Compressed Sensing with Deep Image Prior for Chest CT Signal Denoising

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1 Motivation

Compressed sensing (CS) has emerged as a powerful technique in medical imaging, offering the potential to acquire high-quality data using a few measurements. CS reduces data acquisition times by utilizing random sampling patterns to capture different parts of an image [1]. For medical imaging applications like MRI and CT, this is useful, since MRI data collection is costly and time-consuming due to financial and physiological constraints. Moreover, MRI and CT data contain implicit sparsity in the Fourier domain, due to the large regions of homogenous tissue such as muscle and fat, which have relatively constant signal intensity. Figure 1 shows the noisy MRI image that results from undersampling the k-space, as part of CS. We can represent this problem of recovering an unknown

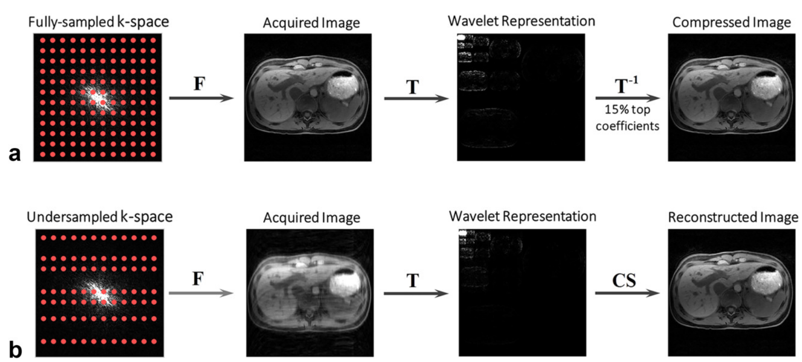

Figure 1: Compressed Sensing exploits inherent sparsity in MRI [2].

signal $x^* \in \mathbb{R}^N$ by observing a set of noisy measurements $y \in \mathbb{R}^m$ as:

$$y = Ax^* + \eta$$

where $A \in \mathbb{R}^{m \times n}$ is the measurement matrix and η is the zero-mean additive Gaussian noise. Since the number of measurements taken is less than the dimension of the unknown vector x^*, we know that $m < n$, which means that this an under-determined system and thus an ill-posed problem. There has been significant work on finding a solution, both classical and learned approaches. In this project, we will implement a deep-image prior and compare its performance against unlearned techniques like ADMM and TVAL3. We will discuss this approach in the next two sections.

2 Related Work

The deep image prior was first proposed by Ulyanov et al ([3]) in 2017. Subsequent papers have used pretrained deep image priors whereby an optimal latent space is learned for the pretrained model from a dataset ([4], [5]). For this project, we rely primarily on the work of [1], which proposes using untrained deep image priors to substantially improve processing performance without losses to reconstruction error. Instead of learning a latent space from existing data, the proposed method fixes a Gaussian, iid. input to an untrained model and instead solves the minimization problem: $\text{argmin}_w ||y - A \cdot M(z; w)||_2$ where w are the weights of the model M with input z, measurement y, and measurement matrix A. In other words, this process leverages the underlying model architecture as a prior rather than an existing dataset. This method is described by [1] as the compressed sensing deep image prior (CS-DPI) since it does not require a pretraining dataset.

3 Project Overview

In this project, our goal is to implement the CS-DIP and evaluate its performance against denoising techniques learned in class, namely ADMM with TV prior. The dataset we will use is [6], which contains 35,747 chest CT scans from 19,661 adult patients. It is the largest volumetric medical imaging dataset in the world, and has been cited several times by medical imaging and machine learning researchers.

A crucial finding of [3] is that the network architecture itself provides a good prior for image denoising. Thus, we also plan on trying another model architecture in addition to the Deep Convolutional Generative Adversarial Network (DCGAN) to our denoising task. Some potential architecture candidates include Variational Autoencoder architectures with convolutional layers. We plan to use PSNR as our figure of merit for comparing the three methods: ADMM with TV prior, CS-DIP with DCGAN architecture, and CS-DIP with custom architecture. If time permits, we will also explore the learned regularization technique discussed in that is shown to improve performance of the CS-DIP denoising algorithm in the presence of more noise.

4 Milestones and Timeline

Here is a proposed timeline for the project:

- Week 7: Define project. Clone repository and organize/preprocess CT-scan dataset.
- Week 8: Train DCGAN (the DIP in paper) on CT-scan images. Run classical/unlearned approaches.
- Week 9: Tune model parameters and architecture to get good qualitative and quantitative results.
- Week 10: Create poster and do write-up. (If time permits, implement learned-regularization technique discussed in [1]).

References

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