Reconstruction of sparsely sampled Magnetic Resonance Imaging measurements with a convolutional neural network

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Abstract

Compressed Sensing accelerated Magnetic Resonance Imaging (MRI) suffers from long image reconstruction times, due to the need for solving ill-posed minimizations. This limits the clinical use of accelerated MRI techniques. We have trained a neural network to decode accelerated, undersampled MR acquisitions, eliminating the need for reconstruction algorithms.

1 Introduction

Magnetic Resonance Imaging (MRI) is widely used in clinical practice, and has become a preferred or necessary tool for medical practitioners. However, long acquisition times are still a bottleneck, limiting MRI use to only a few of the many possible contrasts, limiting spatial resolution and coverage. In addition, long acquisition times have high associated costs and reduce patient comfort.
In the last few years, numerous acceleration techniques have sprung up, combining smart encoding strategies with prior-knowledge reconstruction techniques, in order to reduce scan times.
Compressed Sensing (CS) enables reconstruction of measurements of fewer points than specified by the Nyquist criterion ([1]). It was first used as an MRI acceleration technique by Lustig et al. [3].

Requirements for CS-MRI

- Incoherent sampling of Fourier coefficients can be achieved by sampling random coefficients. A naive reconstruction, such as filling zeroes for all unmeasured Fourier points an performing an inverse FFT, results in *incoherent* undersampling artifacts. These kind of artifacts are noise-like in structure and can be removed in the CS reconstruction.
- MR images are assumed to be sparse in some way, for example the image of a brain, heart or foot usually contains few sharp edges, and large areas of the images consist of connected areas of roughly the same signal intensity. Image transforms (e.g. a wavelet transform) can be performed on these images, and the vast majority of wavelet coefficients will be very close to zero.
- The final problem to be solved after an accelerated measurement can be described as the following optimization:
$$\min \|F_u\vec{x} - \vec{y}\|_2^2 + \lambda \|W\vec{x}\|_1 \tag{1}$$
where F_u is the undersampled Fourier operator, $\vec{x}$ is the desired image, $\vec{y}$ is our measurement and W is a wavelet transform operator. With regularization parameter λ, we can tune the balance between data consistency (the l_2-norm) and minimizing the sparsity (the l_1-norm).

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In the last ten years, a plethora of optimization algorithms aiming to efficiently solve Equation 1 have been devised. However, in general, solving for a multi-dimensional , multi-channel measurement can still take minutes to hours on a dedicated server. On-line reconstruction on the MR computer is unpractical. Furthermore, parameter tuning of λ makes practical application of CS in the clinical technique even more cumbersome.

In this abstract, we present experiments aiming to circumvent the optimization altogether, instead using a *learned decoder*, to recover an artifact-free image from accelerated measurements. This approach has the ability to make on-line reconstruction in clinically acceptable times within reach.

2 Methods

Data preparation To obtain training images, we used the OASIS Alzheimer dataset [4]. Twenty thousand image sections of 64x64 pixels were randomly sampled. Image sections were randomly rotated and reflected. An undersampled single-coil MR acquisition was simulated, using a variable-density sampling mask, which is shown in Figure 1. As MR data is complex-valued, the data was split into a real and imaginary part, before being entered in the network.

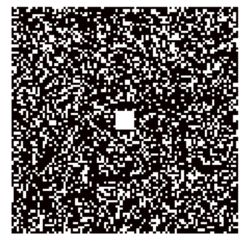
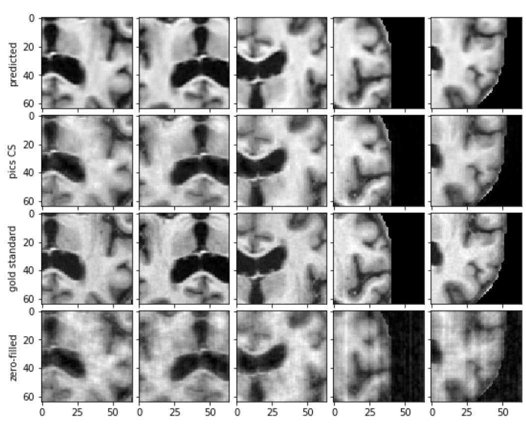


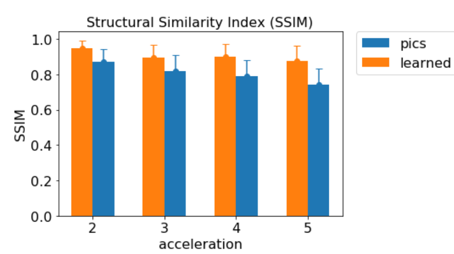
Figure 1: Undersampling mask used in this study (white signifies measured Fourier coefficients, black signifies skipped coefficients).

Network architecture We used the Keras framework to build a neural network, inspired by the general purpose AUTOMAP architecture [7] consisting of one fully connected input layer, two fully connected layers with hyperbolic tangent activation, 3 convolution layers (ReLu activation, 5x5), and a fully connected output layer. The mean-squared error between the gold-standard image and the reconstruction was used as a loss function. A RMSProp optimizer was used for training, with a learning-rate of 0.00002. Total training time was approximately 1 hour on a NVIDIA Titan XP GPU.

Evaluation Evaluation images were reconstructed with the learned network model, and with the *pics* function of the BART toolbox [6] (parameters: wavelet regularization, $\lambda = 0.001$, 100 iterations). For a range of accelerations, the structural similarity index (SSIM) was compared in 50 test images. Zero-filled references were calculated by an inverse FFT of the raw measurement data.



(a) Reconstruction results, for 2 times acceleration, on 5 test images. First row: learned reconstructor. Second row: *pics*. Third row: gold-standard. Fourth row: zero-filled.



(b) Structural Similarity Index (SSIM) + standard deviation for different acceleration factors, ranging from 2 to 5 times. For all accelerations the learned reconstructor has a higher SSIM than the *pics*-algorithm.

Figure 2: Model Evaluation results

3 Results

A comparison between the learned network reconstructions, the *pics*-algorithm, zero-filled reconstructions and a gold standard is shown in Figure 2(a). Reconstruction time was 2 seconds for the *pics*-algoritm, and 2 ms for the learned network. Both methods recover details lost in the zero-filled reconstruction, such as tissue edges. The learned reconstructor seems to have a better white/grey matter contrast than the *pics*-algorithm. For acceleration factors of 2 to 5, the learned reconstructor outperformed *pics* in terms of SSIM (Figure 2(b)).

4 Discussion

We have shown that compressed sensing reconstruction is comparable to state-of-the-art optimization algorithm reconstruction. Recent work has suggested the feasibility of good-quality Deep Learning-based reconstruction of MR data ([7], [2]). Mousavi and Baraniuk [5] have shown that for general compressed sensing (1D), deep learning networks, trained on a particular undersampling pattern, outperformed the best optimization algorithms.

In contrast to optimization-based reconstruction, the machine learning approach is less flexible, requiring MR measurements with a specific mask, while the optimization-based reconstruction could in principle work with every undersampling pattern and resolution. However, a fixed undersampling pattern is easily programmed in an MR scanner. Future work will include prospective measurement of undersampled MR signal and a radiologist-scoring of image quality. Additionally, we will train on larger image sizes and include multi-channel data.

5 Conclusions

We successfully implemented simulated the CS measurement encoding, and used this to train a neural network to do a reconstruction. In our experiments, we saw results superior to the state-of-the-art optimization algorithms.

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