Chapter 1

INTRODUCTION

1.1 Introduction to the Problem

As the modern technology progresses, there is a problem of ever-increasing amounts of data. By now, everyone is aware that most of the data received can be thrown away without almost no perceptual loss. The phenomenon of ubiquitous compressibility raises the general questions: why put in so much effort to acquire all the data when most of what we get will be thrown away? Can’t we just directly measure the part that won’t end up being thrown away?

The traditional way of sampling i.e. the Nyquist-Shannon sampling theorem states that to restore a signal exactly and uniquely, you need to have sampled with at least twice its frequency. Of course, this theorem is still valid; if you skip one byte in a perfectly band-limited signal, you can’t restore the original signal. But most real world signals are not perfectly band-limited. When represented in terms of appropriate basis functions, such as trigonometric functions or wavelets, many signals have relatively few non- zero coefficients. In compressed (or compressive) sensing terminology, they are *sparse*. The paradigm of Shannon’s sampling theory is cumbersome when extended to the emerging wide-band signal systems since high sampling rates may not be viable for implementation in circuitry: high data- rate A/D converters are computationally expensive and require more storage space.

Compressive sampling or compressive sensing serves as the answer to all these questions. Data acquisition protocols based on Compressive Sensing perform as if it were possible to directly acquire just the important information about the signals and not acquire that part of the data that would eventually just be ‘thrown away’ (as in the case of Lossy Compression schemes). These protocols are non-adaptive and parallelizable; they do not require knowledge of the signal to be acquired in advance - other than knowledge that the data will be compressible - and do not attempt any understanding of the underlying object to guide an active or adaptive sensing strategy.

1.2 Problem Statement

To sample a given analog signal at a rate much lower than the Nyquist rate as suggested by the Nyquist-Shannon sampling theorem and to reconstruct the original signal using Convex Relaxation (CR), Greedy Iterative (GI) and Iterative Thresholding (IT) reconstruction schemes.

1.3 Motivation

As our modern technology-driven civilization acquires and exploits ever-increasing amounts of data, ‘everyone’ now knows that most of the data we acquire ‘can be thrown away’ with almost no perceptual loss. The phenomenon of ubiquitous compressibility raises very natural questions: why go to so much effort to acquire all the data when most of what we get will be thrown away? Can’t we just directly measure the part that won’t end up being thrown away? Compressed sensing is a major tool to realize it in reality. It is the next big thing in the domain of data compression and the idea of contributing to this upcoming technology is one that interests us greatly.

1.4 Objective

In the traditional signal processing techniques, we uniformly sample data at Nyquist rate, prior to transmission, to generate ‘n’ samples. These samples are then compressed to ‘m’ samples; discarding n-m samples. This leads to wastage of both time and effort. It is also expensive computationally as it needs more storage space that may later be unused. Our goal is to ensure that the number of samples (i.e. ‘m’) captured is far less as compared to the traditional method (i.e. ‘n’) and to show that signal reconstruction is as effective thereby reducing cost, effort and time needed to implement it.