,a}^2$$

where a is the standard deviation of the Gaussian and V_1 and V_2 represents two similarity windows. The weights associated with this distance are defined by

$$w(i,j)=\frac{1}{Z(i)}e^{\frac{-S(v(N_i),v(N_j))}{h^2}}$$

Where Z(i) = $\sum_j e^{-s(v(N_i),v(N_j))/h^2}$ is the normalization factor and the parameter h controls the decay of the weights and is usually related to the level of noise in the image. Hence, a natural choice for h'' will be of the form h=c. σ where c is a scalar and σ is the level of noise in the image.

The main disadvantage of the algorithm is it's time complexity. The time complexity is O(N.w.s) for an image, where N is the number of pixels in the image, w is the number of pixels in the similarity window and s is the number of comparisons for each similarity window. For DCE MRI, the time complexity is squared relative to 2-D, which often results in non-practical running times.

5) Dynamic Nonlocal Means

In nonlocal means, because of the nonlocal property of the algorithm, it can eliminate the small different parts of similar tissues on the basis of textural similarity; hence it may lead to the elimination of diagnostically important details. This can be overcome by the dynamic nonlocal means algorithm. The drawback is overcome by the modification of similarity metric, which takes into account the local enhancement. Thus the similarity metric becomes

$$\acute{s}(V_1,V_2)=s(V_1,C(V_1,V_2).V_2)$$

$$=\|V_1-C(V_1,V_2).V_2\|_{2,a}^2$$

And the definition of weights be

$$\acute{w}(i,j) = \frac{C(v(N_i)v(N_j))}{Z(i)} e^{\frac{-\acute{S}(v(N_i),v(N_j))}{h^2}}$$

Where

C($$C(V_1,V_2) = \begin{cases} \frac{E(V_1)}{E(V_2)}, t_1 \neq t_2 \wedge \left|E(V_1 - V_2)\right| > \sigma \\ 1, OW \end{cases}$$

Where t_1 and t_2 are the temporal components from which the vectors V_1 and V_2 were selected, σ is the estimated level of noise in the image and $E(V)$ denotes expected value.

The dynamic nonlocal means algorithm filters the image in the spatial domain while exploiting the similarity over the temporal axis without changing the effect of contrast enhancement or blurring in the event of patient movement. Another advantage of DNLM is, the execution time is faster than NLM.

III. ADAPTIVE NONOLOCAL MEANS (ANL-MEANS)

The proposed Adaptive Nonlocal means has three distinct features:

1) It uses Singular Value Decomposition (SVD) and K-means clustering for efficient block classification of the noisy image.
2) Adjust the local window adaptively to match with the local property of the bock.
3) Rotated matching algorithm is applied for better similarity matching.

A.Block Classification

Adaptation of the block is accomplished from the results of block classification. Singular Value Decomposition (SVD) is employed for the block classification and is achieved by the application of SVD to the gradient field in each block. In an image, if the region is smooth then there is no dominant direction and the computed singular values will be small. If the region is edge or texture region, then there is a dominant direction and the computed singular values are larger than the others.

This can be specifically expressed in the mathematical form as follows. For a block of size $n \times n = N$, we can group the gradient values into a matrix G of size $N \times 2$ .And it's SVD can be computed through

$$G = \left[\nabla f(1)^T \quad \nabla f(2)^T \cdots \quad \nabla f(N)^T\right]^T \quad \text{and} \quad G = USV^T$$

(1)

Where

$$\nabla f(i) = \left[\frac{\partial f(i)}{\partial x} \quad \frac{\partial f(i)}{\partial y}\right]^T$$

(2)

is the gradient of image 'f' at a point 'i', U is an N-by-n orthogonal matrix, S is a matrix of size N-by-2 which contains the singular values and V is a 2-by-2 matrix showing the dominant orientation of the gradient field. Block classification is done based on the magnitude of singular values in the dominant direction, with the assumption that the noise does not have any preferred direction assumption that the noise does not have any preferred direction. For performing adaptive classification, we use K-means clustering technique. Let S(i) be the singular value in the dominant direction of the block centred at a pixel 'i'. The K-means algorithm partition into k clusters, $C = \{C_1, C_2, ..C_k\}$ whilst minimising cluster sum of squares as

$$arg_C\, min \sum_{k=1}^{K} \sum_{s(i \in C_k)} \left|S(i) - \mu_k\right|^2 \quad (3)$$

Where μ_k is the median of C_k .

B. Adaptive Window Adjustment and Rotated Matching

To reduce the noise and to exploit the block property, we adaptively choose a matching window size based on the block classification result. For smooth region, as there is no random change, a larger matching window is adopted. For edge or texture region, we employ a small matching window. In practical implementations, we use a window size of 7×7 for edges and texture region, 19×19 for smooth regions and 13×13 for other regions.

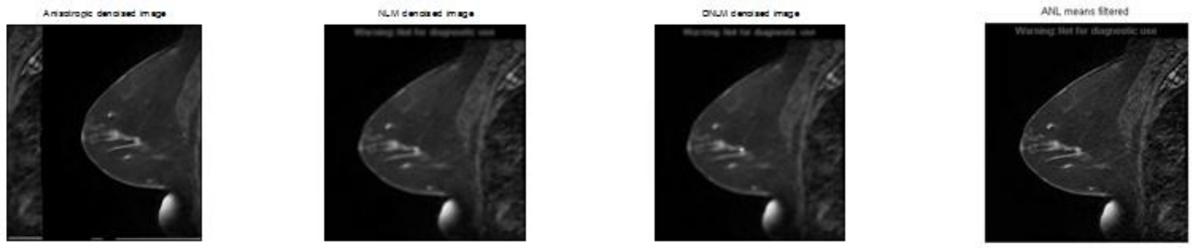
Here, we employ a rotated matching algorithm to include more similar blocks. In conventional Nonlocal means, the only parameter used is the Gaussian weighted Euclidean distance for the similarity block recognition. And here, the distant similar blocks will not be considered as they have large distance value. In effect, it will not use the self similarity in the edges and contours.

ANL means effectively identifies block with shifted orientation as close match. The candidate block can be rotated in different orientations till we get a lowest similarity distance. Here, we consider only the set of rotated blocks that have their dominant direction aligned with that of the target block. This is done to speed up the matching process. The dominant orientation of the gradient field of a given block can calculated as

$$\theta = \arctan\left(\frac{v_1}{v_2}\right)$$

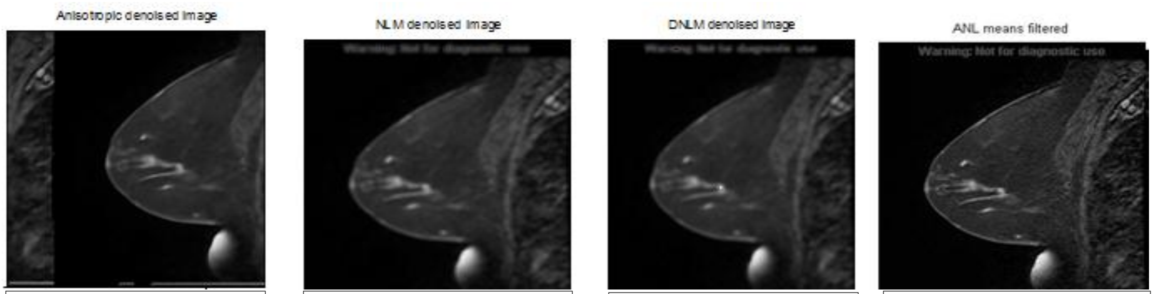
where v_1 and v_2 are the first column members of V in Eq. (1).

As the gradient doesn't have any direction, we create rotated blocks with dominant orientations equal to θ, $\theta + 180$, $-\theta$ and $-\theta + 180$ degrees in order for the alignment of dominant orientation to that of the original block.



IV. EXPERIMENTS AND RESULTS

In this, the performance evaluation of the proposed de-noising algorithm is done by comparing it with other conventional de-noising algorithms:1)Gaussian Filter(GF), 2)Bilateral Filter(BF), 3)Anisotropic Diffusion Filter(ADF), 4)Nonlocal Means Filter(NL-means) and Dynamic Nonlocal means Filter(DNLM). The results of different algorithms are shown in Fig. for visual comparison. The performance is measured in terms of Signal to Noise Ratio(SNR) and Peak Signal to Noise Ratio(PSNR). Based on the SNR and PSNR value, the proposed filter outperforms the other conventional filters.



(d) Anisotropic filtered Image | (e)NLM means Filtered Image | (f)DNLM means Filltered Image | (g) ANL means Filtered Image

Fig.1. Original noisy image and the results of different de-noising algorithms.(a) Original noisy image (b) Gaussian filtered image (c) Bilateral filtered image (d) Anisotropic filtered image (e) NLM filtered image (f) DNLM filtered image (g) ANL means filtered image.

Table 1.: The SNR and PSNR of different Conventional Filtering Methods

TYPE OF FILTER	SNR	PSNR
GAUSSIAN	60.570	77.070
BILATERAL	58.682	75.182
ANISOTROPIC	48.734	65.223
NONLOCAL MEANS	48.198	16.567
DYNAMIC NONLOCAL MEANS	60.579	77.079
ADAPTIVE NONLOCAL MEANS	80.603	97.103

V. CONCLUSION

The proposed Adaptive Nonlocal means was proven to be more effective in the case of images affected by AWGN noises. The algorithm uses Singular Value Decomposition (SVD) and K-means clustering for block classification of the noisy image. The block classified results are further utilized for adjusting the similarity measure window size adaptively. The filtered image will be a blessing for the clinicians and can be further used for other post processes such as segmentation, classification etc. for the detection of cancer.

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