Learning Fast Magnetic Resonance Imaging

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Introduction

Magnetic Resonance Imaging (MRI) is considered today the golden-standard modality for soft tissues. The long acquisition times, however, make it more prone to motion artifacts as well as contribute to its relative high costs.

Over the years, multiple studies concentrated on designing reduced measurement schemes (random, uniform, random variable density and equi-spaced Cartesian) and image reconstruction schemes based on compressive sensing and deep learning for MRI, however these problems have been so far addressed separately.

Contribution. We propose to learn accelerated MR acquisition schemes (in the form of Cartesian trajectories) jointly with the image reconstruction operator.

Proposed method

In our pipeline, we perform the sub-sampling in the k-space domain and the reconstruction in the image domain, following an inverse Fourier transform.

Sub-sampling layer As depicted in Fig. 1, the sub-sampling layer receives a fully sampled k-space, denoted as \( \mathbf{x} \) and outputs the sub-sampled version \( \mathbf{y} = \Phi \mathbf{x} \), where \( \Phi \) is a binary sub-sampling mask. Being restricted to Cartesian trajectories, the sub-sampling mask \( \Phi \) is a column vector, the length of the number of rows of the k-space matrix.

![Figure 1. Accelerated MRI acquisition and reconstruction.](image)

Binary mask. We follow the methodology of [Courbariaux et al., 2015] proposing to keep two versions of the mask: binary, denoted as \( \Phi \), and continuous, denoted as \( \Phi_c \). The two versions are used as follows.

1. During forward and back propagation for calculating the gradients, the binary version \( \Phi \) is used.
2. The gradient step with the calculated weight update \( \Phi \) is applied to the continuous \( \Phi_c \).
3. The continuous mask \( \Phi_c \) is binarized as follows to produce an updated version of \( \Phi_c \):

\[
(\Phi)_j = \begin{cases} 
1, & \text{if } (\Phi_j)_y \leq \tau, \\
0, & \text{otherwise}
\end{cases}
\]

where \( \tau \) is determined as the upper \( q \)-tile of the values of \( \Phi_c \) with \( q \) denoting the decimation rate.

Mask initialization. We randomly initialize \( \Phi \) and then the continuous mask \( \Phi_c \) is initialized by assigning a random value from the uniform distribution \( U(0, 0.5) \) to each row selected in \( \Phi \) and from \( U(0, 0.65) \) otherwise.

Reconstruction network. As the inverse operator, we used a multi-resolution encoder-decoder network with symmetric skip connections, also known as the U-net architecture [Ronneberger et al., 2015].

Experiments & results

We trained our model on the NYU fastMRI database with different decimation rates in two scenarios:

1. Static mask. Only the inverse operator (reconstruction network) is learned with a fixed mask.
2. Learned mask. End-to-end simultaneous training of forward operator (the sub-sampling layer) and inverse operator (the reconstruction network).

Fig. 2 depicts the image distortion (in terms of PSNR, SSIM & NMSE) as a function of the decimation rate; standard deviation was calculated on repeated experiments with different initial central fraction sizes. Notice the increased improvement in the higher decimation rates.

![Figure 2. Comparison of fixed vs. learned masks with respect to SSIM, NMSE, PSNR metrics.](image)

Mask evolution. A key observation is that the model “selects” different frequency lines than the ones of the initial mask, but still preserves similarity to it. This implies that while the final mask is depended on the initialization, the learning process consistently improves the performance of the mask.

![Figure 3. Visual comparison between Fixed/Learned mask for different decimation rates.](image)

4-fold acceleration 8-fold acceleration

![Figure 4. Mask evolution during training. Training progress is shown on the horizontal axis in epochs.](image)

Conclusion & future directions

We demonstrated, as a proof-of-concept, that learning simultaneously the sub-sampling pattern and the reconstruction network improves the end image quality of an MR imaging system.

The main limitation of our work is the restriction of the optimal sub-sampling patterns to Cartesian trajectories. In the future, we plan to extend the proposed approach to the more general case of finding the best k-space trajectory with the constraint on the acquisition time rather than on the number of measurements.

References
