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A VLSI Architecture Based Heart Beat Classification Model for ECG Signal Feature Extraction

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Abstract— **Recently, in medical field we use advanced systems and equipments to analyze disease types and classify the final reports. In order to get effective classification results from the Electro Cardio Gram (ECG) signal, we propose Discrete wavelet Transform (DWT) feature extraction and Probabilistic Neural Network (PNN) classifier based VLSI architecture. This work is to optimize the circuit complexity level and to improve the system quality. Various structural and functional changes associated with ischemic (myocardial infarction) heart because amplitude and spectral changes in signals obtained at different leads of ECG. This information is used by a cardiologist for accurate detection of various life-threatening cardiac disorders. ECG signals are subjected to number of processing for computer aided detection and localization of cardiovascular diseases. In the existing system, various methods are proposed for detection of MI. These include the time-domain method, the wavelet transform based method, PSO feature extraction method and neural network approach. Our proposed work is to analyze the ECG signal to find the coronary diseases. The proposed system will use the different type of algorithm to find the diseases. This analysis is based on the different peaks like R Peak, Q Peak, S Peak and T Peak. These peaks are used to find the abnormal heartbeat. This work is to design DWT feature extraction and PNN classifier from the ECG signal and find whether the signal is normal or abnormal. The aim is to optimize the circuit complexity and the classification accuracy level.**

Keywords— ECG, Butterworth filter, Discrete Wavelet Transform, Feature Extraction, Probabilistic Neural Network (PNN) Classifier.

I. INTRODUCTION

Myocardial infarction (MI) or acute myocardial infarction (AMI) commonly known as a heart attack occurs when blood flow stops to a part of the heart causing damage to the heart muscle. The pathogenesis for most of the MI cases is due to the progressive atherosclerotic plaques in coronary arteries. The myocardium loss perfusion and it is deprived of oxygen and other nutrients. Most MIs occur due to coronary artery disease. Risk factors include high blood pressure smoking,diabetes,lack of exercise,obesity,high blood cholesterol,poor diet and excessive alcohol intake,among others.the mechanism of an MI often involves thecomplete blockage of a coronary artery caused by a rupture of an atherosclerotic plaque. MIs are less commonly caused by coronary artery spasms which may be due to cocaine,significant emotional stress and extreme cold among others. A number of tests are useful to help with diagnosis including electrocardiograms(ECGs),blood tests and coronary angiography. An ECG may confirm an ST elevation MI if ST elevation is present.Aspirin is an appropriate immediate treatment for a suspected MI. In ST elevation MIs treatment which attempt to restore blood flow to the heart are typically recommended and include angioplasty where the arteries are pushed open, or thrombolytic where the blockage is removed using medications. People who have a non-ST elevation myocardial infarction (NSTEMI) are often managed with the blood thinner heparin with the additional use of angioplasty in those at high risk. An MI may cause heart failure, an irregular heartbeat or cardiac arrest. this may also cause a local blood clot known as thrombus due to deposition of fibrin, blood platelets and red blood cells. Sometimes thrombolytic substance is detached from the artery and flows to a distal coronary arterial tree. The consequences are the blocks in arteries at some other points which are called coronary embolus. This interrupts the blood flow and results in myocardial necrosis blood samples show elevated cardiac enzymes (biochemical marker of MI) like creative kinase-MB and cardiac troponin. The elevated levels of above enzymes in blood serum are noticed only after 6 to 9hours.this time delay can be avoided by detecting onset of MI directly from the electrocardiogram (ECG). For detection at on-set stage, the ECG of the patients with suspected MI should be interpreted within 10min. In a standardized system of 12-lead electrocardiogram, each lead views the heart at a unique angle. This helps localize the pathological condition. During MI, multilead recordings from their standard characteristics.

The location of infarction depends on the coronary artery. This evidence can appear in different ECG leads. This requires simultaneous investigation of all the 12-leads various methods are proposed for detection of MI. These include time-domain method, ST-segment analysis, wavelet transform based method and neural network approach. Some of them are based on modelling techniques by training and testing the system. These algorithms use a few electrocardiogram (ECG) leads. Instead of entire ECG segment the analysis is based on ECG components such as ST-segment, ST-T complex etc, this demand for an accurate detection of ST-segments. This requires prior information about the absence of MI in the selected leads. Since various categories of MI evolved in

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different leads. It is expected that monitoring all 12-leads over time will yield a better result in detection and localization. In this project, a multiscale energy and eigen space (MEES) approach for 12-lead ECG is proposed for detection and localization of MI. The work carried out does not consider the real time case with patients suffering from MI. Permission from medical board is required for real time implementations on human subjects. The results are presented using the ability of the proposed method to classify the MI pathology.

Myocardial infarction is the genesis of coronary artery disease (CAD). The left main coronary artery (LCA) splits into left anterior descending (LAD) and left circum flex (LCX) coronary arteries. The anterior left ventricle (LV), the lateral and posterior LV walls, the interventricular septum and the apex get blood supply from these two arteries. The right coronary artery (RCA) supplies blood and nutrients to right ventricle (RV), inferior wall of LV, part of the posterior wall of the LV through the posterior artery and posterior interventricular septum. The myocardial injury can occur in any of the above arteries. Various types of myocardial infarctions are anterior MI, inferior MI, posterior MI, and left lateral MI. The ECG leads V1, V2, V3, and V4 show the signatures of anterior MI and the inferior MI is diagnosed form ECG leads II, III, and VF are shown in fig.1. The pathological characteristics of left lateral MI are observed from ECG leads I, a VL,V5 and V6.posterior MI is due to necrosis in right coronary artery. No ECG lead captures the information of the posterior wall. Hence it is diagnosed by evaluating the reciprocal changes in the anterior lead V1.Based on ST-elevation, myocardial infarctions are categorized as ST elevated MI(STEMI) and Non-ST elevated MI(NSTEMI) the ST elevated MI evolves through the sequence.

- T-wave peaking(hyper acute T-wave) followed by T-wave inversion
- ST-segment elevation
- Appearance of pathological Q-waves.

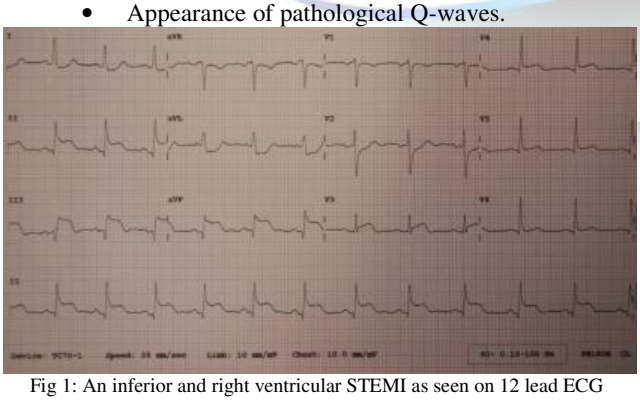

Fig 1: An inferior and right ventricular STEMI as seen on 12 lead ECG

Two main types of acute myocardial infarction based pathology are; (i) Transmural AMI is associated with atherosclerosis involving a major coronary artery. It can be sub classified into anterior, posterior, inferior, lateral, or septal. Transmural infarcts extend through the whole thickness of the heart muscle and are usually a result of complete occlusion of the area's blood supply. In addition, on ECG, ST elevation and Q waves are seen;(ii) Subendocardial AMI involves a small area in the subendocardial wall of the left ventricle, ventricular septum, or papillary muscles. The subendocardial area is particularly susceptible is ischemia. In addition, ST depression may be seen on ECG in addition to T wave changes. The onset of symptoms in myocardial infarction is usually gradual. Over several minutes and rarely instantaneous. Chest pain is the most common symptom of acute MI and is often described as a sensation of tightness, pressure or squeezing. Chest pain due to ischemia (a lack of blood and hence oxygen supply) of the heart muscle is termed angina pectoris. Pain radiates most often to the left arm, but may also radiate to the lower jaw, neck, right arm, back and upper abdomen, where it may mimic heart burn. The discomfort may occasionally feel like heart burn. Other symptoms may include shortness of breath, nausea, feeling faint, a cold sweat, or feeling tired. About 30% of people have typical symptoms with women more likely than men to present atypically. Among those over 75 years old, about 5% have an MI with little or no history of symptoms.

The most common symptoms of MI in women include dyspnoea, weakness and fatigue, sleep disturbances have been reported as frequently occurring symptoms that may manifest as long as one month before the actual clinically manifested ischemic event. In women, chest pain may be less predictive of coronary ischemia than in men. Women may also experience back or jaw pain during an episode. Any group of symptoms compatible with a sudden interruption of the blood flow to the heart which includes STEMI, NSTEMI or unstable angina are called an acute coronary syndrome. Many of the risk factors for myocardial infarction are modifiable and thus many cases may be preventable. Smoking appears to be the cause of about 36% and obesity the cause of 20% of coronary artery disease. Lack of exercise has been linked to 7-12% of cases. Less common causes include stress related causes such as job stress which accounts for about 3% of cases and chronic high stress levels. Tobacco smoking (including second hand smoke) and short-term exposure to air pollution such as carbon monoxide, nitrogen dioxide, and sulphur dioxide (but not ozone) have been associated with MI. Diabetes mellitus(type 1 or 2), high blood pressure, dyslipidemial high levels of blood cholesterol(abnormal levels of lipoproteins in the blood), particularly high low-density lipoprotein, low high-density lipoprotein, high triglycerides, endometriosis in women under the age of 40 and obesity (defined by a body mass index of more than 30kg/m^2, or alternatively by waist circumference or waist hip-ratio) have all been linked to MI. [6] discussed about an eye blinking sensor. Nowadays heart attack patients are increasing day by day."Though it is tough to save the heart attack patients, we can increase the statistics of saving the life of patients & the life of others whom they are responsible for. As of 2013, there is no evidence of benefit from antibiotics or vaccination, however, calling association

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into question. Myocardial infarction can also occur as a late consequence of Kawasaki disease. At any given age, men are more at risk than women particularly before menopause, but because in general women live longer than men, ischemic heart disease cause slightly more total deaths in women. Family history of ischemic heart diseases or MI, particularly if one has a first degree relative(father, mother, brother, sister) who suffered a 'premature' myocardial infarction(defined as occurring at or younger than age 55 years(men)or 65(women)). Heart attacks appear to occur commonly in the morning hours, especially between 6AM and noon. Evidence suggests that heart attacks are at least three times more likely to occur in the morning than in the late evening, old age increases risk of heart attack.

II. PROPOSED METHOD

In our proposed system used to analysis the ECG signal and find the coronary diseases. Here different types of algorithms are used to find the diseases. The ECG is taken from the heart it is electro signal from the heart. It is normal to non-disease. This analysis based on the different peaks like R Peak, Q Peak, S Peak, T Peak. These Peaks may change and is help to find the abnormal heart beat. In our proposed work uses DWT for extract the feature from the ECG signal and find whether the signal is normal or abnormal. Here PNN classifier is used to find the ECG categories and also analysis the weather given signal is the authenticated person or not authenticated person. In this system used to extract the same feature but authentication process to take the feature without peak information because here to analysis the heart beat to find the diseases with also find the authentication details very well accuracy. In this study a Multiscale Energy and Eigen Space (MEES) approach for 12-lead ECG is proposed for the detection and localization of MI. The work carried out does not consider the real-time case with patients suffering from MI. A novel technique on Multiscale Energy and Eigen space(MEES) approach is proposed for the detection and localization of myocardial infarction from multilead electrocardiogram(ECG). Wavelet decomposition of multilead ECG signals grossly segments the clinical components at different sub bands. In MI, pathological characteristics such as hyper acute T-wave, inversion of T-wave changes in ST elevation or pathological Q wave are seen in ECG signals. This pathological information alters the covariance structures of multiscale multivariance matrices at different sales and the corresponding eigen values. The clinically relevant components can be captured by eigen values. In this study Multiscale wavelet energies and eigen values of multiscale covariance matrices are used as diagnostic features. Here we use the PNN classifier to find the ECG categories, datasets which include healthy control and various types of MI, such as anterior, anterio lateral, anterio septal, inferior, inferio lateral, and inferio posterio lateral from the PTB diagnostic ECG database are used for evaluation. The results show that the proposed technique can successfully detect the MI pathologies.

The MEES approach also helps localize different types of MIs.most of the methods reported in the literature are beat-specific and they are based on neural networks and other classifiers. The proposed MEES feature based method for MI detection is compared with the other methods and results are shown. Results reported in this paper are close to the results of MI detection in the literature. Some of these methods used single or fewer ECG leads which are expected to carry MI pathologies. The performance of earlier method depends on the accuracy of detection of ST segments and ST-T complex. The proposed method does not require a prior segmentation of ST segments and ST-T complex. The knowledge of the presence of MI pathology is not necessary as it is based on 12 standard ECG leads. There are five modules in the proposed methodology.

A. ECG

First we browse the input ECG signal in overall database and to read the mat file format. ECG signal need to be generated for processing and analyzing. It acts as electrocardiogram waveform.

B. Pre-processing

Butterworth filter is used to filter the selected ECG signal and to reduce the noise level in given selected ECG signal. The Butterworth filter is a type of signal processing filter designed to have a flat frequency response as possible in the pass band. It is also referred to as a maximally flat magnitude filter.Then to find R Peak values, Q Peak values, S Peak values, and T Peak values from the output of Butterworth filter signal. Input signal needed to be preprocessed before going to process the signal. Here there are many process for preprocessing steps prescribed that is mean subtraction. Moving average filtering and low-pass Butterworth filtering with this methods noise , low-quality signals and asytole will be removed. The Butterworth filter has a maximally flat response i.e., no pass band ripple and roll of minus 20db per pole. The moving average is the most common filter in DSP, mainly because it is the easiest digital filter to understand and use. In spite of its simplicity, the moving average filter is optimal for a common task; reducing random noise while retaining a sharp step response. This makes it the premier filter for time domain encoded signals. The moving average filter and its relatives are all about the same at reducing random noise while maintaining a sharp step response. The ambiguity lies in now the rise time of the step response is measured.

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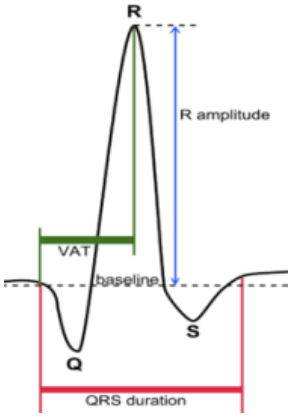

Fig 2: QRS Waveform

C. Feature Extraction

Features are extracted using wavelet transform and statistical features. Feature extraction is the process of collecting the information/data from the input ECG signal. The feature is nothing but the data which consist of the several physical values. In numerical analysis and functional analysis, a DWT is any wavelet transform for which the wavelets are discretely sampled. As with other wavelet transforms a key advantage it has over Fourier transforms is temporal resolution and it captures both frequency and location information. The statistical features are kurtosis, skewness, mean, variance, median, entropy, standard deviation, maximum amplitude, minimum amplitude, central moments, mode, magnitude, phase, frequency and energy.

D. Optimization

Particle swarm optimization (PSO) system is initialized with a population of random solutions and searches for optima by updating generations. However, unlike GA, PSO has no evolution operators such as crossover and mutation. In PSO the potential solutions called particles flythrough the problem space by following the current optimum particles. Each particle keeps track of its coordinates in the problem space which are associated with the best solution (fitness) it has achieved so far and also stored the fitness value. This value is called Pbest. Another best value that is tracked by the particle swarm optimizer is the best value obtained so far by any particle in the neighbors of the particle. This location is called lbest. When a particle takes all the population as its topological neighbors the best value is a global test and is called gbest. The particle swarm optimization concept consists of at each time step, changing the velocity of (acclerating) each particletoward its Pbest and lbest locations (local version of PSO).Acceleration is weighted by a random term with separate random numbers being generated for acceleration toward Pbest and lbest locations.

E. Classification

The neural network used here is the probabilistic neural network which is suitable for recognition and classification problems. The probabilistic neural networks are a kind of radial basis networks. The matlab[net=newpnn] this command creates a new network with a dialog box. For example; net=newpnn(P,T,spread) this command takes two or three arguments where P-RxQ matrix with Qinput vectors T-SxQ matrix with Qtargets class vectors, spread=spread of radial basis functions, default value=0.1 and returns a new probabilistic neural network. If spread is near the zero value the network will act as a nearest neighbor classifier. As the spread value is getting larger, the designed network will take into account several nearby design vectors. The designed probabilistic neural network creates a two-layer network .the first layer has radbas neurons and calculates its weighted inputs with dist and its net input with netprod. The second layer has compet neurons and calculates its weighted input with dotprod and its net inputs with netsum. Only the first layer has biases. The 'newpnn' sets the first layer weights to p and the first layer biases are all set to 0.8326/spread, resulting in radial basis functions that cross 0.5 at weighted inputs of +/- spread. The second layer weights w2 are set to T. A probabilistic neural network is a feed forward neural network which was derived from the Bayesian network and a statistical algorithm called kernel fisher discriminant analysis. In a PNN the operations are organized into a multilayered feed forward network with four layers.

- Input layer
- Hidden layer
- Pattern layer/Summation layer
- Output layer

PNN is often used in classification problems. When an input is present, the first layer computes the distance from the input vector to the training input vectors. This produces a vector where its elements indicate how close the input is to the training input. The second layer sums the contribution for each class of inputs and produces its net output as a vector of probabilities. Finally, a complete transfer function on the output of the second layer picks the maximum of these probabilities and produces a 1(positive identification)for that class and a 0(negative identification) for non-targeted classes. Each neuron in the input layer represents a predictor variable. In categorized variables N-1 neurons are used when there are N numbers of categories. It standardizes the range of values by subtracting the median and dividing by the interquartile range. Then the input neurons feed the values to each of the neurons in the hidden layer. The pattern layer contains one neuron for

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each case in the training dataset. It stores the values of the predictor variables for the case along with the target value. A hidden neuron computes the Euclidean distance of the test case from the neuron's center point and then applies the RBF kernel function using the sigma values. For PNN networks there is one pattern neuron for each category of the target variable. The actual targets category of each training case is stored with each hidden neuron; the weighted value coming out of a hidden neuron is fed only to the pattern neuron that corresponds to the hidden neuron's add the values for the class they present. The output layer compares the weighted votes for each target category accumulated in the pattern layer and uses the largest vote to predict the target category.

The accuracy, sensitivity and specificity of the classifier is measured. The accuracy represents the efficiency of the process. The sensitivity shows how the algorithm gives correct classification. The specificity shows how the algorithm rejects the wrongly classification results. We designed a spatial consistency constraint in a graphical model to improve the detection performance. Our lesion characterization method is based on the Multi-atlas approach. We have improved the appearance constraint for better structure estimation and lower method complexity without the additional structure delineation step. The performance of the process is measured based on the calculation of accuracy, area under curve of the process.

$$ACC = \frac{(TP + TN)}{(FP + TN) + (TP + FN)} \quad (1)$$

Where: TP-True Positive, TN-True Negative, FP-False Positive, FN-False Negative, ACC-Accuracy.

The performance of the process is measured in terms of performance metrics like precision, recall, F measure, and false positive. The

$$recall = \frac{TP}{(TP + FN)} \quad (2)$$

$$precision = \frac{TP}{(TP + FP)} \quad (3)$$

$$F = 2 * \frac{recall.precision}{recall + precision} \quad (4)$$

1. TP is the total number of correctly classified foreground.
2. FN is the total number of false negatives which accounts for the incorrect number of disease type pixels classified as dataset.
3. FP is the total number of false positives which means the pixels are incorrectly classified as images.
4. True Negative=correctly rejected.

The flow diagram (fig.2) gives full information about process how to find input signal is normal or abnormal. Then each process will explained in modules descriptions.

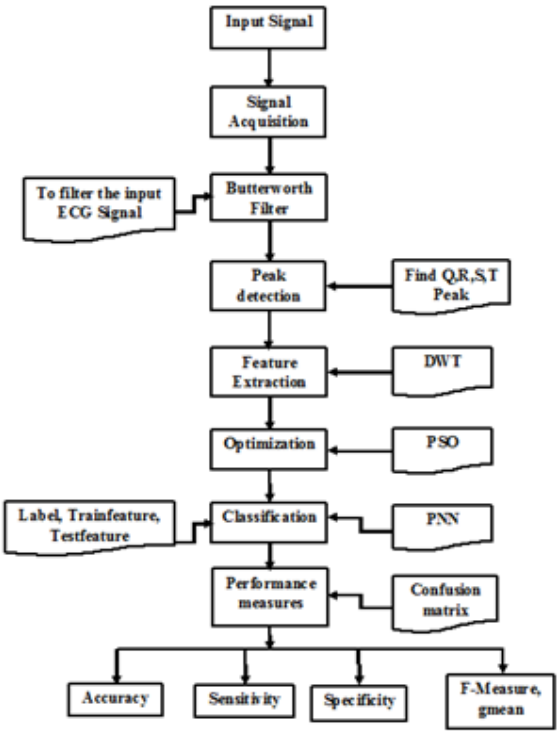
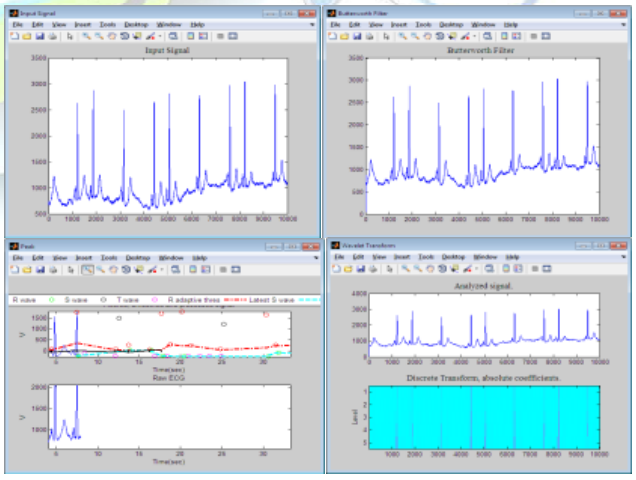


Fig 3: Flow Diagram

III. SIMULATION AND RESULT



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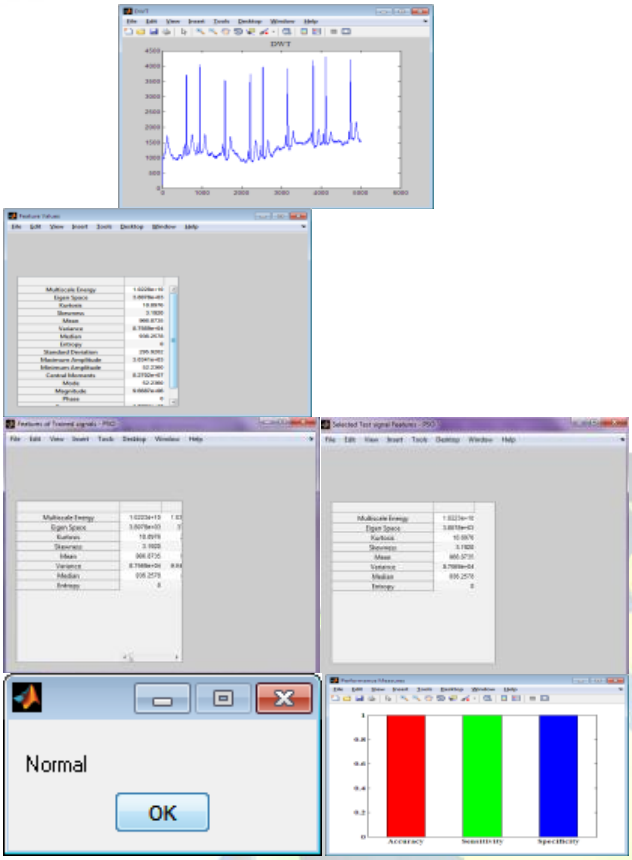

Fig 4: Output Results

IV. CONCLUSION

The proposed MI detection and localization approach from multilead ECG does not require any prior information about the pathologies in leads. This approach is based on the evaluation of multiscale energy and MEES features. Analysis with number of data shows that these features are capable of not only discriminating HC and MI, but also they can differentiate between different types MI pathologies. For MI detection the multilead data matrix is used. The performance of MEES feature vector is evaluated using PSO and PNN classifiers with linear and RBF kernel functions.

References

[1] P. de Chazal, "Automatic classification of heartbeats using ECG morphology and heartbeat interval features," IEEE Transactions on Biomedical Engineering, vol. 51, no. 7, pp. 1196-1206, Jul, 2004.

[2] M. Milanesi, "Independent component analysis applied to the removal of motion artifacts from electrocardiographic signals," Med. Biol. Eng. Comput., vol. 46, no. 3, pp. 251–261, Mar. 2008.

[3] O. Sayadi and M. B. Shamsollahi, "Model-based fiducial points extraction for baseline wandered electrocardiograms," IEEE Trans. Biomed. Eng., vol. 55, no. 1, pp. 347 –351, Jan. 2008.

[4] S. Ari, "ECG signal enhancement using S-Transform," Comput. Biol. Med., vol. 43, no. 6, pp. 649–60, Jul. 2013.

[5] M. Zivanovic and M. Gonz´alez-Izal, "Simultaneous power line interference and baseline wander removal from ECG and EMG signals by sinusoidal modeling," Med. Eng. Phys., vol. 35, no. 10, pp. 1431–441, Oct. 2013.

[6] Christo Ananth, S.Shafiqa Shalaysha, M.Vaishnavi, J.Sasi Rabiyathul Sabena, A.P.L.Sangeetha, M.Santhi, "Realtime Monitoring Of Cardiac Patients At Distance Using Tarang Communication", International Journal of Innovative Research in Engineering & Science (IJIRES), Volume 9, Issue 3,September 2014,pp-15-20

[7] C. Ye, "Heartbeat Classification Using Morphological and Dynamic Features of ECG Signals," Biomedical Engineering, IEEE Transactions on, vol. 59, no. 10, pp. 2930-2941, 2012.

[8] C. A. Bustamante, "ECG delineation and ischemic ST-segment detection based in wavelet transform and support vector machines." pp. 1-7.

[9] L. Mariano and M. Juan Pablo, "Heartbeat classification using feature selection driven by database generalization criteria," IEEE Trans Biomed Eng, vol. 58, no. 3, pp. 616 - 625, 2011.

[10] Oster J, Behar J, Sayadi O, et al. Semi-supervised ECG Ventricular Beat Classification with Novelty Detection Based on Switching Kalman Filters.[J]. IEEE transactions on bio-medical engineering, 62(9):2125-2134, 2015.

[11] L. de Oliveira, "Premature Ventricular beat classification using a dynamic Bayesian network," in Proc. IEEE Int. Conf. Eng. Med. Biol. Soc., Aug./Sep. 2011, pp. 4984–4987.

[12] G. de Lannoy, "Weighted conditional random fields for supervised inter patient heartbeat classification," IEEE Trans. Biomed. Eng., vol. 59, no. 1, pp. 241–247, Jan. 2012..

[13] X. Jiang, "ECG arrhythmias recognition system based on independent component analysis feature extraction," in Proc. IEEE Region 10 Conf., pp. 1–4, Nov. 2006.

[14] T. Ince, "A generic and robust system for automated patient-specific classification of ECG signals," IEEE Trans. Biomed. Eng., vol. 56, no. 5, pp.1415–1426, May 2009.

[15] M. Lagerholm, "Clustering ECG complexes using Hermite functions and self-organizing maps," IEEE Trans. Biomed. Eng., vol. 47, no. 7, pp.838–48, Jul. 2000.

[16] V. S. R. Kumari and P. R. Kumar, "Cardiac Arrhythmia Prediction using improved Multilayer Perceptron Neural Network," Research and Develop.(IJECIERD), vol. 3, no. 4, pp. 73-80, 2013

[17] C. V. Banupriya and S. Karpagavalli, "Electrocardiogram Beat Classification using Probabilistic Neural Network, " Int. J. of Comput.Applicat. (IJCA), pp. 31-37, 2014.

[18] T. Niederhauser, "Graphics-Processor-Unit-Based Parallelization of Optimized Baseline Wander Filtering Algorithms for Long-Term Electrocardiography," IEEE Transactions on Biomedical Engineering, vol.62,no. 6, pp. 1576-1584, Jun, 2015.