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REVIEW OF NOISE REDUCING ALGORITHMS FOR BRAIN MRI IMAGES

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Abstract- The noise degrades performance of image processing algorithms in brain imaging. Image denoising methods are important image processing algorithms which are used to reduce the noise. Brain image denoising is one of the most important parts of clinical diagnostic tools. Brain images mostly contain noise, inhomogeneity and sometimes deviation. Therefore, accurate process of brain images is a very difficult task. However, accurate process of these images is very important and crucial for a correct diagnosis by clinical tools. A review of image denoising methods for brain MRI images is presented. The review covers methods for noise reduction and their comparative evaluations based on reported results.

Keywords: Noise Reducing, Brain, MRI, Image Processing.

I. INTRODUCTION

State-of-art de-noising methods try to fully remove noise from MRI images and preserve the quality of them. There are different de-noising filters [1]: standard and more advanced filters, and general and specific MRI de-noising ones. Each of these methods has advantages and disadvantages. None of them overcome others in respect to boundary preserving, quality of de-noised image, computation cost and noise removing. As a result, noise removing methods can be improved and still is an open research area. Noise is one of obstacle for automatic image processing applications such as image segmentation [2-5].

Linear filters such as Gaussian and wiener filters update value of a pixel by averaging (weighted) of its neighborhood. They reduce noise and are conceptually simple. They have two disadvantages: They degrade image details and the edges of the image. Therefore, de-noised image would be blurred. Instead of linear filters, nonlinear ones preserve edge to more extend. However, degrading fine structure and reducing the resolution of the image are disadvantage of these filters.

Anisotropic nonlinear diffusion [6-9] is a powerful non-linear method. It reduces noise in flat regions to more extend and in mean time preserve edge by reducing the diffusivity at the edges of image. In other words, it reduces the noise and in the mean time preserves the edges of the image. As a result, it is commonly used in MRI de-noising. The disadvantage of this method is adjusting different parameters such as number of iteration. Markov Random Field method (MRF) [10-12] uses spatial correlation information to have more robust result against noise and in mean time preserve fine structure to more extend. In other words, MRF use spatial regularization of the noise estimation to reduce signal smoothing. MRF use iterated conditional modes and simulated annealing to update the value of pixel with maximizing a posterior. Usually, it is computationally expensive.

Wavelet-based methods [13-15] perform in frequency domain. These methods try to separate signal from noise and not to degrade the signal in the de-noising process. On MRI image, these method biases the wavelet and scaling coefficients. To overcome this disadvantage, squared MRI image which is non-central chi-square distributed is used as input for wavelet [16]. With this variation, the scaling coefficients become independent on signal and can be eliminated easily [17]. The disadvantage of these methods is degrading fine details, especially in high noisy images [18].

Analytical correction method used input image to estimate noise and immediately after noise-free image. To estimate noise, this method use Maximum Likelihood Estimation (MLE) [19, 20]. The magnitude data points of input image and estimated noise are used to estimate noise free image. MLE can be adopted to consider different hypothesis for noise. The disadvantage of these methods is assuming constant signal in small area which is not always true. These methods do not preserve edge and degrade fine structures.

In order to preserves the edges of image, non-Local (NL) is proposed by Buades et al. [21-23] which attempts to takes advantage of the redundancy in image. This method assumes that there is redundancy information (pixels with similar neighbourhood) in image. The value of the pixel is updated to the weighted average of other samples with neighbourhood similar to that of the pixel. This method gives very good result in images with high redundancy. For example, in the image with textured or periodic case due to large redundancy, this method reduces noise and preserves edges to best extend [23]. Sometimes noise, complicated structures, blur in acquisition and the partial volume effect cause MRI images to have non-repeated details. This method may eliminate these details. In addition, it is computationally expensive.

In [24], a novel scale-based filtering method is presented which utilizes scale-dependent diffusion conductance. Unlike reported scale-based filtering methods, the proposed method employs a concept called generalized scale, which imposes no shape, size, or anisotropic constraints to obtain object scale information. The object scale information is used to adaptively perform smoothing in the interior of homogeneous regions more than smoothing in regions with fine details. In [25], the Optimized Block wise NL-means filter is proposed to overcome computation time problem of NL-means in 3D images. This approach divides the image volume into blocks with overlapping supports and applies NL-means on these blocks. This approach restores the voxels values based on the restored values of the blocks they belong to. This approach decreases the computational time while preserving the performances of the NL-means filter. In [26], the best values for the parameters of Non-Local Means (NLM) algorithm are estimated. NLM is parametric filter and highly dependent on the setting of its parameters. The authors performed an exhaustive search to find the optimal parameter for NLM in context of MR image de-noising. This paper estimates the optimum parameters for different noise levels.

In [27], a new noise estimation method based on the adaptation of the Median Absolute Deviation (MAD) estimator in the wavelet domain for Rician noise is proposed. Also the impact of noise estimation accuracy on de-noising performance of the 3D Non-Local-Means filter (NLM) is studied. In [28], three different sequential Wiener filters are presented: isotropic is a sequential filter which similar to the classical Wiener filter uses an isotropic neighborhood to estimate its parameters, orientation which uses oriented neighborhoods to estimate the structure orientation present at each voxel and anisotropic which selects locally either isotropic or oriented neighborhoods adaptively. Section II explains two popular noise reducing methods in details. Section III represents comparative study of state-of-arts works in noise reducing area. Table 1 lists the state-of-art denoising algorithms.

II. TWO POPULAR NOISE REDUCING METHODS

A. Anisotropic Filter

Perno and Maik [6] proposed anisotropic diffusion process. The equation is as the follows:

$$I_t(x,y,t) = \mathrm{div}(C(x,y,t)\nabla I) = C(x,y,t)\Delta I + \nabla c.\nabla I \quad (1)$$

where div is divergence operator, $I_t(x,y,t)$ is intensity of input image, t is the iteration number, ∇, Δ are the gradient and Laplacian operators and $C(x,y,t)\nabla I$ is a monotonically decreasing diffusion function of the image gradient magnitude. The gradient magnitude in boundary of region is higher than interior, and diffusion function is monotonically decreasing. Therefore, the diffusion process happens in regions' interior faster and the boundaries of regions would remain sharp. Different diffusion functions are proposed [29]. Zhigeng et al. [30] used the following gauss function as diffusion function:

Table 1. Advantages and disadvantages of noise reduction methods

De-noising method	Advantages	Disadvantages
Linear filters such as Gaussian and wiener filters [6]	Conceptually simple	They degrade image details and the edges of the image. Therefore, de-noised image would be blurred.
Markov Random Field (MRF)-based methods [10, 11]	More robust against noise and preserve fine structure to some extend	It is computationally expensive.
Anisotropic nonlinear diffusion [6]	It reduces noise in flat regions and preserves edges to a higher extend	Adjusting different parameters, such as the number of iterations, is a difficult job. It degrades the fine structure, reducing the resolution of the image
Wavelet-based methods [14]	These methods try to separate signal from noise and not to degrade the signal during the de-noising process.	The wavelet coefficients might be biased. These methods degrade fine details, especially in highly noisy images
Analytical correction methods [20]	These methods use Maximum Likelihood Estimation (MLE), which can be adopted to consider different hypothesis for noise.	These methods assume a constant signal in a small area, which is not always true. Also, these methods do not preserve edges and degrade fine structures.
Non-local Means (NL-Means) method [22]	This method has very good results in images with high redundancy.	This method may eliminate non-repeated details. In addition, it is computationally expensive.

$$C(\nabla I) = e^{|\nabla I|^2/2K^2} \quad (2)$$

where parameter K is the average gradient magnitude in the neighbor of each pixel and specify degree of diffusion. Cattle et al. [31] used $\nabla|G\sigma.u|$ as input for diffusion function which uses smoothed image using Gaussian filter. Also following equation is proposed [28]:

$$C(s) = 1/(1+K) \quad (3)$$

where parameter K is the average of difference of gradient magnitude and maximum gradient magnitude in the neighbor of each pixel.

B. NL-Means Method

In an image I, a neighborhood η_i of pixel i could be defined as an $m\times m$ window around pixel i and the values of pixels in η_i is denoted by $v(\eta_i)$, a vector of intensities. Furthermore, the pixel j, such that η_j is similar to η_i, is a non local neighbor of pixel i. Moreover, similarity of η_i and η_j is defined by similarity of $v(\eta_i)$ and $v(\eta_j)$, which is measured by

Euclidean distance. NL-means obtains s_j, the signal value in the pixel *i*, by averaging the value of pixels in non-local neighborhood of *i*.

$$s_i = \sum_{j \in I} w_{ij} I_j \tag{4}$$

where *w* presents the weight of each non-local neighbor in averaging and is defined as follow:

$$w_{ij} = \frac{1}{Z_i} \mathrm{e}^{-\frac{\|v(\eta_i)-v(\eta_j)}{h^2}} \tag{5}$$

where Z_i is an normalizing factor and defined as follow:

$$Z_{ij} = \sum_j \mathrm{e}^{-\frac{\|v(\eta_i)-v(\eta_j)}{h^2}} \tag{6}$$

where the parameter *h* controls the decay of exponential function. In other words, noise-free value of pixel *i* is computed by weighted average of all the pixels in image, but pixels with similar non-local neighborhood have larger weights in the average. Also, due to decay factor, the pixels with large distance have weights near zero.

III. COMPARATIVE STUDY

The reported results for noise reducing algorithms are presented. In order to investigate their effectiveness, the quantitative and qualitative results of the algorithms are presented.

A. Simulated Images

In [32], Gaussian mixtures [33] with and without MRF is applied on phantom based image from Brainweb. Average Dice similarity index for different algorithms with variant noise levels (3%, 5%, 7%, 9%) are Gaussian mixtures (0.927 0.918 0.853 0.832) and Gaussian mixtures+MRF (0.956, 0.949, 0.936 and 0.929). In the presence of all noise levels, incorporating MRF improves segmentation results. The similarity index of the Gaussian mixtures+MRF decreases more slowly than Gaussian mixtures algorithm when noise level decreases. In [25], the proposed Optimized Blockwise NL-means filter is applied on phantom based image from Brainweb with variant Gaussian levels.

The proposed filter is compared with three noise recuing algorithms: standard NL-means filter [34], AD filter [6] and TV minimization [35]. The best values for the parameters of AD filter and TV minimization scheme are estimated by exhaustive search. The Peak Signal to Noise Ratio (PSNR) was used to qualitatively evaluate the new de-noising algorithm. At studied noise levels, the best PSNR values are for proposed algorithm. Also, the histograms of the de-noised images and the ground truth are compared.

The produced histogram obtained by proposed algorithm is most similar one to histogram of ground truth and has most sharp peaks (highest contrast). The distances between the histograms of the de-noised images and the ground truth are also compared. The distance obtained by proposed algorithm is the least one. Also, de-noised image and removed noised produced by competing methods are compared visually.

The proposed algorithm produces the most homogenous white matter. NL-means-based algorithms remove the high frequencies related to noise while preserve the high frequency information of anatomical structures more than other competing methods. The AD filter spoils the edges especially on the skull. The TV minimization algorithm preserves the edges slightly better but fails to remove all the noise.

The same experiments are performed with Rician noise. Again, the proposed algorithm outperforms the classical ones. The NL-means-based algorithms de-noise corrupted image and emphasizes the three main peaks corresponding to three main tissues in histogram better than other competing algorithms. In compare to previous experiments with Gaussian noise, the denoising of background is worse in the Rician case, but the NL-means filter de-noises correctly the cerebral structures, especially the white matter. The filters perform almost similar to Gaussian case but since for the same level, Rician noise is more pronounce than Gaussian case, the PNSR values slightly decrease.

In [26], the best values for the parameters of Non-Local Means (NLM) algorithm are estimated. The NLM algorithm has three parameters: R_{search} (the radius of search window), R_{sim} (the radius of the neighborhood window which is used to calculate the similarity between each two pixels), *h* (which controls the degree of smoothing). In this experiments, a 11 _ 11 search window (R_{search} = 5) is used as a reasonable size for medical images and 3 phantom based MR images (T_1, *PD* and T_2) from the Brainweb were used to perform experiment. The Root Mean Squared Error (RMSE) was used to qualitatively evaluate NLM algorithm. In presence of variant noise levels (1%, 3%, 5%, 7% and 9%), for each R_{sim} value, RMSE is used to perform an exhaustive search for the optimum h value.

When R_{sim} increases, the RMSE decreases but computation cost increases. R_{sim} = 2 is proposed because further increasing R_{sim} do not improve RMSE noticeable but increase computation time notably. The optimum *h* value has linear relation with noise level. Based on the results, the authors proposed general value of 1.2*r* for *h* with R_{sim} = 2 and R_{search} = 5. The NLM with the proposed parameters are applied on different MR image. In the residuals (difference between de-noised and original image), almost no anatomical information can be noticed. Also, the Rician noise almost is removed. The performance of NLM with optimal estimated parameters is compared qualitatively and quantitatively with two de-noising algorithms, the ADF (parameters manually tuned to get the best possible results) [6] and a wavelet-based de-noising algorithm (the parameters proposed by the authors) [36]. In almost all the cases, the NLM with proposed parameters values produces lower RMSE.

In [24], a novel b-scale-based filtering method is presented which utilizes scale-dependent diffusion conductance. The proposed b-scale-based diffusion (bD) is compared with nonlinear complex diffusion (NCD) [37] , and g-scale-based diffusion (gD) [38] qualitatively and quantitatively.

Several brain MRI data sets including phantom based images from Brainweb are used for qualitative evaluation. The three methods smooth well the interior of homogeneous regions. The bD and gD methods perform better than NCD in preserving fine details and the edges, independent of the body region, the imaging modality and protocol. Most diffusion based methods smooth across edges as side effect. The gD method diffuses well along edges and minimizes diffusion across them even better than bD.

A single g-scale region along a boundary is likely to consist of a run of the boundary voxels due to unrestricted shape of g-scale regions, whereas, every boundary voxel is likely to be in a different b-scale region due to small size of b-scale regions. Therefore, gD achieves diffusion along the boundary more than bD method. 45 MRI phantom based image volumes from Brainweb with three levels of noise (3%, 7%, and 9%), three protocols (PD, T_1, and T_2), and five slice thicknesses (1 mm, 3 mm, 5 mm, 7 mm, and 9 mm) are used for quantitative comparison of the methods. Also, the relative contrast of the object regions (RC), residual noise (RN) and the area under the curve (AUC) of these values are used to evaluate the methods. The higher value of AUC is the more effective the method is.

In term of AUC for every protocol and each level of noise, the scale-based diffusive filtering (bD and gD) outperforms the NCD method and the gD method outperforms the bD method. gD performs smoothing (lower RN) more than bD and NCD for the same level of boundary blur (RC). Additionally, for the same level of noise suppression (RN), it produces boundary blur (higher RC) less than bD and NCD. The gD method performs as quickly as the NCD method for a 256×256 · 51 image and averagely takes under 1 min for three iterations. The bD method requires more iteration and takes about 2 min for roughly the same level of filtering on an image.

B. Real Images

In [28], three different sequential Wiener filters, namely, isotropic, orientation and anisotropic are proposed. The proposed filters is compared in terms of the global MSE with several reported methods: 3D median filter [39] with window length three and five voxels in each dimension; an anisotropic diffusion filter [40] and three methods presented in a flux-diffusion filter [41].

The flux-diffusion filter outperforms other competing methods for MSE measure; however, the simple median filter with window length three voxels in each dimension presents satisfactory result for MSE. Wiener filters in compare to median filter produce de-noised image with less noise; the result of Wiener filters is not more blur than both median filter and flux-diffusion filter. Additionally, the Wiener filter in compare to flux-diffusion filter takes less time and the lower amount of memory in the same machine. Therefore, the proposed filters can be considered as candidate.

In [26], The Non-local Means (NLM) with optimal estimated values for parameters is applied on a T_1-weighted sagittal MP-RAGE scan acquired on a Siemens 1.5 Tesla Vision scanner from the fMRI Data Center database (www.fmridc.org) and two body images acquired on a Philips 3 Tesla scanner from Hospital Quiron of Valencia (Spain). The performance of NLM with optimal estimated parameters is compared qualitatively and quantitatively with two de-noising algorithms, the ADF (parameters manually tuned to get the best possible results) [6] and a wavelet-based denoising algorithm (the parameters proposed by the authors) [36]. The proposed algorithm gives a residual (difference between de-noised and original image) that less anatomical information can be noticed. Also, the Rician noise is removed more than other competing methods. The wavelet-based algorithm shows artefacts in result. Also, unnatural edge enhancement and blurring of small edges are noticeable in ADF results.

In [32], 20 normal images from IBSR are catogerized in two groups: contaminated and uncontaminated image volumes based on their quality. The ten contaminated image volumes contain either the smooth intensity inhomogeneity, or rapid interslice intensity variation. Gaussian mixtures [33] with and without MRF is applied on 10 uncontaminated images (11_3, 12_3, 13_3, 100_23, 110_3, 111_2, 112_2, 191_3, 202_3, 205_3). Jaccard similarity index for different methods are: Gaussian mixtures (0.6, 0.615, 0.6, 0.66, 0.625, 0.6, 0.66, 0.58, 0.61, 0.61) and Gaussian mixtures+MRF (0.725, 0.742, 0.67, 0.71, 0.645, 0.632, 0.662, 0.692, 0.725, 0.72). The average Jaccard indexes are: Gaussian mixtures = 0.62, Gaussian mixtures+MRF = 0.69. The results show that incorporating MRF improves segmentation quality.

Also, Gaussian mixtures [33] with and without MRF is applied on the eighteen newly added image volumes from the IBSR. Jaccard similarity index for different methods are: Gaussian mixtures (0.645, 0.68, 0.725, 0.75, 0.74, 0.73, 0.7, 0.7, 0.625, 0.74, 0.55, 0.68, 0.735, 0.75, 0.8, 0.85, 0.727, 0.76) and Gaussian mixtures+MRF (0.67, 0.73, 0.745, 0.68, 0.71, 0.76, 0.685, 0.73, 0.7, 0.737, 0.614, 0.7, 0.69, 0.745, 0.71, 0.69, 0.707, 0.68). Average Jaccard similarity index for different methods are: Gaussian = 0.715, Gaussian+MRF = 0.705. The Gaussian approach gives better results than those by the Gaussian+MRF model. It seems that MRF models over-regularize the segmentation. When comparing between results for new dataset and results for 20 normal images, the segmentation results are improved. The improvement in segmentation results is related to better quality of new added image data.

In [27], a new noise estimation method based on the adaptation of the Median Absolute Deviation (MAD) estimator in the wavelet domain for Rician noise is proposed. The NLM with proposed and state-of-art noised estimators (ML [42], LMB [43], LVB [43], LVO [43], MAD [44]) has been applied on the T_1-w phantom corrupted with ghosting inhomogeneity and variant noise levels from 2% up to 15%.

The difference between the Peak Signal to Noise Ratio (PSNR) obtained with the noise estimation and the truth noise is used as quality measure. PSNR is related to the root mean square error estimated (RMSE) measure. In most cases, the de-noising with proposed noise estimation method outperforms the other evaluated methods. Also, the Local Means in Background (LMB) method produces good results. The de-noising with proposed noise estimation method outperforms other methods over all the noise levels in terms of mean absolute error.

IV. CONCLUSIONS

Noise is one of obstacles in automatic image understanding and noise reducing is very important to improve the results of this process. Lots of works has been done in this area. But still, it is a research topic. In this paper a critical review of noise reducing techniques for brain images is presented. This paper review recent works in this area. Also, this paper presents Advantages and disadvantages of noise reducing techniques. Moreover, the paper presents comparative study of noise reducing techniques.

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