In vivo accelerated MR parameter mapping using annihilating filter-based low rank Hankel matrix (ALOHA)

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Synopsis

The purpose of this study is to develop an accelerated MR parameter mapping technique. For accelerated T1 and T2 mapping, spin-echo inversion recovery and multi-echo spin echo pulse sequences were redesigned to perform undersampling along phase encoding direction. The highly missing k-space were then interpolated by using recently proposed annihilating filter based low-rank Hankel matrix approach (ALOHA). By exploiting the duality between the transform domain sparsity and the low-rankness of weighted Hankel structured matrix in k-space, ALOHA provided outperforming reconstruction results compared to the existing compressed sensing methods.

Introduction

MR parameter mapping (MRPM) is one of the valuable imaging techniques as a quantitative diagnosis tool for various pathologies[1]. However, standard MRPM techniques usually need long scan time caused by its need of additional information along parametric dimension such as echo time (TE), inversion time (TI), flip angle, etc. Thus, this abstract aims to reduce the prolonged scan time of T_1 and T_2 parameter mapping. Toward this goal, we modified the spin echo inversion recovery (SE-IR) sequence for T_1 mapping and multi-echo spin echo (ME-SE) sequence for T_2 mapping to perform undersampling. Then, we used ALOHA (Annihilating filter based LOw-rank Hankel matrix Approach)[2,3] to reconstruct the undersampled T_1 and T_2 mapping data.

ALOHA is a general framework which unifies parallel MRI and compressed sensing MRI as a weighted k-space interpolation problem. ALOHA utilizes the fundamental duality between spatial and Fourier domain, i.e. K-sparse signal in transform domain can be represented in K-ranked weighted Hankel structured matrix in Fourier domain[2]. Even though the images are not sparse, as long as it can be more sparsified by sparsifying transform such as wavelet transform, ALOHA can be used by constructing weighted Hankel matrix. And a multi-coil extension can be easily derived by stacking the Hankel structured matrix side by side. Therefore, the missing k-space can be reconstructed with the help of low rank matrix completion and inverse weighting step as shown in Fig.1(a).

Material and Methods

To apply ALOHA for parameter mapping, the property of a dynamic parameter images and its relationship with ALOHA should be further investigated. MRPM data have concentrated spectrum at the low frequency regions. It means that MRPM data can be sparsified by using spatial wavelet transform and temporal Fourier transform. This results in rank-deficient weighted Hankel structured matrix in k-t space. To reconstruct the missing k-t space, ALOHA constructs a Hankel matrix using weighted k-t space data and solves a low rank Hankel structured matrix completion problem as a following nuclear norm minimization:

$$\min \| [H(X_1) H(X_2) \ldots H(X_{N_{coil}})] \| \quad \text{subject to} \quad P_\Omega(X) = P_\Omega(\Theta)$$

where X_i denotes weighted k-t space measurement from the i-th coil, P_Ω is an indicator function which projects original k-t space measurements, Θ. The problem is solved using ADMM(Alternating Direction Method of Multiplier)[2,3]. Thanks to the wavelet weighting, the low rank matrix completion problem is solved using pyramidal decomposition in Fig.1(b). This provides faster convergence and noise robust reconstruction.

For T_1 and T_2 mapping, 2D SE-IR and ME-SE sequences were accelerated by undersampling schemes. The phase encoding gradients are controlled to perform the undersampling along phase encoding direction according to Gaussian distribution. Human brain scans in Cartesian coordinate were performed using a 3T MR scanner Siemens Verio. Here are the scan parameters; TR 1650ms, 128x128 matrix, 5mm slice thickness, 4 coils, TE 10ms, TIs 25ms to 1600ms with linearly increasing echo spacing(ESP) for SE-IR sequence, TR 3000ms, 256x256 matrix, 2mm slice thickness, 4 coils, 32 TEs from 10ms to 320ms with 10ms ESP for ME-SE sequence. The T1 and T2 map are fitted by the relaxation($SI=SI_0[1-2e^{-TI/T_1}-e^{-TR/T_1}]$) and decay model($SI=SI_0e^{-t/T_2}$), respectively. SE-IR scan was 8 times undersampled and ME-SE scan was 12.8 times undersampled for acceleration. The ALOHA reconstruction results from the accelerated data were compared with various algorithms, k-t FOCUSS[4], k-t SPARSE[5], patch-based low rank algorithm[6], k-t SLR[7] and C-based LORAKS[8].

Results and Discussion

The SE-IR/ME-SE images and T_1/T_2 maps were reconstructed from real in vivo accelerated data(Fig.2-3). The scan times were reduced from 42min 15sec to 5min 17sec for T_1 mapping and 12min 48sec to 1min for T_2 mapping. Among the various reconstruction, ALOHA shows best reconstruction results as shown in Fig.2-3 and the NMSE values. Also in the quantitative evaluation using retrospective downsampling(Fig.4), both T_1 and T_2 curves from ALOHA were very close to the curves from ground truth. C-based LORAKS is somewhat similar to ALOHA, but provided the inferior reconstruction. The main improvement of ALOHA over C-based LORAKS is that ALOHA utilizes wavelet transform and the pyramidal reconstruction to exploit the transform domain sparsity, whereas C-based LORAKS exploits the finite support condition. Wavelet transform makes the images more sparse and the pyramidal decomposition provides noise robust reconstruction, which made ALOHA outperform the existing approaches.

Conclusion

Acceleration of MRPM is important not only for the convenience of patients but also for clinical image quality. In this study, SE-IR and ME-SE sequences were redesigned for acceleration up to $\times 8$ and $\times 12.8$, respectively. The proposed ALOHA reconstruction still provided accurate reconstruction with excellent time-intensity plots that were as comparable as fully sampled data.

Acknowledgements

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Figures

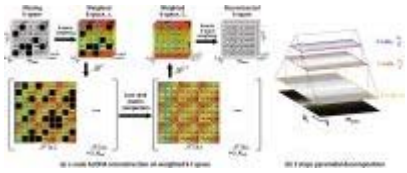

Fig.1 (a) s-scale ALOHA reconstruction on weighted k-t space. $\mathcal{H}^{\dagger}$ represents pseudo-inverse mapping from Hankel structure to original k-t space. (b) 3 steps pyramidal decomposition of k-t space.

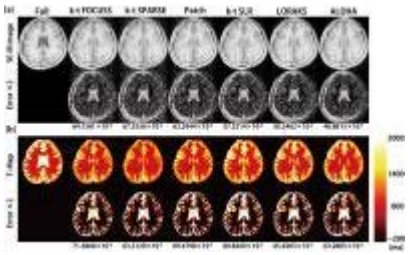

Fig.2 Reconstruction results of in vivo undersampled data for (a) SE-IR images(N_{echo}=9th) and (b) T_1 maps. The 8 times accelerated data were reconstructed using k-t FOCUSS, k-t SPARSE, Patch based low rank algorithm, k-t SLR, C-based LORAKS and ALOHA. The differences are placed under each reconstructed images with NMSE values.

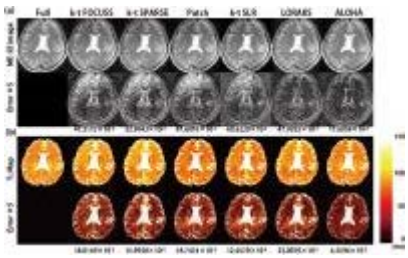

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Fig.3 Reconstruction results of in vivo undersampled data for (a) ME-SE images(N_{echo}=7) and (b) T_2 maps. The 12.8 times accelerated data were reconstructed using k-t FOCUSS, k-t SPARSE, Patch based low rank algorithm, k-t SLR, C-based LORAKS and ALOHA. The differences are placed under each reconstructed images with NMSE values.

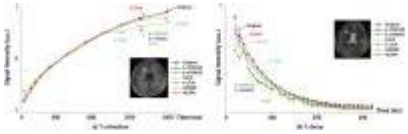

Fig.4 Signal intensity curves of (a) T_1 and (b) T_2 images from 8 times and 12.8 times retrospectively downsampled data, respectively. The signal intensities were calculated as the average of the voxels in each ROI (yellow circle).

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