Performance of three parallel MRI reconstruction methods in the presence of coil sensitivity map errors

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Introduction

Reducing the global imaging time can be of great interest in some MRI applications. For doing so, one can resort to parallel MRI, a technique that relies on under-sampling the k-space by skipping some phase encoding points. Data simultaneously received by several receiver coils with different sensitivity profiles are then used to reconstruct full Field of View (FOV) images. To this end, several reconstruction techniques have been proposed such as the widely-used SENSE[1] method. However, the reconstructed image generally presents artefacts especially when perturbations occur in both the measured data and the estimated coil sensitivity maps. To address this problem and reduce the image quality degradation, Tikhonov regularization has been investigated in the image domain[4]. We study here the robustness of some SENSE-based reconstruction algorithms to errors in the coil sensitivity map estimation.

Methods

The parallel MRI generative model can be formulated in the spatial domain as follows

$$\begin{pmatrix} d_1(m,n) \\ d_2(m,n) \\ . \\ . \\ d_{N_c}(m,n) \end{pmatrix} = \begin{pmatrix} S_1(m,n) & S_1(m+\frac{M}{R},n) & . & . & S_1(m+\frac{(R-1)M}{R},n) \\ S_2(m,n) & S_2(m+\frac{M}{R},n) & . & . & S_2(m+\frac{(R-1)M}{R},n) \\ . & . & . & . & . \\ . & . & . & . & . \\ S_{N_c}(m,n) & S_{N_c}(m+\frac{M}{R},n) & . & . & S_{N_c}(m+\frac{(R-1)M}{R},n) \end{pmatrix} \begin{pmatrix} \rho(m,n) \\ \rho(m+\frac{M}{R},n) \\ . \\ . \\ \rho(m\frac{(R-1)M}{R},n) \end{pmatrix} + \begin{pmatrix} B_1(m,n) \\ B_2(m,n) \\ . \\ . \\ B_{N_c}(m,n) \end{pmatrix}, \quad (1)$$

where $d_1 \ldots d_{Nc}$ are received images, ρ is the unknown full FOV image and $S_1 \ldots S_{Nc}$ are coil sensitivity maps of the N_c used antenna, and $B_1 \ldots B_{Nc}$ are additive Gaussian noise samples. The SENSE method proceeds by inverting this linear problem to estimate the unknown image ρ using the least squares estimator. In the presence of sensitivity map errors, the least squares reconstruction problem can then be written in a matrix form as follows:

$$\boldsymbol{\rho} = [(\mathbf{S}+\Delta\mathbf{S})^{H}\boldsymbol{\psi}^{-1}(\mathbf{S}+\Delta\mathbf{S})]^{-1}(\mathbf{S}+\Delta\mathbf{S})^{H}\boldsymbol{\psi}^{-1}\mathbf{d}, \quad (2)$$

where $\Delta\mathbf{S}$ is the sensitivity maps estimation errors and $\boldsymbol{\psi}$ is the between-coil correlation matrix. Because of the acquisition noise and sensitivity map estimation errors, SENSE suffers from aliasing artefacts in the reconstructed full FOV image. To improve the reconstruction performance, Tikhonov[2] quadratic regularization has been applied since it provides a closed form regularized solution:

$$\boldsymbol{\rho} = \boldsymbol{\rho}_r + [(\mathbf{S}+\Delta\mathbf{S})^{H}\boldsymbol{\psi}^{-1}(\mathbf{S}+\Delta\mathbf{S})+\lambda\mathbf{I}_R]^{-1}(\mathbf{S}+\Delta\mathbf{S})^{H}\boldsymbol{\psi}^{-1}[\mathbf{d}-(\mathbf{S}+\Delta\mathbf{S})\,\boldsymbol{\rho}_r], \quad (3)$$

where $\boldsymbol{\rho}_r$ is a regularization image and $\mathbf{I}_R$ is the R-dimensional identity matrix. λ is the regularization parameter which ensures a trade-off between the closeness to data and penalty term. Quadratic regularization introduces smoothing artefacts in the reconstructed image. Hence, To overcome this problem, we have proposed a regularization algorithm in the Wavelet Transform (WT) domain with edge-preserving penalty terms. This regularization scheme gives reconstructed images of improved quality (i.e. reduced smoothing artefacts) in comparison to the basic SENSE and Tikhonov reconstructions

Figure 1: Simulated received images: coil 1 (left), coil 4 (middle) and coil 8 (right).

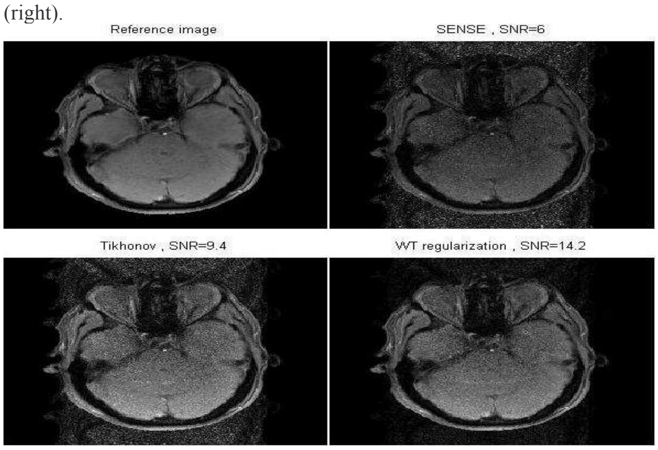

Figure 2: Original image and reconstructed ones using SENSE, Tikhonov and the WT regularization algorithm with $\frac{\|\Delta S\|_2}{\|S\|_2} = 5.4\%$.

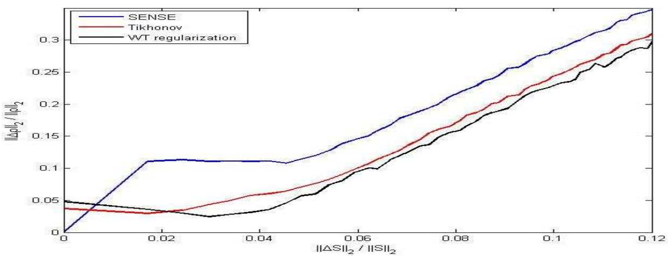

Figure 3: Estimation error percentage with respect to the coil sensitivity maps error percentage.

Experimental procedure

In this work, we have carried out an experimental study of the robustness of the above mentioned reconstruction techniques in the presence of coil sensitivity maps errors. In our experimental set-up, there is no acquisition noise. Indeed, based on a known reference image, we artificially simulated the parallel MRI acquisition process to generate reduced FOV images with perfectly known coil sensitivity maps (8 coils) according to Eq. (1). Using these images, we reconstructed the full FOV image while introducing different coil sensitivity map error-levels. Finally, we analysed the reconstruction performance of the three methods by computing the Signal to Noise Ratio (SNR) and the percentage of error in the estimated full FOV image with respect to the known reference image.

Results

Figure 1 shows an example of three simulated reduced FOV images with known coil sensitivity maps and no acquisition noise. We can easily see aliasing artefacts caused by under-sampling the k-space during the parallel MRI acquisition process. Figure 2 shows the reference and the reconstructed full FOV images using SENSE, Tikhonov and the WT regularization methods with a coil sensitivity map error of 5.4%. It appears that sensitivity errors cause aliasing artefacts in the full FOV image using the SENSE technique, while such distortions are weakened using Tikhonov regularization and even disappear using our approach in the brain. Figure 3 shows the evaluation of the full FOV image reconstruction error with respect to the coil sensitivity map error. As expected, in the absence of acquisition noise and sensitivity errors, SENSE gives an exact reconstruction. In this case, regularized reconstruction may introduce some small reconstruction errors according to the so-called bias-variance trade-off. However, when sensitivity errors become quite important which may occur in practice, the WT regularized reconstruction is more robust to sensitivity errors than SENSE and Tikhonov regularization methods.

Conclusion

We have compared the reconstruction performance of three parallel MRI algorithms in the presence of coil sensitivity maps errors. Our study shows that regularization gives more accurate full FOV reconstructed images in the presence of sensitivity errors in general, and that the regularization scheme in the wavelet domain (3) is the most robust method among the three assessed approaches.

References :

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