2346

Model-based Image Reconstruction in Looping-star MRI

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Synopsis

Looping star is a silent MRI pulse sequence that can be used for quantitative susceptibility mapping (QSM), T2*-weighted imaging and fMRI. The conventional reconstruction approach for looping star MRI that filters out some the k-space data does not fully model the overlapping echoes, and remove potentially useful signals. This work proposes a model-based reconstruction method that can theoretically resolve the overlapping echos and improve the SNR without increasing the scan time.

Introduction

Loud acoustic noise in MRI can cause patient discomfort and anxiety, especially for certain groups of individuals like children or patients with dementia. Furthermore, in fMRI studies, acoustic noise is an additional confounding sensory stimulus, and can impact the blood-oxygen level dependent (BOLD) response as a function of both its loudness [1] and duration [2].

Looping-star [3] is a silent MRI pulse sequence that can be used for quantitative susceptibility mapping (QSM), T2*-weighted imaging and fMRI. It is silent due to the slow-varying gradient, but it also suffers from low SNR and overlapping-echoes due to the burst RF pulses and looping k-space trajectory. Conventional reconstruction approach either trim the k-space to reduce overlapping artifact or use RF phase cycling which doubles the volume TR and make it infeasible for fMRI.In this work, we present a model-based reconstruction method that can resolve the overlapping-echoes and increase the SNR without increasing the scan time.

Methods

Pulse Sequence: Figure 1 shows a typical 2D looping star pulse sequence, consisting of a burst excitation and free induction decay (FID) module and one or more gradient echo (GRE) data acquisition module(s). The FID module has multiple short hard RF pulses that excite multiple k-space trajectories. With the same slowing varying gradient among modules, the k-space trajectories loops through the same circle in k-space for all modules.
Problem Formulation: In looping-star fMRI, assuming we have n_{spk} RF pulses in the FID module and following GRE module(s), there will be up to n_{spk} k-space trajectories, each corresponding to a short hard RF pulses. Therefore, the signal sampled at any time t, denoted by s_t, is a superposition of n_{spk} k-space samples located on corresponding trajectories. The corresponding signal equation of jth receiver coil with sensitivity map is given by [4]

$$s_t(j) = \int c_j(r) f(r) \sum_{1}^{L} e^{z(r)t_l} e^{-i2\pi k(r)\cdot t_l}\, dr,$$

where $c_j(r)$ is the sensitivity map of jth receiver coil, $f(r)$ is the continuous proton density weighted object, $z(r) = \frac{1}{T2^*} + i\Delta B0(r)$ is the "rate map", and L is the number of RF pulses that has been applied before time t.
Theoretically, the sampled signal model is the sum of signals from all those spokes. But in practice, 2 out of the n_{spk} signals are located at low-frequency k-space, namely 'echo-in' and 'echo-out' signal, are at least 3 order of magnitude larger than others signals. So in the signal model, only 'echo-in' and 'echo out' spokes are included. Figure 2 shows simulated signals from a 2D Shepp-Logan phantom simulation and how 'echo-in' and 'echo-out' spokes are overlapping in time domain.
After discretization, we build the final system matrix as

$$A = A_1 + A_2,$$

where each element of the lth sub-system matrix is $a_{jil} = \sum_{j=1}^{J} \sum_{i=1}^{\text{res}} c_j(r_i) f(r_i) e^{z(r_i)t_l} e^{-i2\pi k(r_i)\cdot t_l}$.
With the combined system matrix, we used conjugate gradient method for iterative image construction to optimize the following cost function

$$\hat{x} = \arg\min_x \|y - Ax\|_2^2 + \beta R(x),$$

where $R(x) = \|x\|_2^2$ here is a quadratic regularizer.
Compared to the conventional reconstruction method using k-space windowing to mitigate the overlapping echoes or RF phase cycling, the model-based approach can theoretically model and resolve the overlapping echoes, thus reducing the artifacts without increasing the scan time. The model-based approach uses echo-in and echo-out k-space information in higher k-space, thus improving the spatial resolution as well.
Experiments: We compare the proposed reconstruction method to the gridding reconstruction with 3D inverse Fourier transform (IFT) in a structured phantom and human study. We also designed a finger-tapping fMRI test with alternating 20s tapping and 20s resting. The model-based reconstruction using non-uniform Fourier transform and sensitivity map is called MB-v1, and overlapping-echoes resolved reconstruction is called MB-v2. The sequences were programmed via TOPPE [5] and implemented on a GE MR750 3.0T scanner with a Nova Medical 32RX head coil. Subjects gave informed consent under local IRB approval.

Results

Figure 3 shows the reconstruction of a structured phantom using gridding and model-based approach. Compared to the conventional gridding and Fermi filter approach, it is clear that the proposed MB-v2 has reduced artifacts.

Figure 4 shows 4 slices of a human brain reconstruction versus different k-space radius. The model-based method outperforms the gridding method at all times. The case with full k-space data shows that the model-based approach can fully resolve the k-space overlapping echo and reduce artifacts. The fully model-based method with sensitivity map also allows for better suppression of undersampling artifacts than the gridding method.

Figure 5 shows a fMRI time courses and activation maps. The activation map using proposed MB-v2 has less noise and higher correlation coefficients. The time course also fits the reference better with less noise.

Conclusion

The proposed model based reconstruction showed better image quality on both phantom and brain study, and higher correlation coefficients and less noise in fMRI study. For further study, field inhomogeneity can be incorporated into the signal model and joint reconstruction of FID and GRE signals can also be explored.

Acknowledgements

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References

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Figures

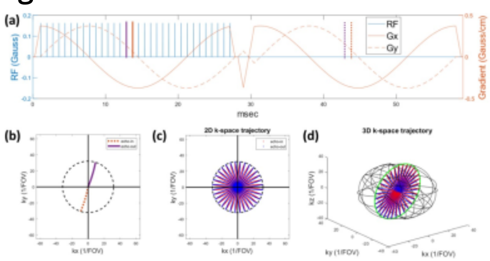

Figure 1: (a) A typical 2D looping star pulse sequence with one excitation/FID module and one GRE/data acquisition module (ramp-up & down gradient is required by TOPPE), the max slew rate for all module (including ramps) is 5 mT/m/ms; (b) Illustration of overlapping echoes in GRE module: the echo-out signal from purple RF pulse overlapped the echo-in signal from orange RF pulse in time; (c) 2D GRE k-space trajectory: echo-in and echo-out trajectories are curved spokes generated by sinusoidal gradient; (d) 3D k-space trajectory generated by randomly rotating the 2D trajectory in 3D.

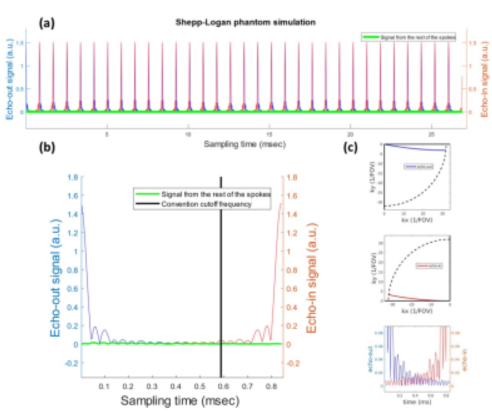

Figure 2: (a) Simulated Shepp-Logan phantom: the rest of the signals other than echo-out and echo-in is trivial due to its high-frequency locations. (b) Overlapping echoes in a single segment: filtering out the k-space data using conventional cutoff frequency will lose potentially useful k-space information (red curve). (c) Zoomed-in echo-out and echo-in signal overlapping in time domain: in the middle of the segment, echo-in and echo-out signal are mixed.

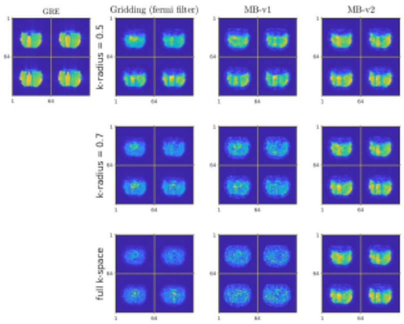

Figure 3: left to right: standard 3D gradient echo pulse sequence gridding reconstruction (scan time: 1:54 min), looping star (scan time = 1.9 s) gridding recon (with Fermi filter), looping star model-based reconstruction MB-v1, and looping star model-based reconstruction MB-v2.

First row: k-space data is trimmed to 0.5 of the maximum to remove most of overlapping artifacts at the cost of losing high-frequency signals. Second row: k-space data is trimmed to 0.7 of the maximum to reduce overlapping artifacts. Third row: full k-space data that has complete overlapping artifacts.

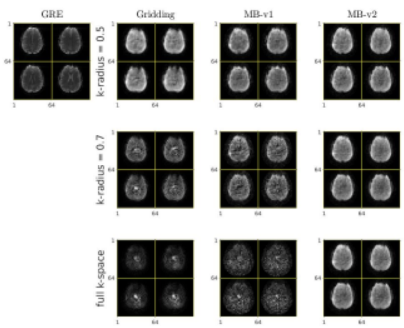

Figure 4: Reconstruction of brain: standard 3D GRE (scan time: 1:54 min) images for reference; All other images are from the same looping-star sequence (scan time = 1.9 s).

First, second and third rows show different reconstruction method using 0.5 of k-space data, 0.7 of k-space data, and full k-space data respectively. The proposed MB-v2 is robust to different range of k-space radius. It also produces higher quality images and could allow more k-space to be used in the image reconstruction.

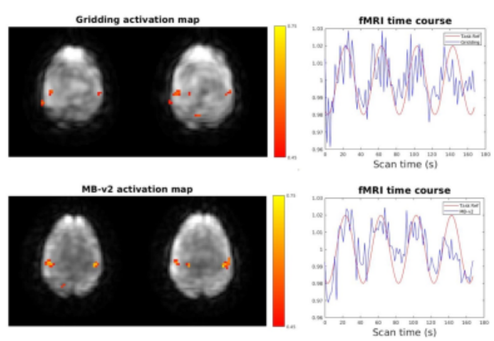

Figure 5: Activation maps and time courses for finger-tapping fMRI task using gridding and MB-v2 reconstruction. We apply Fermi filter with 0.5 and 0.6 cutoff frequency to gridding and MB-v2 k-space data to reduce high frequency noise. For the activation maps, the threshold is r = 0.45 with 3 voxel contiguity requirement. Activation map using MB-v2 reconstruction shows higher correlation coefficient and less noise. Its time course also has less noise across frames and fits the task reference curve better.

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2346