De-Noising MRI Data – An Iterative Method for Filter Parameter Optimization

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Abstract. In this paper an automatic parameter optimization method for anisotropic diffusion filters used to de-noise MR images is presented. This method is based on the incorporation of the filtering process into a closed-loop system where the monitoring of the image improvement is realized indirectly. The optimization is driven by comparing the characteristics of the suppressed noise to those from the assumed noise model at the optimum point. In order to verify the methods performance, experimental results obtained with this method are presented together with the results obtained by Median and k-Nearest Neighbor filters.

1 Introduction

High-resolution MR images are often affected by noise that results in undesired intensity overlapping of represented tissues, making posterior segmentation and classification difficult. Traditional noise-reduction linear filters, such as Mean or Gaussian filters do not acknowledge the boundaries produced between regions with different intensities. This results in the smoothing of these edges and the elimination of sharp details. As a result, the produced images are blurred and diffuse. Anisotropic diffusion filters overcome these shortcomings by adjusting its diffusion strengths as a function of the local gradient magnitude. This approach results in the reduction of the noise while the edges are preserved. The integration of such filters into a closed-loop system will open the possibility to adjust the filter parameters according to the intermediate results, improving the performance of these methods.

2 State of the art

Anisotropic diffusion filters were introduced by Perona and Malik based on the scale-space theory [1]. They proposed two diffusion functions to adjust the diffusion strength according to the region boundaries. Additional diffusion functions were proposed by Black et. al. [2] and Weickert [3]. For all of these functions the main parameters that control the behavior of the smoothing process are the *diffusion factor* and the *number of iterations*. The *diffusion factor* determines the level of gradient intensity at which the filter maximizes its diffusion. For de-noising applications, this *diffusion factor* needs to be adjusted in accordance to the noise level. The estimation of the noise is usually performed by applying some statistical methods that search for global characteristics or by hand-picking some homogeneous areas and measuring the local variance.

The adjustment of the *number of iterations* is frequently made by hand, but can also be estimated using an auto-stop criterion. Namely, the program can consider the number of pixel (voxel) modifications occurred between the two last iterations, an approach that also depends on the selection of the diffusion factor. Obviously, an optimal selection of these parameters is crucial for a successful reduction of the noise.

3 Main contribution

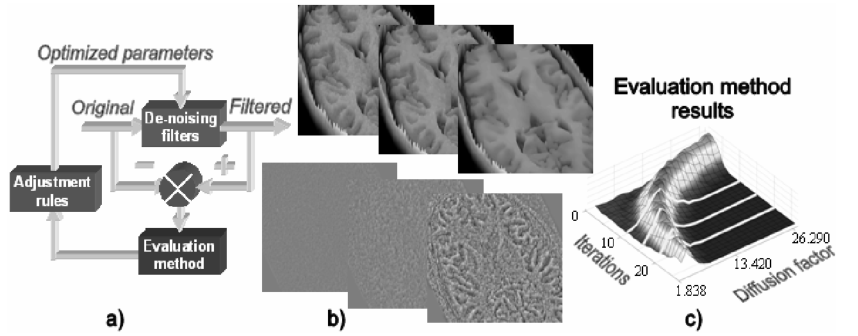
An automatic method is presented that produces an optimized estimate of the two main filter parameters. This optimization is achieved by integrating the filtering process into a closed-loop system, where the results of the filtering are analyzed in order to adjust the parameters before the next iteration of the loop. Because of the inherent difficulties in objectively determining the improvement of the image without the use of references, an indirect monitoring method has been conceived. This method compares the characteristics of the suppressed noise against the expected characteristics of the noise at the optimum.

4 Methods

Three basic modules compose the close-loop system, the *de-noising filters*, the *evaluations method* and the *adjustment rules* (Fig. 1a). The *de-noising filters* module contains several anisotropic diffusion functions (e.g., PMAD2) to process the data. A second set of these filters were also implemented following the biased anisotropic formulation proposed by Nordström [4]. (e.g., PMAD2_bias). All these functions were implemented considering a regularized (smoothed) version of the gradient.

The *evaluation method* was designed to produce the required feedback information about the improvement or degradation of the processed image. In contrast to other techniques, such as *image compression*, de-noising techniques do not have access to un-corrupted references, which could be used to control the process by minimizing the error between the resulting and the reference images. The proposed evaluation method uses the residual information obtained by subtracting the original image from the resulting one in order to analyze their characteristics (Figure 1a). An assumption is made that when an optimal parameterization has been achieved, the residual image will contain only the part of the image that corresponds to the noise. Thus, it would be possible to identify

Fig. 1. a) Schematic representation of the closed-loop system; b) some results from the anisotropic filter and from the residual image. The three examples correspond to a lightly smoothed, near optimum smoothed and heavily smoothed MR image; c) results of the evaluation function.

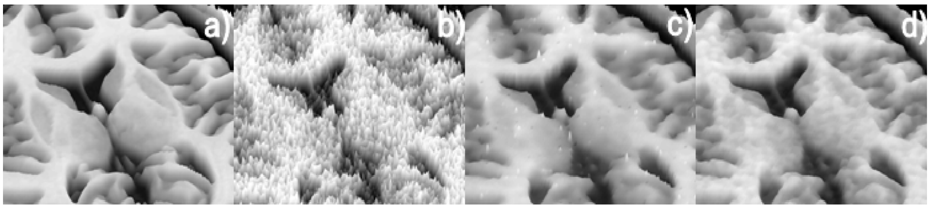


this point because the characteristics of the noise in magnitude MR images are sufficiently known [5]. In this case, it is expected to obtain Rice distributed noise with homogeneous intensity across the entire data set. If large texture variations are present in this image, this means that either the image is not filtered enough or that the image was strongly smoothed and some anatomical structures have started to emerge in this residual picture (Figure 1b).

Three main steps compose the *evaluation module*. The first step contains a local variance operator that measures the variance with a 3x3 kernel at each point of the residual image in order to produce a picture of the noise. In the second step, the histogram of this noise is calculated to extract the distribution of the obtained variance values. Finally, in the last step, an evaluation function [6] produces the feedback value based on the maximum height, full width and symmetry of the histogram. This feedback value becomes large when the local variance of the differential image has a maximum height and a minimum width. By plotting the results of this function a surface is generated (Fig. 1c). Here the pairs *diffusion factor-number of iterations* corresponding to the maximum values in the figure are considered to be close to the optimal parameters.

The *adjustment rules* module was implemented to avoid the evaluation of each combination of parameters on the surface while searching for the optimum. These rules take samples of the surface (represented as white lines in Fig. 1c) by fixing the *number of iterations* and examining the results of the *evaluation function* along the *diffusion factor* axis. The optimum *diffusion factor* value of each sample is obtained through a successive approximation scheme, which determines the new *diffusion factor* based on its actual and previous values and on the corresponding results produced by the *evaluation function*. The sampling process is repeated several times changing the *number of iterations*. From the obtained parameters of the samples, the median *diffusion factor* value and its respective *number of iterations* are taken to finally process the image. This iterative schema permits to reduce the searching time with respect to the complete plotting of the surface around 4 times.

Fig. 2. a) original image, b) corrupted image with Rician noise (σ=18.330), c) results from the anisotropic filter (PMAD2) using 10 iterations and 10.938 as *diffusion factor*, d) results from the k-Nearest Neighbor filter.



5 Results

In order to evaluate the proposed method, a group of corrupted data sets with increasing noise intensity was prepared. These data sets represent different overlapping levels between the most significant brain tissues (cerebrospinal fluid, gray and white matter). The reference image was an averaged real image taken from the MNI database [7] and the simulated Rician noise was generated following the model $x = \sqrt{((a + n1(\sigma))^2 + (n2(\sigma))^2)}$, where **a** is the original image and $\mathbf{n1}(\sigma)$ and $\mathbf{n2}(\sigma)$ are two independent 3D images with zero-mean Gaussian-distributed noise. The standard deviations (σ) used to produce three noisy data sets were 9.166, 13.749 and 18.330.

These data sets were processed with the proposed optimization method using the second Perona-Malik function PMAD2 and PMAD2_bias. The same data sets were also processed using a Median filter (1 iteration) and a k-Nearest Neighbor (KNN) filter with k=14 (3 iterations). In all the cases, the data was processed considering a 26 voxel neighborhood. In Figure 2, some results are presented. Here, the PMAD2 filter produces a good approximation of the original image but some speckle noise has not been reduced. The KNN filter also produces good results, though less smooth in comparison with the anisotropic filter.

The corrupted data and the results were evaluated using the mean-absolute error (MAE), the root-mean-square error (RMSE), the signal-to-noise ratio (SNR), the peak signal-to-noise ratio (PSNR) and the structural similarity index (SSIM) [8]. Table 1 resumes the results obtained. In the first line of each section, the values corresponding to the corrupted image are presented as a reference. The MAE and RMSE indicators, as usual, deliver smaller values when the image is closer to the reference, on the contrary, the SNR, PSNR and the SSIM produces larger values when the similarity between the images is large. In all three cases the automatic parameterization of the PMAD2 filter produces the best results. The results obtained with the k-Nearest Neighbor were the second best at medium and large noise levels, only outperformed by the PMAD2_bias in the lower noise-level case. The results of the Median filter were always inferior.

Table 1. Experimental results obtained comparing the original MNI data set against the corrupted and processed images.

MNI data set		MAE	RMSE	SNR	PSNR	SSIM
σ=9.166	Data + noise	10.0040	11.7578	21.8225	37.3934	0.9453
	PMAD2	6.9734	7.5798	23.7292	39.3001	0.9784
	PMAD2-Bias	7.4531	8.2321	23.3706	38.9416	0.9716
	KNN	7.5586	8.3694	23.2988	38.8698	0.9702
	Median	8.4830	9.4823	22.7566	38.3275	0.9604
σ=13.749	Data + noise	14.9891	17.6222	20.0651	35.6361	0.8863
	PMAD2	10.3752	11.3314	21.9829	37.5538	0.9477
	PMAD2-Bias	11.6387	12.9623	21.3989	36.9698	0.9314
	KNN	11.2986	12.6254	21.5133	37.0842	0.9338
	Median	12.4390	13.9867	21.0686	36.6395	0.9202
σ=18.330	Data + noise	19.4649	23.4785	18.8190	34.3900	0.8145
	PMAD2	14.2163	15.7418	20.5552	36.1261	0.9017
	PMAD2-Bias	15.8457	17.7252	20.0398	35.6108	0.8804
	KNN	15.1200	17.0076	20.2193	35.7902	0.8882
	Median	16.4562	18.5450	19.8435	35.4144	0.8718

6 Discussion

The definition of the procedure to evaluate the filtering results is based on the characteristics of the expected noise model and therefore, enables the implementation of a closed-loop system to automatically optimize the filter parameters. The obtained results, when compared to those obtained with the Median and k-Nearest Neighbor filters, indicate that our method is not only viable but also produces better results. In the near future, we intend to incorporate adaptive versions of the anisotropic diffusion filters into the *de-noising filters* module. These filters will additionally adjust the *diffusion factor* according to the time (number of filter iterations) and to the local homogeneity characteristics of the image. In addition, we plan to optimize the behavior of the evaluation method according to the Rician noise model. We expect these measures to increase the robustness and performance of the method.

References

1. Perona P, Malik J. Scale-space and Edge detection using anisotropic diffusion. IEEE Trans In Pattern Analysis and Machine Intelligence 1990;12(7):629–639.
2. Black M, Sapiro G, et al. Robust Anisotropic Diffusion. IEEE Trans Image Processing 1998;7(3):421–432.
3. Weickert J. Anisotropic Diffusion in Image Processing. ECMI. Teubner; 1998.
4. Nordström N. Biased anisotropic diffusion - A unified regularization and diffusion approach to edge detection. In: 1st European Conf. on Comp. Vision; 1990. p. 18–27.
5. Sijbers J. Signal and Noise Estimation from MR Images. Phd. thesis. University of Antwerp; 1998.
6. Castellanos J, Wagenknecht G, Tolxdorff T. Advances of a 3D noise supression method for MRI data. In: Tagungsband 2. Remagener Physiktage. VDE; 2004.
7. Collins DL, Neelin P, Evans AC, et al. Automatic 3D registration of MR volumetric data in standardized talairach space. J Comput Assist Tomogr 1994;18(2):192–205.
8. Wang Z, Bovik A, Sheikh HR. Structural similarity based image quality assessment. In: Digital Video Image Quality and Perceptual Coding. Marcel Dekker series in Signal Processing and Communications; 2004.