University of Brasilia at Gama – FGA/UnB
Software Engineering

Generative Adversarial Network Prior Information for Improved Compressed Sensing Magnetic Resonance Image Reconstruction

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Resumo

A versão final do documento incluirá um resumo de todo o trabalho, incluindo metodologia, resultados e conclusão.

Abstract

The final version of this document will include an abstract. This will summarize the introduction (contextualization, objectives, justification), the methodology, the results, and the conclusion.

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MR Magnetic Resonance xii

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ML Machine Learning xii

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CNN Convolutional Neural Network xiii

GPU Graphics Processing Units xii

CV Computer Vision xiii

NLP Natural Language Processing xiii

CS Compressed Sensing xii

MLP Multilayer Perceptron xvi

DFN Deep Feedforward Networks xvi

1 Introduction

In this thesis, we propose a Generative Adversarial Network (GAN) approach for prior information extraction to feed a Compressed Sensing (CS) algorithm, aiming to reconstruct images with both reduced signal-to-noise error and less acquisition time compared to conventional CS. Achieving higher quality with reduced number of samples allows faster exam procedures, making Magnetic Resonance Imaging (MRI) cheaper, faster and more convenient for both patients and clinics.

1.1 Context

MRI is a widely used imaging modality in medical practice because of its great tissue contrast capabilities, it has evolved into the richest and most versatile biomedical imaging technique today[2], making MRI the best option for medical imaging whenever it is possible to use.

However, like everything in life, there is a trade-off to consider when using MRI. Typically, reconstructing an MRI is an ill-posed linear inverse task (a problem that has either none or infinite solutions in the desired class). Problems of this nature impose a trade-off between *accuracy* and *speed*[3]. The information obtained from Magnetic Resonance (MR) is commonly represented by individual samples in the k-space, which translates to the Fourier transform of the image to be reconstructed[4]. This MR sampling sparse nature makes CS a liable technique to use when reconstructing MRI, hence we here propose a novel CS prior information approach for better results.

CS has been for years the state-of-art technique in MRI reconstruction and has been improved later by the use of prior information[4]. CS uses the premise that given a signal with a sparse representation in some known domain, it is possible to reconstruct the signal using limited linear measurements taken from a non-sparse representation.

Machine Learning (ML) methods have been utterly developed and improved recently with the use of higher computing power derived from the invention of Graphics Processing

Units (GPU) and other hardware improvements, allowing ANN to come to practicality. These ANN models, often referenced as Deep Learning (DL), have become the state-of-art in various areas, such as Computer Vision (CV), Natural Language Processing (NLP), Recommendation Systems, amongst other fields[5, 6, 7]. These fast-paced developments led to improvements in medical data processing using DL as well. ML techniques can be used in several different manners to improve medical analysis, here we focus on applying GAN in the process of attaining improved prior information to feed the CS algorithm obtaining higher signal-to-noise ratios and faster computation procedures.

1.2 Scientific Problem Definition and Proposal

MRI is great for high-quality tissue images, but there are some drawbacks: MRI exams are often very long and require the patient to be in a static position throughout the whole process, this makes the exam challenging for patients that have difficulties in keeping a still position for several minutes. Another intrinsic complication in MRI procedures is that it is nearly impossible to get images from moving tissues like a beating heart or flowing blood veins as that would require an enormous amount of samples, which with current technologies used in clinics is not viable. Algorithms that reconstruct MRI try to tackle this sampling issue by producing the best possible quality images for the least amount of samples collected, making the exams faster and less sample-dependent.

CS algorithms have been the state-of-art in MRI reconstruction for the past few years, and now with the advances of DL, new techniques are being produced taking advantages of how ANN are powerful in imaging processing, especially Convolutional Neural Network (CNN) and, more recently, GAN networks are becoming the new state-of-art techniques in several computer vision areas. A problem with CS applications is that the reconstruction process can be very slow. Newer CS algorithms try to tackle this issue by adding prior information to make the algorithm abstract static information in the region analysed.

Prior information for CS can go from previous MRI frames and exams to even medical records. Prior information is normally generated by simplistic mathematical approaches like filtering and thresholding on the images. Besides the simpler technique applied, these information extraction procedures oftentimes is restricted to few frames and does not take into account the nature of organs and tissues structures, a feature that DL should be able to identify and use in order to generate better quality information. This means that there is a lot of room for improvement towards prior information engineering techniques, as DL models have been proven superior in tasks of this nature.

Within this context, we propose a modern prior information engineering system with the usage of GAN, aiming for higher quality prior information to feed the CS and reducing the number of samples dependability. This will reduce the number of samples needed, making the MRI exams faster and, consequently, cheaper.

1.3 Objectives

1.3.1 General Objective

This thesis' goal is to develop an MR prior information system retriever based on GAN architecture to analyse if the quality of the prior information fed to CS algorithms can be improved, hence improving quality in reconstructed MRI and decreased necessity for larger sampling.

1.3.2 Specific Objective

In order to achieve the general objective described above, we have set the following specific goals:

- Implement direct and indirect CS MRI reconstruction algorithm and apply to *k-space* measurements.
- Evaluate CS MRI reconstructions with real image data.
- Implement a GAN for regular image generation with a known CV dataset.
- Implement a GAN architecture for prior information retrieval and train it against *k-space* measurements.
- Evaluate the use of GAN architecture for prior information retrieval against state-of-art prior information techniques.

2 Theory Foundation and State-of-Art

2.1 Magnetic Resonance Imagery

medical imaging...

2.2 Artificial Neural Networks

2.2.1 Biological Inspirations

ANNs, as the name suggests, have been (loosely) inpired by biological neural networks (brains) from animals. The concept of using many layers of vector-valued representation is drawn from neuroscience. The choice of the functions $f^{(i)}(x)$ used to compute these representations is also loosely guided by neuroscientific observations about the functions that biological neurons compute[8]. Another trait they share is that just like the human brain can be trained to pass forward only meaningful signals to achieve larger goals of the brain, the neurons on a neural network can be trained to pass along only useful signal[9].

2.2.2 Multilayer Perceptron

The most basic unit in ANNs is the *artificial neuron.* These artificial neurons that are modeled mirroring the biological neurons behaviour as both of them are stimulated by inputs. Each artificial neuron play an analogous role to a neuron carrying some information they receive to other artificial neurons in the ANN. Artificial neurons take in inputs $x_1, x_2, \ldots, x_n$, each and multiply them by their respective weights $w_1, w_2, \ldots, w_n$. Then these weighted inputs are summed together producing the *logit* of the artificial neuron, $z = \sum_{i=0}^{n} w_i x_i + b$, with b being a constant number added called *bias.* After this, the logit is passed to a function f in order to generate the value $y = f(z)$.

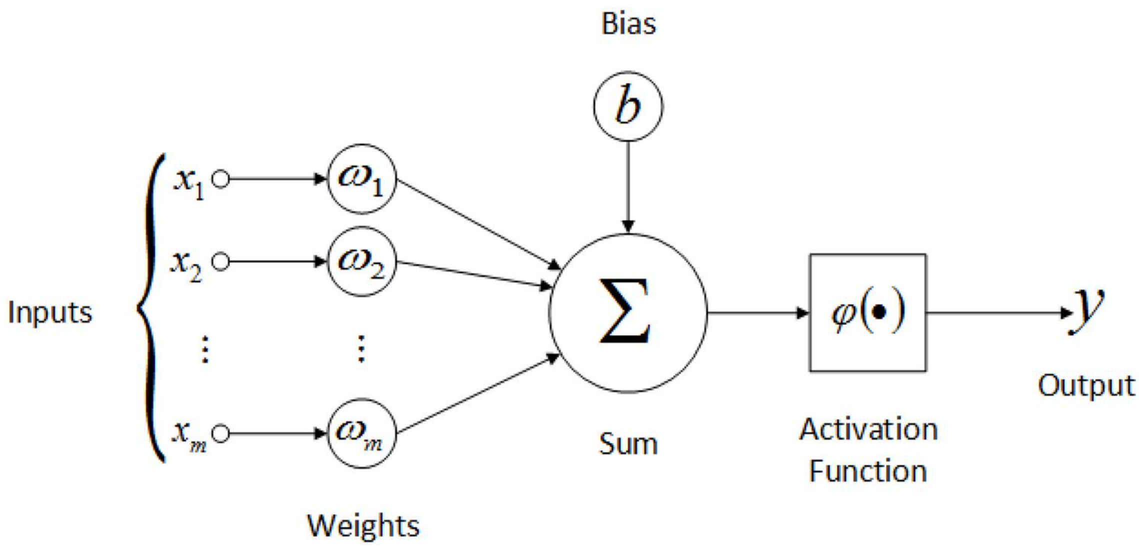

Figura 2.1. Schematic of an Artificial Neuron[1].

Deep Feedforward Networks (DFN) or Multilayer Perceptron (MLP)s are a type of ANN very commonly used. It is the foundation to many famous architectures like CNNs. DFNs have an input layer followed by one or many hidden layers and a single output layer. Each layer is fully connected to the adjacent layer.

MLPs are computational models that flow information throuth the function being evaluated from $\mathbf{x}$. The goal is to approximate some function $f*$, for instance, for a classifier, $y = f*(x)$ maps an input x to a category y. The feedforward defines a mapping $y = f(x;\theta)$ and learns the value of the parameters θ that result in the best function approximation[8].

The behaviour of an ANN is shaped by its architecture, which describes the number of units it should have and how these units connect to each other.

Most ANNs are organized into rows of neurons called layers. These layers are arranged in a chain-like structure, with each layer being a function of the layer before it. These layers' goal is to extract *representations* out of the data fed and generalize what is meaningful towards minimizing the error rate. This architecture scheme is represented by the following equation:

$$h^{(i)} = g^{(i)}(W^{(i)T}x + b^{(i)})$$

Where i is the layer index

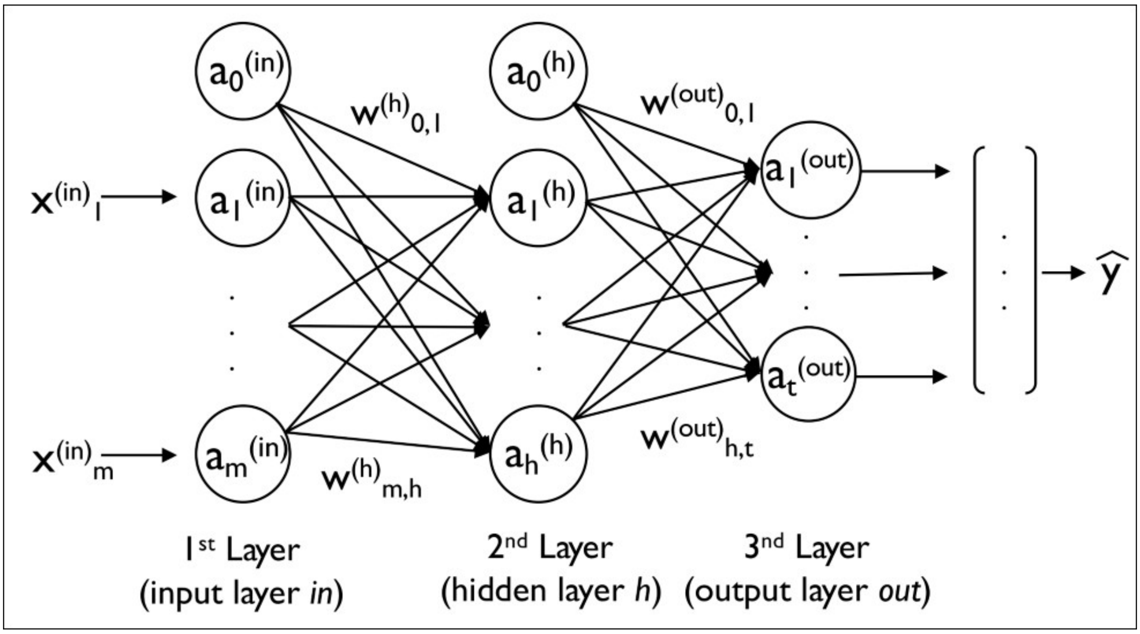

Figura 2.2. ANN Architecture Sample.

2.2.3 Activation Functions

2.2.4 Loss Functions

2.2.5 Hyperparameters

2.2.6 Backpropagation

2.2.7 Gradient Descent

2.3 Generative Adversarial Networks

2.4 Compressed Sensing

CS is an extremely powerful algorithm that was introduced in 2004 proposing a novel technique for the acquisition of signals of sparse or compressible nature. CS has disrupted the signal processing field as it has broken the *Shannon's theorem*: the sampling signal rate must be at least twice the maximum frequency present in the signal (Nyquist rate). CS has been proven to sample the signal at a much lower rate than the Nyquist sampling rate. The idea came from questioning the necessity of extracting large portions of samples when much of these samples are discarded, exposing the inefficiency of trying to gather all signal.

“Why go to so much effort to acquire all the data when most of what we get will be thrown away? Can we not just directly measure the part that will not end up being thrown away?[10]”

CS tackles the necessity to reconstruct signals with

CS parts from the principle that if given x, a digital image or signal has a sparse representation in a orthonormal basis (e.g.wavelet, Fourier), then the N most important coeffiecients in that expasion allow reconstruction with l_2 error $O(N^{1/2-1/p})$[10].

2.4.1 Sampling

3 METHODOLOGY

4 Results

5 Conclusion

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