Reconstruction of Phase images by Compressed Sensing using Low-pass filter

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Introduction: Image phase contains unique information regarding tissue composition, and has been studied for the various research purposes such as venography using susceptibility weighted imaging, measuring iron concentration using susceptibility mapping, visualization of gray matter and white matter contrast using phase shift, and so on [1,2]. To obtain the high resolution 3D phase image, however, long echo time is needed in order to accumulate sufficient phase shift. This will increase the data acquisition time dramatically. Thus it would be desirable to reduce the imaging acquisition time by using advanced data undersampling scheme while maintain the fidelity of the resulting phase maps. In this abstract, we have applied the widely used compressed sensing (CS) method [3] to accelerate the data acquisition.

Theory and Methods: Smooth varying signals can be effectively reconstructed using constrained reconstruction methods than rapidly varying signal [4]. The method in Ref.[4], however, is based on the reordering of the magnitude images. It is difficult to apply to phase image, therefore, we applied the low-pass filter as a preconditioning function to make smooth varying signal and high-pass filter [5] to recover original k-space data at the first step and third step of the process, respectively (Fig.1.).

Mathematically, the CS algorithm that was used in this study, can be written as

$$\text{minimize } ||\Psi(m)||_1 + \alpha\, TV(m) \quad \text{s.t. } ||F_u(m) - y||_2 < \varepsilon,$$

where vector m represents the image of interest, Ψ denotes the sparsifying transform (we used wavelet transform), F_u is the (undersampled) Fourier transform, y is the measured k-space data, TV is the total-variation and its weighting α.

We used variable density random undersampled k-space data (k_x: fully sampled and k_y & k_z: randomly undersampled). To verify the reconstruction performance of the proposed algorithm, we compared it with the conventional CS algorithm using simulated phantom (sampling ratio = 30%) and in vivo MR data (sampling ratio = 50%). To evaluate the image quality of the reconstructed images, the difference map between reference image and reconstructed images and root mean square error (RMSE) are used. RMSE values are estimated using the magnitude values of reconstructed images for magnitude images and the real values for phase images, respectively.

To obtain the phase images, we used laplacian method for phase unwrapping [6] and sphere mean filtering to remove the background phase [7].

In vivo data were collected using a 3T GE MRI scanners (TR = 50 ms, TE = 42 ms, Flip angle = 20°, FOV = 256 x 256 mm, Matrix size = 256 x 256 x 180, Voxel size = 1.0 x 1.0 x 1.0 mm^3). All simulations and data reconstruction were performed using MATLAB R2009b.

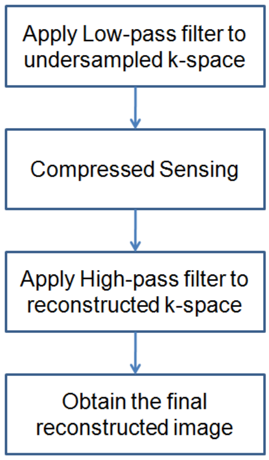

Figure 1: Flow chart of the proposed algorithm.

Results: Fig.2. shows the reconstructed images and their difference images of the phantom. For the reconstructed image case, there are few differences. The difference image case, however, the reconstructed image by proposed method has smaller error (especially, at the expressed regions in Fig.2.) than the conventional CS algorithm and also has slightly lower RMSE value (RMSE = 2.93%) than conventional CS method (RMSE = 3.07%).

In Fig.3, reconstructed in vivo images and their phase images are shown using each algorithm. Few differences can be noticed visibly. Similar to the phantom studies, but, RMSE values (*Magnitude images:* Proposed algorithm = 3.20% & CS = 4.13%, *Phase images:* Proposed algorithm = 3.49% & CS = 5.16%) shows that our proposed algorithm is more accurate than the conventional CS for both magnitude and phase images.

Conclusion: One of the drawbacks of the high resolution 3D phase image is its long scan time. To solve this problem, we applied CS algorithm to randomly undersampled k-space data. Moreover, we used low-pass filter (as a preconditioning method) and high-pass filter to improve the reconstruction performance of the CS algorithm for both the magnitude and phase images. And from the results, although reconstructed image is a little blurred when the undersampling ratio is increased (not shown here), sufficiently accurate estimation is possible from the undersampled data.

Acknowledgements: This work has been supported by Yonsei University Institute of TMS Information Technology, a Brain Korea 21 program, Korea & the Korea Science and Engineering Foundation (KOSEF) grant funded by the Korea government (MEST) (2010-0016421).

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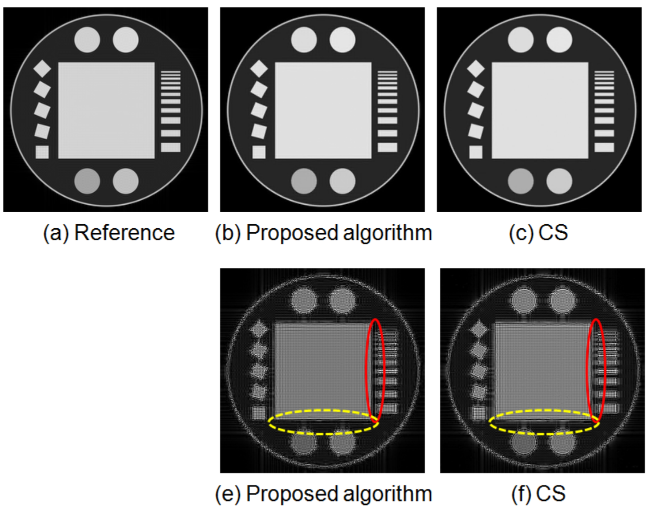

Figure 2: Reconstructed magnitude phantom images by (a) Reference, (b) Proposed algorithm, and (c) CS. And difference maps of (d) Proposed algorithm and (e) CS, respectively.

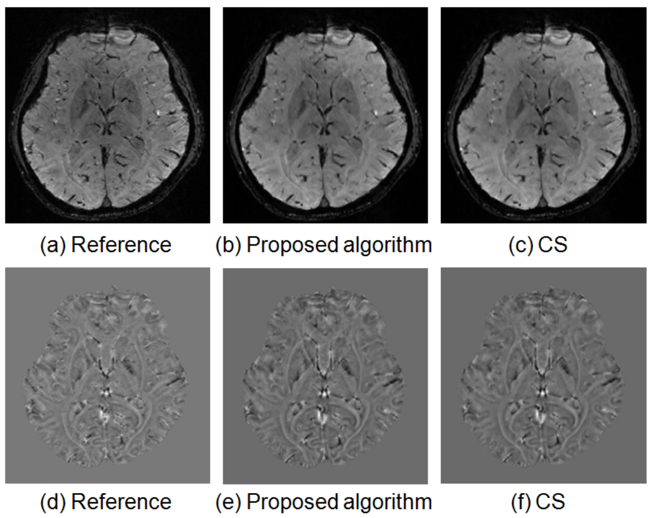

Figure 3: Reconstructed in vivo magnitude images: (a) Reference, (b) Proposed algorithm, and (c) CS. And their phase images: (d) Reference, (e) Proposed algorithm and (f) CS, respectively.