Fast Multicoil Total Variation Reconstruction of Cardiac Perfusion Images

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Introduction: Acquiring good quality dynamic contrast enhanced (DCE) cardiac perfusion images with high spatial and high temporal resolution is a challenge. Undersampling the k-space data helps improve the temporal resolution, but at the cost of loss of spatial resolution. Compressed sensing (CS) [1] based multicoil reconstruction techniques can be used to significantly improve the image quality, though the use of traditional gradient descent based methods often lead to slow reconstruction speeds. In this abstract we develop a multicoil reconstruction method for cardiac perfusion imaging that uses a combination of Split Bregman (SB) [2] and fast iterative shrinkage-thresholding algorithms (FISTA) [3] for faster minimization of the multicoil dynamic reconstruction problem. The method was tested on gated and ungated [4] cardiac perfusion images.

Methods: The multicoil version of spatio-temporal constrained reconstruction (STCR) cost functional is given by

$$\min_m \|\nabla_s m\|_1, \|\nabla_t m\|_1; \; s.t. \sum_{i=1}^{NoCoils} \|EC_i m - d_i\|_2^2 \le \sigma^2 \qquad (1)$$

where E is the encoding matrix that includes the Fourier transform and the sampling operator, C_i is the coil sensitivity for the different coils, d_i the measured k-space data, m is the image being estimated, ∇_s is the spatial gradient operator and ∇_t the temporal gradient operator. μ, λ_1 and λ_2 are weights that control how strongly the differently terms are enforced. Using surrogate variables P_i, S and T to enforce $C_i m = P_i$, $\nabla_s m = S$ and $\nabla_t m = T$ using SB, (1) can be rewritten as

$$\min_{m,P,S,T,\hat{P},\hat{S},\hat{T}} \mu \sum_{i=1}^{NoCoils} \|EP_i - d_i\|_2^2 + \lambda_1\|S\|_1 + \lambda_2\|T\|_1 + \alpha_1 \sum_{i=1}^{NoCoils} \|P_i - C_i m - \hat{P}_i\|_2^2 + \alpha_2\|S - \nabla_s m - \hat{S}\|_2^2 + \alpha_3\|T - \nabla_t m - \hat{T}\|_2^2 \qquad (2)$$

$$d_i^{l+1} = d_i^l + (d_i^0 - EC_i m) \qquad (3)$$

Eqn (3) is the multicoil version of the "adding noise back" step [2]. The variables S and T which act as surrogates for the spatial and temporal gradients respectively can be minimized quickly using the soft thresholding [2]., The surrogate variables can be minimized using a linear update step: $\hat{P}_i^{k+1} = \hat{P}_i^k + (C_i m - P_i^k)$, $\hat{S}_i^{k+1} = \hat{S}_i^k + (\nabla_s m - S_i^k)$ and $\hat{T}_i^{k+1} = \hat{T}_i^k + (\nabla_t m - T_i^k)$. m and P were minimized using the iterative weighting scheme used in FISTA. The method was tested on 30 ray gated radial perfusion data acquired on dogs (acquisition matrix=288×30, 90 time frames) and 24 ray ungated cardiac perfusion data on humans (acquisition matrix=288×24,240 time frames). The data was acquired on a Siemens 3T scanner using a saturation recovery turbo FLASH sequence with TR/TE=2.2/1.2 ms, 10 degree flip angle and 8mm slice thickness. A 32 channel coil array was used to acquire the data and was reduced to 8 coils using PCA based coil compression [5]. The eigen vector method [6] was used to generate the coil sensitivity maps using a reference image that was created by combining the last few frames from the data. For the ungated acquisition, the data was binned into near systolic and near diastolic frames using self-gating [4]. To reduce the effect of motion, coil sensitivity maps were generated for systolic and diastolic frames separately such that systolic and diastolic frames had their own reference image and coil sensitivity map.

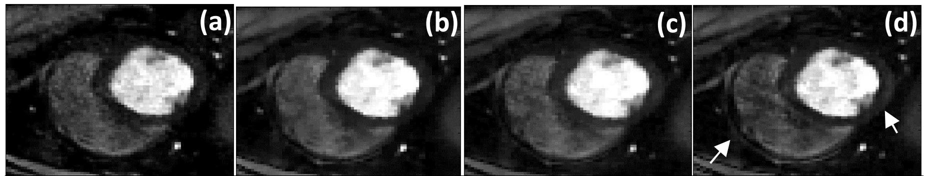

Fig1. Spatio-temporal constraint based reconstructions on 30 ray dog dataset. **(a)** Each coil reconstructed individually and combined using square-root-of-sum-of-squares (SOS), **(b)** multicoil reconstruction (eqn (1)) using gradient descent, **(c)** multicoil reconstruction using the proposed method, without the use of the "adding-noise-back" update step (in eq (2)) and **(d)** multicoil reconstruction using the proposed method, with the use of the "adding-noise-back" update step in eqn (2). The arrow shows regions where the reconstructed image in **(d)** has sharper edges and better contrast.

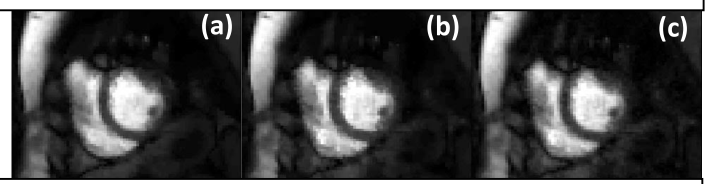

Fig 2. Multicoil spatio-temporal constraint based reconstructions on ungated 24 ray cardiac perfusion dataset. A diastolic frame is shown. **(a)** Reconstruction of the Lagrangian version of eqn(1) using gradient descent, **(b)** multicoil reconstruction using the proposed method, without the use of "adding-noise-back" update step in eqn (3) and **(d)** multicoil reconstruction using the proposed method, with the use of the "adding-noise-back".

Results and Discussion: Our experiments showed that the multicoil images had better image quality than SOS images. An example of a dog dataset is shown in Fig1. The images in Fig1 (b)-(d) have better images quality as compared to the SOS image in Fig 1(a). Between the different multicoil methods, the SB based method that included the "adding noise back" step was able to reconstruct images with sharper edges and better contrast. The white arrow shows regions where the proposed SB based method performs better than SOS images and the multicoil STCR minimized using gradient descent based implementation. Fig 2 shows an example of the multicoil method applied to ungated DCE cardiac perfusion images in a human. A diastolic frame is shown. Overall the image quality of the SB based methods match the gradient descent based implementation, though the edges are slightly sharper in the SB based images. This may be due to the fact that gradient descent based implementation approximates the L_1 norm by adding a small positive constant to avoid singularities while the SB based implementations use soft thresholding to minimize the L_1 norm. The Augmented Lagrangian (AL) based method [7] developed for multicoil imaging uses only spatial constraints and has not been tested on dynamic data. Addition of temporal constraints make the transfer function more ill conditioned. The method developed here for DCE MRI is promising and helped achieve faster reconstructions, with a speedup of ~2.3 compared to gradient descent reconstructions.

Reference:[1] D.L. Donoho,"Compressed Sensing" ITIT 2006. [2] T. Goldstein et al,"The Split Bregman method for L_1-regularized problems" Siam J. Img Sci 2009. [3] A. Beck et al,"A fast iterative shrinkage-thresholding algorithm for linear inverse problems" Siam J. Imag Sci 2009. [4] A. Harrison et al,"Rapid ungated myocardial perfusion cardiovascular magnetic resonance: preliminary diagnostic accuracy" JCMR 2013. [5] T. Zhang et al,"Coil compression for accelerated imaging with Cartesian sampling" MRM 2013. [6] D.O. Walsh et al,"Adaptive reconstruction of phased array MR imagery" MRM 2000.[7] S. Ramani et al,"Parallel MR image reconstruction using Augmented Lagrangian methods" ITMI 2011.