Case-PDM Optimized Random Acquisition in High Quality Compressed Sensing MR Image Reconstruction

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INTRODUCTION

Compresses Sensing (CS) has been recently introduced to speed MR imaging [1]. Among the parameters of CS, the undersampling scheme in k-space is vital to the success of the algorithm. To date, variable-density (VD) undersampling in phase-encodes is the most-used scheme in 2D Cartesian CS. However, VD schemes are based up experience rather than systematic optimization. In this paper, we use a perceptual difference model (Case-PDM) [2-4] to optimize VD schemes based on image quality. Experiments are conducted on a variety of brain data sets so as to ensure robustness across different MR systems, coils, pulse sequences, and subjects.

METHODS

To optimize VD, we parameterize the underlying probability density function (PDF) to consist of two equally weighted 1D Gaussians symmetric about the center of k-space, giving two parameters to optimize (σ and d). The PDF is used to control random acquisition for CS reconstruction, as described in Ref [1]. Case-PDM gives a scalar measure of image quality. On a training set of image data, we exhaustively evaluated a grid of PDF parameters, reconstructed images, and evaluated them using Case-PDM. To test the applicability of the optimized trajectory, we evaluated results on other test data sets. We used 5 brain data sets: D1 and D2 were transverse and saggital data acquired on a GE 3T using T1 FLAIR sequence; D3 and D4 were acquired on a Philips 3T system with an IR pulse sequence with different inversion times; D5 was acquired on a SIEMENS 1.5 T. (D1,D2,D3,D4) and (D5) were acquired with 8-channel and 4-channel head coils, respectively, from Invivo Corp, Gainesville, USA. 6 reduction factors were used. In total, 3600 images with a wide range of image quality were evaluated.

RESULTS

Figs. 1a and 2a show the comparison of the PDM scores of images reconstructed with different optimized trajectory and the experience-based trajectory [1] for different reduction factors. More low frequency signals and less high frequency signals are sampled by the optimized trajectory than those by the experience-based trajectory. When averaged across different reduction factors, the image quality improvement is 26% for the data set used for training, and 23% when the optimized trajectory was applied to other data sets. This demonstrates that acquisition trajectory parameters optimized from one training data set can be applied to other data sets of different slice/ subject/ pulse sequence/ scanner/ coil and maintain high image quality in CS reconstruction, as long as the two data sets share similar anatomical structures. The improvement of image quality and the application of the optimized trajectory can be further observed in Figs. 1 and 2.

CONCLUSIONS

The results demonstrate the applicability of Case-PDM on image quality evaluation of CS reconstruction. And we conclude that the PDM-optimized random acquisition trajectory can generate better CS reconstruction than the experience-based one. The optimized trajectory is robust across subjects and hardware configurations; that is, CS reconstructions with optimal acquisition trajectory maintain high image quality when the test dataset is different from the training dataset. Re-calibration is only necessary if the dataset has a different anatomical structure.

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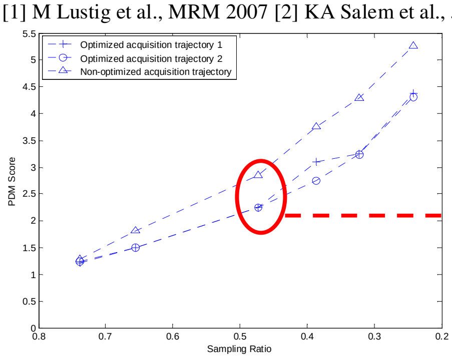
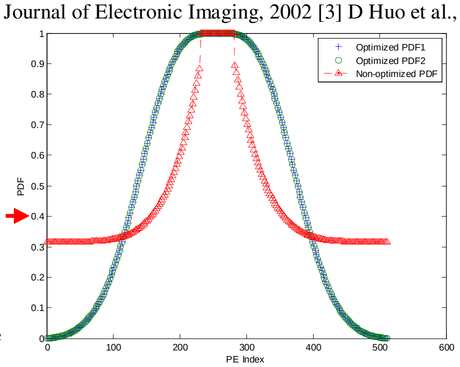
REFERENCES

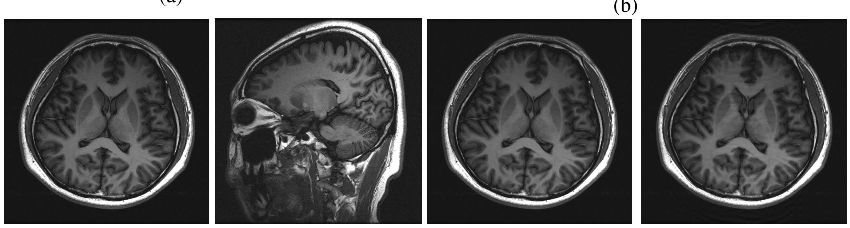
[1] M Lustig et al., MRM 2007 [2] KA Salem et al., Journal of Electronic Imaging, 2002 [3] D Huo et al., J Magn Reson 2008 [4] J Miao et al., Medical Physics 2008



(a)



(b)



(c) (d) (e) (f)

Fig. 1 Two sets of optimized trajectory parameters (P1 and P2) were obtained at each different sampling ratio. P1 was from training Dataset 1 created from raw image (c) and P2 from training Dataset 2 created from raw image (d). When either P1 or P2 was used in the same data set (Dataset 1), the CS reconstructions had better image quality (or lower PDM score) than the one using experience-based trajectory as shown in plot (a) where cross and circle represent P1 and P2, respectively. The PDF's of P1, P2 and experienced-based trajectory at sampling ratio of 0.52 are also displayed in plot (b). More low frequency signals and less high frequency signals are sampled by optimized trajectory, as compared to experience-based one. The images reconstructed by CS using P1 trajectory and experience-based trajectory at sampling ratio of 0.52 are displayed in (e) and (f), respectively. A significant image quality improvement can be seen when comparing image (e) to image (f).

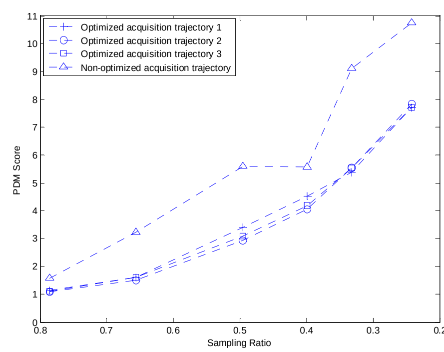


Fig. 2 Three sets of optimized trajectory parameters (P3, P4 and P5) were obtained at each different sampling ratio from training data sets Dataset 3, Dataset 4, and Dataset 5, respectively. When P3, P4 and P5 were all used in the same data set (Dataset 3), for each sampling ratio the CS reconstructions had better image quality (or lower PDM score) than the one using experience-based sampling scheme as shown in plots where cross, circle and square represent P3, P4 and P5, respectively.