Noise Behavior of DCE-MRI Reconstructions Using Compressed Sensing Based Method

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INTRODUCTION

MR Image quality highly depends on the noise propagating behavior of the image reconstruction method. For example, the noise behavior of SENSE reconstruction due to is fully characterized by the g-factor[1]. As an emerging reconstruction technique, compressed sensing (CS) has demonstrated great potential to reconstruct high quality images from undersampled k-space data [2]. However, to the best of our knowledge, the noise behavior of CS reconstruction in MRI remains largely unexplored. It limits the application of CS in clinical practice. The objective of this work is to analyze how noise is distributed and changed with different reduction factors. We particularly focus on dynamic contrast-enhanced imaging (DCE-MRI)[3], in which CS holds great potential for significant improvement in spatiotemporal resolution. The temporal and spatial noise behavior in CS-based DCE-MRI is characterized using the Marcenko-Pastur (MP)-Law method [4], because this method is applicable to any image reconstruction algorithms and can deal with the cases where organs of interest are moving or image contrast is changing over time.

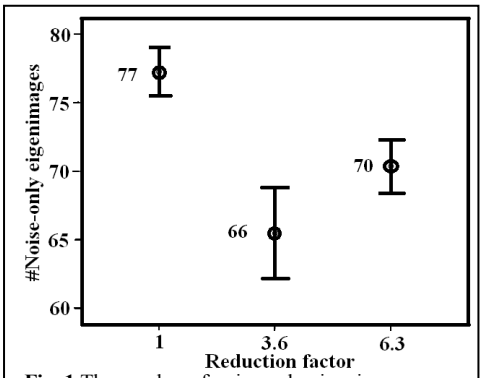

Fig. 1 The number of noise-only eigenimages over all subjects for different reduction factors.

METHODS

The study was IRB approved. 9 subjects with written informed consent were recruited in the study. Full DCE-MRI scans of each subject was acquired on a 1.5T scanner (Magnetom Avanto, SIEMENS,Erlangen, Germany) using a 2D Turbo Flash sequence. The reconstruction matrix was 208×256. 90 frames were acquired. The datasets were resampled and reconstructed using the k-t ISD method with a scan time reduction factors of R=3.6 and R=6.3. This method is a dynamic imaging method based on CS with partial known support theory by exploiting the additional prior information on the support of spatial and temporal–frequency (x-f) domain [5]. After reconstruction, the eigen-images and corresponding eigen-values were calculated from reconstructed image series using Karhunen-Loeve transform (KLT). The noise-only eigen-images were then identified by iteratively fitting their distribution to MP distribution demonstrated in random matrix theory. The temporal noise variance for each pixel was then evaluated from the intensity fluctuation across these eigen-images. The variance of all pixels consists of one noise-variance map for one series of images. A series of 90 spatial noise maps were generated by the inverse KLT of the noise-only eigen-images [4].

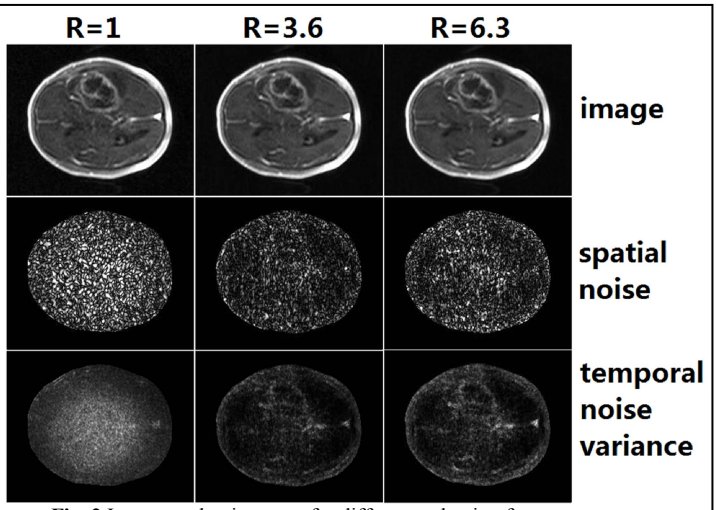

Fig. 2 Images and noise maps for different reduction factors.

RESULTS AND DISCUSSION

Fig.1 plots the averages (circle) and standard deviations (lines) of noise-only eigen-images for R=1 (no CS), 3.6 and 6.3 over all 9 subjects. We can see that Fourier reconstruction without acceleration has the most noise-only eigen-images. The CS reconstruction with R=3.6 has fewer than that with R=6.3. Fig.2 shows the reconstructions, corresponding spatial noise maps of a single time frame, and the temporal noise variance maps of a single subject (top to bottom) with R=1, 3.6 and 6.3 from left to right. The maps in the same category (spatial or temporal) are shown on the same scale for different reduction factors. There are no visible artifacts in the reconstructions with R=3.6 and 6.3. Similar results were obtained from other subjects. From the aforementioned figures, it is seen that:

(1) The noise level of the Fourier reconstruction from full data is higher than those of reconstructions by CS-based method. It may due to additive noise in measurements. Please note, the nonuniformity of noise in Fourier reconstruction is due to the spatial normalization using low-resolution image and elliptical filtering in each frame.

(2) The denoising capability of CS-based method has been demonstrated before only from reconstructions [2]. There is no evaluation such as noise map to illustrate the distribution of noise after CS reconstructing. In Fig.2, the spatial noise distributed randomly, while the temporal noise variance in CS reconstruction is spatially variant. It can be observed that regions with more dynamical changes present a higher level of noise fluctuation. The reason could be first, k-t ISD reconstructs x-f space from undersampled data; second the regularization in CS may be change the distribution of noise due to the nonlinearity and the image-content-dependent constraint (image is transform sparse) used in CS reconstruction.

(3) The noise level from CS reconstruction increases with reduction factors. This is in agreement with the number of noise-only eigen-images shown in Fig.1, and with the observations in Ref [4] that when higher reduction factors are used, noise level increases and signal eigen-images with small eigen-values may become indistinguishable from noise.

CONCLUSION

In this work, the MP-Law method is used to evaluate the spatial and temporal noise in DCE-MRI series reconstructed using CS-based method. The results provide a qualitative understand of the noise behavior in CS reconstructed DCE images. Such understanding will accelerate application of CS in clinical practice. Future work will carry out quantitative study of noise behavior of a number of CS reconstruction methods.

REFERENCES

[1] pruessmann KP, et al. *MRM*, 42:952-962. [2] Lustig M. et al. *MRM* 2007. [3] Tofts P.et al. *MRM* 1991. [4] Ding Y, et al. *MRM*, 2011. [5] Liang D, et al. *MRM*, in press.