ISSN: 0975-8585

Research Journal of Pharmaceutical, Biological and Chemical Sciences

Effective Implementation of Compressive Sensing On ECG Signal.

Raeshmi Noel J*, Illuri Sreenidhi, and RM Joany.

Department of Electronics and Communication Engineering, Faculty of Electrical and Electronics, Sathyabama University, India.

ABSTRACT

Electrocardiogram (ECG) is a commonly used method to study and understand heart-related diseases. People with a history of heart ailments have the long record of ECGs for diagnostic purposes, which results in the requirement of a large amount of storage space and huge manual labor. Hence, there is a need for an automatic system which involves digital signal integration and analysis. This is done effectively using Compressive Sensing. In this study, we propose Compressive Sensing as a way to convert ECG information from paper charts into digital ECG signals using an MATLAB based tool. This is done by using Pan Tompkins algorithm for detection of QRS complex in the ECG signal and Huffman coding for compression and encryption. The compression rate of proposed algorithm is found to be 92 %. The proposed method has been validated using the ECG records from the MIT-BIH arrhythmia database. It also outperforms other well-known methods in pathological ECG signals in terms of performance measures such as SNR and Threshold.

Keywords: ECG, Digital signal integration, Compressive Sensing, Pan Tompkins, Arrhythmia, etc.

Corresponding author

ISSN: 0975-8585

INTRODUCTION

The ECG is a diagnostic tool that is used to assess the electrical and muscular functions of the heart. The heart's electrical activity is be measured by the electrodes placed on the skin. The ECG is used to measure the rate and rhythm of the heartbeat and also provide indirect evidence of blood flow to the heart. Ten electrodes are needed to generate 12 electrical views of the heart. One electrode is placed on both arms and legs while six are placed across the chest. From each electrode, the signals are received and recorded. The electrocardiogram is the printed view of these recordings. A typical ECG waveform consists of the P-complex, the QRS-complex, the T- complex and the U-complex. The important component of the ECG is the QRS complex and it indicates the electrical depolarization of the ventricle muscles in the heart. Usually, ECG has to be printed on a thermal paper for further, inspection by medical practitioners. A cardiac patient with the history of heart diseases will always have to maintain a load of such ECG reports while visiting a physician for consultation. Further, these ECG records are very hard to be shared among doctors. Our goal is to design a system that transforms a 12-lead ECG on paper into a stream of digital data that can be interpreted and measured by a computerized ECG analysis program using Compressive Sensing which is commercially available. Digitizing the ECG signal will help solve the storage problem and it also becomes cost effective when comes to sharing and diagnosis.

Compressive Sensing is an emerging technique which uses the sparsity of a signal in a particular domain to significantly reduce the number of samples needed to reconstruct the signal.It requires far fewer samples than Nyquist sampling. The Nyquist sampling theorem states that when sampling a signal, the sampling rate must be at least twice the bandwidth of that signal i.e. the Nyquist Rate. The conventional approach to compress a waveform has the following drawbacks: If the signal sampled has a very wide bandwidth, it results in a very high sampling rate generating large amounts of data. A substantial number of signal elements can also be found unnecessary and discarded. This occurs if the signal is sparse after decomposition, even if during the compression process, it is not sparse in the time domain. In contrast, Compressive Sensing acquires a small number of samples representing a sparse signal and uses mathematical techniques to recover the original signal during decompression. A typical ECG signal comprises of a high activity QRS complex subsequently followed by a low activity region between complexes and is also sparse in the time domain. Pan-Tompkins Algorithm has been adapted to realize the QRS Complex. There are eight steps involved such as sampling, normalization, low pass filter, high pass filter (band pass filter), derivation, squaring, averaging and QRS detection.

RELATED WORK

An efficient arrhythmia detection algorithm using correlation coefficient for detection of QRS complex, the correlation coefficient, and RR interval in ECG signal were utilized to calculate the similarity of arrhythmia is presented by Chung-chien et al[1.] S.C.Saxena et al[2] has done combined modified Wavelet transform tech and Quadratic spline wavelet is used for QRS detection and Daubechies six coefficient wavelet is used P and T detection and diagnosis of cardiac disease. Pedro R. Gomes et al.[3] emphasized the wavelet transform and hidden market models. Experimental results obtained using real data from MIT-BIH arrhythmia database show that it performs better than the conventional standard linear segmentation. Discrete wavelet transform and neural networks are used for processing ECG recording and extracting some arrhythmia and ANN performs the classification task in Made Kiani Sarkaleh et al[4]. This method has 96.4% accuracy. Stefan Gradl et al.[5] has carried out an analysis of A)Pan-Tompkins algorithm for QRS detection(B) template formation and adaptation; (C) feature extraction; (D) beat classification. More than 98% of QRS complexes were detected by the algorithm. Overall sensitivity for abnormal beat detection was 89.4% with a specificity of 80.6%. Fahoum et al.[6] has analyzed dealing with the classification of four different arrhythmias: Ventricular Fibrillation Normal Sinus Rhythm, Atrial Fibrillation and Ventricular Tachycardia, RPS. The Nonlinear dynamical behaviour of the ECG arrhythmia is used to identify the cardiac arrhythmias. Narendra Kohli et al.[7] has presented the SVM methods i.e. four algorithms: One against All (OAA), One against One (OAO), Fuzzy Decision Function (FDF) and Decision Directed Acyclic Graph (DDAG). Results are obtained from SVM methods shows that One Against All (OAA) gives better results than classification without feature selection. V.Rathikarani et al.[8] has carried out the linear predictive coefficients, Mel-frequency cepstral coefficients and Linear predictive cepstral coefficients This method can precisely classify and distinguish the difference between normal ECG signal and arrhythmia affected signal with an accuracy of 94%. A new approach that combines a new camera architecture

based on a digital micro-mirror device with the help of mathematical theories and algorithms of compressive sampling is seen in the work of R. M. Joany et al.[9]

METHODOLOGY

The algorithm for ECG processing is given in Fig 1.

PREPROCESSING

Pan Tompkins Algorithm

The Pan and Tompkins algorithm identifies the QRS complexes based on the digital analysis of the ECG data's slope, amplitude, and width. This algorithm uses a digital band pass filter. It reduces false detection caused by the various types of interference present in the ECG signal. The accuracy of the ECG waveform extraction plays an important role in helping a better diagnosis of heart-related illnesses. A part of a normal ECG consists of a P wave, QRS complex, and a T wave. A normal ECG signal is given below in Fig 2,

These waves reflect the heart's activity such as P-waves are produced by muscle contraction of Atria and its duration indicates the Atrial enlargement. Q waves give the first negative value and typically supposed to be 45% less than the R-waves value. The algorithm adjusts the parameters and thresholds periodically to adapt the changes in QRS morphology and heart rate automatically,

It consists of the following processing steps

- Band-pass filtering.
- Differentiation.
- Squaring.
- Moving window integration.
- Threshold adjustment.

Bandpass Filtering

The noise in the ECG signal is reduced by matching the spectrum of the average QRS complex by using Band pass filtering. This attenuates noise due to muscle noise, T wave interference and power line interference. The pass band that maximizes the QRS energy is in the 5Hz-45Hz range. The filter implemented in this algorithm consists of a cascaded high pass and low pass Butterworth IIR filters.
The low-pass filter is described by the formula:

$$y(n)\_=4y(n-1)-y(n-4)-x(n)-4x(n-6)-x(n-14) \quad \text{..... (1)}$$

The high-pass one is described by:

$$y(n) =y(n-1) –1/44x(n)-x(n-16)-x(n-17)+1/44x(n-44) \quad \text{..... (2)}$$

Differentiation

The next step in processing is differentiation which is a model technique for finding the high slopes that will distinguish the QRS complexes from other ECG waves. This procedure suppresses the low-frequency components of P and T waves and also provides a large gain to the high-frequency components derived from the high slopes of the QRS Complex.

$$y(n)=1/8[4x(n)+ x n-1)-x(n-4)-4x(n-4)] \quad \text{..... (3)}$$

Squaring

The operation of squaring makes the result positive and highlights large differences resulting from QRS complexes while the small differences arising from P and T waves are suppressed. The high-frequency components in the signal related to the QRS complex are more emphasized. This is a nonlinear transformation that consists of point by point squaring of the signal samples.

$$y(n)= x^4 (n) \text{ ..... } (4)$$

Integration

The squared waveform passes through a moving window integrator. This sums the area under the square waveform over a suitable interval advances one sample interval and also integrates the new predefined interval window. The half-width of the window is chosen to be 47 to include the time duration of extended abnormal QRS complexes and also so it does not overlap both a QRS complex and a T-wave.
The moving window integrator is described using the formula,

$$Y(nT) = 1/N[X(nT-(N-1)T)+---+X(nT)] \text{ ..... } (5)$$

Where, N=1+4M is the number of samples in the width of the moving window. M is Half-width of moving average filter.

FEATURE EXTRACTION

IMPLEMENTATION OF SVM FOR QRS DETECTION

LIBSVM software is used in QRS detection of ECG signal. LIBSVM is an integrated software package used for support vector classification, regression, and distribution estimation. It uses a modified sequential minimal optimization (SMO) algorithm to perform training of SVMs. In QRS detection, SVM is built using sigmoid kernel K(x, xi) =tanh (γ).(I xx +v) with two parameters γ and v. The parameter γ is used as a scaling parameter for the input, and v is used as a shifting parameter that will control the mapping threshold. For Sigmoid kernel the values of γ > 0 and v< 0 are appropriate. The training set consists of 9707 samples with normalized entropy values covering a variety of QRS morphologies. A set of normalized entropy values includes from the input vector x1 to the support vector classifier. During the training of SVM, two synchronizing sliding windows of the size often because a larger or a smaller value leads to under or over capturing the ECG, are moved over the two entropy values from the training set. Once the window lies in the QRS region, the desired output of the SVM is set to 1 and in the on QRS region, the desired output is set to -1. Hence, a series of 1's is obtained at the output of SVM when the windows pass through the QRS region and -1 for the no QRS region. When the P or T waves are peaky in nature, the SVM gives a series of 1's but of a smaller duration when compared to that of the QRS complex. In order to differentiate between series of 1's for both the QRS complex and that for the P or T waves, an average duration of all the series of 1's is calculated. Those series whose duration is greater than average pulse duration is taken up as the QRS complexes by the algorithm and those which are smaller are discarded. Thus, false positive detection of QRS complexes can be reduced.

CLASSIFICATION

Based on the features extracted (RR, PR intervals, and QRS duration), decision rules can be derived. In the algorithm, we take the average of 8 RR, PR interval, and QRS widths. Hence, the intervals considered are the averaged ones.4 decision rules have been formed from studying arrhythmias such as Bradycardia, Tachycardia, Ventricular Tachycardia and Asystole (Complete Heart Block). Some of the classifying decision rules for arrhythmias are:

For Bradycardia

ISSN: 0975-8585

If (QRS == 0.11&&PR>0.2 && abnormalbeats==0&&PR<0.2)

For Tachycardia

If (QRS == 0.11&&PR<0.2 && RR<0.85 && (abnormalbeats==0))

RESULTS

From the MIT-BIH arrhythmia database, the ECG records in the .dat format are taken as the input signal in fig 3. For removing the noise from ECG signal band pass filtering is done in fig 5 & 6. In fig 7, for distinguishing QRS complex from other ECG signal differentiation is done. Using squaring and averaging process, QRS complex is enhanced in fig 8 & 9. A moving window integrator is introduced for passing the square wave in fig 10.In fig 11, QRS complex is detected using SVM classifier. In fig 12 & 13 the process of disease detection is shown.

FIGURES:

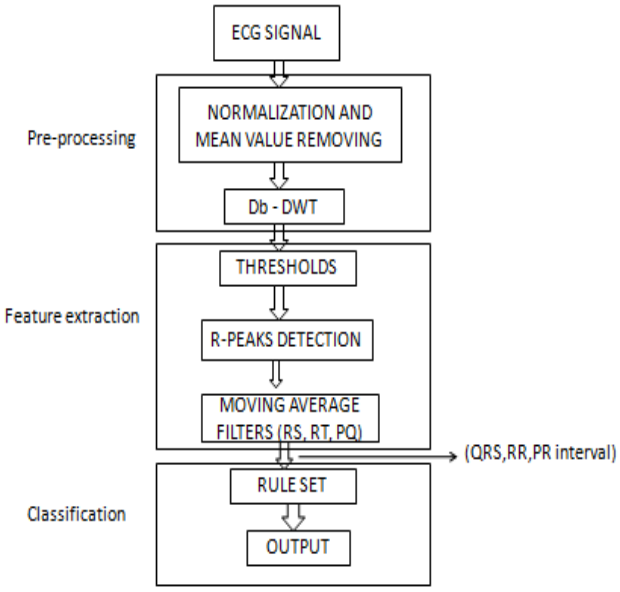

Fig 1: Algorithm of ECG signal processing

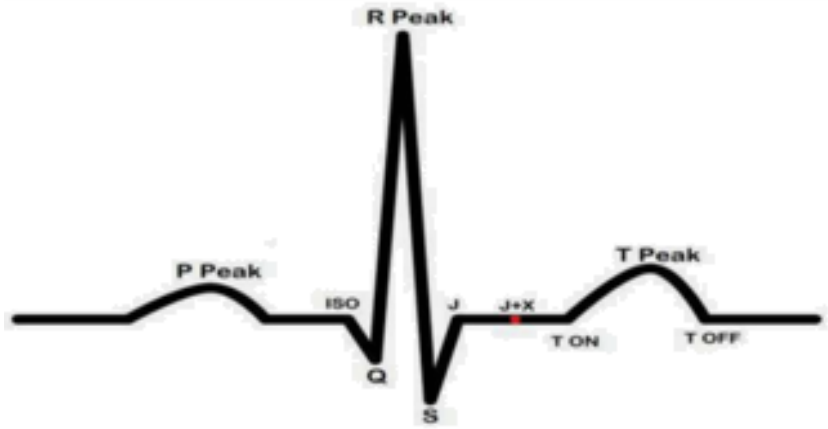

Fig 2: Normal ECG signal

ISSN: 0975-8585

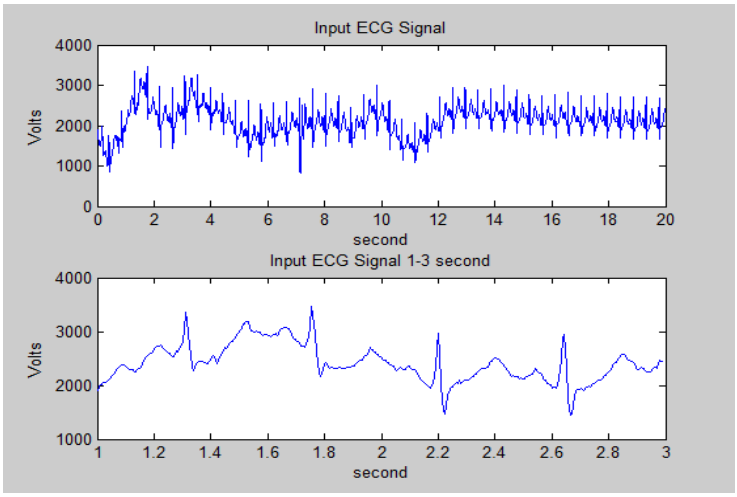

Fig 3: Input signal

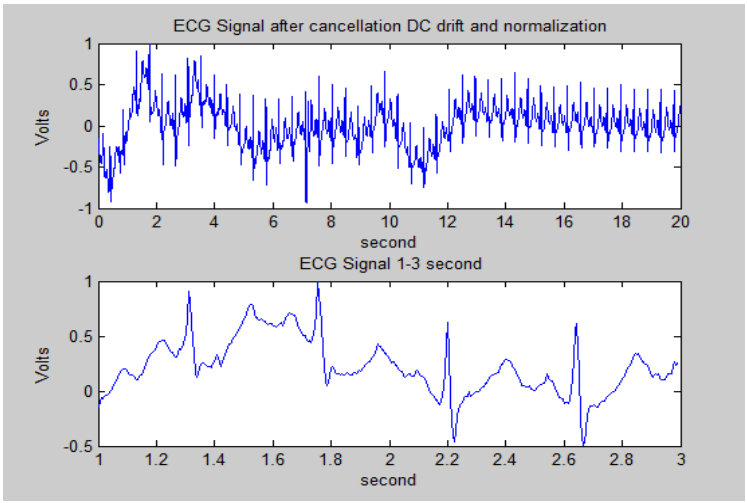

Fig 4: Drifting and Normalization

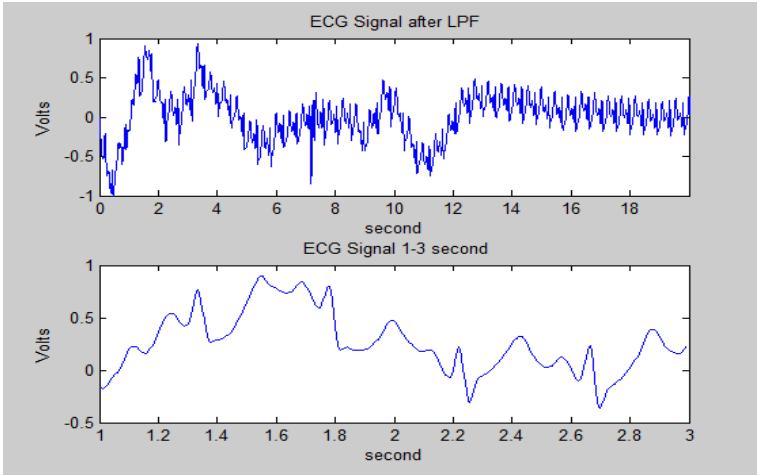

Fig 5: Low pass filter

ISSN: 0975-8585

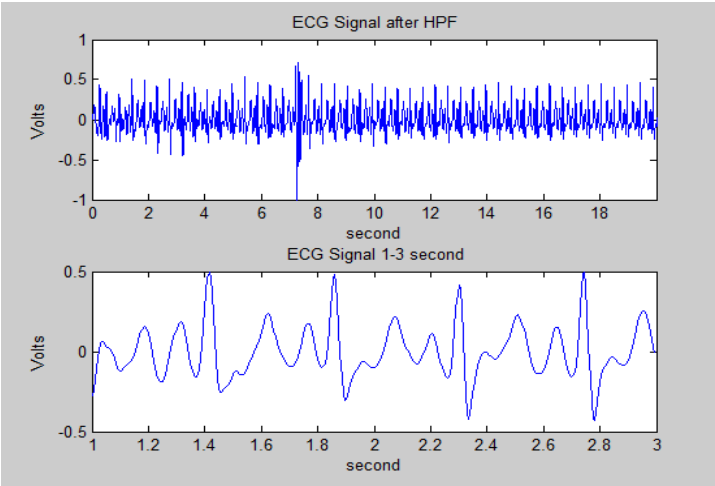

Fig 6: High pass filter

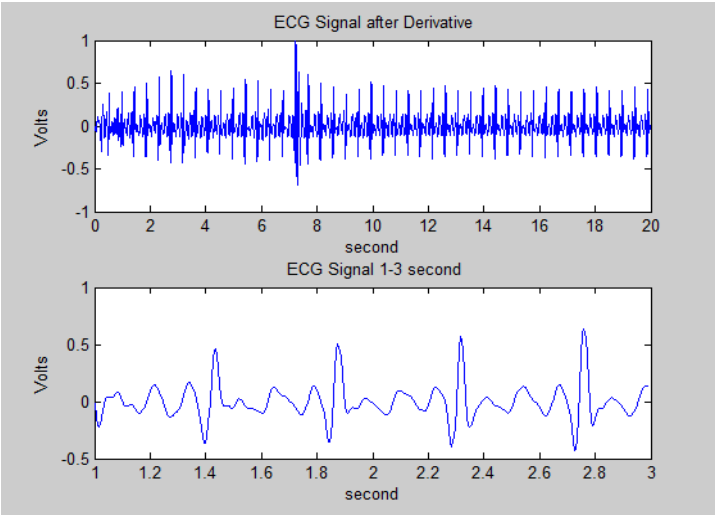

Fig 7: Differentiation

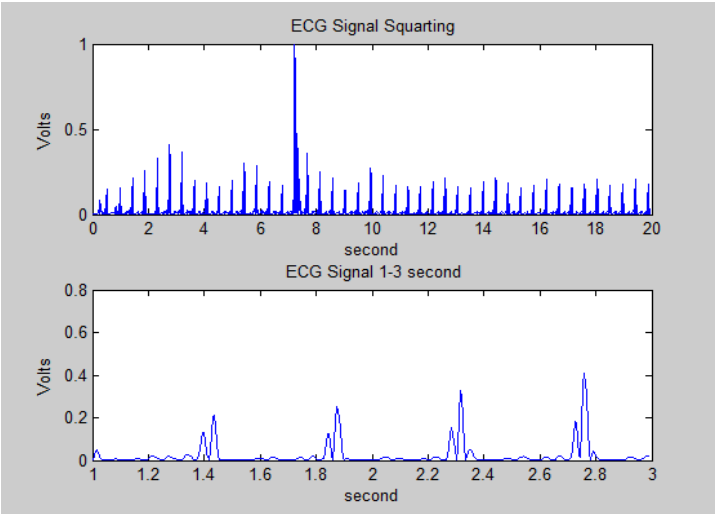

Fig 8: Squaring

ISSN: 0975-8585

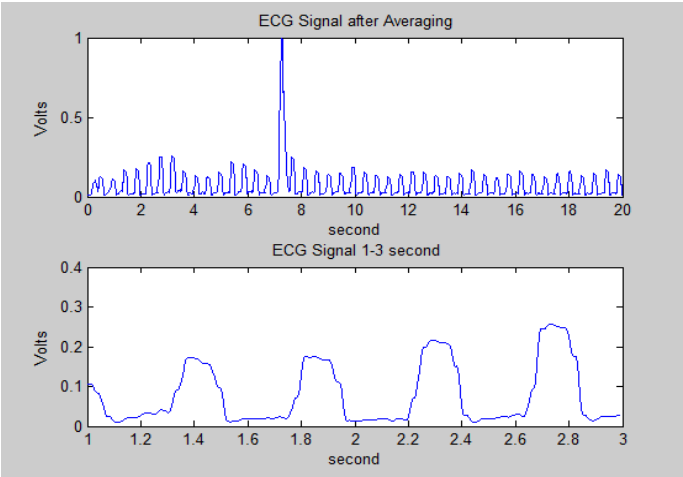

Fig 9: Averaging

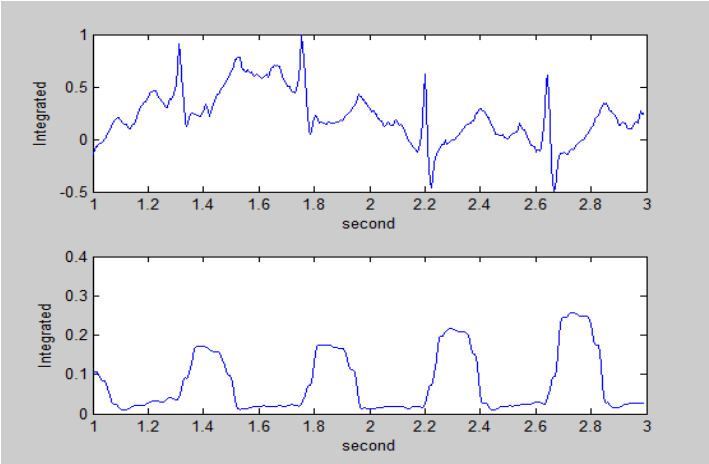

Fig 10:Integration

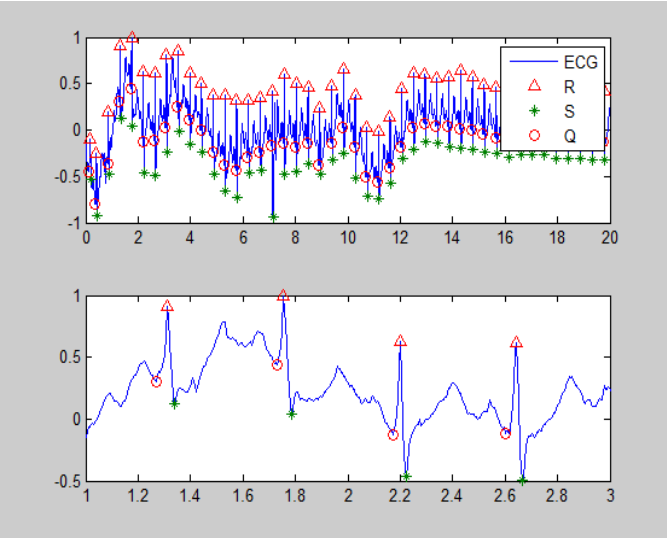

Fig 11:QRS complex Detection

ISSN: 0975-8585

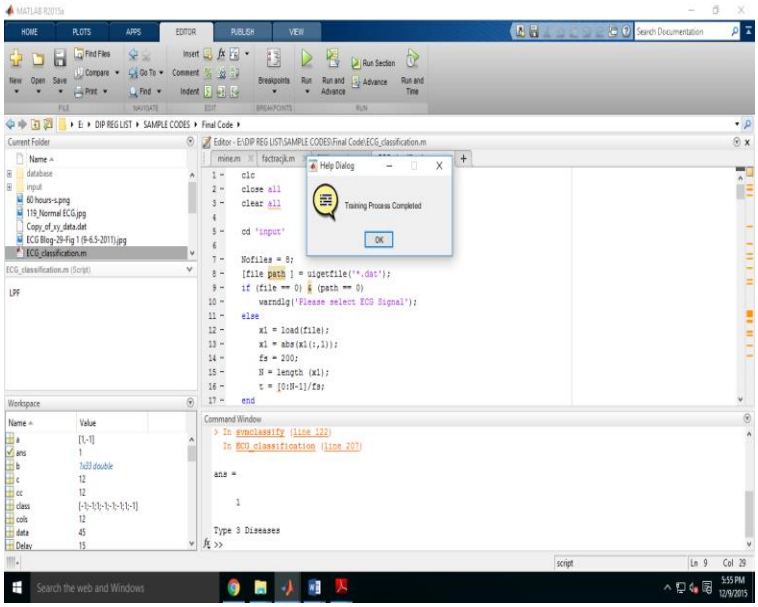

Fig 12:SVM Classifier

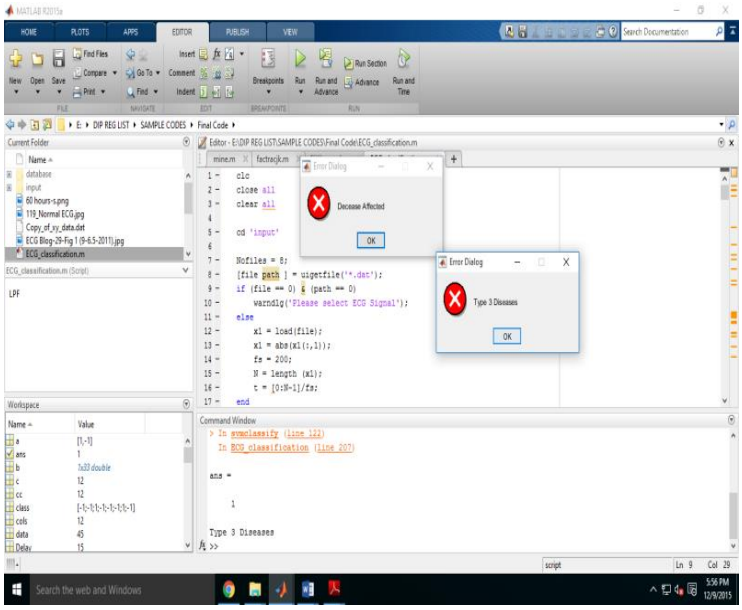

Fig 13: Type of Disease

CONCLUSION

In this paper, an effective method for extraction and digitization of ECG signal is done using Compressive Sensing. This methodology produces a fairly accurate waveform in MATLAB software using for Pan and Tompkins QRS detection algorithm and SVM Classifier for detection of diseases related to the heart.

FUTURE WORK

Further work can be done to enhance the overall efficiency of the method and also a fuzzy based expert system can be developed that can assist a doctor in both diagnosis and generating automatic diagnosis reports.

ISSN: 0975-8585

REFERENCES

[1] Chung-chien chiu tong hong " using correlation coefficient in ECG waveform for Arrhythmia detection" Biomedical engineering applications basis communications June 2005 vol.17 no-4,147-152.

[2] S.C.Saxena, V. Kumar and S. T. Hamad, "Feature extraction from ECG signals using wavelet transforms for disease diagnostic" International Journal of Systems Science, 2002, volume 33, number 13, pages 1073–1085.

[3] Pedro R. Gomes, Filomena O. Soares, J. H. Correia, C. S. Lima, "Cardiac arrhythmia classification using Wavelets and Hidden Markov Models – A comparative approach" 31st Annual International Conference of the IEEE EMBS Minneapolis, Minnesota, USA, September 2-6, 2009.

[4] Made Kiani Sarkaleh and Asadollah Shahbahrami, "Classification of ECG Arrhythmias using Wavelet Transform and Neural network" (IJCSEA) Vol.2, No.1, February 2012.

[5] Stefan Gradl1, Patrick Kugler1, "Real-time ECG monitoring and arrhythmia detection using Android-based mobile devices" Engineering in Medicine and Biology Society (EMBC), 2012 Annual International Conference of the IEEE.

[6] Fahoum and AM qasamech "ECG arrhythmia classification Using simple reconstructed phase space approach" ISSN 0276-6547 computers in cardiology 2006, 33:757-760.

[7] NarendraKohli and Nishchal K. Verma, "Arrhythmia classification using SVM with selected features" International Journal of Engineering, Science, and Technology, Vol. 3, No. 8, 2011, pp. 122-131.

[8] V.Rathikarani .Dhanalakshmi,"Automatic classification of ECG signal for Identifying Arrhythmia" International Journal of Computer Science, Engineering and Applications (IJCSEA) Vol.2, No.1.

[9] R. M. Joany and E. Logashanmugam, "Evaluation of efficient method to control the functionality of DMD," Communications and Signal Processing (ICCSP), 2015 International Conference on, Melmaruvathur, 2015, pp. 0015-0019.

[10] J. Lee, K. L. Park, M. H. Song and K. J. Lee, "Arrhythmia Classification with Reduced Features by Linear Discriminate Analysis" Proceedings of the 2005 IEEE Engineering in Medicine and Biology 27th Annual Conference, Shanghai, China, September1-4.

[11] A Dliou , a latif And M Laaboubi, "Arrhythmia ECG Signal Analysis using NonParametric Time-Frequency Techniques" International Journal of Computer Applications(0975 – 8887) Volume 41–No.4, March 2012.

[12] Rose T.Fatihah, Munther A.Dahleh, Gail K.Adler, Elizabeth B.Klerman, Emery N.Brown,"Quantifying Pituitary-Adrenal Dynamics and Deconvolution of Concurrent Cortisol and Adrenocorticotrophic Hormone Data by Compressed Sensing" IEEE Transactions on Biomedical Engineering 2015.