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Iterative Low-Rank Infilling Approach for Zero Echo-Time (ZTE) Imaging

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Synopsis

Keywords: Image Reconstruction, Parallel Imaging

Motivation: The short, but non-zero, time taken to switch between transmit and receive results in a dead-time gap in Zero Echo-Time (ZTE) imaging, which leads to substantial reconstruction artifacts.

Goal(s): Determine the missing data in the dead-time gap without any additional acquisition.

Approach: We reformulate the reconstruction problem as a nuclear norm minimization problem to implicitly fill the missing data through iterative reconstruction.

Results: The proposed method demonstrates that the missing data can be filled using low-rank without sacrificing image quality.

Impact: We present a method for filling the dead-time gap in ZTE imaging using low-rank that does not require the collection of additional data.

Introduction

Zero Echo-Time (ZTE) imaging is instrumental in capturing signals from tissues characterized by extremely short T_2 components, which otherwise remain undetectable using conventional MRI sequences. However, a true zero TE is practically unattainable due to a brief dead-time gap, typically spanning several microseconds, attributable to the RF pulse duration and Transmit/Receive (Tx/Rx) switching¹⁻² (Figure 1). This gap leads to the absence of a few data samples in the central region of k -space, potentially resulting in substantial reconstruction artifacts. Current solutions typically require the acquisition of additional low-resolution k -space data or the inclusion of supplementary single-point acquisitions. However, filling the central k -space gap without the need for extra PETRA³ or WASPI⁴ acquisitions still remains an unresolved challenge⁵. More recently, parallel imaging-based strategies using GRAPPA⁶ (ZINFANDEL) and SENSE⁷ (CG SENSE) have been proposed to explicitly or implicitly fill in the missing k -space data. In this work, we present a new calibrationless low-rank-based method to implicitly fill the missing data without the need to acquire any additional data or coil sensitivity maps.

Methods

Our proposed technique aims to address the challenge of the missing data in the ZTE acquisition by enforcing self-consistency among neighboring k -space points in Cartesian space. We reformulate the problem of the missing data in the center of k -space as a structured matrix nuclear norm minimization problem, as expressed by the following:

$$\begin{aligned} \min_x \quad & \|HFx\|_* \\ \text{s.t.} \quad & \|Dx - y\|^2 < \epsilon \end{aligned}$$

Here, H represents the matrix lifting operator, which converts 3D Cartesian data into a structured Hankel matrix; F stands for the non-uniform Fourier encoding operator; $*$ denotes the nuclear norm; D is the sampling operator, responsible for selecting acquired data from the radial spokes, and y represents the acquired data.

As shown by Figure 2, the proposed method begins by gridding the non-Cartesian radial data into a 3D Cartesian grid. The Cartesian data are grouped into GRAPPA like kernels and each of these kernels is then flattened, forming columns within the 2D Hankel matrix. This process is iterated by convolving the kernel across either the entire k -space or a predefined center region. In instances where a fully sampled ZTE acquisition is in use, only the center data is absent, thus only the center volume is needed. To enforce self-consistency, we apply the Singular Value Thresholding (SVT) to the Hankel matrix. Subsequently, the Cartesian data is inverse-transformed into non-Cartesian space to preserve data consistency. This operation is iteratively repeated until convergence is achieved.

To validate the effectiveness of our method, we performed a computer simulation using a digital brain phantom to assess its performance as a function of different gap sizes. The method was then evaluated using acquisitions of a phantom and a normal volunteer. The data was acquired on a 3.0 T scanner (Signa Premier XT, GE Healthcare, Waukesha, WI) using a 48 channel head-coil. The in-vivo brain image was acquired with an isotropic spatial resolution of 3.0mm and a field-of-view of 384 mm. The flip angle was set to 1° , and the readout bandwidth was set at ± 31.25 kHz/pixel with $2\times$ readout oversampling. A dead-time gap of five samples is introduced under this setting. In order to reduce computation time, we manually selected nine coils from the 48-channel head coil to validate our method.

The reconstruction was conducted offline using Matlab. The product ZTE acquisition, using WASPI for the center of k -space, served as the ground truth. The non-Cartesian data was reconstructed on a $2\times$ oversampled grid. We implemented the SAKE⁸ formulation with a 3D isotropic kernel of size 5 as the matrix lifting operator. The conjugate-gradient NUFFT is employed as the adjoint transformation for all cases.

Results

Figure 3 shows the low-rank reconstruction of the simulated digital brain phantom. The absence of samples in the center of k -space leads to a DC offset at small gap sizes and low-frequency modulation at larger gap sizes. Figure 4 presents the reconstruction for both the phantom and in-vivo brain. The low-rank reconstruction provides an artifact-free reconstruction with a gap size of 5 samples.

Discussion

Some residual low spatial frequency differences exist between the low-rank reconstruction and the reference. This can be attributed, partially, to the different T_2^* weighting introduced by the WASPI acquisition.

To address the issue of radial undersampling and further improve the reconstruction, it is possible to introduce additional constraints, such as transform domain sparsity, virtual coils augmentation, and the incorporation of smooth phase information⁹⁻¹¹.

Conclusion

In this study, we proposed a new ZTE implicit data in-filling approach based on low-rank, which enables artifact-free reconstruction without the requirement for collecting additional data.

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Figures

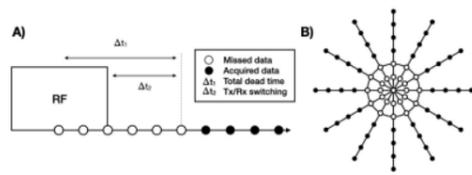


Figure 1: Schematics of ZTE for A) one TR and B) the 3D radial ZTE trajectory in x-y plane. The total dead time is determined by the RF pulse duration and the hardware switching time. As illustrated, a TE of zero cannot be achieved on clinical MRI systems because there is a short dead-time gap of several microseconds due to the RF pulse duration and the Tx/Rx switching time. This gap results in a few low-frequency Fourier coefficients not being acquired, which in turn can lead to reconstruction artifacts. Figure reproduced from E. Ljungberg, "MRI with Zero Echo Time: Quick, Quiet, Quantitative"

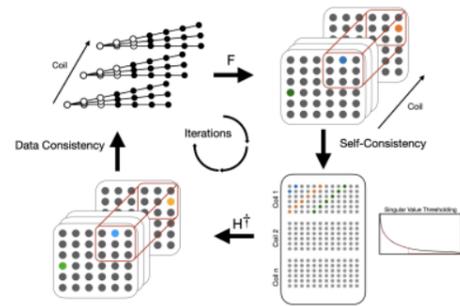


Figure 2: Flow chart of the proposed low rank reconstruction. The z-dimension is ignored in the flow chart for simplicity. To enforce self-consistency, the Cartesian data is reorganized into a structured Hankel matrix, where SVT is performed to shrink the singular values to a predefined range. Data consistency is enforced by transforming the Cartesian data back to the non-Cartesian space, where synthesized data is replaced with the acquired measurements.

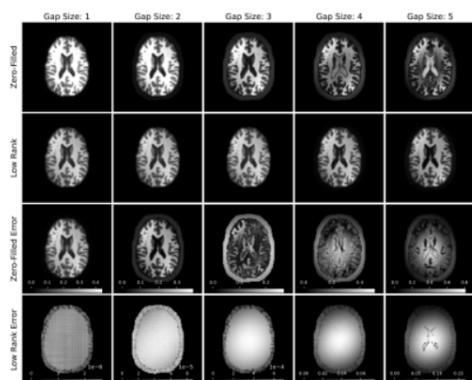


Figure 3: The performance of low-rank reconstruction at different gap sizes. Analytical coil sensitivity maps, corresponding to 4-channel receivers, were generated using the Michigan Image Reconstruction Toolbox (MIRT) to spatially encode the simulated brain phantom¹².

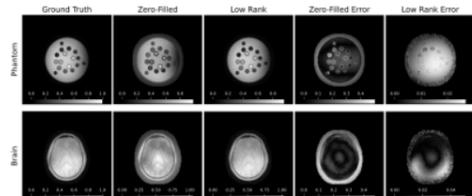


Figure 4: Example low rank reconstruction for the phantom and in-vivo brain. Both are acquired at readout bandwidth of ± 31.25 kHz/pixel with the commercial ZTE acquisition resulting in a dead-time gap of five samples.