k-t CaLM: CALIBRATION-LESS MULTI-COIL DYNAMIC MRI RECONSTRUCTION

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INTRODUCTION

In this work we address the problem of reconstructing dynamic MRI sequence acquired by parallel partial imaging. The receiver coils have different sensitivity profiles based on their field-of-view (FOV). Mathematically, the joint estimation of sensitivity profiles and MR image poses to be a bi-linear non-convex optimization problem, which cannot be solved perfectly. Researchers estimate the sensitivity maps (for SENSE/SMASH like methods) or its associated interpolation weights (for GRAPPA like methods) through calibration scans (time-consuming) or from the ACS lines (sensitive to calibration parameters and are error-prone).

In this work, we propose to reconstruct the dynamic MRI sequence in an offline fashion that would not require any explicit (sensitivity maps) or implicit (interpolation weights) estimation of the sensitivity profiles.

THEORY

The data acquisition model for multi-coil dynamic MRI can be expressed as $y_{c,t} = R_t F_{2D} x_{S_c t} + \eta_t$ where c denotes the c^{th} receiver channel (C in all), t denotes the t^{th} time frame (T in all). Here $y_{c,t}$ denotes the K-space data for c^{th} frame at the t^{th} instant, R_t is the sub-sampling mask, F_{2D} is the Fourier transform from the image domain to the K-space, $x_{S_c t}$ is the sensitivity encoded image from the c^{th} coil at the t^{th} instant and $\eta_t \sim N(0, \sigma^2)$ is the noise. This can be expressed as multiple measurement vector (MMV) notation as $Y_t = R_t F_{2D} X_t + \eta$ where $Y_t = \left[y_{1,t} | ... | y_{C,t} \right]$, $X_t = \left[x_{S_1,t} | ... | x_{S_C,t} \right]$ and similarly for η. We can combine the equations for all the time instants as $Y = RFX + \eta$, where Y and X consists of Y_t's and X_t's stacked vertically, R is a block diagonal matrix comprising of the R_t's along the diagonal and F is a block diagonal matrix consisting of F_{2D} in each diagonal block..

The problem is to solve X. Since it is an under-determined inverse problem, we use Compressed Sensing techniques to solve it. Following previous studies in dynamic MRI [1, 2], wavelet transform is used to sparsify the image in the spatial direction and Fourier transform is used to sparsify the image in the temporal direction.

Wavelet transform encodes the discontinuity (edges) in images, i.e. the transform coefficients are high valued where there are edges and are zeros in smooth areas. In this work, we assume that the sensitivity profiles are smooth. This assumption has been used implicitly by all previous works in parallel MRI reconstruction. The individual coil images (for the t^{th} frame) when encoded by the sensitivity maps, do not change the position of the edges. Thus, the wavelet transform coefficients of the different sensitivity encoded images (for a given time frame) will have high valued coefficients at the same locations. In other words, the wavelet transform coefficients for each X_t will be row-sparse.

The reconstruction problem is solved by $\min_X \|X\|_{2,1}$ subject to $\|Y - RFSX\|_F^2 \le C \cdot T \cdot n \cdot \sigma^2$, where n is the number of pixels in the image. Here $\|Z\|_{2,1} = \sum_{j=1}^{n} \|Z^{j\rightarrow}\|_2$ ($Z^{j\rightarrow}$ is the vector whose entries form the j^{th} row of Z).This is an offline technique. The image for each time frame is obtained by sum-of-sqaures reconstruction of all the coil images corresponding to that instant.

METHOD

The data for the Larynx, Cardiac and Vocal Tract datasets were collected using single channel MRI scanner from which the multi-channel data was simulated using the B1 simulator. Owing to limitations in space, we are unable to discuss the data acquisition in detail. The ground-truth datasets comprised of fully sampled K-space. Partial sampling was simulated by Variable Density (VD) random sampling on the Cartesian grid. 33% of the total samples were used for densely sampling the center of the K-space while the remaining were randomly distributed across rest of the K-space. A net acceleration factor of 4 was used for all the datasets.

RESULTS

In this study, our proposed method is compared against k-t FOCUSS [3] and k-t GRAPPA [4]. The reconstruction accuracy is measured in terms of Relative Mean Squared Error (RMSE) (Table 1). Also reconstructed and difference images are shown for qualitative evaluation. The difference images are magnified 5 times for clarity.

Table 1. RMSE's from different Methods

Dataset	k-t FOCUSS	k-t GRAPPA	Proposed
Larynx	0.04	0.06	0.05
Cardiac	0.05	0.06	0.06
Vocal Tract	0.22	0.24	0.18

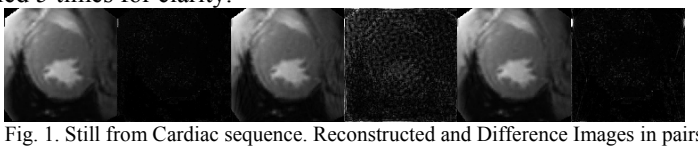

Fig. 1. Still from Cardiac sequence. Reconstructed and Difference Images in pairs. L-R: k-t FOCUSS, k-t GRAPPA and k-t CAlM

CONCLUSIONS

Quantitatively our method gives similar reconstruction accuracy as k-t FOCUSS and k-t GRAPPA. But by visual evaluation it can be discerned that k-t CAlM and k-t FOCUSS yields accurate reconstruction (difference image is almost dark) but k-t GRAPPA shows severe reconstruction artifacts. The main purpose of this work is to show that we are able to get reconstruction accuracy comparable to state-of-the-art methods without estimating the sensitivity maps.

REFERENCES

[1] Gamper U, et al, MRM 59:365 - 373, 2008. [2] Lustig M, et al, ISMRM 2006. [3] Jung H, et al, MRM 61: 103-116, 2009. [4] Huang F, et al, MRM 54: 1172-84, 2005.