Accelerating MRI with k-space Undersampling Pattern learned by CNN

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Abstract

Undersampling the k-space is now widely considered as a way to accelerate Magnetic Resonance Imaging (MRI) scans. In this paper, we jointly optimized the k-space undersampling pattern with the MRI images classification. Since the under-sampling process in k-space can be viewed as dot-producting the full k-space with a binary mask, we simulated the whole physical process by feeding the full-sampled MRI images into a convolution layer with only one kernel. And in our proposed method, we also apply the centrosymmetry constraint to this kernel to ensure that the mask in k-space is only real-valued. We then test our proposed optimized subsampling pattern on Alzheimer Classification Dataset with another two traditional subsampling pattern for speeding up MRI acquisition. As a result, we demonstrate that our proposed subsampling pattern will not sacrifice the MRI images classification accuracy and accelerate the 50% of the MRI acquisition time.

1 Introduction

One challenge of the modern medical science on the topic of Alzheimer's disease (AD) has been the difficulty to acquire and store a large amount of evidence sufficient to diagnose. Most of the studies on Alzheimer's disease have been carried out using medical images.

In this article, Magnetic resonance imaging (MRI) images will be employed. MRI is a commercially available device that clearly describes particular findings of AD. The stages can be divided into Very Mild demented, Mild demented, Moderate demented and Non demented, in respect of symptoms. Among these, exudative changes between mild and moderate are the key indication for most physicians to initiate therapy and evaluate the therapeutic effect.

On the other hand, the common acquisition time of MRI has determined the large amount of time, efforts and compliance physicians require from potential patients. Nevertheless, a method to wisely adjust the acquisition mask in frequency space, in order to shorten the process and decrease the data size, while the performance on AD recognition keeps the same, is needed.

Advances in machine-learning techniques provide a solution for addressing this issue. In particular, convolution neural networks (CNNs) have greatly advanced the classification of medical images using multi-layer neural networks and deep-learning algorithms. In neuroscience, the excellent accuracy of CNNs has already been reported in the classification of single neuro [Soltanian-Zadeh, 2019 971] etc. The impressive performance of neural networks in the classification of AD images has also been reported for the automated detection of AD features for guidance of therapy and monitoring disease progression [Fisher, 2019 978]. In this article, we propose a CNN model with a physical layer, to reduce the information we require in frequency domain, while keeping a similar performance with benchmark.

2 Related Works

Several papers have discussed recent developments of accelerating MRI through optimized k-space undersampling. Jing Liu et al [1] proposed CIRcular Cartesian UnderSampling (CIRCUS) method

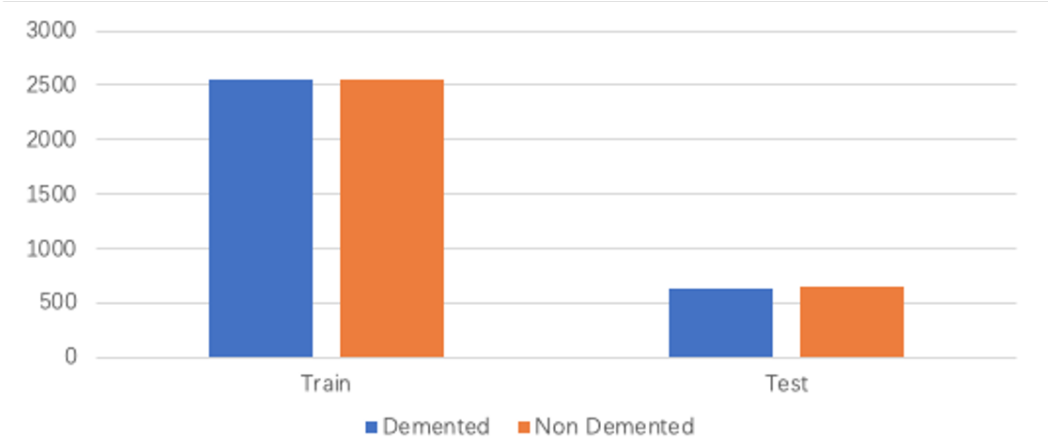


Figure 1: dataset distribution

to design subsampling patterns for Cartesian imaging using Compressed Sensing or Parallel Imaging reconstruction. It is demonstrated in their paper that trustable image reconstructions with the proposed randomized CIRCUS patterns are better than those with uniform random samplings. Haldar J.P. et al [2] apply the information-theoretic Cramer-Rao bound to obtain a deterministic subsampling pattern by their OEDIPUS framework. Bahadir C.D. et al [3] present a joint learning method which optimizes the probabilistic sub-sampling mask together with a reconstruction neural network, called Learning based Optimization of the Under-sampling Pattern (LOUPE).

Below, we will describe our method, that simply optimizes a convolution layer ahead of a classification neural network instead of learning the sub-sampling mask in k-space directly. Our algorithm is very easy to implement and converge. It also yields significant improvement compared to the traditional sub-sampling method.

3 Method

3.1 Learning under-sampling mask in spatial domain

In this section, we describe the details of how we optimize the k-space undersampling pattern in image domain by a simple convolution layer. The pipeline of the whole process is shown in Fig 2.

In MRI acquisition process, the magnetic coils first receive signals of each point in k-space. One common way to accelerate MRI acquisition is to undersample the whole MRI k-space, which means the collected data is lossy. This undersampling operation is mathematically equal to dot-producting a binary mask with the original k-space. The dot-product in Fourier domain is equivalent to convolution in time domain. With the help of this fact, we could directly optimize a convolution layer in image domain instead of a mask in k-space. To implement this simulation via programming, we utilize the MRI images in Alzheimer dataset which are reconstructed by full-sampled k-space signals. In training, we input the images into a convolution layer ahead of the CNN used for classification in order to optimize the undersampling pattern in image domain. In testing, we transform both images and kernels into k-space and then we use the kernel to filter the MRI k-space signals. We then transform the filtered signals back to the image domain and input it into classification CNN.

3.2 Constraints on the kernel

To ensure optimizing the convolution kernel works the same as optimizing the sampling mask in k-space, we add one constraint on the kernel.

The Fourier transform of a real-valued symmetric function is also a real-valued symmetric function. Taking advantage of this fact, we force the convolution kernel to be centrosymmetry. To implement this constraint, we create one small convolution kernel that is trainable. And then we copy this kernel three times and flip them horizontally, vertically and both at the same time. The centrosymmetry kernel then can be merged from these four mutually mirrored kernels.

3.3 Binarization of optimized sampling mask

To simulate the sampling process, we binarize the learned mask using the median value as the threshold. As a result, 50% of datapoints are filtered out. The median value is picked by testing different percentage of datapoints should be preserved so that the final classification accuracy will not be affected. Due to the time and page limit, we did not make a thorough analysis of how many k-space datapoints should be kept.

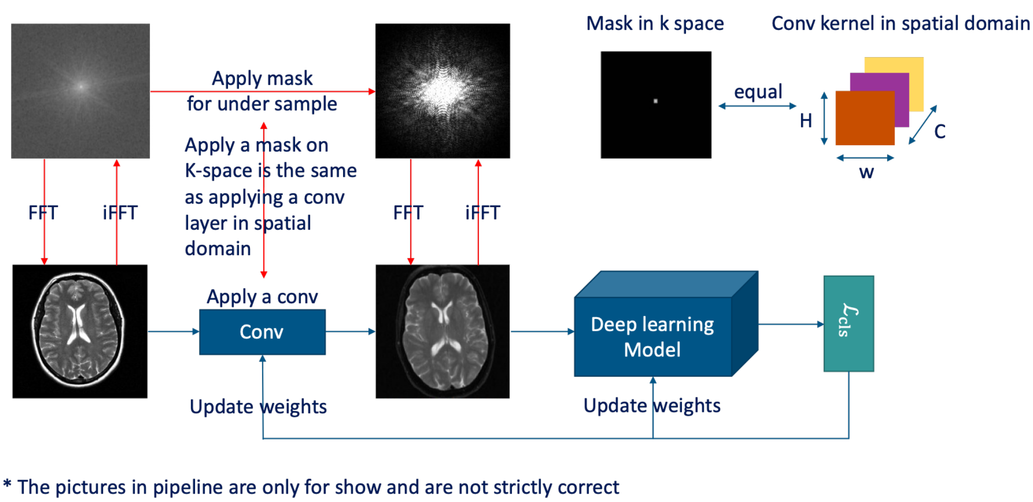


Figure 2: pipline of our method

4 Experiments

The dataset we used comes from Kaggle, where the goal is to distinguish the patients with demented or not. The dataset consists of 4 classes of images: Very Mild demented, Mild demented, Moderate demented and Non demented, which are all full resolution images. We split those 4 classes into 2 classes: with demented and Non demented. So, our training dataset has 2561 positive images (i.e. with demented) and 2560 negative images, and our testing dataset has 639 positive images and 640 negative images. All the images have same dimension of 208×176. Figure 2.1 shows the distribution of different classes in datasets.

According to the analysis from previous section, our simulated physical layer is a single convolution layer, which can be added on the top of a standard classification model during training. During evaluating, we binarized our learned mask by using threshold 0.5.

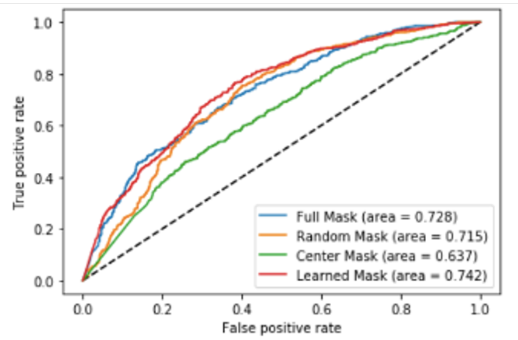
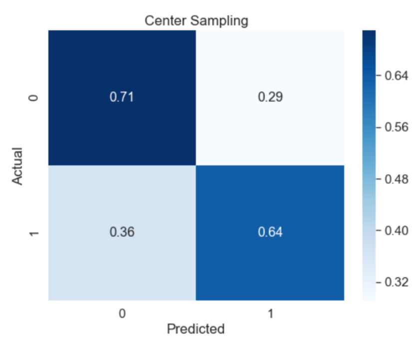


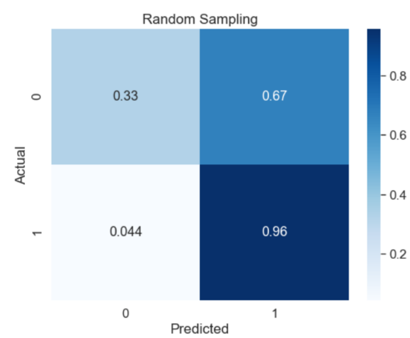
Figure 3: ROC curves

Mask Type	Accuracy
Full Mask	0.6915
Random Mask	0.6907
Center Mask	0.6705
Our Mask	0.7091

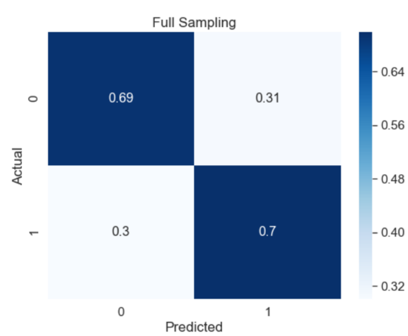
Table 1: Classification Accuracy



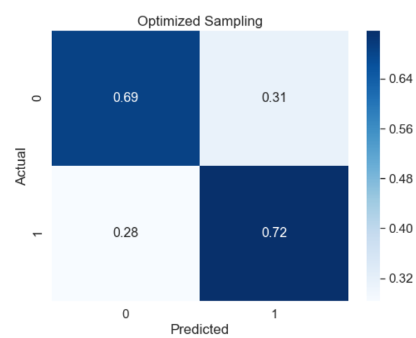
(a) center confusion



(b) random confusion



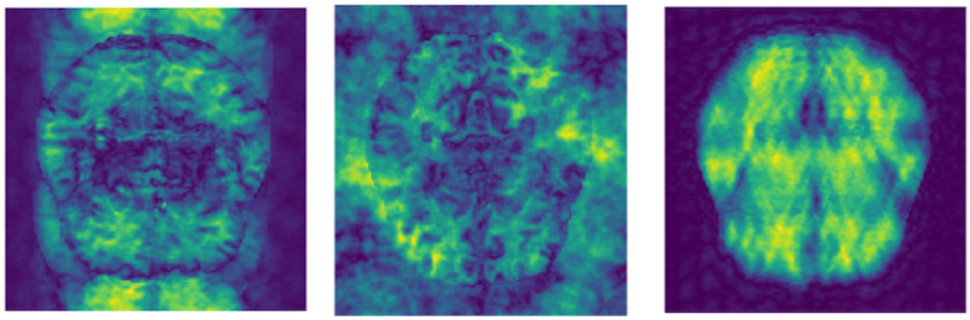
(c) full confusion



(d) our confusion

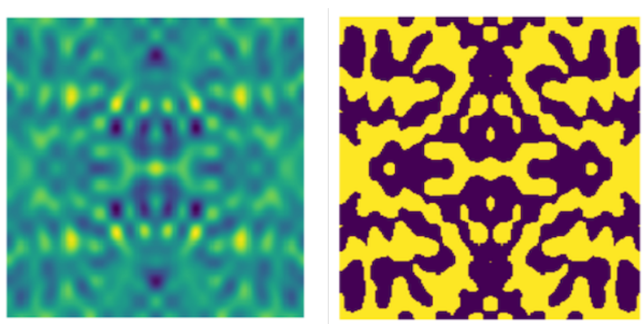
Figure 4: different masks confusion matrix

We compared our learned mask with circle mask, random gaussian mask and full mask. Table 1 lists classification accuracy for different masks. Our learned mask improved the classification accuracy compared with other three masks to extent. Figure 3 shows the ROC curve and AUC for different masks. Although the ROC curves show that our mask is better than other compared masks, there are still a lot of improvement room for our mask. Figure 5 shows the confusion matrices for different masks. It is clear that our mask can get better performance than circle(center) mask and full mask. Although the true negative of random mask is better than our mask, the true positive of random mask is very low. This situation means that random mask will leads the model into being inclined to predict all images as negative (with demented). From this point, our mask can help model to get more correct predictions than random mask. Figure 2 shows the learned mask image and the learned mask image after binarization. Combined figure 2 and table 1, we indeed sparse the mask a lot, which means our binarized mask can reduce the runtime of MRI, as well as improve the performance of classification.



(a) circle mask (b) random Gaussian mask (c) our mask

Figure 5: different masks images



(a) before binarization (b) after binarization

Figure 6: learned masks before and after binarization

5 Discussion

We achieved promising results on the problem of finding the best sampling pattern for MRI by using a conv layer to simulate the physical layer and combining it with a deep learning model. Our sampling pattern is capable of reducing 50% of the runtime of MRI, as well as improving the performance of model compared with traditional sampling pattern.

References

[1] Liu, Jing, and David Saloner. "Accelerated MRI with CIRcular Cartesian UnderSampling (CIRCUS): a variable density Cartesian sampling strategy for compressed sensing and parallel imaging." Quantitative imaging in medicine and surgery 4.1 (2014): 57.

[2] Haldar, Justin P., and Daeun Kim. "OEDIPUS: An experiment design framework for sparsity-constrained MRI." IEEE transactions on medical imaging 38.7 (2019): 1545-1558.

[3] Bahadir, Cagla Deniz, Adrian V. Dalca, and Mert R. Sabuncu. "Learning-based optimization of the under-sampling pattern in MRI." International Conference on Information Processing in Medical Imaging. Springer, Cham, 2019.