Optimizing SENSE for Dynamic Imaging

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INTRODUCTION

Although parallel imaging, such as SMASH [1] and SENSE [2], has been widely used in various MRI applications, these techniques have not yet been fully optimized to achieve the maximum speed enhancement for dynamic imaging applications. For a receiver system with L channels, the maximum acceleration factor R is L. However, when R approaches L, the SENSE model matrix can become very ill-conditioned, resulting in significant image artifacts. This paper addresses two key issues in SENSE dynamic imaging: (a) optimal k-space sampling, and (b) regularization, by exploiting the inherent structure of various dynamic imaging problems.

PROPOSED METHOD

A. Data Acquisition

The data acquisition scheme of the proposed method is depicted in Fig. 1, which collects one reference data set and a series of reduced dynamic data sets at each receiver channel. The reference data are collected at the Nyquist rate, while variable-density sampling of k-space is used for collecting the dynamic data sets. Specifically, about 8 phase encodings are collected at the center of k-space at the Nyquist rate, while the outer region of k-space is sampled well below the Nyquist rate where the M phase encoding lines are pre-determined using an optimization algorithm that minimizes the following sum-of-squared error (SSE) of the reconstructed image:

$$E\left(\left\|\boldsymbol{\rho}-\boldsymbol{\rho}_{\mathrm{rec}}\right\|^2\right)=\mathrm{trace}\left(\left(\tilde{\mathbf{S}}^{\mathrm{H}}\boldsymbol{\Psi}^{-1}\tilde{\mathbf{S}}+\lambda^2\mathbf{I}\right)^{-1}\right) \qquad (1)$$

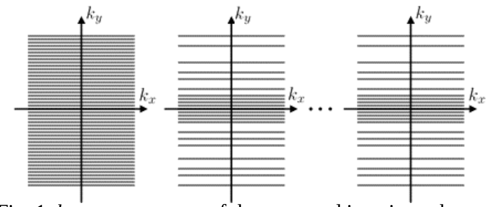

Fig. 1. k-space coverage of the proposed imaging scheme. One high-resolution reference data set is first obtained at each receiver channel, followed by a sequence of reduced dynamic data sets, where the central part of the k-space is sampled at Nyquist rate, and the rest of the k-space is sampled at optimized phase encoding locations.

In Eq. (1), $\boldsymbol{\rho}$ is the vectorized image, $\tilde{\mathbf{S}}$ is obtained by choosing LMN rows (for an $N\times N$ image) of the sensitivity profile matrix $\mathbf{S}$ that corresponds to full encodings, $\boldsymbol{\rho}_{\mathrm{rec}}$ is the vectorized reconstruction using Tikhonov regularization, to be described in the next section, $\boldsymbol{\Psi}$ is the noise correlation matrix, λ is the regularization parameter and $\mathbf{I}$ is the identity matrix. A key contribution of the paper is an efficient algorithm for choosing the optimal phase encoding locations by minimizing Eq. (1). Another contribution is the use of the central k-space data to derive a regularization image. Both steps can significantly enhance the performance and robustness of SENSE for achieving large acceleration factors.

B. Image Reconstruction

The image reconstruction algorithm consists of two major steps. First, an intermediate image sequence $\hat{\rho}_q(x), q=1,2,...$ is reconstructed for each receiver channel based on the reference image and the dynamic data at the central k-space using a generalized series model [3], similar to the process in [4]. The next step of the proposed algorithm is to improve $\hat{\rho}_q(x)$ using all the dynamic data collected at all the k-space locations for each time point. This is done by solving the imaging equation $\bar{\mathbf{S}}\boldsymbol{\rho}=\bar{\mathbf{d}}$ with Tikhonov regularization, where the variables with an over-bar correspond to the optimal locations of phase encoding lines. Specifically, setting the regularization image, $\boldsymbol{\rho}_{\mathrm{r}}$, to $\hat{\boldsymbol{\rho}}_q$, the vectorized $\hat{\rho}_q(x)$, we have

$$\boldsymbol{\rho}_{\mathrm{rec}}=\boldsymbol{\rho}_{\mathrm{r}}+\left(\bar{\mathbf{S}}^{\mathrm{H}}\boldsymbol{\Psi}^{-1}\bar{\mathbf{S}}+\lambda^2\mathbf{I}\right)^{-1}\bar{\mathbf{S}}^{\mathrm{H}}\boldsymbol{\Psi}^{-1}\left(\bar{\mathbf{d}}-\bar{\mathbf{S}}\boldsymbol{\rho}_{\mathrm{r}}\right) \qquad (2)$$

where selection of λ is done in a spatially-dependent fashion using the algorithm described in [4].

RESULTS

The proposed method has been validated using real experimental data to create various scenarios. A set of representative results is shown in Fig. 2, where the original data was collected using a spiral imaging sequence from a patient with a breast tumor after injection of a contrast agent. The data was weighted using 4 rotated Gaussian sensitivity functions, and processed using three reconstruction methods, SENSE, regularized SENSE with uniform phase-encodings (PGSD [4]), and regularized SENSE with optimal phase-encodings chosen by the proposed algorithm. One temporal frame of the reconstructed images is shown in (a-d) where a gold standard image reconstructed using 128 full encoding lines is also displayed for comparing the results. As can be seen, the conventional SENSE reconstruction contains significant image artifacts because of a very ill-conditioned model matrix. This problem is effectively alleviated using the proposed regularization method. Optimization of the phase-encoding steps further improves the reconstruction results, as shown in the SSE curve in (e).

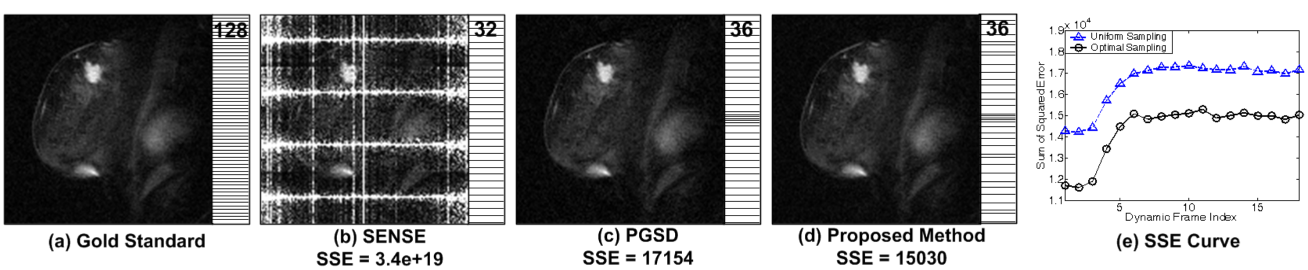

Fig. 2. (a-d) One temporal frame of the reconstructed breast images after injection of contrast agent using different methods. The number and k-space locations of the phase encoding lines used for each method are shown next to the image. Note that the proposed method gives the smallest SSE. (e) SSE for dynamic frames. The proposed method gives smaller SSE with optimized phase-encoding steps than with uniform sampling.

CONCLUSION

This paper addresses two key issues in SENSE dynamic imaging: (a) optimal k-space sampling, and (b) regularization, by exploiting the inherent structure of various dynamic imaging problems. An effective algorithm is presented, which can find the optimal phase-encoding steps efficiently and solve the corresponding image reconstruction problem using Tikhonov regularization. Computer simulation based on real experimental data shows that the proposed method can significantly enhance the performance and robustness of SENSE especially when the acceleration factor is approaching the number of receiver channels.

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