Comparison of Randomly Undersampled Magnetic Resonance Imaging Reconstruction Methods

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Introduction

Acquisition time is important in many MRI applications, such as cardiac imaging and functional MRI. However, due to the limitations of hardware (gradient amplitude and slew rate) and physiological constraints (nerve stimulation), undersampling in k-space, the Fourier domain in MRI, is one of the most widely used techniques to reduce the scan time. However, reducing the amount of acquired data in k-space leads to severe artifacts presented in Figure 1. Reconstruction of a high-quality image from undersampled k-space data is important not only for clinical diagnosis but also for automatic processing.

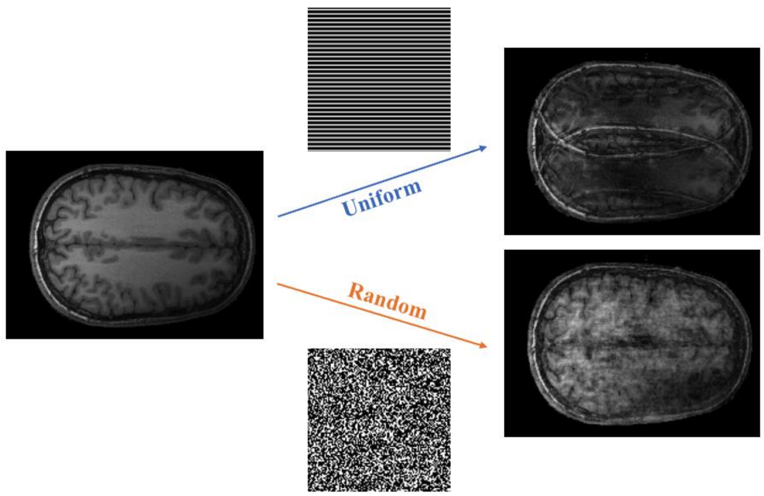

Figure 1. Example of undersampling patterns and resultant images. Uniform undersampling (top) leads to coherent, aliasing artifacts due to reduced field of view. Random undersampling (bottom) results in incoherent artifacts. Image source: http://web.stanford.edu/class/ee369c/data/brain_8ch.mat

In this project, we aim to focus on the random undersampling pattern, and use a variety of methods that we learned in class to mitigate the incoherent artifacts. The methods would be evaluated with different undersampling rates and compared with one conventional technique – Conjugate Gradient (CG) SENSE.

Related Work

Currently, there are two major methods that can be used for random undersampling patterns, CG SENSE and SPIRiT. CG SENSE is a highly efficient reconstruction method proposed by Pruessmann *et al* [2]. The forward model can be written as

$$F = Em$$

where m is the vectorized reconstructed image, F is the vectorized sampled data in k-space, E is the encoding matrix including terms of coil sensitivity and spatial encoding. Artifact reduced image is acquired by solving m using conjugate gradient descent. One disadvantage of this method is that it requires accurate coil sensitivity maps.

SPIRiT, which is an iterative method proposed by Lustig *et al* [3]. It recovers missing data points in k-space by exploiting correlations between neighboring k-space points. Within each iteration, weights of neighboring data points are estimated using calibration data set. Missing data points are filled by convolving the kernel with k-space until stop criteria is met. Compared to CG SENSE, SPIRiT is relatively computationally intensive.

Project Overview

In this project, we will examine three approaches to reconstruct randomly undersampled MRI: 1) Non-local Means (NLM) algorithm, 2) ADMM with prior, 3) CNN based method. Methods will be applied to retrospective undersampled data with variant undersampling rates, and results will be evaluated by both PSNR and error maps.

Non-local Means

Non-local Means (NLM) algorithm is an image denoising method by taking the weighted average of pixel neighborhoods. In this project, we will use NLM to resolve the incoherent artifacts from random undersampling. Building on the denoising algorithm, a step of data consistency will be added by reinserting the originally sampled k-space data into the k-space of estimated image.

ADMM

Alternating Direction Method of Multipliers (ADMM) is a widely used optimization algorithm for constrained problems. In this project, we will try to exploit different priors including Anisotropic Total Variation, Isotropic Total Variation and Frobenius Norm of Hessian (FH).

CNN based

With the fast development of convolution neural networks, deep CNNs have also been commonly used for image reconstruction. In [5], Schlemper *et al.* proposed a cascade convolutional neural networks for MRI Reconstruction from undersampled data. This framework used cascade blocks to simulate the iterations of reconstruction in DL-based methods and achieved promising results at a fast speed.

Database for CNN:

We will conduct experiments for the CNN model based on the Stanford University School of Medicine MRNet Dataset. MRNet contains 1,370 knee MRI exams from Stanford University Medical Center where all exams are performed with standard knee MRI coil and a routine non-contrast knee MRI protocol.

Milestones

Week 8 (Feb. 21 – Feb. 27)	• CG SENSE • Non-local Means • ADMM
Week 9 (Feb. 28 - Mar. 6)	• ADMM (cont.) • CNN
Week 10 (Mar. 7 – Mar. 11)	• Prepare presentation and report

References

[1] Hamilton J, Franson D, Seiberlich N. Recent advances in parallel imaging for MRI. Prog Nucl Magn Reson Spectrosc. 2017 Aug;101:71-95. doi: 10.1016/j.pnmrs.2017.04.002. Epub 2017 May 2. PMID: 28844222; PMCID: PMC5927614.

[2] Pruessmann KP, Weiger M, Börnert P, Boesiger P. Advances in sensitivity encoding with arbitrary k-space trajectories. Magn Reson Med. 2001 Oct;46(4):638-51. doi: 10.1002/mrm.1241. PMID: 11590639.

[3] Lustig M, Pauly JM. SPIRiT: Iterative self-consistent parallel imaging reconstruction from arbitrary k-space. Magn Reson Med. 2010 Aug;64(2):457-71. doi: 10.1002/mrm.22428. PMID: 20665790; PMCID: PMC2925465.

[4] Bien N, Rajpurkar P, Ball RL, Irvin J, Park A, Jones E, Bereket M, Patel BN, Yeom KW, Shpanskaya K, Halabi S, Zucker E, Fanton G, Amanatullah DF, Beaulieu CF, Riley GM, Stewart RJ, Blankenberg FG, Larson DB, Jones RH, Langlotz CP, Ng AY, Lungren MP. Deep-learning-assisted diagnosis for knee magnetic resonance imaging: Development and retrospective validation of MRNet. PLoS Med. 2018 Nov 27;15(11):e1002699. doi: 10.1371/journal.pmed.1002699. PMID: 30481176; PMCID: PMC6258509.

[5] Schlemper J, Caballero J, Hajnal JV, Price AN, Rueckert D. A Deep Cascade of Convolutional Neural Networks for Dynamic MR Image Reconstruction. IEEE Trans Med Imaging. 2018 Feb;37(2):491-503. doi: 10.1109/TMI.2017.2760978. Epub 2017 Oct 13. PMID: 29035212.

[6] Adluru G, Tasdizen T, Whitaker R, DiBella E. Improving Undersampled MRI Reconstruction Using Non-local Means. 2010 20th International Conference on Pattern Recognition. 2010: 4000-4003.

[7] Buades A, Coll B, Morel JM. A Review of Image Denoising Algorithms, With a New One. Multiscale Model. Simul. 2005. 4(2), pp 490-530.

[8] Boyd S, Parikh N, Chu E, Peleato B, Eckstein, J. Distributed optimization and statistical learning via the alternating direction method of multipliers. Foundations and Trends in Machine Learning. 2001. 3, 1, 1–122.

[9] Lefkimmiatis S, Bourquard A, Unser M. Hessian-based norm regularization for image restoration with biomedical applications. IEEE Trans Image Process. 2012 Mar;21(3):983-95. doi: 10.1109/TIP.2011.2168232. Epub 2011 Sep 19. PMID: 21937351.