CHAPTER 1

INTRODUCTION

1.1 Background of the Problem

Compressed Sensing (CS), or compressive sampling, is a new technique for acquiring and reconstructing digital signals with potential benefits in many applications. CS methods utilize the scarcity of signals in a given domain to significantly reduce the number of samples required to reconstruct a signal. In general, CS requires significantly fewer samples than Nyquist sampling, which has been the basic principle governing signal acquisition for many years. The Nyquist sampling theorem states that when sampling a signal, the sampling rate should be at least twice the bandwidth of that signal.

The conventional approach to compressing waveforms takes the following steps: First, the signal is sampled at the Nyquist rate, then the sampled signal is compressed using methods such as wavelet or Fourier transforms, calculating the relevant coefficients, and discarding the coefficients deemed unnecessary. The signal can then be stored or transmitted, after which it is decompressed and an estimate of the original signal is recovered. Problems arise when the measured signal has a very wide bandwidth, as this would require a very high sampling rate, resulting in a large amount of data. It can also be considered an inefficient process if numerous signal elements are then deemed unnecessary and discarded. This is often the case if the signal is sparse after decomposition during the compression process, even though it is not sparse in the time domain [3].

Telemedicine is technology-assisted healthcare [10]. The technology in question is IoT technology where the IoT device is usually sensor-based that can capture health information such as electrocardiography (ECG) signals, heart rate, respiratory rate, electroencephalography (EEG) signals and blood pressure needed by the medical team to diagnose the patient's condition [1]. In [10], research was conducted to collect patient health data, including electrocardiography (ECG) signals. The data obtained is then sent to the server computer to carry out the process of diagnosing the patient's condition. The data is so massive that in the near future, the problem that arises can be in the form of limited data storage space. The problem requires a solution in the form of data compression before the data is stored without reducing the important content of the data message.

In CS coding applications for ECG signal compression, usually the sensing matrix Φ is randomly constructed based on some probability density functions[7]. For example, in [7], the authors compare the reconstruction performance of CS methods, which adopt three different distributions to determine the sensing: (i) Gaussian distribution, (ii) Bernoulli distribution, and (iii) sparse distribution (i.e., uniform non-sampling). The main disadvantage of adopting a randomly constructed matrix is that the reconstruction performance may vary significantly depending on the correlation between the sensing matrix elements and the acquired samples. In this study, this limitation is overcome by adopting a sensing matrix that is not randomly generated but depends on the ECG signal to be compressed (*Dynamic Sensing Matrix*) [1].

In research [1][21][9][14][5] has successfully found a new way to build a sensing matrix / measurement matrix in the CS process dynamically using the first lead data as a reference of the observed data. The SNR results obtained are significantly consistent compared to the sensing matrix / measurement matrix built using a random sensing matrix generator. However, the disadvantage of the method is that sometimes the SNR value obtained is still below the SNR generated using the random sensing matrix generator, and the processing time is still much longer than using the random sensing matrix generator.

1.2 Research purposes

Develop a *sensing matrix* with the *dataset* used based on existing reference sources so that the signal reconstruction results show good results with a high *compression rate* (CR) or *measurement rate* (MR) and *Signal Noise Ratio* (SNR) assessment parameters and still have a light computational complexity in the reconstruction process so that the *Processing Time* required is shorter.

1.3 Statement of the Problem

How to determine the right sensing matrix that matches the selected *dataset* in order to produce a good signal reconstruction based on customized *Signal to Noise Ratio* (SNR) and *Processing Time* measurements?

1.4 Hypotheses

In previous research, the Φ gauge matrix was constructed based on the ECG signal to be compressed. This method produces a fairly high and consistent SNR value so that the SNR value does not have a high variance. However, the Processing Time is quite far adrift compared to the randomly constructed gauge matrix but it is still within the limit to be applied to systems that have limited resources.

This research tries to modify the measuring matrix based on previous research to improve the SNR *(Signal Noise Ratio)* value and shorten the *processing time*. The results obtained from the modification are proven to increase the SNR value better and shorten the *Processing Time* than before.

1.5 Research Method

The research method applied in the completion of this thesis is by collecting datasets selected from the open-source website physionet.org. Then the retrieved data will be processed to determine a suitable measuring matrix for the parsed dataset so that the data reconstruction process produces good value from the compressive sensing process based on the assessment of Signal Noise Ratio (SNR) and Processing Time..

1.6 Problem Limitation

The problem boundaries to limit this research are:

1. Using ECG data as observed data.
2. This research uses secondary data sets.
3. The *Sparsification* and *Reconstruction* processes use Discrete Cosine Transform (DCT).
4. The *Reconstruction* processes use Orthogonal Matching Pursuit (OMP).