Title: Reconstruction of sparsely-sampled dynamic MRI data using Iterative "Error Energy" [1] Reduction

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Introduction

A well-known reconstruction technique developed by Gerchberg, based on "error energy" reduction [1], is extended in this study to sparsely sampled dynamic cardiac magnetic resonance imaging (CMRI). A-priori knowledge of static and dynamic regions in the FOV is used to sample a subset of phase-encoding views on a regular Cartesian grid, allowing a reduction in overall imaging time. Similar to the direct-inversion Noquist method [2], the iterative reconstruction does not use either data-substitution or temporal interpolation. Instead, the inherent temporally band-limited properties of the spatially bounded object, the static FOV, are used to recover additional resolution from information embedded in sparse *k-t* samples. The algorithm iteratively "corrects" the data applying the band-limited constraint in the image domain and the acquired data in the Fourier domain. The proposed method is compared to a full-grid reconstruction ("truth"), the original Noquist reconstruction and to a method that uses temporal interpolation (UNFOLD). Convergence properties and noise amplification due to undersampled data are investigated.

Methods

The cardiac phantom introduced in [2] was used in simulation (Fig 3). Typically observed cardiac dynamics, such as concentric contraction (1) from systole (3b) to diastole (3c), vertical (2), horizontal (3) translational motion and sinusoidal (4) and transient (5) intensity events are simulated in k-space. Temporal changes were sampled uniformly at 16 phases during the cardiac cycle with a nominal full-grid spatial resolution of 256 x 256. Noisy datasets had normally distributed white noise with 10 dB SNR added to k-space data. Figure 1. shows acquisition patterns as per the Stairwell and UNFOLD algorithms (49.6% and 50 % data reduction respectively). Iterative reconstruction (Figure 2) begins with first producing estimated images from the sparse data using temporal nearest-neighbor substitution to generate a full dataset. This result is transformed to the Fourier domain and corrected by replacing all phase-encoding views that were sampled with the corresponding original data. These k-space data are returned to image domain via inverse Fourier transform. The error in the known static region due to residual dynamic content is minimized by temporal low-pass filtering in this region. This process continues until convergence, (no further change in error energy) is achieved.

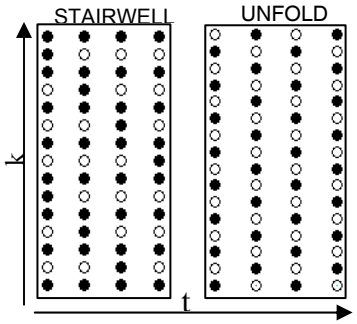

Figure 1.

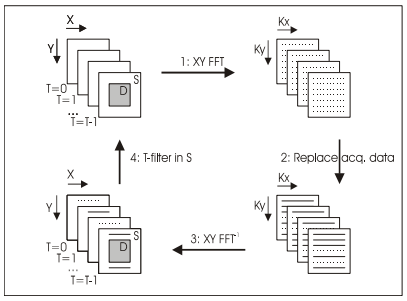

Figure 2.

Results and Discussion

The convergence patterns shown in Figure 3f. suggest ideal reconstruction, similar to direct inversion [2] for the Stairwell algorithm as seen (Fig 3a,b), while the UNFOLD reconstruction (Fig 3c) shows residual artifact due to incomplete estimation of the dynamic spectrum. The proposed iterative process however, yields improvements relative to the original UNFOLD temporal interpolation method (Fig 3g). Diastolic (Fig 3d) and systolic (Fig 3h) iterative reconstructions of a cardiac-gated CMRI acquisition (normal volunteer) show anticipated noise amplification in dynamic regions relative to full-matrix (Fig 3e). Table 1. quantifies this SNR reduction in a sample dynamic region in 10 dB phantom reconstructions.

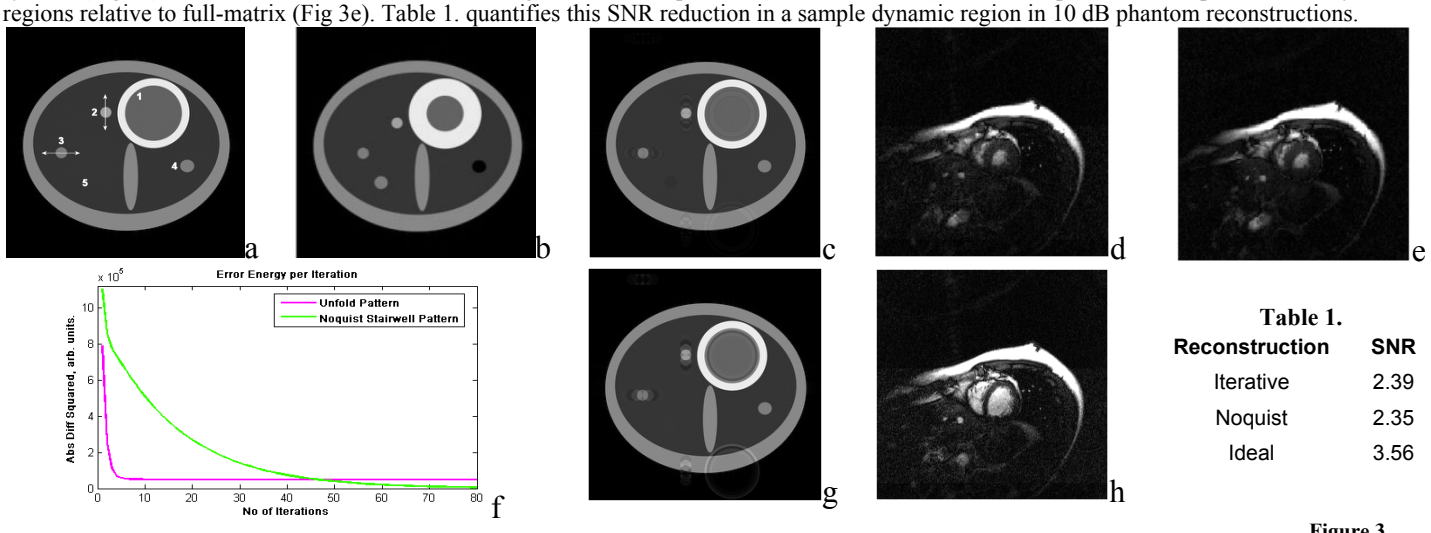

Table 1.

Reconstruction	SNR
Iterative	2.39
Noquist	2.35
Ideal	3.56

Figure 3.

Conclusions

The iterative error energy reduction method can be successfully implemented for reconstructing CMRI data with results equivalent to direct-inversion with the advantage of significantly reduced computational costs. The convergence properties are closely related to the sampling patterns. The proposed iterative process lends itself to flexibility in both selection of dynamic and static FOVs as well as k-space sampling schemes for further investigations. In addition non-Cartesian sampling such as radial and spiral sampling grids can be considered.

References

1. Gerchberg R. *Optica Acta* 1974;21:709-720. 2. Brummer ME, et. al. *Magn Reson Med* 2004;51:331-42. 3. Madore B et. al. *Magn Reson Med* 1999;42:813–828. This work was supported in part by grant R01 HL077627 from the National Institutes of Health.