Compressed Sensing System Design for biomedical signal acquisition

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Masters in Technology

in

Electronics and Electrical Communication Engineering

by

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Under the supervision of

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Spring Semester, 2021-22

April 24, 2022

DECLARATION

I certify that

(a) The work contained in this report has been done by me under the guidance of my supervisor.

(b) The work has not been submitted to any other Institute for any degree or diploma.

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INDIAN INSTITUTE OF TECHNOLOGY KHARAGPUR

KHARAGPUR - 721302, INDIA

CERTIFICATE

This is to certify that the project report entitled "**Compressed Sensing System Design for biomedical signal acquisition**" submitted by **Gautam Jha** (Roll No. 17EC32005) to Indian Institute of Technology Kharagpur towards partial fulfilment of requirements for the award of degree of Masters in Technology in Electronics and Electrical Communication Engineering is a record of bona fide work carried out by him under my supervision and guidance during Spring Semester, 2021-22.

Date: April 24, 2022

Place: Kharagpur

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Abstract

Name of the student: **Gautam Jha** Roll No: **17EC32005**

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With advances in speed of operation of electronic devices, the required power for signal acquisiton and transmission is going up day by day. We can utilize some recent developments in Compressive Sensing (CS) to acquire signals at sub-nyquist frequency thus realizing low power performance. Part of this work demonstrates a sub-nyquist signal acquisition system on circuit level in LTSpice. Implementation of CS on LTSpice is based on sparsity of signal in frequency domain. In addition to that, we try to test this compressive sensing paradigm on real life biomedical signal, namely ECG which present sparsity in time domain. Here we present several system level considerations for CS acquisition systems for biomedical signals. We demonstrate how compression before signal transmission can reduce power consumption in wireless sensor nodes. The described system is also implemented in RTL on behavioural level. Results show upto 4x savings in transmitter power consumption without significant loss in received signal SNR.

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I would like to whole heartedly thank my project guide, Prof. Pradip Mandal for his constant guidance and supervision during the tenure of the project. I would also like to thank him for making me realize the importance of learning while doing the project and encouraging me to drive ahead. I would also like to thank my parents and family members who have helped me have a positive outlook in these uncertain times. Finally I would like to thank the Department of Electronics and Electrical Communication Engineering for providing me this opportunity. I would like to express my sincere gratitude to all the staff of this department and my friends for their help rendered in the completion of this project work.

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Abbreviations

SNR	**S**ignal to **N**oise **R**atio
CS	**C**ompressed **S**ensing
PRBS	**P**seudo **R**andom **B**inary **S**equence
LFSR	**L**inear **F**eedback **S**hift **R**egister
OMP	**O**rthogonal **M**atching **P**ursuit
ADU	**A**nalog to **D**igital **U**nits
EEG	**E**lectro**e**ncephalo**g**raphy
ECG	**E**lectro**c**ardio**g**ram
EMG	**E**lectro**m**yo**g**raphy
RTL	**R**egister **T**ransfer **L**evel

Chapter 1

Compressed Sensing Overview and Previous Work

1.1 Nyquist Sampling and its limitations

Current signal acquisition systems sample a signal at frequencies greater than twice the bandwidth of the signal as per Nyquist-Shannon Sampling Theorem. This theorem underlies the design of all kinds of devices - consumer electronics, medical imaging devices, radio receivers, etc. But with improvement in CMOS fabrication process and technological scaling, the speed requirement of these devices continue to grow. As per nyquist theorem the sampling frequency should also increase, but making devices at such high frequencies and reasonable SNR is very challenging.

Signal acquisition systems based on nyquist sampling only utilize one characteristic of data - bandlimitedness in frequency. But many real world signals have additional characteristics which can be exploited to design signal acquisition systems. One such characteristic is the **sparsity** of signal. A signal is said to be sparse in some domain (called sparsifying domain) if the basis coefficients of the signal in that basis domain have very few non zero entries.

Mathematically, A signal of dimension N having basis vector $\alpha_{N\times1}$ in sparsifying domain Ψ_{NXN} is said to be sparse if very few elements of α are non zero. This number of nonzero elements, K is called the sparsity of signal. Some examples of sparse signals are: ECG signals in wavelet domain (Gangopadhyay et al., 2014), EEG Signals in Gabor dictionary (Chen et al., 2010) and EMG signals are approximately sparse in time/frequency domain (Dixon et al., 2012).

1.2 Compressed Sensing Encoding

Compressed Sensing is a modern signal processing paradigm that processes sparse signals at sub nyquist sampling rates. This effectively samples signals at their *information rate* rather than their data rate.

We consider and N dimensional signal $X_{N\times1}$ in the sparsifying basis $\Psi_{N\times N}$ having a sparity of K :

$$X = \Psi\alpha \tag{1.1}$$

This N dimensional signal is projected onto a lower dimension $M(< N)$ using a measurement matrix $\Phi_{M\times N}$ to obtain $Y_{M\times1}$

$$Y = \Phi X \tag{1.2}$$

This measurement matrix consists of random elements taken from some allowed random distributions (Bernoulli, Gaussian and Uniform). Multiplying signal with this random matrix results in spreading of signal content in the sparsifying domain. Equation 1.1 and 1.2 we get the following system of linear equation:

$$Y = \Theta\alpha$$

Where $\Theta = \Phi\Psi$, In this equation we know M measurements: Y and we need to recover α. This is an underdetermined system of equation which cannot be solved using conventional techniques.

(Candes et al., 2006) describe that under certain constraints that measurement matrix Φ should follow, we can recover the original signal completely. This method to obtain original N dimensional signal α from Y samples is through l_1 norm optimization:

$$\hat{\alpha} = arg\,min\,\|\alpha\|_1 \quad s.t. \quad y = \Theta\alpha$$

1.3 Motivation of the work

In this project we aim to implement the advances in compressive sensing theory for the purpose of signal reconstruction. We try to test these on naturally sparse signals - sinusoidal signal in frequency domain and biomedical signals in time/freq/wavelet domain. We also aim to implement the system using basic circuit element blocks in LTSpice and in RTL respectively and demonstrate that perfect recovery is possible even after sub-nyquist sampling of bandlimited signals. Finally, we demonstrate the results of applying compressive sensing to real life sparse signal, namely ECG signals. For the case of ECG signals, compression is not needed for sampling because their bandwidths are in the range of few KHz and hence do not pose problem in signal acquisition. Rather the power hungry elements of biomedical sensor nodes are transmitters. So we attempt to implement compression after signal acquisiton in digital domain for the case of ECG signal so as to reduce wireless transmission power. In the chapters that follow, we demonstrate each of the different systems we have implemented in detail and finally present the results of this work.

Chapter 2

Compressive Sensing Applications

2.1 Compressive Sensing for sinusoidal signal

We have previously implemented a compressed sensing signal acquisition system in LTSpice using basic circuit element blocks as shown in Figure 2.1. For the purpose of randomization of signal, we use a 7 bit PRBS which is generated from a Fibonacci based Linear Feedback shift register (LFSR).

We have input signal V_{in} sampled by ideal sample and hold block. This signal is fed to 2 voltage controlled current integrator blocks. Each block operates in complementary cycles - For the first $4(= CF)$ cycles, the upper voltage controlled current integrator operates on the sampled signal and for the next $4(= CF)$ cycles the lower voltage controlled current integrator operates on the sampled signal. The current sources integrate or remove charge from the capacitor in a quantity proportional to the value of the V_{SnH}. Charging or Discharging is controlled by a control circuit that depends on PRBS value at that instant.

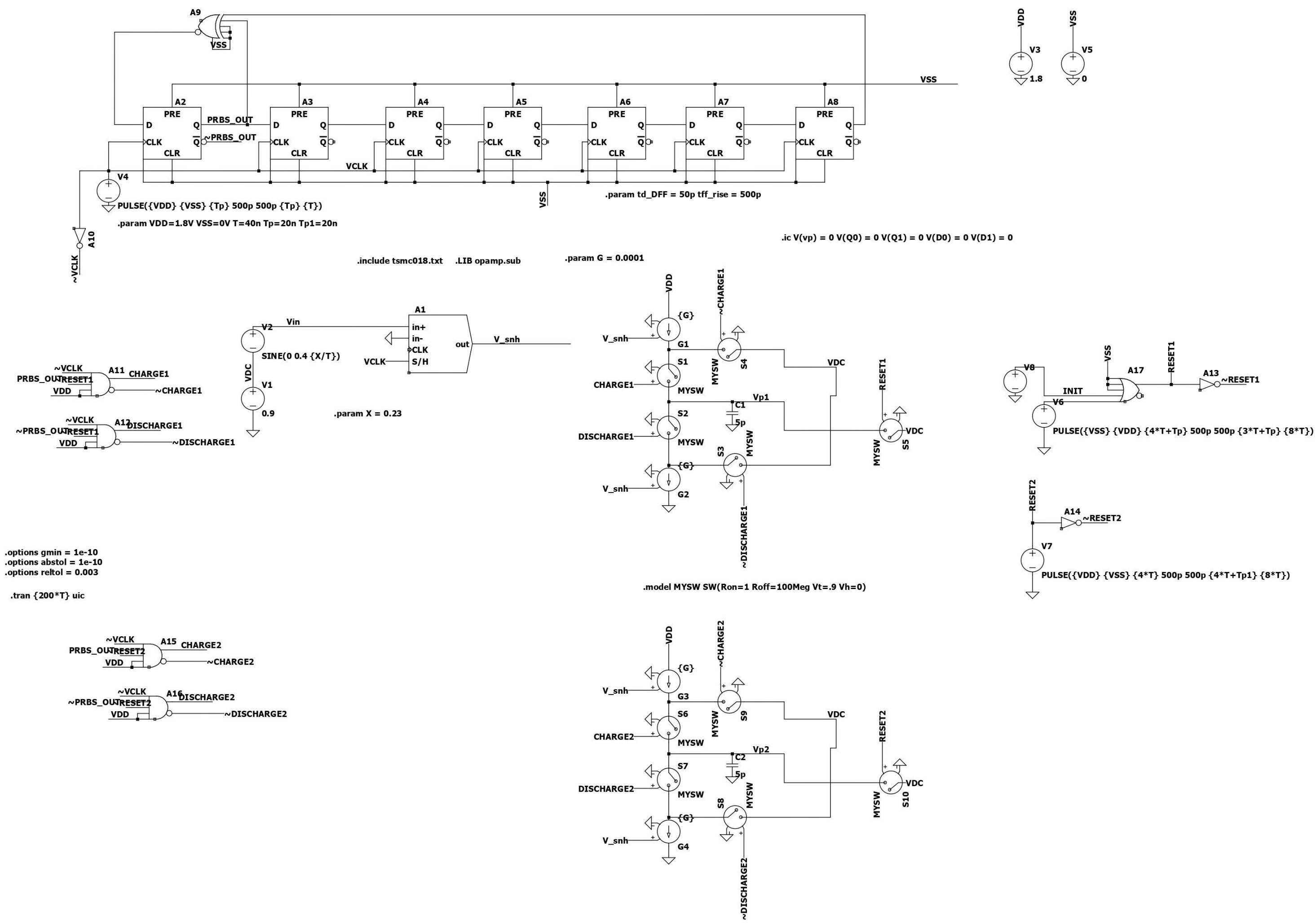

FIGURE 2.1: LTSpice implementation of compressed sensing signal acquisition

This way we get the resultant measured values in capacitor voltages V_{p1} and V_{p2}. These M values are transferred to MATLAB from LTSpice .raw simulation file. Reconstruction and further processing is then done in MATLAB.

In MATLAB we extract values of different signals from .raw file. The two signal V_{p1} and V_{p2} are combined alternately to give the resultant M measured values. Compression is performed in the circuit on both the input signal and V_{DC}. So first, the effect of DC is removed by multiplying DC value vector with measurement matrix and subtracting this from measured values. This vector is then finally sent to OMP algorithm for signal reconstruction.

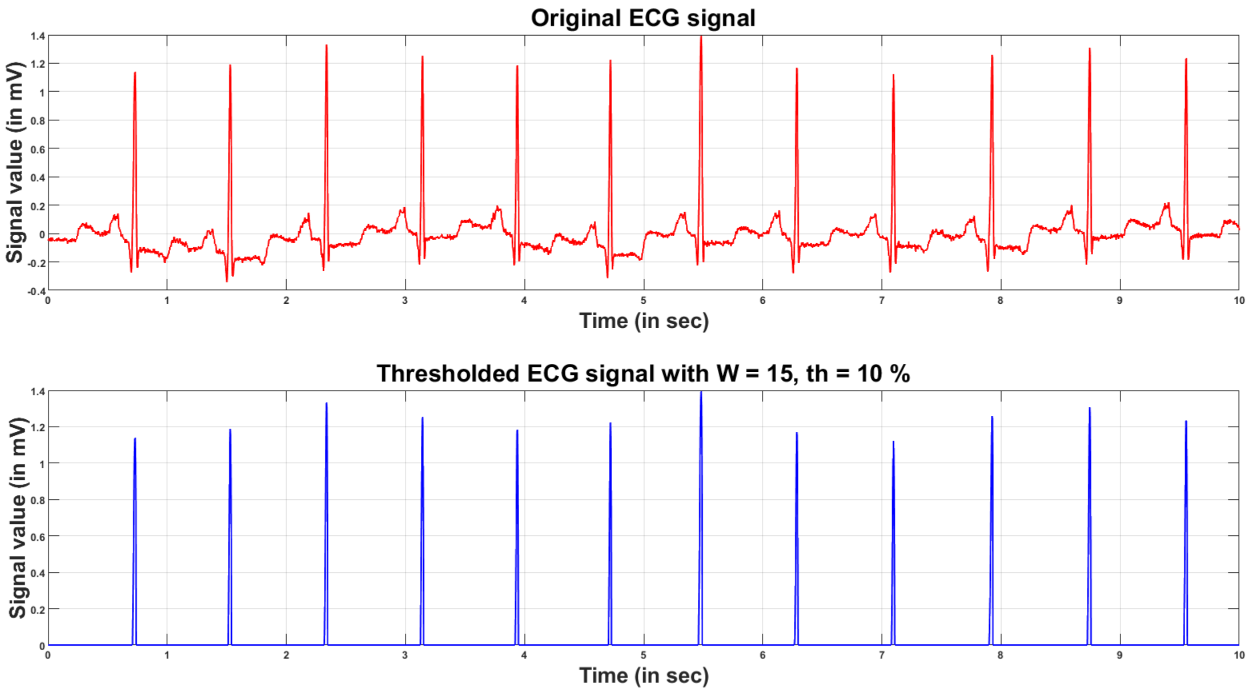

FIGURE 2.2: Effect of thresholding on ECG signal with window length = 15 and 10% thresholding

2.2 Compressive Sensing for biomedical signal

In addition to applying compressive sensing for detection of sinusoidal signals in LT-Spice, we have also tried to explore the possibility of applying this paradigm for the detection/transmission of biomedical signals. For applying compressive sensing to biomedical sensor nodes, we need to increase the sparsity of the input signal. This is done through dynamic thresholding (Allstot et al., 2010). It compares an input data sample with a moving average window of length W. When the difference between the magnitude of the current data and the current moving average is greater than a certain threshold, only then we select this sample, otherwise we set the value of that sample to zero. The threshold is selected to be a certain fraction of the peak amplitude. In this way we set all non significant low magnitude signals in the low activity region to zero and only retain the the signals in high activity region.

This method trades the SNR of the signal with sparsity, that is it increases sparsity at the cost of reduced SNR. Figure 2.2 shows the effect of dyamic thresholding. Increasing window size will lead to greater number of low amplitude noise signals getting included in the thresholded signal. Increasing threshold will result in lower number of samples in the peak region because more number of smaller samples near the peak will get zeroed after thresholding. After increasing the sparsity of signal, we project it onto lower dimension using a bernoulli random matrix. This lower dimensional vector is then transmitted, so that transmission power is reduced by a factor of CF. Finally, on receiver side, the received vector is reconstructed using OMP algorithm to get back the original ECG signal.

Chapter 3

Compressed Sensing Acquisition for wireless ECG sensors

3.1 First version using dynamic thresholding

Electrocardiogram (ECG) signals have been shown to have sparse representation in wavelet domain (Gangopadhyay et al., 2014). Plot of ECG signals also shows their approximate sparsity in time domain. For low resolution, low SNR applications (like ambulatory applications) we can consider using compressive sensing for signal transmission. We have previously developed system level design of compressed sensing signal acquisition system for wireless ECG sensors. The system processes digital words acquired from sensors to compress them before transmission so as to reduce transmission power.

Previously we have implemented ECG signal reconstruction from reduced number of samples in MATLAB. The system takes sample ECG data from Physionet service (Pławiak, 2018). Then we perform dynamic thresholding on the samples to increase the sparsity of the original ECG signal. It compares an input data sample with a

moving average window of length W. When the difference between the magnitude of the current data and the current moving average is greater than a certain threshold then we select this sample, otherwise we set the value of that sample to zero.
cod

Thereafter we project the data onto lower dimension using bernoulli measurement matrix generated using PRBS. Finally we perform the recovery of signal using OMP algorithm that takes reconstruction matrix as measurement matrix because sparsifying basis Ψ is Identity matrix for the case of time domain sparsity.

3.2 Modified Thresholding algorithm

The current thresholding algorithm only selects the peaks of the signal denoting heart beats in ECG. The rest of the part of the signal excluding the peaks is henceforth referred to as the residue signal. Instead of completely neglecting the residue we have tried to modify the existing thresholding algorithm to also transmit the residue signal.

For each sample, we check whether it satisfies the thresholding criteria defined in section 2.2 . If it does not than we make the sparse component of the signal zero and the current sample is sent to the residue part of signal. Otherwise, the current sample is sent to the sparse component and the residue component is assigned a value equal to it's current moving average which is maintained separately for the residue signal. This is done so as to avoid sharp jumps to zero in the residue when the current sample is greater than the threshold. Figure 3.1 shows the sparse component and the residue component of the original ECG signal obtained using modified thresholding algorithm.

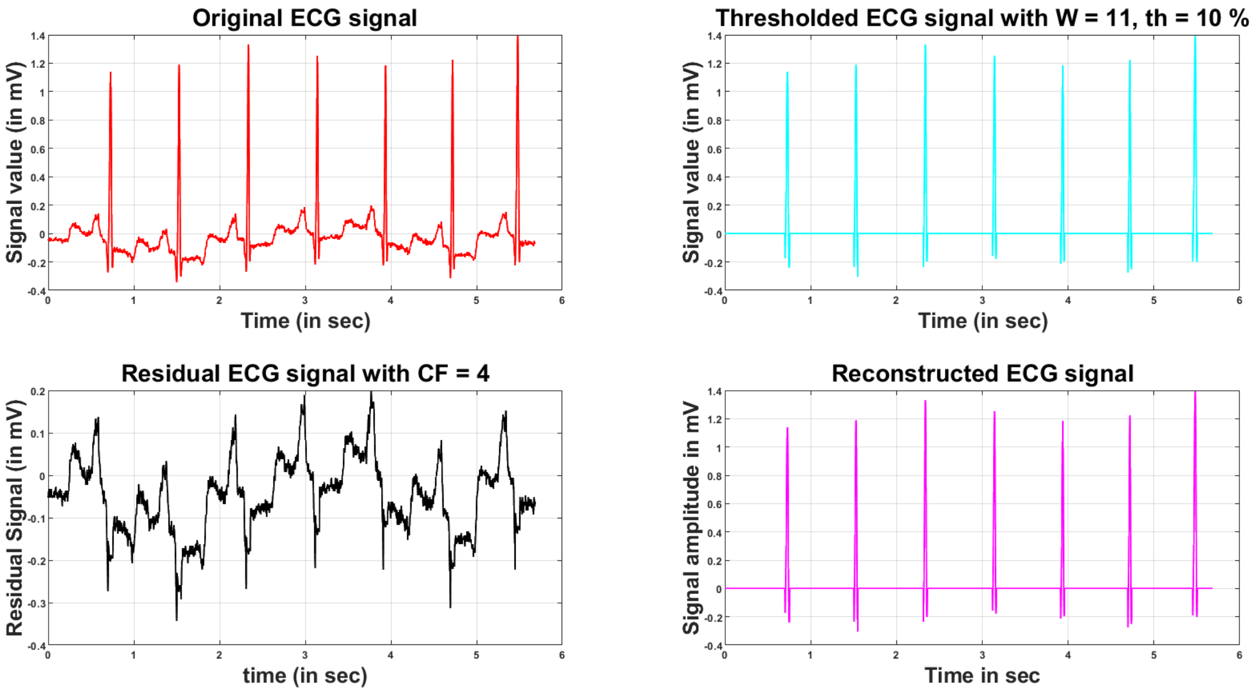

FIGURE 3.1: Sparse part of signal and the residue

3.3 Reconstructing complete shape of ECG signal

Observing the complete structure of ECG signal shows that the non peak portion of the signal repeats in time domain demonstrating significant low frequency components in the residue part of the signal. Frequency analysis of this residue reveals that this signal occupies much smaller bandwidth compared to the sampling frequency of the signal. This low bandwidth can be leveraged to reduce the data rate by low pass filtering and downsampling the residue part of signal. This downsampled signal is transmitted in a separate channel.

Hence we have divided the original signal into two parts - the sparse component and the residue component and both are compressed by a factor of CF (through PRBS and downsampling respectively). These two parts are then transmitted in separate channels to finally get an effective compression factor of $\frac{CF}{2}$. On receiving

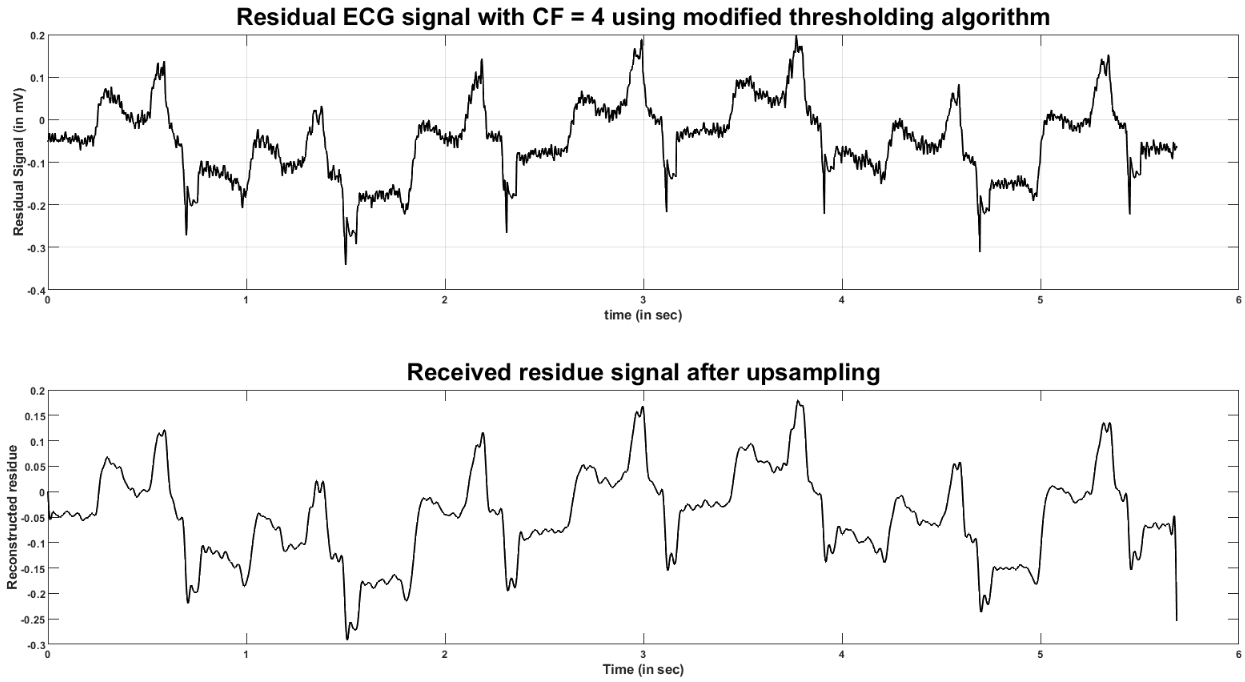

FIGURE 3.2: Residue signal and its reconstructed version after compression

these two channels, the sparse component is reconstructed using OMP algorithm and the residue component is upsampled and low pass filtered to obtain the original residue. Figure 3.2 compares the original residue and the residue reconstructed from compressed number of samples. These two components are added to finally obtain the complete ECG waveform. Reconstruction SNR and final plots for system level simulation are shown in section 4.1 .

Implementing the reconstruction of residue signal requires zero phase filter implementations on RTL which may complicate the design and increase the power overhead of the system. So the current implementation on RTL focuses on implementing the transmission of compressed version of sparse component of the signal and its subsequent recovery on receiver side.

Chapter 4

RTL implementation of compressed sensing system

4.1 Dynamic thresholding

We implement Pipelined Compressed sensing encoder on RTL in Verilog. We use sample data from physionet service for ECG digital words as inputs. We assume that we get maximum 2048 samples from the sensor. The overall system diagram implemented in RTL is shown in Figure 4.1. The outputs from sensor are fed one by one to thresholding module which either transmits the current sample or makes it zero depending on dynamic thresholding criteria as described in section 2.2 . These thresholded samples are now sparse and are sent to encoder module to implement matrix multiplication with random bernoulli entries that are provided by the PRBS generator. Using these values, Encoder generates the compressed N/CF number of samples by operating on inputs in pipelined manner without needing to store any of the input words.

Assuming we get 12 bit digital words as input to the system, we implement pipelined dynamic thresholding in a verilog module. Here we maintain a constant window of

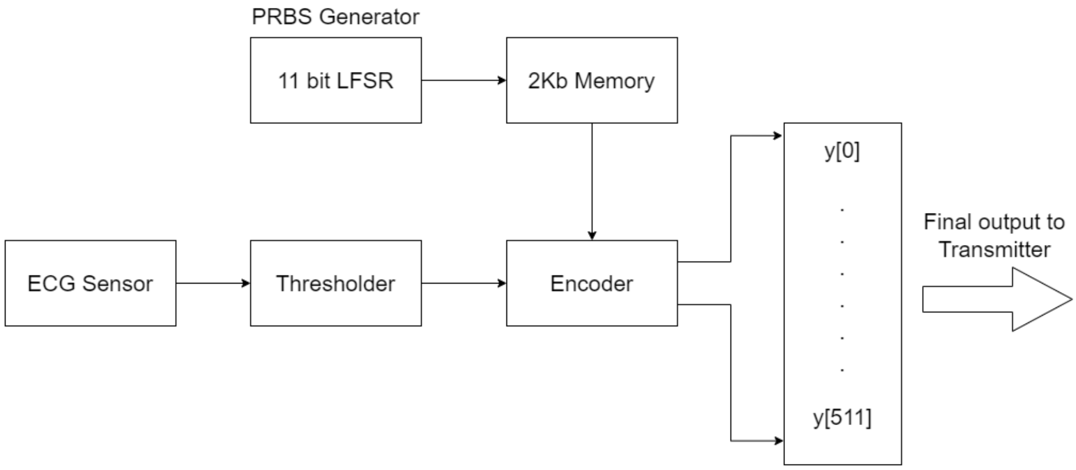

FIGURE 4.1: Block diagram of CS Encoder implemented in RTL

length W, a register $MEAN$ initialized with 0, and a register *threshold* and two registers *min* and *max*. $MEAN$ is updated by updating the sum of values, *min* and *max* are updated in each cycle using the current signal value. *threshold* as a result gets updated using the following equation:

$$threshold = 0.15 * (max - min)$$

threshold needs to be a small fraction of the signal amplitude and is set to a fixed value (0.15 in this case) for the system.

4.2 Modified measurement matrix

Measurement matrix consisting of ± 1 random entries generated using LFSR equations is used in system level design on MATLAB. But using the full matrix on RTL too will require 2048 multiplications and additions operations for each output to get generated, in addition to that we will need to store all 2048 input words to implement multiplication with a full rank matrix.

To avoid this issue of storing all values, we use a partially filled bernoulli matrix for projecting on the smaller dimension. For the particular case of M = 512, N = 2048 we fill only 256 consecutive entries in each row of the matrix and keep the rest 0. So, first row has [0 - 255] index non-zero, second row has [256 - 511] index non-zero and so on. This matrix was tested for its ability of signal recovery on MATLAB and was found to perfectly recover the input signal. Hence this matrix is used for implementing matrix multiplication on RTL.

4.3 Encoder

Since the multiplication needed is with ± 1 we can simply use variable adder/subtractor depending on sign of PRBS. Also, the construction of measurement matrix having only 256 entries nonzero for each output, we arrive at the following set of equations:

```
for(int i = index; i < index + 64; i = i + 1){
    y[i] = y[i] + p[256 * index + (i - index)/8 + cnt] * threshold_sig;
}
```

So at each cycle, 64 output $y[i]$ values are updated. Here *index* is 3 bit register denoting the least significant 3 bits of *id* (where *id* is the index of output from thresholding module i.e. $id \in [0, 2047]$). $p[0]...p[2047]$ are PRBS bit values. *threshold_sig* is the 12 bit signed output of thresholding module. *cnt* is a 8 bit count variable counting the index of the current column of the matrix out of the 256 consecutive indices. So encoder only uses 2Kb of additional memory other than the output; for storing PRBS bit values. In this way, after a latency of 2048 cycles, all 512 encoded outputs are available. This work assumes a maximum of $N = 2048$ and $M = 256$. All RTL codes designed can be modified for any N and M that are powers of 2 by suitably setting parameters of the modules.

Chapter 5

Results

5.1 CS reconstruction of Sinusoidal signal from LTSpice

For testing the circuit made in LTSpice we give sinusoidal voltage as input to the circuit and after compression we transfer the data to MATLAB and perform signal reconstruction there. Figure 5.1 shows 2 such samples of result - one for single tone input and one for double tone input. The number of input samples is limited to 200 because of the limitation of speed of LTSpice. compression factor is 4 and random measurements are made with the help of PRBS sequence generated using 7 bit maximum length LFSR.

Single tone signal reconstruction has been tested for all f_{in} from $[0, f_s/2)$. The detection of frequency is correct for all input frequencies and the amplitudes of FFT output are correct within the limits of simulation artifacts. For the case of double tone reconstruction as well, both the input frequencies have been varied from $[0, f_s/2)$ and reconstruction has been tested. The reconstructed amplitudes are found to be correct within the limits of simulation error.

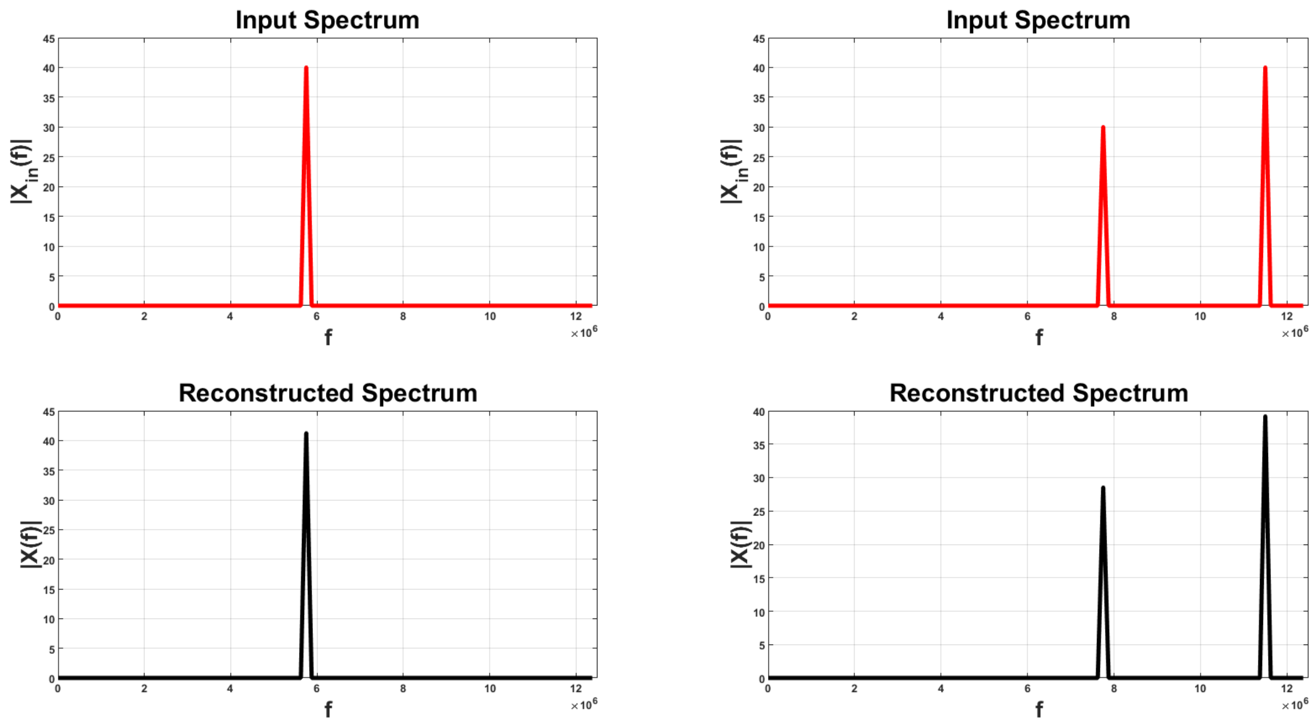

Figure 5.1: Single tone and Multitone reconstruction for circuit in LTSpice with N = 200, M = 50 and CF = 4

5.2 CS implementation of ECG signal on MATLAB

The figure 5.2 shows the comparison for final reconstructed output from the system and the original signal which compresses the input datastream using both compressive sensing as well as downsampling. We have observed the performance of the system for many different real life ecg signals obtained from physionet service. We have observed an average reconstruction SNR of 57 dB only for the sparse part of the input reconstructed using OMP. For the complete signal (sparse part + residue part) we have observed an average reconstruction SNR of 19 dB over many different input samples.

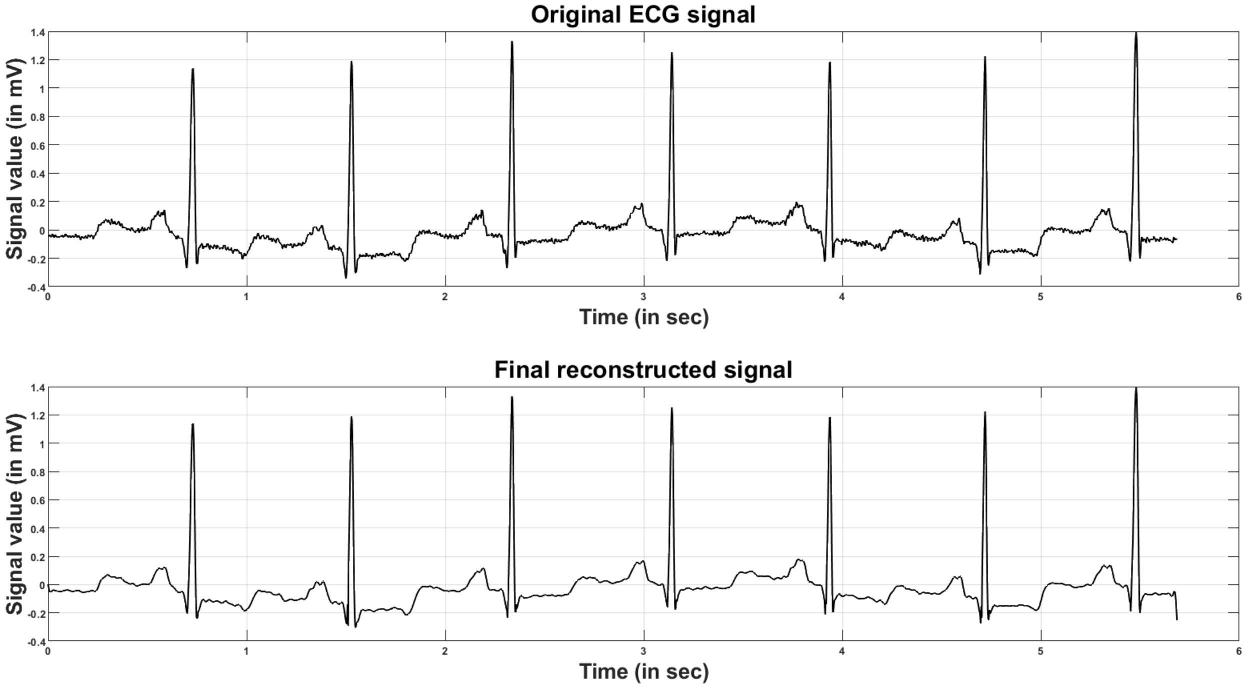

FIGURE 5.2: Original and reconstructed ECG signal using compressive sensing and downsampling

Both the modified thresholding algorithm and downsampling followed by upsampling were found to be robust algorithms because of their ability to reconstruct all components of the input signal for variety of different types of ECG signal obtained from different physical sources as described by the physionet service.

5.3 CS implementation of ECG signal on RTL

We export input ecg data from physionet into a .mif file in MATLAB. This file is stored in Verilog project directory from where it is sent to the thresholding module in pipelined manner. The final results obtained from encoder module as well as some intermediate results are captured in a text file from verilog testbench and these are then read by MATLAB to compare the content of this module with those of variables stored in MATLAB workspace. The results obtained from RTL simulation match

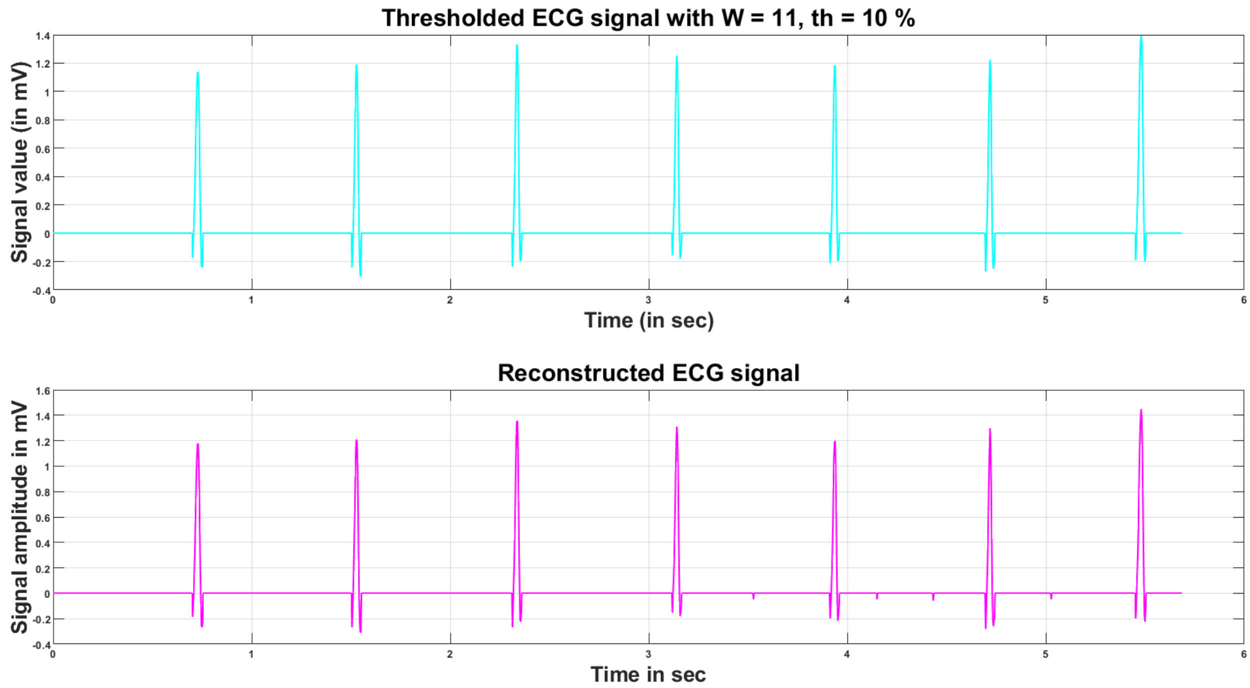

FIGURE 5.3: Thresholded signal in MATLAB compared with reconstructed thresholded signal from RTL

those obtained on system level in MATLAB within some percent of errors. Current implementation is only based on integer part; and floating point division operation to implement mean has not been done, as a result the fractional part of MATLAB results are missing from the results of RTL.

Average observed SNR over multiple test examples is 32 dB for the sparse component of input compared to 57 dB that we get on system level in MATLAB. Results in MATLAB can be an overestimate because of floating point precision used by MATLAB for simulating results.

Chapter 6

Conclusion

6.1 Conclusion from Simulation

In this work we have tried to implement the theory of a new signal processing paradigm of compressed sensing on hardware. We explored possiblities of implementation of this system on hardware for variety of different applications ranging from detection of sinusoidal signal in LTSpice to low power transmission of ECG signals. Simulation results suggest that this system is capable of signal recovery from incomplete measurements for both frequency domain and time domain sparse signals.

System performance observed currently is limited by simulation facilities of LT-Spice. The system level implementation gets stuck for quite a range of frequencies and hence it becomes difficult to collect data on all data points. This issue can be resolved by implementing the system on professional circuit simulation tools like Cadence Virtuoso and then performing reconstruction in MATLAB. Results from RTL show possibility of pipelined implementation of this system with overhead appearing in memory storage and latency.

Throughout our work on compressive sensing for various cases of sparsity and various applications, we have been able to demonstrate that the system is able to recover signal from incomplete measurements for variety of different cases of sparsity - in time domain or in frequency domain.

6.2 Future Work

Simulation on behavioural level indicates that we can recover sparse component of ECG signal from incomplete frequency measurements. Implementation of the reconstruction of residue part on RTL has not been covered in this work. Scope of project application can be improved by completing the following works in future:

- Synthesize the RTL codes on FPGA and test with ECG signals.
- Implement filtering and downsampling in RTL to modify current implementation to include the reconstruction of residue signal.

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