Denoising effect on T2* values in magnetic resonance imaging with application in iron load of patients with thalassaemia major

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Purpose

Thalassemia is the most common genetic disorder worldwide [30], and about 150 million people carry #*-thalassemia genes [13]. Patients with such chronic hemolytic anemia need to repeat blood transfusions which lead to iron overload and tissue damage especially the heart and the liver. Iron-mediated cardiomyopathy is the most lethal complication of thalassemia major. Therefore, there is an important clinical need for the early diagnosis and risk stratification.

Magnetic resonance imaging (MRI) has been a helpful and noninvasive diagnostic tool for detecting and quantifying iron content in the myocardium and liver worldwide [2, 24, 21]. Nowadays, T2* MRI is the best way for the early detection of iron overload [22, 1, 31]. T2* is a unique MR parameter measured in milliseconds and shortened in relation to the iron level due to paramagnetic properties [22, 9].

MR images are normally corrupted by random noise from the acquisition process due to various factors such as sensor type, pixel dimensions, temperature, exposure time, etc [4]. Usually, additive Gaussian noise and Rician noise are contaminated in MRI images [4]. Such a noise affects both human and computer-based analysis of the images. The noise level in an MR image can be effectively reduced by averaging multiple acquisitions directly in the scanner, and this is not a common practice in the clinical settings as this technique increases the acquisition time. Instead, denoising in the postprocessing stages seems to be beneficial for improvement of image quality for T2* estimation [3]. A critical issue in image restoration is the problem of noise removal while keeping the integrity of relevant image information.

Denoising methods have the drawback that while removing noise, they may also remove high-frequency signal components, thereby blurring the edges in the image and introducing some bias in the quantification process. However, advanced image denoising methods can mitigate this drawback.

Anisotropic Diffusion Filters [25, 12] are able to remove noise while respecting important image structures. Also more recently, wavelet-based filters have been applied successfully to MR denoising [10, 26]. Finally, a Non-Local Means (NL-means) filter, first introduced by Buades et al. [5], has been recently improved and applied to MR data yielding the best results qualitatively and quantitatively when compared to other filtering techniques [6, 7, 28].

A large number of edge-preserving methods have been proposed to overcome the blurring side effect denoising. For example, anisotropic diffusion filters [12] can remove noise using gradient information while respecting important image structures. Recently, Krissian and Aja-Fernandez [15] proposed an anisotropic diffusion filter based on a linear minimum mean squared error estimation and partial difference equations for Rician noise removal that has achieved state-of-the-art results.
Wavelet-based filters have also been applied successfully to the denoising of MR images [26]. Such filters are rooted in the processing of images in a transformed domain. Other transforms that have been implemented to denoise images include principal component analysis [20] and the discrete cosine transform [33]. Many transform domain filters derive from variations of the transform-threshold-inverse transform principle.

The aim of this work is to compare the effect of different denoising methods with different level of Gaussian and Rician noise, on an evaluation of T2* MR images.
Methods and materials

MR data acquisition

20 thalassemia patients (14 males and 6 females, 19 # 40 years old, mean 28.30 years) undertaken MRI to estimate the T2* value of the interventricular septum in Shahid Faghihi Hospital of Shiraz. Shiraz is the referral center in Iran which is located in middle of thalassemia belt. ECG-gated cardiac MRI has been performed on a Magnetom Avanto 1.5 T MR scanner, version B15 (Siemens Medical Solutions, Erlangen, Germany). The T2*relaxometry was done using eight T2*short axis images with an echo time range of 3.33-30.18 ms, a repetition time of 450 ms, and a #ip angle of 20 degrees. Also, the multi-echo sequence parameters were as: the #eld of view 75 cm, the image reconstruction matrix 192×144 pixels, and thickness 10 mm.

Image Processing

Using the Digital Imaging and Communications in Medicine (DICOM) protocol, all acquired images are transferred to a workstation computer. After that images were exported from DICOM and measurement of T2* was performed o#-line through the freely available software Segment version 2.0 R4665 (http://segment.heiberg .se) [14]. The basic idea of T2* is to image the myocardium a few times with di#erent time echoes (TE), using a gradient echo technique [2]. So, in T2* MR imagery we have a sequence of MR images. Therefore, one can see T2* MR imagery as a 3D MR image just by stacking the MR images and the #ltering can be done using 3D denoising methods. Since T2* value estimation of interventricular septum is the best quantitative indicator of the iron load in thalassemia patients [1, 27, 32, 18, 19, 23], manual full thickness ROI were measured in interventricular septum as shown in Figure 1. In this paper, T2*(w) indicates the T2* value of interventricular septum regarding image w.

Gaussian and Rician noises with di#erent levels are applied to the imported DICOM images. To evaluate the e#ect of di#erent denoising method on T2* value, the di#erent level of noises are considered. Depends on the type of noise, restoration of images are done using Optimized Non Local Means #Iter for 3D MRI (ONLM), Spatially Adaptive Non Local Means #Iter for 3D MRI (ANLM), Denoising based on Sparseness and Self-Similarity for 3D MRI (ODCT), Prona-Malik (PM), Block-Matching 3D (BM3D), Spectral Subtraction for image Denoising (SSD), Bilateral Filtering. All denoising algorithms used in this paper are implemented in Matlab R2015b.
Results

In this section we investigate and present the effect of denoising methods considered previously, on improving signal-to-noise ratio (SNR) and computing T2* value in MR images. All results are implemented with the software Matlab R2015b (The Mathworks, Inc.). The ONLM, AONLM, and ODCT codes that we used are available online at (https://sites.google.com/site/pierrickcoupe/softwares/denoising-for-medical-imaging/mri-denoising). The PM, BM3D, Bilateral, and SSD are implemented regarding the original proposal algorithm through Matlab. We have compared the algorithms at the different level of noises, where Gaussian noise level (nl) was 2, 4, 6, 8, 10 and in the case of Rician was 0.5, 1.0, 1.5, 2.0, 2.5, 3.0.

To measure performance of each algorithm on a reference image \( u \) after adding a noise and denoising we compute

\[
\text{SNR}(w, \bar{u}) = 10 \log_{10} \left( \frac{\text{mean}(w^2)}{\text{mean}((w - \bar{u})^2)} \right),
\]

Fig. 16

References: Radiology, Medical Imaging Research Center - Shiraz/IR

and the inverse of the discrepancy of T2*

\[
D_{T^*}(w, \bar{u}) = \frac{1}{|T^*_2(w) - T^*_2(\bar{u})|},
\]

Fig. 13

References: Radiology, Medical Imaging Research Center - Shiraz/IR
where \( w \) is either noisy (\( ^\ast u \)) or retrieved (\( u \)) images. Also, to quantify the rate of SNR and \( T2^* \) improvements, first, we sub-track the \( T2^*(u) \) from the corresponding retrieved and noisy MR images. Then computing rate of effectiveness as

\[
EF_{\text{snr}}(u, \hat{u}, \bar{u}) = \frac{\text{SNR}(u, \bar{u})}{\text{SNR}(\hat{u}, \bar{u})}
\]

Fig. 14

References: Radiology, Medical Imaging Research Center - Shiraz/IR

and

\[
EF_{T2^*}(u, \hat{u}, \bar{u}) = \frac{D_{T2^*}(u, \bar{u})}{D_{T2^*}(\hat{u}, \bar{u})}.
\]

Fig. 15

References: Radiology, Medical Imaging Research Center - Shiraz/IR

From the definition of effectiveness, we say that an algorithm is effective when the rate of effectiveness is greater than one and non-decreasing. The higher rates represent higher effectiveness and less discrepancy.

Gaussian noise
This section is devoted to a comparison between the three state-of-the-art MRI denoising algorithms in case of Gaussian noise, namely, BM3D, SSD, and Bilateral.

First, we discuss results concerning the quality improvement of input images. Generally, within each noise level, the SNR of denoised images are increased comparing the input regardless of the corresponding algorithm, see Figure 2.

However, the amount of improvement depends on algorithm and level of noise. BM3D approach outperformed the two other methods by producing images with a higher SNR. Moreover, the Bilateral method was the worst in this scenario.

A closer look shows that a higher improvement of SNR is achieved in presence of a stronger noise. In another word, the effectiveness of algorithms is increased when the level of noise was greater, see Figure 3 for box plot of the rate of improvement and Figure 4 for the median of improvement. From the displayed results of BM3D and SSD one sees that when the level of noise increases decrements of SNR of retrieved image and effectiveness rate become less and less. These facts suggest that BM3D and SSD performed robustly on inputs. Comparing to SNR a similar result did not observe regarding the T2* value. The first observation was that by adding noise the T2* value remains close to the original T2*. However, a stronger noise usually makes the T2* value varies more, see Figure 5.

To investigate similarity, a Kruskal-Wallis nonparametric analysis of variance (KWAV) was used to assess the differences. A p-value of 0.05 is considered significant in the course of the analysis, see Table 1. The exhibited results confirm no significant statistical difference between T2* values. see Table 1 and Figure 5.

<table>
<thead>
<tr>
<th>Gaussian noise Level</th>
<th>2</th>
<th>4</th>
<th>6</th>
<th>8</th>
<th>10</th>
</tr>
</thead>
<tbody>
<tr>
<td>A: Noisy</td>
<td>0.9569</td>
<td>0.9138</td>
<td>0.9461</td>
<td>0.9353</td>
<td>0.9138</td>
</tr>
<tr>
<td>B: BM3D</td>
<td>0.8924</td>
<td>0.9138</td>
<td>0.9138</td>
<td>1</td>
<td>0.9892</td>
</tr>
<tr>
<td>0.9676</td>
<td>0.9569</td>
<td>0.8924</td>
<td>0.9676</td>
<td>0.9138</td>
<td></td>
</tr>
<tr>
<td>SSD</td>
<td>0.9569</td>
<td>0.9246</td>
<td>0.9784</td>
<td>0.9892</td>
<td>0.9353</td>
</tr>
<tr>
<td>0.9892</td>
<td>0.9784</td>
<td>0.9246</td>
<td>0.9676</td>
<td>0.9461</td>
<td></td>
</tr>
<tr>
<td>Bilateral</td>
<td>0.8924</td>
<td>0.8924</td>
<td>0.9569</td>
<td>0.8924</td>
<td>0.8077</td>
</tr>
<tr>
<td>0.9461</td>
<td>0.8392</td>
<td>0.8817</td>
<td>0.9353</td>
<td>0.9676</td>
<td></td>
</tr>
</tbody>
</table>

Table 1: A: Kruskal-Wallis test of $T2^*(u)$ and $T2^*(u)$, B: Kruskal-Wallis test of: first row $T2^*(u)$ and $T2^*(u)$, second row $T2^*(u)$ and $T2^*(u)$. 
To measure and compare performances of aforementioned methods we also computed the rate of effectiveness for each method, see Figures 6 and 7. The performance of SSD on input images was such that the median of rates is bigger than one and decreases regarding increment of the noise level. In the case of BM3D and Bilateral, one sees that median of effectiveness rate is less than one which means that after denoising the T2* value is getting far from the original one. The obtained results confirm that effectiveness is improved in presence of a stronger noise.

Rician noise

This section is devoted to a comparison between the four state-of-the-art MRI denoising algorithms in case of Rician noise, namely, ONLM, AONLM, OCDT, and PM denoising #lters. Similar to Gaussian noise, within each noise level, performances of underline algorithms were such that the SNR of input images are increased comparing the input, see Figure 8.

Also, from the reported result, one can see that ONLM approach outperformed other methods by recovering images with a higher SNR. Moreover, PM method had the poorest performance in this scenario. To compare the effectiveness of aforementioned algorithm rates were computed, see Figure 9. The displayed results show that a higher improvement of SNR is achieved in presence of a stronger noise. In another word, the effectiveness of algorithms are increased when the level of noise was greater, see Figure 9 for box plot of the rate of improvement and Figure 10 for the median of improvement. Moreover, All algorithms were effective; however, ONLM outperformed other algorithms in the sense of effectiveness and PM had the worst effectiveness rate. A similar result did not observe regarding the T2* value comparing to SNR results. However, comparing to Gaussian noise, we noticed that by adding noise the T2* value does not remain always close to the original T2* and a stronger noise usually makes the T2* value di#ers more.

To investigate similarity, a KWAV was performed to assess the di#erences between T2* values. The setting of analysis was like before. The exhibited results confirm no significant statistical difference between T2* values, see Table 2. However, when the level of noise is increasing, one sees that similarity of original and noisy images are decreasing. In the opposite, the similarity of retrieved images using ODCT and ONLM are non-decreasing and ODCT has a dominant similarity with the original.

Rician noise level

<table>
<thead>
<tr>
<th>A:</th>
<th>0.5</th>
<th>1</th>
<th>1.5</th>
<th>2</th>
<th>2.5</th>
<th>3</th>
</tr>
</thead>
</table>
Table 2: A: Kruskal-Wallis test of $T_2^*(\hat{u})$ and $T_2^*(u)$, B: Kruskal-Wallis test of: first row $T_2^*(u)$ and $T_2^*(\hat{u})$, second row $T_2^*(u)$ and $T_2^*(\hat{u})$.

To measure effectiveness we have computed the rate of improvement of $T_2^*$ for each method, see Figures 11 and 12. The performance of AONLM and ODCT on input images were such that median of effectiveness rates is bigger than one and increases by an increment of the noise level. In other words, AONLM and ODCT were effective on inputs. Also, in the case of ONLM and PM, one sees that median of effectiveness rate is less than one and increases in case of ONLM and decreases in case of PM. Lately, ODCT outperformed another algorithm by producing images with a $T_2^*$ value more close to original one. In the opposite PM was the worst and its effectiveness rates were diminishing in presence of a stronger noise, see Figure 12.
Fig. 2: Box plot of SNR improvement in the presence of Gaussian noise levels

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Fig. 8: Box plot of SNR improvement in the presence of Rician noise levels
Fig. 3: Box plot of SNR effectiveness in the presence of Gaussian noise levels

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**Fig. 9:** Box plot of SNR effectiveness in the presence of Rician noise levels

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**Fig. 4:** Median of SNR effectiveness in the presence of Gaussian noise levels

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Fig. 10: Median of SNR effectiveness in the presence of Rician noise levels

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Fig. 5: Box plot of T2 improvement in the presence of Gaussian noise levels

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Fig. 6: Box plot of T2 effectiveness in the presence of Gaussian noise levels

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Fig. 11: Box plot of T# 2 e#ectiveness in the presence of Rician noise levels

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Fig. 12: Median of $T_2$ effectiveness in the presence of Rician noise levels

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Fig. 7: Median of T#2 effectiveness in the presence of Gaussian noise levels

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**Fig. 1**: full thickness ROI in interventricular septum

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Conclusion

In this paper, we investigated seven state-of-art Gaussian denoising algorithms when they applied to twenty T2* MR images. To quantify the impact of denoising on quality improvement of T2* MR images we computed SNR before and after applying the algorithms. The results confirmed that quality of inputs is improved. We measured an amount of improvement by computing rate of effectiveness by dividing SNR of denoised image over noisy one. Reported results demonstrate that the performance of algorithms on inputs is effective. Displayed results show that BM3D approach outperformed other algorithms in the sense of SNR effectiveness when a Gaussian noise is imposed. For the Rician noise, the ONLM approach has the dominant performance.

In addition, in the case of the existence of Gaussian noise, the reported results confirmed that there is no statistical difference between T2* values of original and noisy MR images. The Kruskal-Wallis nonparametric analysis of variance was used to assess the differences between T2* values. Based on the obtained results, when the level of noise is increased similarity of T2* values of noisy and original images are decreased. Displayed results show that BM3D was no more effective and yet had not the leading performance. It was SSD approach with a dominant performance with respect to effectiveness. Moreover, since rates of T2* effectiveness of SSD approach are decreased, it was also not effective.

In the case of image distortion by Rician noise, four state-of-art denoising algorithms ONLM, AONLM, ODCT, and PM have applied. Like Gaussian noise, T2* improvement of MR images was investigated. From reported results, the quality improvements rates of methods were increasing and bigger that one except PM. Therefore, the methods performed effective on the inputs except for PM. Moreover, ONLM surpasses the other methods by recovering images with the highest rates of effectiveness. Therefore, one can conclude that among the underline methods ONLM is the best to improve the quality of T2* MR images. Also, based on the results, one sees that performance of ODCT approach exceeds other algorithms in the sense of effectiveness. Based on the above discussion one concludes that when a Rician noise is imposed the ODCT method could be applied to improve quality and T2* simultaneously. In another word, among the underline methods, the ODCT approach is the best one in the case of Rician noise.
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