Improving ktSENSE by Adaptively Selecting the Regularization Image

D. Xu[1], K. F. King[2], Z-P. Liang[1]

[1]Department of Electrical and Computer Engineering, University of Illinois at Urbana-Champaign, Urbana, IL, United States, [2]General Electric Healthcare, Milwaukee, WI, United States

INTRODUCTION

An effective strategy to improve temporal resolution for dynamic imaging is to sparsely sample k-space for each temporal data frame. Many methods have been proposed to implement this strategy, among which ktSENSE [1] is perhaps the most popular and has produced very encouraging results with a factor of 5-8 improvement in temporal resolution. However, ktSENSE uses the temporal average (DC) term of the collected data for regularizing image reconstruction, which can significantly decrease the temporal resolution of the resulting image sequence. In this paper, we propose a new method to derive the regularization term (adaptively chosen for each time point) for ktSENSE so as to further improve spatiotemporal resolution of the resulting images.

PROPOSED METHOD

The basic idea of the proposed method is to use the generalized series model (often known as RIGR [2] (reduced-encoding by generalized series reconstruction)) to reconstruct a high-resolution regularization image for ktSENSE. The regularization image is updated at each time point using a few central k-space points (described below in the Data Acquisition section). The method requires collecting some extra phase encoding lines in the first and last temporal frames, which is feasible in various dynamic imaging applications.

A. Data Acquisition

The proposed method uses a variable-density (VD), sequentially-interleaved sampling pattern with reference data, as illustrated in Fig. 1. Specifically, the first and last temporal frames are collected with full samples (or a small reduction factor to ensure high-quality SENSE reconstruction). For all other temporal frames, VD sampling is used, where the center k-space region is sampled at the Nyquist rate, while the outer portion is sampled with a factor *R* below the Nyquist rate (*R* is often called the outer reduction factor). Outer phase encodings are sequentially interleaved by starting with the ith phase encode, i = 1,2,…*R*. Compared to the ktSENSE sampling pattern, the training stage is integrated into the data collection process, therefore eliminating potential misregistration problem with a minimum increase of data collection time.

B. Image Reconstruction

The acquired data are decomposed into three subsets (as shown in Fig. 1) for different purposes in image reconstruction: a) the undersampled dynamic data at sequentially interleaved locations in k-t space (d_U) are used for unaliasing in the y-f domain, b) two fully sampled reference data sets and the central dynamic encodings (d_R) are used for RIGR reconstruction ($\boldsymbol{\rho}_{RIGR}$), and c) the center dynamic encodings (d_T) are used as training data to estimate the energy distribution of the reconstruction (**E**). Let **S** denote the coil sensitivity matrix, $\boldsymbol{\Psi}$ denote the noise correlation matrix, and $\boldsymbol{\rho}_{alias}$ denote the vector that groups the aliased intensities (sensitivity weighted) from all coils (because of undersampling), the entire reconstruction process can be summarized as (in a similar fashion as ktSENSE)

$$\boldsymbol{\rho} = \boldsymbol{\rho}_{\text{RIGR}} + \left(\mathbf{S}^{\text{H}}\boldsymbol{\Psi}^{-1}\mathbf{S} + \mathbf{E}^{-2}\right)^{-1}\mathbf{S}^{\text{H}}\boldsymbol{\Psi}^{-1}\left(\boldsymbol{\rho}_{\text{alias}} - \mathbf{S}\boldsymbol{\rho}_{\text{RIGR}}\right). \qquad (1)$$

RESULTS

Peripheral-gated breathhold cardiac imaging experiments were conducted on a healthy volunteer on a GE Signa EXCITE 1.5 T scanner with eight-channel cardiac array coils. A FIESTA sequence was used to acquire a full data set of short-axis images. The data were then decimated to the desired sampling pattern, which were postprocessed using various reconstruction methods implemented in MATLAB (the Mathworks, Natick, MA). As shown in Fig. 2, SENSE [3] has low SNR due to ill-conditioning. The SNR of UNFOLD-SENSE [4] is significantly improved over SENSE, but image artifacts are still noticeable, which are mainly due to improper filtering. The image from ktSENSE has high SNR, but a lower temporal resolution than the true images; this is shown as edge-like artifacts. The proposed method has the highest temporal resolution and minimum image artifacts. We also plotted the average intensity curve over time of a 3 by 3 window in the region-of-interest (location shown in the SENSE reconstruction). Again, the proposed method is able to track rapid changes and has the least error as compared to ktSENSE and UNFOLD-SENSE.

CONCLUSION

The paper presents an improvement to ktSENSE for high-resolution dynamic imaging. Compared to ktSENSE, the proposed method has higher temporal resolution and less image artifacts.

REFERENCES

[1] J. Tsao et al., *MRM*, vol. 50, pp.1031-1042, 2003.
[2] Z.-P. Liang et al., *IEEE-TMI*, vol. 13, pp.677-686, 1994.
[3] K. P. Pruessmann et al., *MRM*, vol. 42, pp. 952-962, 1999.
[4] B. Madore et al., *MRM*, vol. 52, pp. 310-320, 2004.

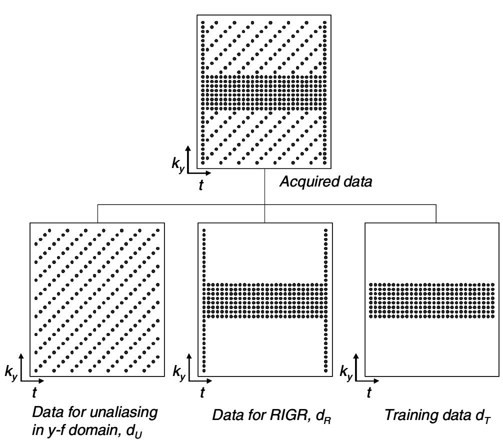

Fig. 1. Data acquisition scheme of the proposed method. The acquired data are divided into three subsets for different purposes in image reconstruction.

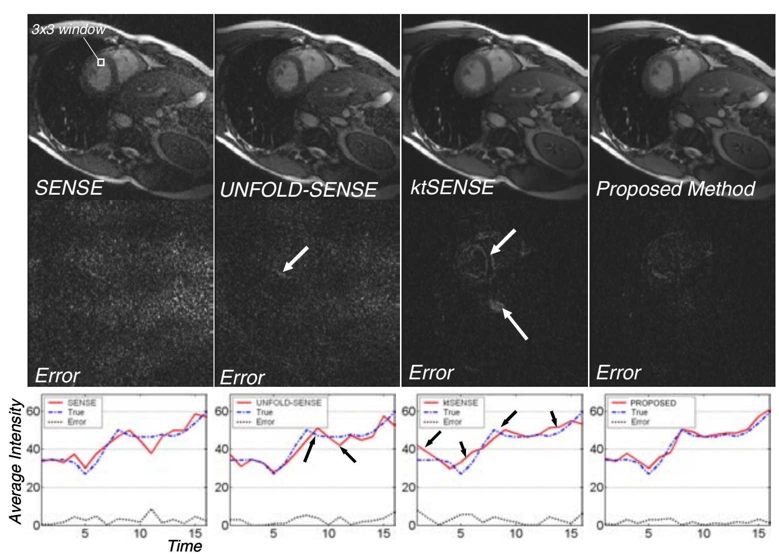

Fig. 2. Reconstructions by various methods at 4x speedup using volunteer data acquired with an 8-channel cardiac coil. For UNFOLD-SENSE, ktSENSE and the proposed method, 16 center PEs are used. Error images are also displayed and scaled to a quarter of the maximum intensity of the true image to reveal details.