Compressed Sensing 3D Ultrashort Echo Time (COMPUTE) Imaging

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Introduction During the past decade, ultra-short echo-time (UTE) MRI has evolved into a promising technique for directly imaging tissues with very short- T_2 relaxation time on the order of hundreds of microseconds (1). In order to capture the fast-decay signal, effective echo times (TEs) in UTE sequences need to be on the order of tens of microseconds or less, which can be accomplished custom designed RF pulses, such as half or hard pulses, and sampling strategies, e.g. radial center-out trajectory. However, 2D UTE imaging is inherently time-inefficient: half-pulse excitation requires two scans with opposite slice-selection gradient polarities to achieve spatial selectivity; radial center-out sampling doubles the scan time for full k-space coverage. In this work, to improve UTE efficiency, we developed 3D Compressed Sensing (CS) (2) UTE (COMPUTE) imaging with a hybrid-radial encoding strategy (3), thereby achieving an acceleration factor of 10. Phantom and *in vivo* results demonstrated the feasibility to apply CS to UTE imaging.

Methods Pulse Sequence Compared with 2D UTE, 3D UTE provides volume coverage and higher SNR efficiency. Since a hard pulse is employed, 3D UTE is also immune to artifacts associated with half-pulse excitation and obviates the need for two scans with opposite slice-selection gradient polarities. A hybrid stack-of-radial pattern, rather than pure 3D radial

RF

ADC

Radial readout with ramp sampling

G_z

G_y

TE (variable)

Fig. 1 Hybrid UTE pulse sequence

acquisition was chosen as the sampling trajectory for the following reasons: 1. It is more straightforward to achieve anisotropic FOV considering that the dimensions of most target anatomies are not spherical, (e.g., tibia); 2. Compared with 3D gridding, the image reconstruction is faster by first applying IFFT in slice dimension followed by 2D gridding reconstruction in each clies, expecially considering that iterative image reconstruction algorithm used in

by 2D gridding reconstruction in each slice, especially considering that iterative image reconstruction algorithm used in this work is time-consuming. As shown in Fig.1, the hybrid encoding is achieved via radial readout with ramp sampling on the kx-ky plane and Fourier encoding along kz. To minimize the signal loss from T_2* decay during the phase-encoding period, the duration (rather than amplitude) of the trapezoidal gradients is stepped, thereby minimizing TE at kz=0. To test the feasibility and evaluate the performance of COMPUTE, the full data sets were acquired in both phantom and mid-tibia *in vivo* on a Siemens 3T scanner with the following scan parameters: FOV=160×160×250mm³, TE_{min}/TR=50µs/10ms, FA=10° with 20µs pulse duration, 500 half-projections (corresponding to an undersampling factor of 1.6) and 180 readout points per projection, readout bandwidth= \pm 125kHz, 128 slices, reconstructed image matrix=256×256×128, total scan time=10minutes. A four-channel head coil and an eight-channel knee coil were used to image phantom and mid-tibia, respectively.

Simulation The undersampled data were synthesized by randomly sampling kz and variably undersampling the projection views. A power of 5 of distance from the kz center was chosen as the sampling probability density function to achieve an undersampling factor of 2 in the kz dimension. 250 equiangular views were selected in the central kz portion and 125 views in the edge kz region. With this undersampling strategy, a total acceleration factor of 10 was achieved.

and 125 views in the edge kz region. With this undersampling strategy, a total acceleration factor of 10 was achieved. **CS Reconstruction** The images were reconstructed by solving the following optimization problem with total variation (TV) as the sparsity constraint (2): $\hat{m} = \underset{m}{\text{arg min}} ||F_u m - y||_2^2 + \lambda ||Dm||_1$ [1]. Here \hat{m} is the reconstructed image, y

(TV) as the sparsity constraint (2): $\hat{m} = \arg\min_{m} \|F_{u}m - y\|_{2}^{2} + \lambda \|Dm\|_{1}$ [1]. Here \hat{m} is the reconstructed image, y signal profiles along red dashed lines (d) denotes the undersampled k-space data and λ is the regularization parameter. F_{u} represents the undersampled Fourier transform operator that maps the image onto the k-space data according to the sampling pattern in COMPUTE, and D is the finite difference operator. $\|\cdot\|_{p}$ denotes the vector's p-norm. A nonlinear Conjugate Gradient algorithm was used for solving Eq.1 (2). The images were also reconstructed from the undersampled data by zero-filling with density compensation (ZF-w/dc), which consists of zero-filling the missing k-space data.

with density compensation (ZF-w/dc), which consists of zero-filling the missing k-space data, multiplying with k-space density compensation factor (DCF), IFFT along kz and NUFFT (4) on the kx-ky plane. DCF is computed from the probability density function with random sampling, the variable density of radial views along kz and the radial ramp sampling. For comparison, full data sets were used to reconstruct the reference images analogous to ZF-w/dc but without zero-filling.

Results Axial phantom images reconstructed from full and undersampled data sets with CS and ZF-w/dc are shown in Fig. 2. The streaking artifacts are apparent with ZF-w/dc reconstruction (Fig. 2c). These artifacts are significantly reduced with CS reconstruction (Fig. 2b). To further compare the reconstruction accuracy, the signal profiles along the dashed lines indicated in Fig. 2a-c are plotted in Fig. 2d, demonstrating that the CS reconstruction recovered the signal from undersampled k-space data with high accuracy. Fig. 3 shows images of the mid-tibia of a 25-year-old male volunteer in axial and coronal planes with different reconstructions. The CS reconstructed images are still comparable to the fully sampled images but correspond to one sixth of the original scan time. Some smoothing effects are observed in the images from CS reconstruction. Optimization of the regularization parameter λ would further improve the CS reconstructed images.

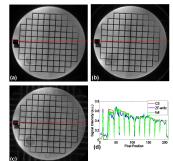


Fig. 2 Phantom images reconstructed from full data set (a), from undersampled data set with CS (b) and ZF-w/dc (c), with the signal profiles along red dashed lines (d)

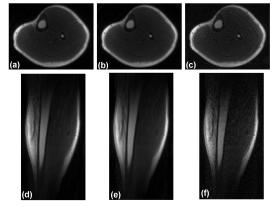


Fig. 3 in vivo mid-tibia images reconstructed from full data set (a, d), from undersampled data set with CS (b, e) and ZF-w/dc (c, f). (a-c) are in the axial plane and (d-f) are in the coronal plane.

<u>Conclusion</u> COMPUTE, consisting of a custom-designed hybrid 3D UTE sequence, combined with CS reconstruction, has achieved an acceleration factor of 10 with no perceptible image quality degradation. In work in progress, long- T_2 suppression modules are being incorporated into COMPUTE, allowing spatial sparsity of the soft-tissue suppressed images to be exploited to achieve even higher acceleration factors. We anticipate COMPUTE to be particularly beneficial to *in vivo* applications of 3D IR-UTE imaging, which provides the highest and most uniform short- T_2 contrast, but currently suffers from impractically long scan time (5).

References 1. Gatehouse PD et al. Clin Radiol 2003:58(1):1-19; 2. Lustig M et al. Magn Reson Med 58:1182-1195 (2007); 3. Rad HS et al.NMR Biomed 2011; 4. Grenengard L et al. Siam Rev 2004;46(3):443-454; 5. Li C et al. Magn Reson Med 2011(in press). Acknowledgements NIH Grant RO1 AR50068.