Implementation of Compressed Sensing for Online Reconstruction

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Introduction: Compressed sensing (CS) has been proposed as a technique to enable acquisition and reconstruction of images that are sparse or compressible with little to no loss of image quality [1]. The technique has been demonstrated to be especially useful in applications such as MR angiography, cardiac MR and interventional MR in which the acquired images are inherently sparse or a simple sparsifying transform can be performed [2]. However, the existing work in CS literature has been focused on offline reconstruction and simulation, partially due to the concern of the time-consuming steps of the sparsifying transform and non-linear interative reconstruction. In this work, we demonstrated the feasibility of an online implementation of CS to achieve real-time image reconstruction on a clinical MR scanner.

Methods: <u>*CS algorithm:*</u> Two criteria were used to determine the performance of the CS algorithm, i.e., reconstruction time and the ability to preserve the image content. Total Variation based Compressed MRI (TVCMRI) has been reported as an efficient and robust CS reconstruction approach [3] which was evaluated and selected for implementation in the Image Calculation Environment (ICE) for Siemens clinical scanners. The reconstruction images were obtained by solving the optimization model in Equation (1), where x is the desired image and b is undersampled k-space data. α and β are two positive parameters. R denotes a partial Fourier transform and Φ a sparsifying transform. *TV* stands for total variation transform. $\|\bullet\|_1$ denotes l_1 norm and $\|\bullet\|_2$ l_2 norm.

$$\min_x F(x) = \alpha TV(\Phi^{-1}x) + \beta\|x\|_1 + \frac{1}{2}\|R\Phi^{-1}x - b\|_2^2 \qquad (1)$$

<u>*Validation Study:*</u> Images reconstructed by the ICE implementation (TVCMRI-ICE) were compared with those obtained by an open source MATLAB (MathWorks, Inc., Natick, MA) reconstruction (TVCRMI-MATLAB) [3] to validate the equality of the image reconstruction.

<u>*Phantom study:*</u> Two random undersampling schemes with sampling ratios of 50% and 25% were designed and successfully implemented in a 2D SSFP sequence (Figure 1). Phantom studies were performed on a 3T clinical MR scanner (MAGNETOM Trio a Tim System, Siemens Healthcare, Erlangen, Germany). The validation study was carried out by imaging a plastic board (thickness = 0.5cm) with round holes (r=0.6cm, 0.5cm apart) emerged in a water container. A transverse slice was acquired with 50% undersampling ratio. To test the online reconstruction, one slice of a water bottle phantom was acquired. The imaging parameters were: matrix size=256×256, FOV=300×300 mm^2, slice thickness=10mm, bandwidth=501 Hz/Pixel, TE/TR=2.48/5ms. TVCMRI was performed on images acquired with 50% and 25% undersamplining ratios. For fully sampled data (ground truth), standard Fourier transform reconstruction was used.

Results and Discussions: The TVCMRI-MATLAB reconstruction [3] took approximately 2 s for 50% or 25% sampled dataset with matrix size of 256×256 (Table 1) using a standard laptop (Intel single CPU, 1.66GHz, 1GB RAM). The validation results are shown in Figure 2. The image intensity along the cyan line in the imaging object was well matched by the implementation in MATLAB and ICE. Figure 3 displays the online reconstructed phantom images with different undersampling ratios. No visual difference was observed between the ground truth and images acquired with sampling ratios of 50% and 25%. The image intensities of the difference images were multiplied by a factor of 10 to visualize TVCMRI reconstruction artifacts. Table 1 lists the corresponding acquisition time and reconstruction time in both MATLAB and ICE. The reconstruction time was boosted 8 to 10 fold when moving from MATLAB to ICE. Even though the online CS reconstruction took significantly longer time compared to standard FT reconstruction, the CS reconstruction rate remains below the acquisition rate, suggesting the feasibility to apply this work to clinical applications which require real-time imaging, such as interventional MRI and dynamic imaging.

Conclusion: In this study, we demonstrated a successful implementation of CS to achieve real-time image reconstruction. To our knowledge, this is the first implementation of CS on a clinical MR scanner with both online image acquisition and reconstruction. The performance of TVCMRI algorithm used in online implementation was effective in producing reconstructed images close to ground truth with rapid reconstruction speed.

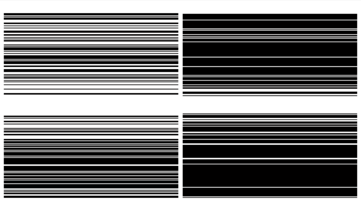

Figure 1: The sampling schemes for 50% (a) and 25% (b) undersampling ratios.

Sampling ratio	100%	50%	25%
Acquisition time (ms)	1200	600	400
Reconstruction time in MATLAB (ms)	70	~2000	~2000
Reconstruction time in ICE (ms)	0.4	247.1	207.1

Table 1: Acquisition time and the reconstruction time in MATLAB and ICE, respectively, for different sampling ratios.

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References:

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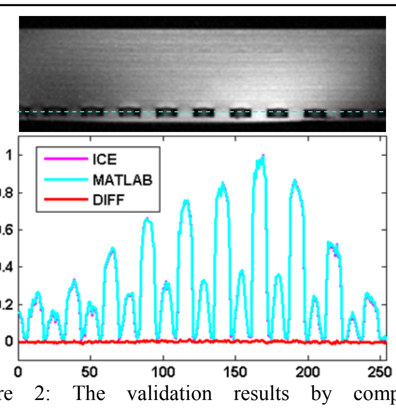

Figure 2: The validation results by comparing reconstructed image intensities along the cyan line in the phantom: TVCMRI-ICE (pink); TVCMRI-MATLAB (cyan); difference (red). 50% sampling ratio was used.

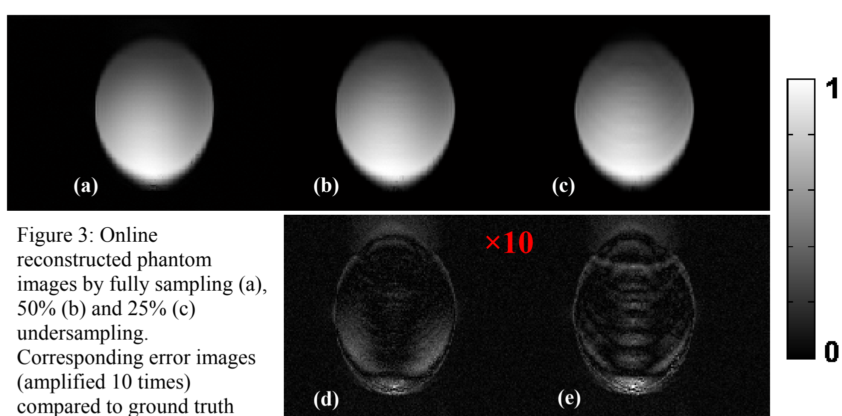

Figure 3: Online reconstructed phantom images by fully sampling (a), 50% (b) and 25% (c) undersampling. Corresponding error images (amplified 10 times) compared to ground truth were shown in (d) and (e).