Iterative Compressed Sensing Reconstruction Using Forward Model Based on MR Multi-Parameter

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Introduction

Magnetic resonance fingerprinting (MRF) is a method that can quantitatively estimate MR parameters such as T1, T2, T2*, etc of specific tissues, by matching pattern of signal evolution obtained from the scanner with the pattern of signal evolution that is generated from MR forward modelling (dictionaries) [1]. For fast MRF method in [1], multiple images with different TR and FA were obtained using IR-bssfp sequence with variable density spiral (VDS) trajectory. However, VDS trajectory is not robust to implement depending on MR systems, especially for clinical settings. Furthermore, application to high-resolution images may be limited due to its long readout. Therefore, the well-accepted Cartesian trajectory needs to be considered for robust implementation of MRF. However, it is difficult to accelerate the acquisition time using the similar undersampling scheme to VDS when Cartesian trajectory is used for MRF because the general limit of the reduction factor in Cartesian undersampling is known to be up to 5. In this study, efficient iterative compressed sensing (CS) reconstruction method is proposed to highly accelerate the Cartesian-trajectory based acquisition for MRF, leading to the reduction factor up to 16.

Methods

We proposed an iterative CS reconstruction method that incorporates iterative matching procedure between the CS reconstructed signal evolution and the forward-modelled signal evolution (dictionaries) which can effectively estimate the missing k-space data through iterations. Similar work can be found in [3], albeit forward modelling and matching approaches are different. The proposed method can be explained as follows: the acquired data from scanner is $\boldsymbol{y}$ in *k*-space, and the reconstruction data using iterative matching is $\boldsymbol{x}$. They consist of M multiple images $\boldsymbol{x_m}$ where m=1,…,M and each image of $\boldsymbol{x}$ and $\boldsymbol{y}$ consists of N voxels, where n=1,…,N, and the dictionary consists of L forward-modelled signal evolutions, where l=1,…,L.

Iterative Compressed Sensing Algorithm For MRF

Parameter and data :

- $\boldsymbol{y}$: k-space measurements of each iterative step
- $\boldsymbol{x}$: reconstruction data using iterative algorithm
- $\boldsymbol{\mathcal{F}_u}$: undersampled Fourier transform operator
- $\boldsymbol{D}$: dictionary data consisting of forward modeling
- $\boldsymbol{A}\cdot\boldsymbol{B} = \frac{\sum_i a_i b_i}{\sum_i a_i \sum_i b_i}$: inner product for pattern matching

Initial Condition : $\boldsymbol{y^0} = \boldsymbol{y}, \boldsymbol{x^0} = \boldsymbol{x}$

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

1. $\boldsymbol{x_m} = \boldsymbol{\mathcal{F}_u^{-1} y_m}$ for m= 1,…,M
2. Find maximum coefficient of $\boldsymbol{x_n}\cdot\boldsymbol{D_l}$, for n = 1,…,N and l = 1,…,L
3. New reconstruction data $\boldsymbol{x_n} = \boldsymbol{D_l}$ for l is index of maximum coefficient of forward modeling
4. $\boldsymbol{y'_m} = \boldsymbol{\mathcal{F}_u x_m}$ for non-sampled phase-encoding line of $\boldsymbol{y^0}$.
5. $\boldsymbol{y_m} = \boldsymbol{y^0} + \boldsymbol{y'_m}$ for m= 1,…,M

Result :

Acquire multi-parameter map(T1, T2. ∆B map) corresponding to last iterative maximum dictionary

The goal is the quantitative estimate of multi-parameter map (T1, T2. ∆B map) and the result gets improved as the iteration number increases. Furthermore, we incorporated into the proposed iterative CS method, additional polynomial fitting process to increase the accuracy of ∆B map considering the smooth variation of ∆B over space.

For simulation data 1, piece-wise flat MR parameter maps based on actual 1.5T MR scanner were used. The synthetic MR data consists of white matter(WM), gray matter(GM) and cerebrospinal fluid(CSF), and matrix resolution=128x128 and the number of images = 1000 with different flip angles and repetition time. For simulation data 2, multiple images based on 3T MRI scanner were generated. Unlike simulation data 1, simulation data 2 consists of more realistic distribution of MR tissue parameters. Both synthetic data have undersampled pattern with reduction factor 8 and 16. Dictionary was generated on the basis of the Bloch-equation with T1, T2, ∆B parameter and the number of forward modeling was 563,784 used to perform multi-parameter matching. All processing were performed using MATLAB (The MathWorks.Inc. Natick, MA).

Results

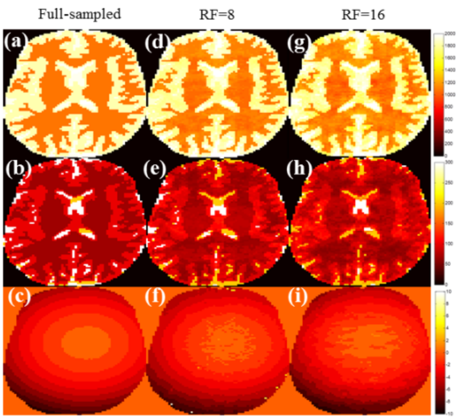

Fig 1. Parameter map image for simulation data 1 using iterative CS algorithm. Parameter map for full-sampled data T1 map (a), T2 map (b) and ∆B map (c). Parameter map for RF=8 and Iteration 8, T1 map (d), T2 map (e) and ∆B map (f). Parameter map for RF =16 and Iteration 8, T1 map (g), T2 map (h), ∆B map (i)

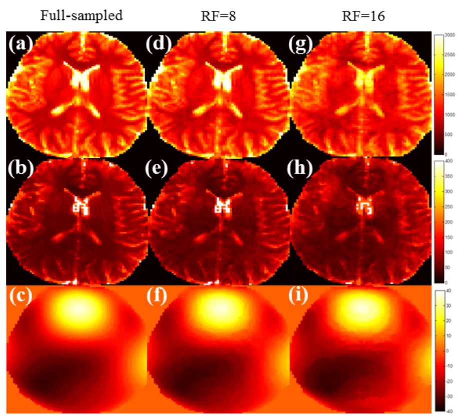

Fig 2. Parameter map image for simulation data 2 using iterative CS algorithm. Parameter map for full-sampled data T1 map (a), T2 map (b) and ∆B map (c). Parameter map for RF=8 and Iteration 8, T1 map (d), T2 map (e) and ∆B map (f). Parameter map for RF =16 and Iteration 8, T1 map (g), T2 map (h), ∆B map (i)

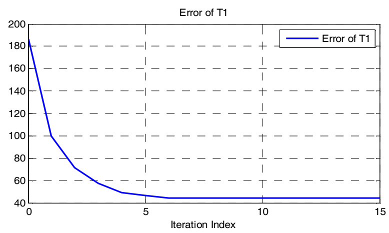

Fig 3. RMSE of T1 with iteration numbers

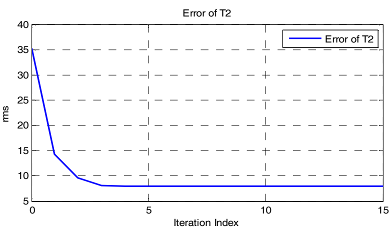

Fig 4. RMSE of T2 with iteration numbers

Fig 1 shows iterative CS algorithm results from the simulation data 1 with 8 iterations. (a)-(c) are the parameter maps obtained from the full sampled data, (d)-(f) from the undersampled data with reduction factor of 8, and (g)-(i) with reduction factor of 16. In case of reduction factor of 8, T1 and T2 maps are almost the same as the full-sampled ones with a slight increase of noise. Even with the very high reduction factor of 16, reasonable parameter maps were obtained (g-i). The structures of WM, GM and CSF remain clear. Fig 2 shows iterative CS algorithm results from the simulation data 2 with 8 iterations. (a)-(c) are the parameter maps from the full sampled data, (d)-(f) with reduction factor of 8 and (g)-(i) with reduction factor of 16. Similar results were obtained for these realistic distribution of the parameter maps. Figure 3 and 4 show that the error of T1 and T2 estimation decreases as the iteration number increases.

Conclusion This study demonstrates the feasibility of the proposed iterative CS method for highly undersampled Cartesian trajectory acquisition for MRF. With the current implementation of the proposed method, the undersampling scheme is possible up to the reduction factor of 16, which will increase the robustness in the application of MRF to the current clinical settings with Cartesian trajectory acquisition.

Acknowledgement

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Reference
[1] MA, Dan, et al. *Nature*, 2013, 495.7440: 187-192. [2] Lustig, Michael, David Donoho, and John M. Pauly. *Magnetic resonance in medicine* 58.6 (2007): 1182-1195. [3] Doneva, Mariya, et al. *Magnetic Resonance in Medicine* 64.4 (2010): 1114-1120.