AUGMENTED JSENSE: FASTER CONVERGENCE AND LESS SENSITIVE TO REGULARIZATION PARAMETER

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TARGET AUDIENCE: Scientists and clinicians interested in highly accelerated MRI.

PURPOSE

Partially parallel imaging (PPI) has been used routinely for many clinical MR applications. SENSE[1,2] is one of the most commonly used methods in PPI, which theoretically can result in the optimal signal-to-noise ratio (SNR). However, the quality of SENSE reconstruction is highly depending on the accuracy of coil sensitivity maps. Several iterative methods, such as JSENSE[3] by Ying et al., IRGN-TV/TGV[4,5] by Uecker et al. and Knoll et al., have been proposed to jointly reconstruct image and estimate sensitivity maps. These prior arts have demonstrated that the accuracy of coil sensitivity maps can be improved iteratively, and hence can improve the quality of SENSE reconstruction. However, these algorithms still suffer two numerical problems. One is the sensitivity to the choice of regularization parameters, and the other is the high computational cost. The target of this work is to tackle these two issues in the existing methods.

METHODS

Without loss of generality, we use IRGN-TV/TGV as basis to explain our method. To improve the robustness, we applied a maximum likelihood estimation (MLE) based method. In IRGN-TV/TGV, there are two terms: the data fidelity term and the regularization term. The proposed method is based on the assumption that, for each *j*th channel, the residues of the data fitting ($MFS_j u - f_j$) in *k*-space in the data fidelity term obey identical and independent Gaussian distribution with mean 0 and variance δ. Here, f_j is the observed partial *k*-space data, S_j the sensitivity map, *F* the Fourier transform and *M* a mask (a binary matrix) presenting the scanned locations in the *k*-space and u is the to-be reconstructed image. The objective function is to maximize the likelihood function, which is the product of the joint probability density for all the channels, $LE(\delta \mid \{S_j u\}_j) = \prod_{j=1}^{K} \left(1/\sqrt{2\pi\delta}\right) \exp\{-\|MFS_j u - f_j\|_\Omega^2 / 2\delta^2\}$, where *K* is the number of channels. We rewrite the likelihood function into an equivalent minimization problem by taking negative-logarithm, which gives us the data fidelity term and the auto-adjusting term. Combined with the regularization term for the underlying image, our proposed model becomes: $\min_{S,u,\delta} \lambda\|u\|_{TV} + \left(1/2\delta^2\right)\sum_{j=1}^{K}\|MFS_j u - f_j\|_2^2 + \left(|\Omega|/2\right)\ln\delta$, named Augmented JSENSE (AJSENSE), where $|\Omega|$ is the area of the domain of each *j*th *k*-space, and the non-negative parameter λ is a scalar for the regularization. Since δ is updated during the iteration of reconstruction, the parameter λ is auto-adjusted. δ is getting smaller with the decreasing of data fitting error. Hence the weights on data fidelity will automatically be emphasized. To reduce the computational cost, we adopted the numerical algorithm in [6]. Introducing auxiliary variables in the model, the original problem is splitted into several easy-and-fast-to-be-solved subproblems.

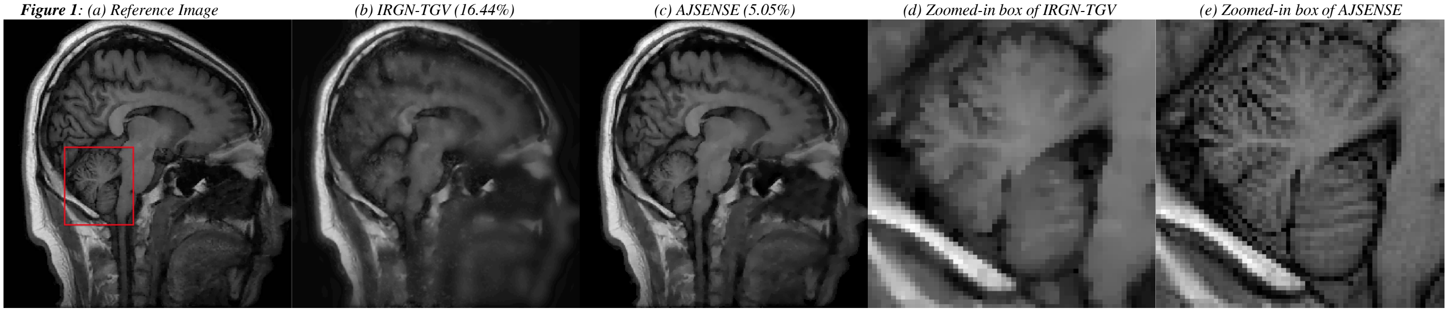

***Figure 1**: (a) Reference Image* *(b) IRGN-TGV (16.44%)* *(c) AJSENSE (5.05%)* *(d) Zoomed-in box of IRGN-TGV* *(e) Zoomed-in box of AJSENSE*

RESULTS

A set of Sagittal brain data was acquired with an 8-channel coil (Invivo Corp., Gainesville, USA). The fully acquired data were artificially down-sampled at net reduction factor 4 using Poisson disk mask. We generated the initial coil sensitivity maps using central 32*32 fully acquired data. The experiments were designed to demonstrate the efficiency, accuracy and robustness of AJSENSE. For comparison, IRGN-TGV was implemented according to [5]. First, in the Figure 1, we show the quality of reconstructions by AJSENSE (Figure 1b, 1d) and IRGN-TGV (Figure 1c, 1e) while the numbers in Figure 1 caption indicating the root-mean-square-error (RMSE) of the reconstructions. As for the CPU time, AJSENSE cost 71.5 seconds but IRGN-TGV consumed 129.3 seconds. Secondly, in the Table 1, we change the parameters for two algorithms in the same ratio, λ from 10^{-5} to 10^{-2} for AJSENSE and β_0 from 0.1 to 100 for IRGN-TGV, to test the robustness to the choice of parameters.

λ		10^{-5}	10^{-4}	10^{-3}	10^{-2}
w/o MLE	SNR	24.41	23.80	21.08	15.52
	RMSE	5.09%	5.31%	7.20%	13.09%
AJSENSE	SNR	24.43	24.43	24.45	24.41
	RMSE	5.07%	5.07%	5.05%	5.09%
$\beta_0 = \lambda \times 10^4$		10^{-1}	1	10	100
IRGN-TGV	SNR	N.C.	N.C.	13.31	12.60
	RMSE	N.C.	N.C.	16.44%	17.83%

***Table 1:** Robustness (N.C.: not convergence)*

DISCUSSION

From the results, it can be seen that the proposed method is not only faster but also more robust than IRGN-TGV. For IRGN-TGV, the result is sensitive to regularization parameter. As shown in Figures 1b and 1d, the reconstructed image by IRGN-TGV is oversmoothed. However, the algorithm was not converged when we decreased the parameters for 10 times to avoid the oversmoothing. On the contrary, the Augmented JSENSE is less sensitive to the initialization of regularization parameter and consistently generated at least comparable results than IRGN-TGV. To test the effect of MLE approach, we ran AJSENSE without MLE. The results in Table 1 show MLE is the crucial factor for robustness. This is because the regularization parameter is automatically adjusted during the iteration.

CONCLUSION

We enhanced joint estimation of coil sensitivity maps and image and result in faster convergence and less sensitive to the selections of regularization parameters.

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