Model-based compressed sensing method using weighted data consistency coeffcient

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Introduction

Multiple contrast MR images and their acquisitions are gaining high interest for in-depth diagnosis, MR parameter mapping, musculoskeletal imaging, quantification of water and myelin contents, and high-quality venography [1]. However, the acquisition of multi-contrast images usually takes a long scan time, which makes it difficult to apply to clinical settings. Along with several fast imaging techniques, compressed sensing (CS) techniques have been developed to reduce acquisition time via undersampling schemes, which use sparse characteristics of MR image for reconstruction. However, conventional CS methods are still limited to moderate levels of undersampling, such as reduction factors of 2 or 4 [2]. This abstract proposes a model-based compressed sensing technique with an incorporation of weighted data consistency coefficients,that can make it applicable to the reduction factors up to 8 or higher.

Methods

We proposed model-based CS reconstruction method with weighted data consistency coefficients, that incorporates CS and iterative fitting which is least square method based on Bloch MR model, such as mono exponential decay in case of T2(*) multi contrast images. Multi-contrast images consist of M multiple images $\boldsymbol{x_m}$ where *m*=1,…,M.

Model-based compressed sensing using weighted data consistency (iterative processing)

Parameter and data :

$\boldsymbol{y}$: k-space measurements from scanner (Measure data from scanner)

$\boldsymbol{\tilde{y}}$: k-space measurements of each iterative step which has non-sampling pattern

$\boldsymbol{x}$: reconstruction multi-contrast images using model-based CS

$\boldsymbol{\mathcal{F}_u}$: under-sampled Fourier transform operator which has sampling k-space pattern in scanner

$\boldsymbol{\widetilde{\mathcal{F}_u}}$: under-sampled Fourier transform operator which has non-sampling pattern in scanner

At first, fitting algorithm is performed to reduce first acquired under-sampling images ($\boldsymbol{x^0}$ **:** initial multi-contrast image) that is multi measurements imaging to exponential decay model using least square algorithm.

For $\boldsymbol{i^{th}}$ iteration

1. find $\boldsymbol{x_m}^{\boldsymbol{i}}$ using weighted data consistency for m= 1,…,*M*

$$\min_{x_m^i} \|\boldsymbol{\mathcal{F}_u x_m}^{\boldsymbol{i}} - \boldsymbol{y}\|_2 + w\left\|\boldsymbol{\widetilde{\mathcal{F}_u} x_m}^{\boldsymbol{i}} - \boldsymbol{\widetilde{y^{i-1}}}\right\|_2 + \lambda\|\psi \boldsymbol{x_m}^{\boldsymbol{i}}\|_1$$

2. ith acquired data at non-sampling pattern in k-space image $\boldsymbol{\tilde{y}^i} = \boldsymbol{\widetilde{\mathcal{F}_u} x_m}^{\boldsymbol{i}}$
3. After CS, multi-contrast image of each measurements $\boldsymbol{\widetilde{x_m}^i} = \boldsymbol{F^{-1}}(\boldsymbol{y} + \boldsymbol{\tilde{y}^i})$, $\boldsymbol{F^{-1}}$ is inverse Fourier operator
4. Final image series $\boldsymbol{x^i}$ are acquired by fitting $\boldsymbol{\tilde{x}^i}$ to bloch MR model (in case of T2 weighted images, that is mono-exponential decay)

Result :

Acquired multi contrast images (multi T2(*) contrast images)

Briefly, model-based fitting (least square method) is first performed. Next, compressed sensing with weighted data consistency is proceeds. Finally, acquiring data from this algorithm and measured data is combined in cartesian k-domain and this process is repeated. The introduction of the weighted data consistency term stabilizes the overall CS reconstruction leading to reduction of the aliasing artifacts. Non-linear complex conjugate gradient method is used for minimization of L1 in CS [2]. Optimal weighting factor w in data consistency is decided through simulation experiment. The goal of this algorithm is to obtain full sampling multi-contrast image. This algorithm can process compressed sensing, using model-based fitted images as well as true scanner data with weighted data consistency coefficient. For in vivo and brain experiments, normal person was scanned with a multi gradient echo (MGRE) sequence imaging using a 3T Siemens MRI system (Erlangen, Germany). Matrix resolution is 256x256 and echo number is 64. For under-sampling experiments, we make sampling pattern and mask and this is used to full-sampling T2(*) weighted data. Under-sampling patterns are random and different between multiple contrast images. All processing were performed using MATLAB (The MathWorks.Inc. Natick, MA).

Results

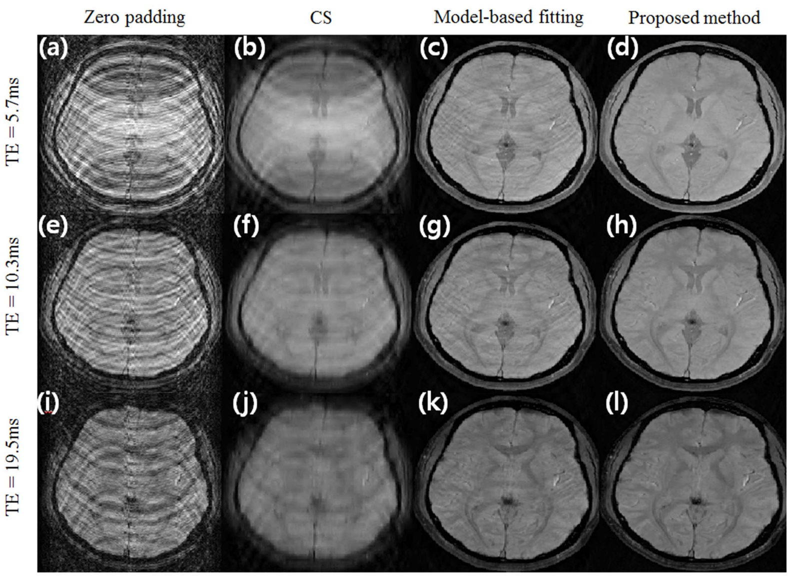

Fig 1. Reduction factor is 8. Comparison with zero padding, CS, Model-based fitting and proposed method in T2* multi contrast images. (a)~(d) are 5th echo images, (e)~(h) are 10th echo images, and (i)~(l) are 20th echo images (a),(e),(i) are under-sampled image using zero padding, (b), (f), (j) are compressed sensing result [2], (c),(g),(k) are model-based T2(*) fitting image and (d), (h), (i) are result of proposed method.

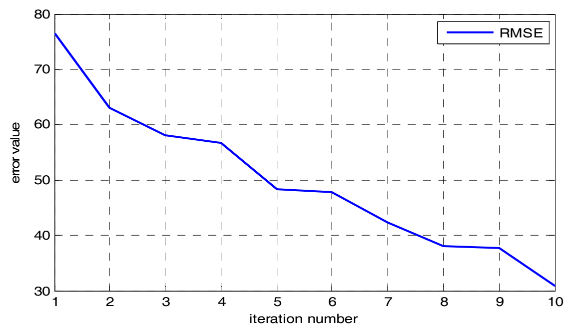

Fig 2. RMSE of each iteration result between reconstruction image and full-sampling image in 10th echo image

Fig 1 shows that proposed method has lower aliasing artifact than other method. Especially, result of CS has very blur effect due to very low scanned data. But because of using model-based information, proposed method shows detailed tissue information. Fitting result is good in late echo images but there is a little aliasing effect, compared with model-based result.

Fig 2 shows that RMSE which is acquired by comparing full-sampling and proposed method result in 10th echo image is reduced as the iterative algorithm repeated.

Conclusion This paper demonstrates model-based iterative CS method for under-sampled Cartesian trajectory acquisition for multi-contrast images such as T2(*) weighted images. By studying this research of the proposed method, Multi-contrast images which rarely have aliasing pattern are reconstructed to full-sampling. This technique is possible to use diffusion tensor imaging, dynamic MR imaging and steady-state free precession such as magnetic resonance fingerprinting [4] and other model-based multi-contrast imaging field for fast acquisition.

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