4th Iranian Human Brain Mapping Congress

چهارمین همایش نقشه برداری مغز ایران

25-27 October 2017 / ۱۳۹۶ ۳-۵ آبان

مرکز همایشهای بین المللی ابوریحان-دانشگاه شهید بهشتی

Iranian Society for Cognitive Science & Technology

CERTIFICATE of PRESENTATION

This is to certify that

Sajjad Jafari

presented a poster entitled:

Two New 1- Dimension Under-Sampling Scheme in Compressed Sensing Algorithm for Brain Magnetic

at the 4th Iranian Human Brain Mapping Congress

held in Shahid Beheshti University, Tehran, I.R. Iran

October 25-27, 2017

Prof. Mojtaba Zarei, MD, PhD, FRCP (UK)
President of IHBM2017

Dr. Ehsan Kamrani, PhD
Scientific Secretary of IHBM2017

Two New 1D Under-Sampling Schemes for Compressed Sensing of Brain Magnetic Resonance Images

Sajjad Jafari [1], Mahdi Saadatmand-Tarzjan [1], Javad Safaie [2*]

[1] Medical Imaging Lab, Department of Electrical Engineering, Faculty of Engineering, Ferdowsi University of Mashhad, 9177948974 Mashhad, Iran

[2] Department of Electrical Engineering, Faculty of Engineering, Ferdowsi University of Mashhad, 9177948974 Mashhad, Iran

Background and Aim

Nowadays,MRI plays an important role in the diagnosis of neurodegenerative diseases. Unfortunately,this brilliant technology is suffered by the so much time, which has to be spent for extracting the k-space information.The k-space subsampling methods(e.g. compressed sensing(CS)[1])are used to overcome this problem.Since the middle part of k-space contains the main part of information,under-sampling should be intense in the center.Moreover,high degree of subsampling randomness ameliorates the CS performance.1-Dimension variable polynomial density(1DP)is a typical under-sampling mask in different CSMRI methods[1,3,4],which we try to improve it in this study.

Methods

Two 1D masks are proposed.In the first step,the k-space is under-sampled by 33.5%(86-from-256 lines).Afterwards,in order to increase the randomness and decrease the amount of data(which reduce the computational time),the next polynomial mask(in other k-space

direction)is applied on the 70% of given samples from previous step.This combined mask is called ProposedMask1(PM1).

In another proposed mask, the *k*-space is divided into 3 equal segments.The central part is undersampled differently from the two lateral segments.This mask undersamples 26.8%(68-from-256 lines)from the central part by polynomial method,and 3.35%(9-from-256 lines)from each lateral ones by random method.This mask is called ProposedMask2(PM2).

Results

All mentioned masks were implemented simultaneously with the M.Lustig toolbox reconstruction CSMRI[2] and just the under-sampling scheme was changed.The proposed masks were compared with the M.Lustig's 1DP mask[1].Fig.1 represents the applied masks.All of them undersample 33.5% with a polynomial degree of two.The simulations have been done for 3images:MatlabPhantom(P1),T1-weightedBMRI,and GuerquinPhantom.Average PSNRs of 10-trials for all masks and the related error bars are shown in table1/Fig.2.

Conclusion

The simulation shows that PM2 has a better reconstruction quality than the 1DP due to a better sampling of the central k-space region and a high degree of randomness.Moreover,it is true that the PM1 slightly reduces the quality compare to the 1DP,but it decreases the amount of data as well,which results in computational time reduction.

References

[1] Lustig, M., Donoho, D., Pauly, J.M., (2007), 'Sparse MRI: the application of compressed sensing for rapid MR imaging', Magn.Reson. Med., vol. 58, no. 6, pp. 1182-95.

[2] Lustig,M.(2007)‘Simulated CSMRI toolbox’, people.eecs.berkeley.edu/~mlustig/software/sparseMRI_v0.2.tar.gz

[3] Baker, C. (2016) ‘Comparison of MRI under-sampling techniques for compressed sensing with translation invariant wavelets using FastTestCS: a flexible simulation tool.’ Journal of Signal and Information Processing, vol. 7, no. 4, pp. 252-271.

[4] Zhan,Z., Cai,J.F., Guo,D., Liu,Y., Chen,Z., Qu,X., (2016) ‘Fast multiclass dictionaries learning with geometrical Directions in MRI reconstruction’ IEEE Transactions on Biomedical Engineering, vol. 63, no. 9, pp. 1850-61.

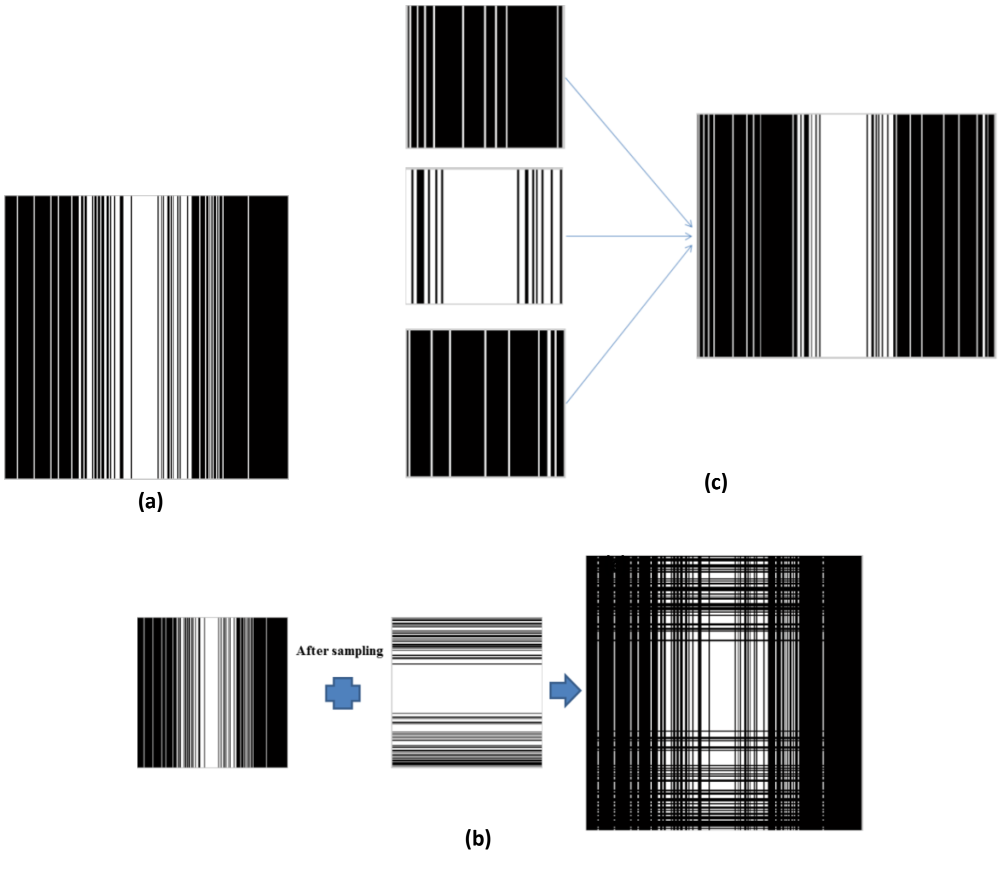

Fig. 1. The applied masks, (a) 1DP Lustig et al. (2007). (b) PM1. (c) PM2

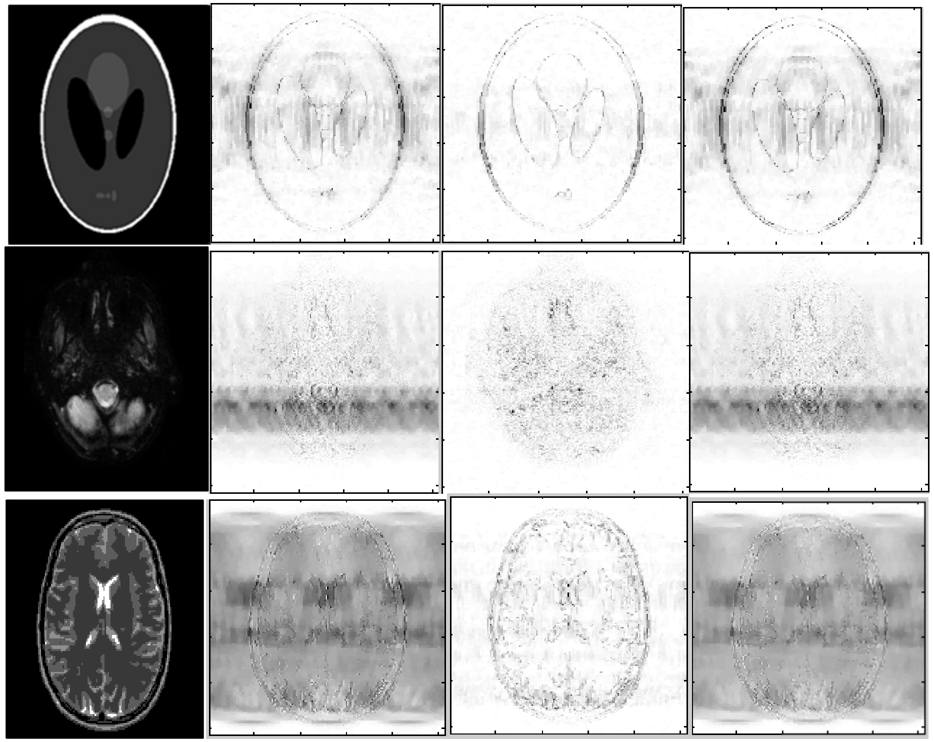

Fig. 2. The error map reconstruction for three different phantom MR images with: 1DP Lustig et al. (2007) (2nd column), PM1 (3rd column), and PM2 (4^{th} column).

Table 1. Comparing the PSNR of our proposed masks with 1DP Lustig et al. (2007) for three phantom images, which are presented in Fig. 2. The best results were highlighted bold text.

Benchmark Images	1DP	MP1	MP2
Matlab Phantom	34.3	33.7	**38.8**
T1weighted BMRI	34.5	34.0	**35.6**
GuerquinPhantom	31.3	30.9	**32.5**
Average±STD	33.4 ± 2.1	32.9 ± 1.9	$\mathbf{35.6 \pm 6.6}$