MRI denoising based on Sparseness and Self-Similarity

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Introduction

In this paper, we present two new approaches for MRI denoising. The first is an extension of the original method proposed by Guleryuz (2007). Based on local 3D DCT hard thresholding, our proposed method has been adapted to deal with Rician noise (typical of magnitude MR images) using a pseudo-oracle principle. The second proposed method is a new rotationally invariant 3D version of the Rician-adapted Non Local Means filter (Buades, 2005, Coupé 2008a, Wiest-Daesslé 2008) that uses a prefiltered image.

Methods

Typically, the observed noisy MR image *y* is considered to be a linear combination of a noise-free image *x* and a white noise realization *n* from the measurement process. Therefore, the goal of any denoising algorithm is to find a good estimate $\hat{x}$, given *y*. This section describes two new methods for image denoising based on two different image properties and compares them to two state-of-the-art denoising methods.

Denoising using sparseness

In Guleryuz's (2007) method, the estimate of the noise-free image $\hat{x}$ is obtained using a hard thresholding method. An overcomplete set of 3D block DCTs (4×4×4 block size) is used (Guleryuz used 8×8 blocks in his 2D method, which yields the same number of coefficients). The local denoised estimate at block *j*, $\hat{x}_j$, is obtained by applying a hard thresholding rule. Finally, all local estimates $\hat{x}_j(i)$ are combined from all overlapping *j* blocks at position *i*. On the other hand, Oracle-based filters assume that, if the null coefficients of the original noise-free image are known, they can be used to improve the denoising. Unfortunately, in practice no noise-free image *x* is available; hence, this approach is unfeasible. However, if we relax the Oracle condition, we can use a prefiltered image $\hat{x}^{pre}$ with, for example, the described DCT3D method as an approximation of the noise-free image. With this approach, each block of coefficients of the noisy image *y* can be better thresholded using the corresponding block coefficients of the prefiltered image. The final image reconstruction is performed using the same approach described above. We will refer to this method as Oracle DCT3D (ODCT3D). The only parameter of this method is the threshold τ from the prefiltering step. In all of our experiments, we used a τ value of 2.7 σ (where σ is the standard deviation of the noise), which is common in DCT and wavelet thresholding methods (Mallat, 1999).

Denoising using self-similarity

Originally proposed by Buades et al. (2005), the NLM filter takes advantage of the high level of pattern redundancy in an image, achieving high-quality image denoising by averaging similar realizations of the noisy signals. Basically, this filter reduces the noise in an image by averaging voxels that originally had the same intensity in the noise-free image. To this end, Buades et al. (2005) suggested that voxels with similar neighborhoods (small 3D patches in our volumetric case) tend to have similar original values. However, if the images are prefiltered using the described ODCT3D method there is no need to compare 3D patches to measure voxel similarities. In this case, the voxel value and the local mean can be used to efficiently estimate the voxel similarity. Furthermore, the similarity so defined is rotationally invariant and thus the number similar voxels around each voxel will be increased if compared to the original method. We will refer to this method as PRI-NLM3D.

Results

The proposed methods were compared with two state of the art MRI denoising methods: WSM from Coupe (2008b) and ONRAD from Krisian (2009).. Example results using simulated data from the well-known Brainweb phantom can be observed in Fig. 1. An example of the application of the PRI-NLM3D method over real data can be observed in Fig. 2.

Conclusion

To new methods for MRI denoising have been presented. The new methods are able to better reduce the random noise in the images when compared with other state-of-the-art methods. Both methods run in less than a minute, making them usable in most research and clinical settings.

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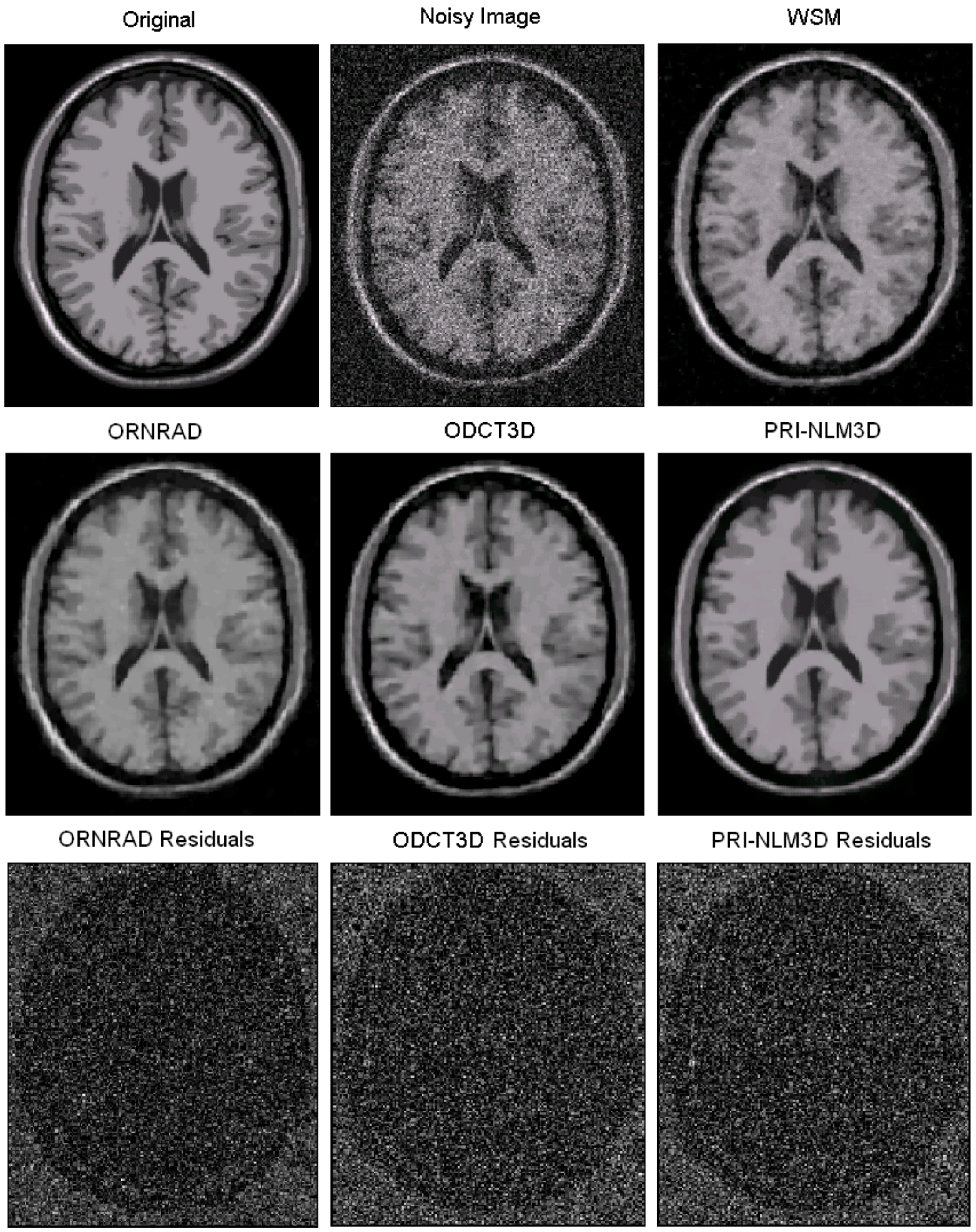

Fig.1 Example filtering results for an axial slice of the T1w BrainWeb phantom (Rician noise level of 15%). The third row shows the absolute value of the image residuals for the different methods.

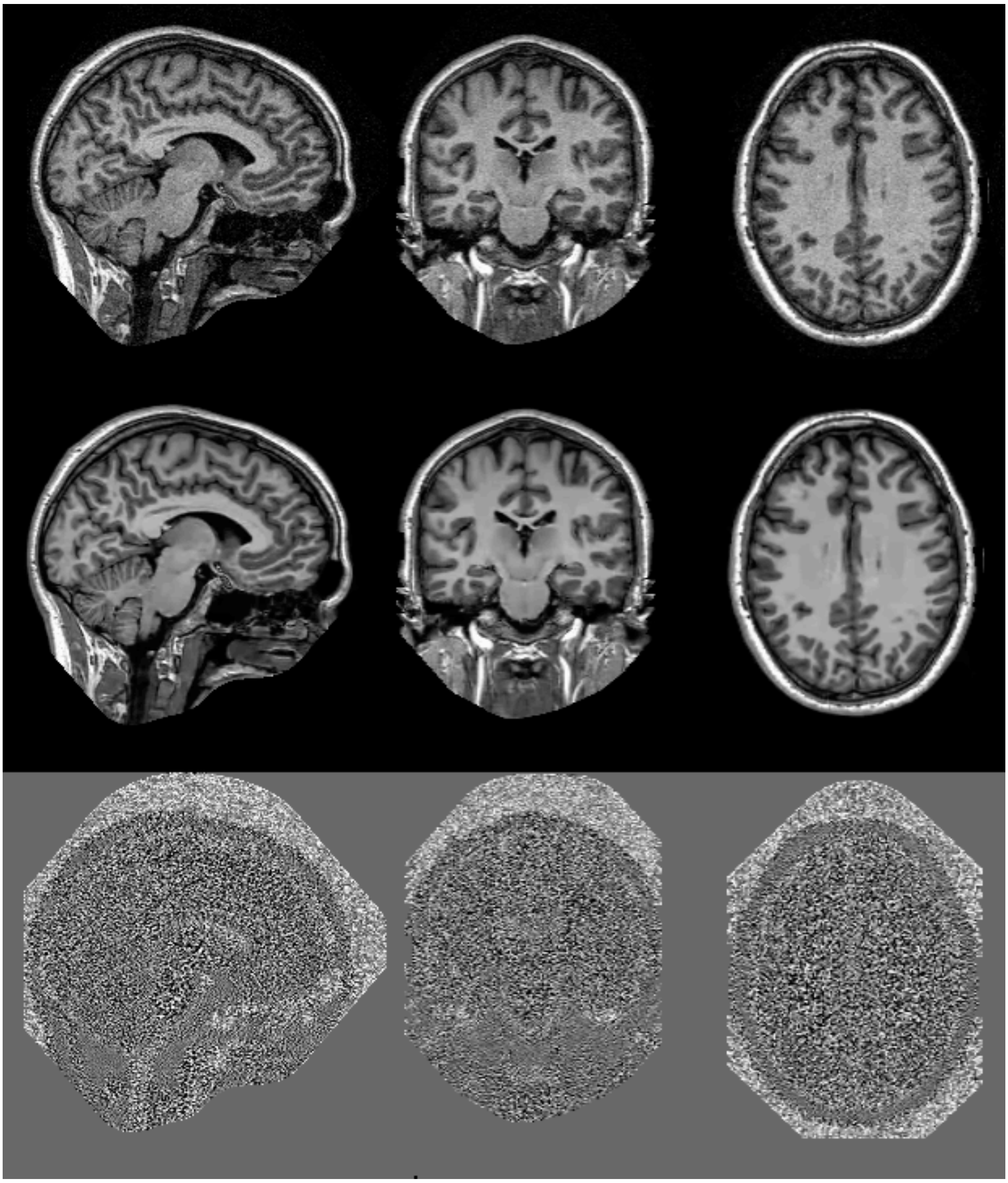

Fig. 2 – Example results of the proposed PRI-NLM3D filter on real data (Rician noise level of 2%). The background and part of the face were removed by a defacer program to preserve the anonymity of the subject. From top to bottom: Original noise volume, denoised volume using the proposed method, and the corresponding residuals.