Multi-tissue based Coil Sensitivity Estimation for Optimal SNR Reconstruction in Phased Array MRI

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Introduction

In typical MR studies, the sum-of-squares (SoS) algorithm [1] is applied for the combination of phased array MR images. The intensity of the SoS reconstructed image is modulated by a spatially variable function due to the non-uniformity of coil sensitivities and also has sub-optimal SNR and intensity bias. A multitude of techniques have been developed for removing the noise bias and intensity non-uniformity in the SoS images. The reliability of these approaches directly depends on the validity of approximating the intensity inhomogeneity in the SoS reconstructed images by a slowly varying function, which is not always true. In this work, we present an iterative algorithm for estimating individual coil sensitivities using a multi-tissue Gaussian model. The estimated complex coil sensitivities are used for optimal SNR reconstruction, giving images with intensity modulation removed and with reduced intensity bias.

Theory

The equation for signal at location $\mathbf{r}$¸in an image acquired by the i-th coil, $R_i(\mathbf{r})$, is given by: $R_i(\mathbf{r}) = I(\mathbf{r})\, S_i(\mathbf{r}) + N_i(\mathbf{r})$, where $I(\mathbf{r})$ is the true image, $S_i(\mathbf{r})$, the complex coil sensitivity and $N_i(\mathbf{r})$, the additive white Gaussian noise. The proposed algorithm estimates the individual coil sensitivities using an extension of the technique developed in [2] but using the knowledge of multiple tissue types which makes the iterative technique more efficient and accurate. This is due to the inclusion of an increased number of data points distributed throughout the image for the estimation of sensitivity maps. The flow chart for the developed iterative algorithm is shown in Fig. 1 and the main steps of the algorithm are presented below:

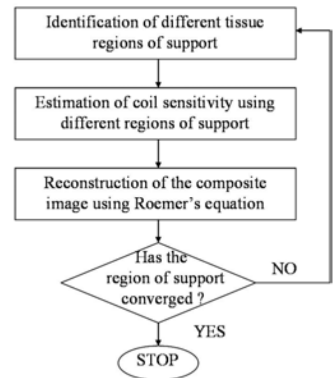

Fig 1. Flow chart of the algorithm.

Preliminary Steps: Unbiasing, estimation of individual coil phase maps and noise correlation matrix as presented in [2].

1. Identification of region of support for multiple tissue types: In high SNR MR images, the intensity distribution can be described as a linear combination of Gaussian distributions. This assumption has been widely used in a number of statistics-based techniques for segmenting brain tissues in MR images. A similar approach is utilized in our method to identify spatial distributions of the tissue types presented by a significant number of pixels in the image. If the histogram h of the MRI image can be modeled by a linear combination of Gaussian distributions $G(\mu_k,\sigma_k)$, then the region of support of the k^{th} tissue type in the n-th iteration, $M^{(n,k)}(\mathbf{r})$, is identified using the image estimate $I^{(n-1)}(\mathbf{r})$ obtained at the $(n-1)$-th iteration as:
$$M^{(n,k)}(\mathbf{r}) = \begin{cases} 1 & \mu_k - 2\sigma_k < I^{(n-1)}(\mathbf{r}) < \mu_k + 2\sigma_k \\ 0 & otherwise \end{cases} \quad (1)$$
where $I^{(0)}(\mathbf{r})$ is initiated using the original SoS reconstructed image.
2. Estimation of the individual coil sensitivities: A mask of the whole image data (containing the regions of all tissue types) is obtained in each coil by normalizing the respective means of the tissue types to 1. The image used for estimation of the i-th coil sensitivity is given by
$$M_i^{(n)}(\mathbf{r}) = \left(\sum_k \left(\frac{M^{(n,k)}(\mathbf{r})}{\mu_k}\right)\right) R_i(\mathbf{r}) \quad (2)$$
In the absence of noise and the accurate estimation of the masks for each tissue type, the expression in Eq (2) reduces to $S_i(\mathbf{r})$. The magnitude of the coil sensitivity is estimated by fitting the image obtained using Eq (2) to a third degree polynomial as presented in [2].
3. Reconstruction of the composite images using Roemer's Equation: Once the sensitivity maps are found, a new image estimate $I^{(n)}(\mathbf{r})$ is calculated using Roemer's uniform sensitivity/ SENSE equation [1, 3]. If the sensitivity estimates are accurate, then each tissue type in the composite image has uniform intensity throughout the image.
4. Termination of the algorithm: In each iteration, coil sensitivity maps and the image estimate are updated based on the current regions of support. Then the image estimate is used to re-identify the regions of support for the next iteration. This process is repeated untill the tissue regions of support do not change anymore. This would cause the estimated sensitivity map to remain constant yielding the same image estimate. At this point, the algorithm is terminated.

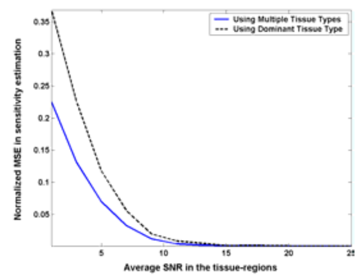

Fig 2. Simulation results showing that the normalized MSE in the sensitivity estimation is improved by utilizing information from multiple tissue types.

Results

The proposed technique was tested on computer generated as well as real MR images acquired on a 1.5 Tesla GE SIGNA Lx 8.4 MR scanner (GE Medical Systems, Waukesha, WI) with NV/CVi gradients and on a 3 Tesla Siemens Trio MR scanner (Siemens Medical Solutions, Erlangen, Germany) with Sonata gradients using standard clinical imaging pulse sequences. A computer model consisting of three different tissue types occupying the image in the ratio 5:3:1 was generated and theortically generated sensitivity map for a rectangular loop from [4] was used for testing the accuracy of the algorithm. As shown in Fig 2, the normalized-MSE is smaller for the sensitivity estimates when multiple tissue types rather than just the dominant tissue are included in the processing. This is because an increased number of data points distributed through the image is used to estimate the parameters of the fit. Fig. 3 demonstrates that carotid and brain MR images reconstructed by the proposed algorithm have uniform intensity (Fig 3(b) and (d)) as opposed to those reconstructed by the SoS algorithm (Fig 3 (a) and (c)).

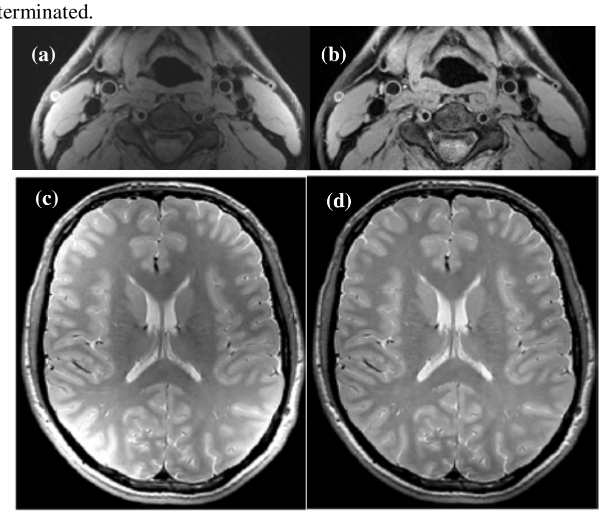

Fig 3. Carotid image and brain images reconstructed using (a,c) SoS algorithm and (b,d) the proposed algorithm respectively.

Discussion and Conclusions

The application of the proposed algorithm to computer generated and real MRI data has demonstrated considerable suppression of intensity inhomogeneity in comparison with the original SoS images. The proposed technique is computationally efficient as well as completely automated. The incorporation of the multi-tissue model makes the technique more robust especially in cases when either the dominant tissue type has localized image support or low SNR.

Acknowledgments:
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References: [1] Roemer PB, et al.; MRM 1990;16:192-225. [2] Vemuri P, et al.; Lecture Notes in Comp. Sci 2005;3565:603-14. [3] Pruessmann K, et al.; MRM 1999;42:952-62. [4] Misakian M; J. Res. Natl. Inst. Stand. Technol 2000;105:557-64.