Parallel imaging technique using localized gradients (PatLoc) reconstruction using compressed sensing (CS)

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INTRODUCTION

Parallel acquisition with localized gradient (PatLoc) is a new approach to further increase degrees of freedom in spatial encoding by using a combination of surface gradient coils [1]. Due to non-bijective encoding, PatLoc requires a radio-frequency coil array to uniquely localize the magnetization using the parallel MRI approach [1]. Preliminary results of PatLoc image reconstructions focused on the accelerated acquisitions not exceeding the number of RF coil in the array [2,3,4,5]. Recently, based on the assumption of image sparsity, compressed sensing (CS) has been proposed to achieve MRI acceleration using random sampling k-space and reconstructing vastly reduced data using a nonlinear algorithm [6]. In this study, we investigate the feasibility of reconstructing highly accelerated PatLoc images using CS. Specifically, we hypothesize that PatLoc can provide better reconstructed images compared to traditional orthogonal linear gradient systems because of higher degree of freedom in spatial encoding.

METHOD

The CS theory suggested that it is possible to reconstruct a *n*-dimensional *k*-sparse complex vector **x**, which means that at most $k < n$ components of **x** are nonzero. Here we are interested in collecting information about the sparse **x** by measuring *m* linear combinations of the components of **x** ($1 \leqq k \leqq m \leqq n$). A vector measurement **y** can be described as **y** = **Ax**. In this case, the system **y** = **Ax** is underdetermined. Since **x** is *k*-sparse, a useful choice of the prior to yield a unique estimate of **x** is to solve the following convex minimization problem: min $||\mathbf{Tx}||_1$ s.t. **y=Ax**, where $||\cdot||_1$ denotes ℓ_p-norm: $||\mathbf{x}||_p = (\text{sum}(|x_i|^p))^{1/p}$ with $p = 1$. **T** is the transformation to obtain a sparse representation of a natural image. The minimization of the ℓ_1 norm is known to naturally promote sparsity. CS PatLoc reconstruction was implemented by using a nonlinear conjugated gradient method [6] to minimize the cost of $||\mathbf{y} - \mathbf{Ax}||_2 + \square||\mathbf{Tx}||_1$, where **T** is the wavelet transform using Daubechies 4 wavelets. **A** was implemented using time-domain reconstruction to explicitly calculate the k-space data s(t) from SEMs: $s(t) = \text{integrate}\ \{\rho(\mathbf{r})\exp(-2\pi j(k_{freq}(t) + k_{phase}(t)))\}dr$, where $\rho(\mathbf{r})$is the spin density at location **r**. $k_{freq}(t)$ and $k_{phase}(t)$ respectively represent the phase encoded by the chosen SEM at time *t*. For example, $k_{freq}(t)=\gamma B_{freq}(t)$, $B_{freq}(t)$ is the chosen SEM connected to the time table of the traditional frequency encoding gradient. The simulation used anatomical image obtained from an axial slice MPRAGE image (TR/TE/flip angle= 2530 ms/3.49 ms/7°, $1mm^3$ isotropic spatial resolution) measured on a 3T system (Tim Trio, Siemens Medical Solutions, Erlangen, Germany). We used Bio-Savart's law to simulate the B_1 sensitivity maps and the spatial encoding magnetic fields (SEMs) of the 8-channel PatLoc system with an 8-channel RF coil array (**Figure 1**). Our previous study suggested that the combination of modes from the singular value decomposition (SVD) of SEMs can generate a better reconstruction than using a pair of multipolar SEMs [5]. The chosen two pairs of the SEMs are shown in **Figure 1**. The strengths of the SEMs were adjusted based on the traditional phase-encoding steps, which were calculated from the specified FOV, image matrix, and the maximal and minimal values of the SEM across the FOV. The sampling pattern was determined from at 2D Gaussian distribution with the mean at DC (center of the" k-space") and a variance of $0.05K_{max}$, the edge of the k-space. The acceleration rate R is calculated as $R=N_{full}/N_{acc}/N_{SEM}$, where N_{full} is the number of image voxel, N_{acc} is the number of acquired data, and N_{SEM} is the number of pair of used SEMs.

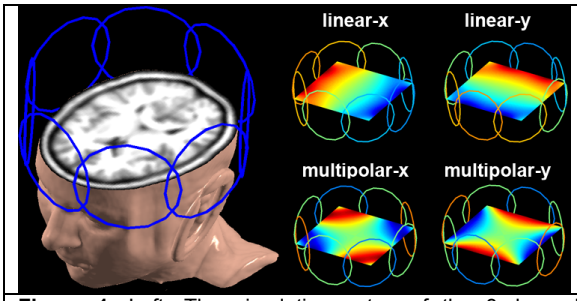

Figure 1. Left: The simulation setup of the 8-channel PatLoc system with an 8-channel RF coil array. Right: two pairs of spatial encoding magnetic fields (SEMs) used in PatLoc. This includes one pair of traditional orthogonal linear SEM and one pair of multipolar SEM.

RESULTS

Reconstructed images using PatLoc and traditional linear gradient with R=8, 12, 16, and 20 are shown in **Figure 2**. The fully sampled sum-of-squares image is also shown for comparison. The residual error (blue texts in **Figure 2**) grows progressively at higher acceleration rates. CS reconstructions of both PatLoc and linear gradient images show reduced anatomical details. This is consistent with the previous sparse MRI study showing reduced image contrast because of compression [6]. Another reason is that the sampling preferred samples at low spatial frequency. Also, Patloc intrinsically has a higher spatial resolution at the periphery of FOV. However, at higher acceleration rates, PatLoc reconstructions are more stable than reconstructions using linear gradients in terms of showing less aliasing artifacts and more anatomical details.

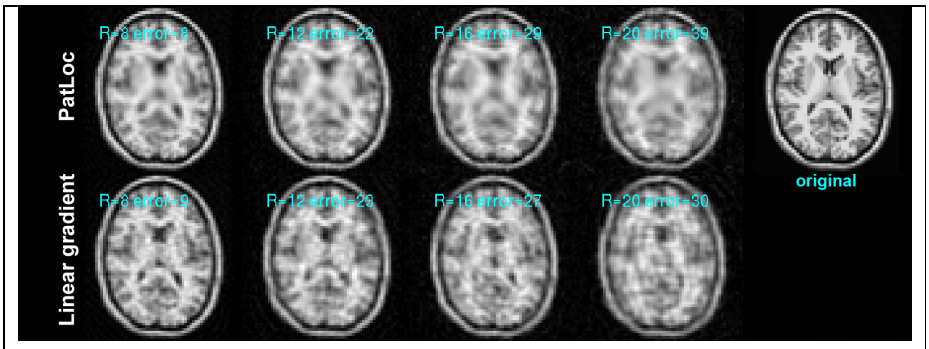

Figure 2. Reconstruction of CS PatLoc images at R=8, 12, 16, and 20. For comparison CS reconstructions using traditional linear gradients and the original image are also shown.

DISCUSSION

CS is a useful framework to further accelerate MRI. We found that CS can be used to reconstruct PatLoc images at accelerations higher than the number of the RF coils in an array. Furthermore, we found CS PatLoc reconstructions outperform the CS reconstructions using traditional linear gradient. However, due to the complexity in anatomical image, it is difficult reconstruct vastly accelerated acquisitions. We speculate that a tailored sparsity transformation can improve the reconstruction. Further optimization on the sampling pattern and weightings of the SEMs are of crucial importance to optimize the reconstruction quality. The computational load is also high due to nonlinear reconstruction in CS and time-domain reconstruction of the PatLoc data. This challenge may be mitigated by code and hardware optimization.

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