Fetal Magnetic Resonance Image Denoising Based on Homogeneity Testing and Non Local Means

K Haris[1,2], G Kantasis[1,2], N Maglaveras[1], AH Aletras[1,2]

[1] Lab. of Medical Informatics, Aristotle University of Thessaloniki, Greece
[2] Department of Clinical Physiology, Lund University, Sweden

Abstract

A novel edge-preserving denoising method for MR images is proposed. Local statistical homogeneity testing is combined with the well-known for structure preserving properties, Non Local Means (NLM) denoising method. The detection of homogeneity reduces remarkably the computational effort required by NLM which is applied only to information-rich image areas. Preliminary qualitative results on fetal and cardiac MR images are shown. These initial results are positive proving the effective noise reduction with less computational load.

1. Introduction

Despite the fact that MR acquisition technology has undergone substantial improvements over the last years, random noise is still one of the main causes of image quality degradation. Effective noise reduction is still the first step in almost all image processing tasks, because noise affects all subsequent computations causing the introduction and propagation of errors thus limiting the accuracy of quantitative measurements. In addition, noise degrades the diagnostic value of medical images since it limits the benefits of their visual inspection. The common drawback of all existing denoising techniques is that, although they effectively remove noise, they also alter the image information content by modifying the image areas where abrupt intensity changes occur (edges). Thus, edge-preservation is considered an important feature of a successful denoising method and extensive research effort has been devoted towards this direction.

In addition, the introduction of new technologies like multiple coil acquisition (parallel MRI) and the use of new reconstruction techniques , affects the statistical characteristics of noise thus imposing new research problems and challenges concerning its estimation and reduction [1].

In this study, a novel edge-preserving denoising method for MR images is proposed and investigated. In Section 2, after the presentation the of the statistical homogeneity test (subsection 2.1) and the standard NLM method (subsection 2.2), the proposed denoising method is described and analyzed. Finally, preliminary qualitative results on synthetic and real (fetal and cardiac) MR images are shown and discussed.

2. Methods

In the proposed image denoising method, statistical homogeneity testing is used to decide if the square neighborhood of the current pixel is homogeneous and, therefore, simple averaging is appropriate for both optimal value estimation and computational efficiency. In case of heterogeneity, the NLM algorithm is applied for the estimation of the central pixel value.

2.1. Statistical Homogeneity Testing

The proposed image denoising algorithm operates locally: The image I is sequentially scanned and for each pixel $p = (i, j)$, the presence or absence of homogeneity is statistically decided based on its $n \times n$ square neighborhood $\mathcal{N}_n(p)$, where n is odd. By assuming that the image noise is approximately white Gaussian, a homogeneous neighbourhood $\mathcal{N}_n(p)$ is considered a sample of size $N = n \times n$ of a normal random variable with mean μ and variance σ^2. According to the above formulation, the maximum likelihood (ML) ratio hypothesis test gives

$$\mathcal{N}_n(p) \text{ is homogeneous, if } \quad \hat{S}^2 \leq (1 + C)\sigma^2 \,, \quad (1)$$

where $\hat{S}^2$ is the sample variance of $\mathcal{N}_n(p)$ and $\hat{I}(p)$ the sample mean of $\mathcal{N}_n(p)$ [2].

Parameter C is determined by the significance level of the test (i.e. the probability of wrongly accepting homogeneity), based on the fact that the random variable $N\hat{S}^2/\sigma^2$ is distributed according to χ^2_{N-1}, under the homogeneity hypothesis.

If $\mathcal{N}_n(p)$ is decided to be homogeneous, then the true value of pixel p is estimated by the sample mean of $\mathcal{N}_n(p)$ which is the best estimator (unbiased and of minimum variance) for the case of Gaussian noise.

2.2. Non Local Means Denoising

Non Local Means (NLM) is a relatively recent image denoising method that achieves excellent noise reduction while, at the same time, preserves image information encoded in intensity changes (edges) [3]. This is accomplished by exploiting the intrinsic pattern redundancy of the images i.e. the repetition of relatively small number of spatial patterns over the image space. Indeed, if the same spatial pattern is available in many noisy copies then their averaging is the most appropriate operation for the restoration of their original value. However, for a given spatial pattern (the neighborhood of a pixel, for example), the locations of similar patterns is not known in advance, and therefore, a search operation is needed. During the search, the similarity between the neighborhoods is evaluated and used for the computation of the restored values.

In mathematical terms, the restored value of each image pixel p, $\hat{I}(p)$, is computed as the weighted average of all image pixel intensities, $I(q)$:

$$\hat{I}(p) = \sum_{q \in D_I} w(p,q)\ I(q)\ , \tag{2}$$

where $D_I = \{(i,j) : 1 \leq i \leq N_r, 1 \leq j \leq N_c\}$ are the spatial coordinates of a pixel in the N_r-row by N_c-column image I. The weight $w(p,q)$ in Eq. (2) is determined by the *similarity* of the neighborhoods $\mathcal{N}(p)$ and $\mathcal{N}(q)$.

$$w(p,q) = \frac{1}{Z_p} \exp\left(-\frac{d(p,q)}{h^2}\right)\ , \tag{3}$$

where Z_p is a normalizing constant so that $\sum_q w(p,q) = 1$, and $d(p,q)$ is the Euclidean distance between the square neighborhoods centered at p and q, respectively. Parameter h controls the decay of the exponential function and should be proportional to the noise variance, σ^2 [4]. Typical values of h^2 belong to the interval $[0.8\sigma^2, 1.2\sigma^2]$.

2.3. Heterogeneity-based NLM

In the proposed denoising method, the square neighborhood of every pixel p, $\mathcal{N}(p)$ is processed in order to be decided if it contains structure or not (Section 2.1).

The absence of structure in $\mathcal{N}(p)$ (homogeneity) means that all its pixels have the same initial intensity and, hence, all variation is due to noise. Therefore, $\mathcal{N}(p)$ can be considered to be a sample of size $N = n \times n$ of a normal (Gaussian) random variable with mean μ and variance σ^2. In this case, the optimal estimator of the restored value of p, $\hat{I}(p)$ is the sample mean of $\mathcal{N}(p)$, $\bar{I}(p)$.

On the other hand, the presence of structure in $\mathcal{N}(p)$ (heterogeneity) indicates that there is an unknown structural pattern which in combination with noise is responsible for the observed intensity variation in $\mathcal{N}(p)$. In this case, the following variation of the NLM method is applied: the restored value of each image pixel p, $\hat{I}(p)$, is computed as the weighted average of all image pixel intensities, $I(q)$, the neighborhood of which, $\mathcal{N}(q)$, is *heterogeneous* (Eq. 1). In addition, in order to further reduce the computational burden of computing the similarity of neighborhoods as implied by Eq. (3), we apply the *pixel selection rule* proposed in [5]. According to this rule, the similarity between two neighborhoods, $\mathcal{N}(p)$, $\mathcal{N}(q)$ is worth the computation if they have almost equal mean values and variances. In this way, Eq. (3) becomes

$$w'(p,q) = \begin{cases} \frac{1}{Z_p}\exp\left(-\frac{d(p,q)}{h^2}\right) & \text{if } \mu_1 < \frac{\bar{I}(p)}{\bar{I}(p)} < \frac{1}{\mu_1} \\ & \sigma_1^2 < \frac{\text{Var}(p)}{\text{Var}(q)} < \frac{1}{\sigma_1^2} \\ 0 & \text{otherwise,} \end{cases} \tag{4}$$

where μ_1, σ_1 are parameters with typical values 0.95 and 0.5, respectively. Therefore, the final restored value of pixel p with heterogeneous neighborhood is given by

$$\hat{I}(p) = \sum_{q \in \Omega_p} w'(p,q)\ I(q)\ , \tag{5}$$

where $\Omega_p = \{r \in D_I :\ \mathcal{N}(r) \text{ is heterogenious}\}$.

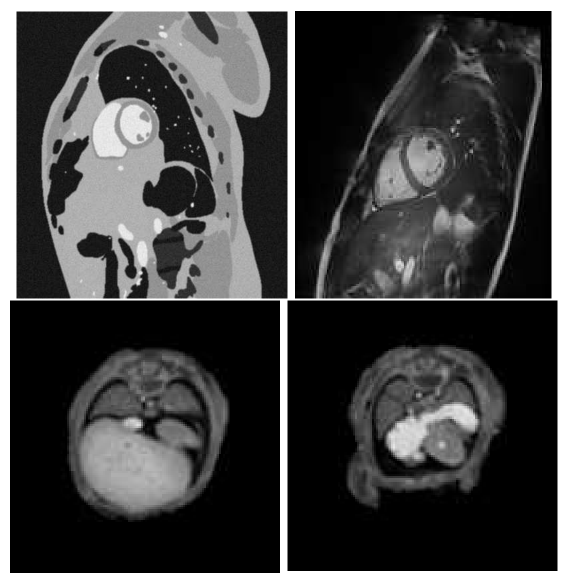

Figure 1. *Top:* Synthetic (*left*) & real (*right*) short-axis CINE cardiac images. *Bottom:* Fetal MR images. Transverse T1 (*left*) & T2 (*right*).

3. Results

Several combinations of the involved parameters such as the neighborhood size, the significance level of the homogeneity test, and the smoothing parameter h were tested.

The proposed algorithm was applied to synthetic and real MR images. Fig. 1(*Top*) shows a noisy synthetic (*left*) and a real frame (*right*) from CINE short-axis cardiac sequences. The synthetic cardiac sequence was created by the MRXCAT simulator [6]. Real fetal MR images (9.4T, T1- & T2-weighted) are shown in Fig. 1 (*Bottom*).

A qualitative indicator of the denoising performance of the proposed method is the *method noise image (MNI)* defined as the difference between the noisy image and the denoised one [3]. MNIs should ideally contain only pure noise without any structural information. This is confirmed in Figs 2 (*top right*) and 4 (*top & bottom right*).

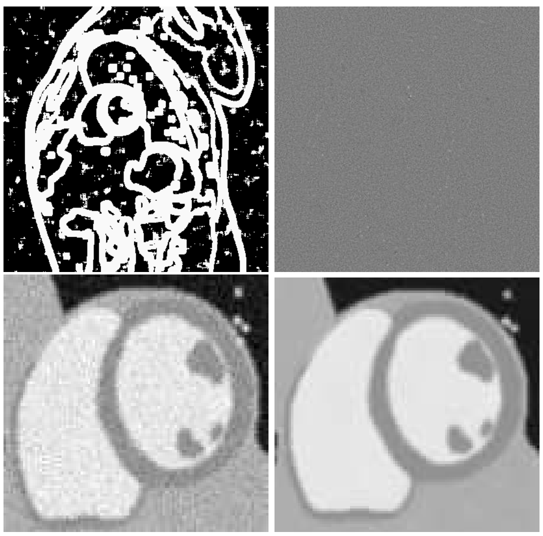

Figure 2. *Top Row*: *Left:* Heterogeneity Map of image at Fig. 1(*left*), *Right:* Corresponding *method noise image*, *Bottom Row*: The ROI containing LV and RV regions before (*Left*) and after (*Right*) denoising.

As expected the computational demands are significantly lower than the original NLM method. The speedup factor ranges between 2 to more that 50 depending on the percentage of heterogeneous areas of the input image.

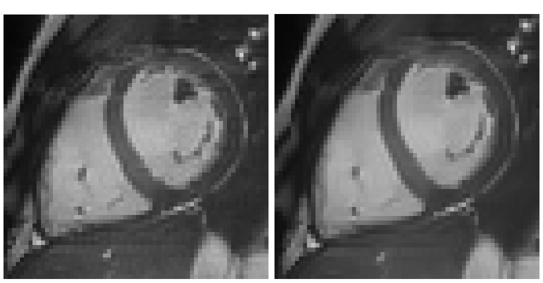

Figure 3. *Left:* A ROI in the real CINE image in Fig. 1 (*right*), and *Right:* the corresponding ROI in the denoised image.

4. Conclussions

A novel edge preserving denoising method that combines local statistical homogeneity testing with the Non Local Means method was proposed and preliminary results on fetal and cardiac MR images were shown. The computational demands of the method were significantly reduced.

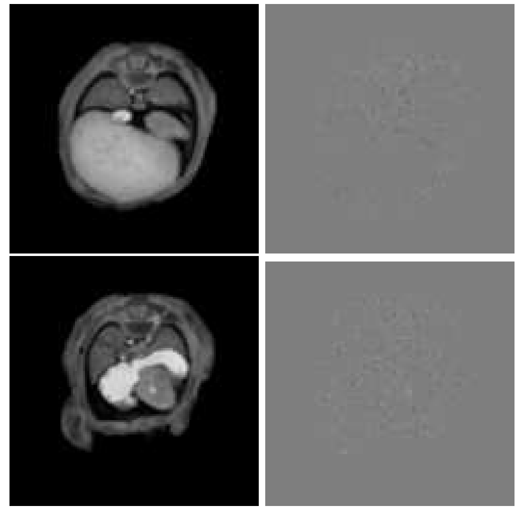

Figure 4. Denoised fetal images & corresponding method noise.

References

[1] Mohan J, Krishnaveni V, Guo Y. A survey on the magnetic resonance image denoising methods. Biomedical Signal Processing and Control 2014;9:56 – 69. ISSN 1746-8094.

[2] Wu Z. Homogeneity Testing for Unlabeled Data: A Performance Evaluation. CVGIP Graphical Models and Image Processing September 1993;55(5):370–380.

[3] Buades A, Coll B, Morel J. A review of image denoising algorithms, with a new one. Multiscale Modeling and Simulation 2005;4(2):490–530.

[4] Manjon J. et al MRI denoising using non-local means. Medical Image Analysis 2008;12(4):514–523.

[5] Coupe P. et al An optimized blockwise nonloc means denoising filter for 3dMR images. IEEE TMI 2008;27(4):425–41.

[6] Wissmann L. et al. MRXCAT: Realistic numerical phantoms for cardiovascular magnetic resonance. JCMR 2014;16(1).

Address for correspondence:

Prof. Anthony H. Aletras
Aristotle University of Thessaloniki
School of Medicine, Box 323
Thessaloniki, GR-54124,
Greece
tel: +30 (2310) 999256, +46 (76) 2822988
email: aletras@auth.gr