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Multiscale Spectral Coding for ECG Analysis and Diagnosis

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Abstract

Objectives: This paper aims at development of efficient ECG diagnosing system for detection of MI within small span, using novel filtering technique to remove the external noises present in ECG signal. **Methods/Statistical Analysis:** The medical experts study the electrical activity of the human heart in order to detect heart diseases from the electrocardiogram (ECG) of the heart patients. A Myocardial Infarction (MI) or Heart Attack is a heart disease that occurs due to a block (blood clot) in the pathway of one or more coronary blood vessels (arteries) which supplies blood to the heart muscle. The abnormalities in the heart can be identified by the changes in the ECG signal. The conventional approaches are time consuming & require too much time for the analysis of ECG signal. In this paper new technique for filtering is being introduces for removing the external noises present in ECG signal. **Findings:** The proposed approach evaluates the Power Spectral Density of noise filtered bands and then classification is done by using classifier. The classifier performs the comparison between the features of query database and the features of sample database and reveals the type of heart disease. By using proposed technique in this paper, the diagnosing accuracy is increased up to 96.82%. **Application/Improvements:** This proposes technique is best suited for all modern ECG instrument for better accuracy and analysis of ECG signal.

Keywords: ECG diagnosis, Myocardial Infarction (MI), PSD, Spectral Bands

1. Introduction

An Electrocardiogram (ECG) is a signal generated by the electrical activity of the heart. The signal demonstrates the functioning of heart. An ECG can provide useful information for cardiologists about the functioning and rhythm of the heart. The specialists can discover different types of abnormalities through the ECG recordings. However, as the ECG recording time increases, the time required for the analysis also increases. Thus there is a need of automated tools/techniques/methodsto accurately analyze the large amount of ECG data. Automated classification of long-term ECG recordings is becoming a universal need in clinical applications today. Myocardial Infarction (MI), commonly known as heart attack, is due to the blocking of one of the coronary arteries or one of its smaller branches. The detection of MI can be done by analyzing the levels of enzymes in blood serum. This process is time consuming and requires time delay. This time delay can be avoided by detecting MI through the analysis of ECG signal of the suspected patient(s). The ECG signal of a suspected patient can be analyzed byusingDigital Signal Processing (DSP) techniques. The analysis using DSP techniques requires preprocessing and feature extraction of an ECG signal. Various techniques were proposed in earlier to perform ECG classification. An R-peak detection[1] approach extracts the all R-peaks present in the ECG data. To localize the QRS regions, the squared double difference of the ECG signal is used. The complete process of R-peak detection is carried out in three phases: sorting and thresholding of squared double difference of ECG signal to localize the optimal QRS regions, approximate R-peak detection through the relative magnitude comparison of localized QRS regions and processing of RR interval to detect the accuracy of peaks. Though the ECG classification through R-peak detection

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give better performance, the ECG signal consists of external noise which needs to be removed to further analyze. In[2], an ECG signal denoising approach was proposed through soft thresholding criterion to filter PLI noise[3]. According to the distribution of spectral energy, there may be difference between the normal ECG and abnormal ECG. To analyze this difference effectively, there is a need to filter all noises present in ECG signal. Hence, proposed a wavelet base soft thresholding technique to filter the unwanted noise from an ECG signal. The determination of wavelet parameters and the threshold was also discussed. Through thresholding, the signal components which are below the threshold will be discarded. This removes few wanted samples also. To overcome this problem, K-nearest neighbor (KNN) algorithm was proposed in[4] to classify the QRS complex in ECG. Applies a band-pass filter to suppress the noise and interference present in ECG further to reduce false detection. This approach considered the gradient of the ECG signal as a feature for QRS detection. This approach was tested over two manually annotated standard databases, CSE and MIT-BIH Arrhythmia database. To further remove the noise in ECG, an appropriate band-pass FIR filter was proposed in[5]. Evaluates totally six features for QRS complex detection and delineation by sliding a uniform length window sample by sample. They are curve length, sum of absolute second order differentiation, sum of absolute first order differentiation, variance, area and sum of non-linearly amplified Hilbert transform. These all features are normalized and are processed to define a new multi order derivative wavelet based measure (MDWM) for ECG event detection and delineation. The complete testing was carried for a three lead Holter data by evaluating the Euclidean distance norm between the samples of three leads. For classification, a Nyman Pearson classifier was used which is a simple (False-Alarm Probability) FAP tester. The complexity of is observed to be high due to the extraction of six features. In[6] a simple segmentation approach was proposed based on information optimized decision static. In this approach, a uniform length sliding window slide on the preprocessed ECG data to extract some geometrical features based a new matric called as Discriminant Analyzed Geometric Index (DAGI). The evaluation of DAGI will be done by the application of non-linear orthonormal projection on the preprocessed data. After the feature extraction, the Nyman Pearson classifier was applied to classify. The performance of the classifier mainly depends on the features and its dimensions. As there are efficient features which represent entire ECG data information along with less size, the classifier will give correct results within the less time. So, to enhance the performance of any ECG classification system, there is a need to extract the exact features with fewer dimensions. Various feature extraction and dimensionality reduction techniques were proposed in earlier. Wavelet transform techniques improve the performance of ECG classification system by extracting the features in in adaptive way. The obtained features can be used for Arrhythmia detection. The proposed approach in[7] not only considers the P, QRS and T waves as features, but also considers the relation between the temporal sequences as long as they observed. Used wavelet transform for effective feature detection. Initially, QRS complexes were detected. Further, each QRS was defined by the detection of peaks of individual waves and also complex onset and end. Finally, the determination of P and T wave peaks, onsets and ends is performed. A novel and innovative technique proposed in[8] tries to enhance the ECG classification accuracy by differentiating different heart diseases, such as, Atrial Flutter, Atrial Fibrillation, Myocardial Infraction and Branch Bundle Block. Tries to give perfect results about the patient, that is whether he/her is suffering from single or multiple heart diseases[8]. The complete analysis was done through the feature extraction using discrete wavelet transform. After locating heart disease, the system evaluates the criticality of disease. The proposed system considers the relationship between factors such as criticality and age of patient. It is an efficient classification approach but increases the complexity due to the light variations among the feature of ECG signal. In[9], a geometrical feature extraction technique was proposed based on the QRS region and its corresponding DWT features. The DWT feature of QRS region was totally divided into eight polar sectors. Then the curve length of each segment is evaluated and used as feature space. Further to increases the robustness of proposed approach; it was tested over different classifiers such as Probabilistic Neural Network (PNN), Support Vector Machine (SVM) and two Multi-Layer Perceptron-Back Propagation (MLP-BP) with different topologies. A new ischemia detection approach was proposed in[10] based on wavelet features and SVM classifier. This approach removes the baseline wandering and detects time positions of QRS complexes in ECG signal. The features of ECG were obtained through the morphology of ECG waveform explicitly and DWT. This approach used a new kernel density classifier (KDE), can change the kernel bandwidths automatically. i.e., no need of provision of initial parameter in advance. A new metric, dissimilarity factor (D) proposed in[11] performs the classification without any extraction of direct clinical feature information. The obtained D can classify the normal attributes from myocardial infraction data. Filtering, DWT followed by PCA were applied on the ECG data to obtain multivariate time series data. In this approach, the QRS segment and T segment of MI dataset from lead II, III and a VF were extracted and compared directly with the corresponding feature of healthy patients. Aims to process and classify an ECG signal as healthy subject or subject diagnosed with Myocardial Infarction (MI) using Artificial Neural Networks (ANN) and SVM (Support Vector Machine)[12]. LIBSVM is utilized for the classification with SVM and back propagation artificial neural networks with varying hidden layers and nodes are also implemented for performance analysis. The direct application of DWT on ECG gives the information of that particular signal only. Along with feature information, if the relation among the ECG feature were found, it will give more accuracy compared to conventional DWT. The cross wavelet transform (XWT) based ECG classification was proposed in[13]. The XWT gives the measure of similarity between two time domain signals. The application of XWT on the pair of ECG data yields wavelet coherence (WCOH) and wavelet cross spectrum (WCS). The WCS and WCOH of various ECG patterns show distinguishing characteristics over two specific regions R1 and R2, where R1 is the QRS complex area and R2 is the T-wave region. In[14] wavelet entropy (WE) based atrial fibrillation detection was proposed for ECG dataset with AF. Initially, this approach filters the noise present in TQ segments. Then the wavelet entropy of median TQ segment was evaluated by considering 10 previous noise free beats under study.In this manner, the P-waves or the fibrillatory waves present in the recording were highlighted or attenuated, respectively, thus enabling the patient's rhythm identification (sinus rhythm or AF). A signature based ECG classification approach proposed in[15] considered the frequency description of P, T, QRS segments as a signature and processed for ECG classification. This approach is for high resolution ECG (HR-ECG) for Arrhythmia detection. This is a two-step wavelet analysis and synthesis performed in the ECG dataset with Myocardial Infraction (MI). In[16] a novel approach for generating the wavelet that best represents the ECG beats in terms of discrimination capability is proposed. It makes use of the poly-phase representation of the wavelet filter bank and formulates the design problem within a Particle Swarm Optimization (PSO) framework. Based on the property of bats, an ECG classification approach was proposed in[17]. In[18] an ECG classification technique on multiscale energy and Eigen space (MSC) is proposed for detectionof myocardial infarction from multi-lead Electrocardiogram (ECG). Considered the Eigen values of spectral features of ECG as features for MI classification. However, the main problem associated within is the decomposition of ECG into sub bands is carried out in six levels which consumes more time. As well as the classification didn't consider all the obtained spectral features at all levels this reduces the classification accuracy. In this approach, a new ECG classification approach is proposed to perform MI detection from ECG through the power spectral characteristics and normalized coefficient coding. The proposed approach extracts the all components of ECG which gives sufficient information about MI. The rest of the paper is organized as follows: Section II illustrates the basic ECH signal analysis and its parameters. Section III illustrates the basic system model developed for ECG classification. Section IV describes the details of conventional approaches. The complete details of proposed approach are illustrated in section V. The experimental results are represented in section V and finally the conclusions are provided in section VII.

2. ECG Analysis

An ECG signal represents electrical activity of the heart. The ECG signal can be obtained using the electrical potentials measured at various points of body using leads & electrodes. To obtain the useful and diagnostic information from an ECG, the knowledge of normal vectors of repolarization and depolarization and various waves' information is important.A normal ECG signal is shown in Figure 1.

As shown in Figure 1(a) normal ECG signal consists of a P wave, a QRS complex, a T wave, and a U wave. For a normal healthy person's ECG, the baseline is equal to isoelectric line (0 mV). The zero voltage baselinedemonstrates the ideal situations of heart, i.e., there is no current towards either the positive or negative ends of ECD leads. But, in the case of diseased heart, the baseline may be elevated (myocardial infarction)[19] or may be depressed (cardiac ischemia) with respect to the isoelectric line. It is due to the injury currents when the ventricles are at rest and during PR and TP intervals. The entire analysis of ECG is present in the deflections such as P, QRS, T and U. For each and every deflection there will be a prospective. The atria activation is represented by P wave, the depolarization or ventricular activation is represented by QRS complex, the repolarization or ventricular recovery is represented by T wave and ST segment and the combination of U wave and T wave gives the total duration of ventricular recovery. The time interval details are shown in Table 1.

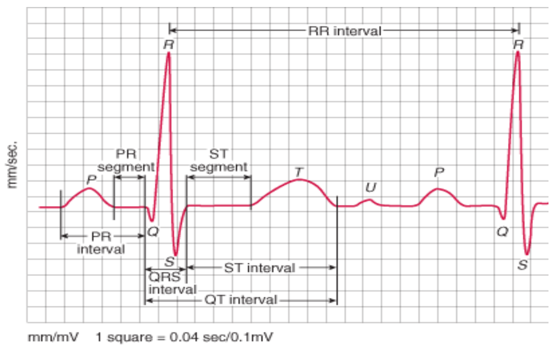

Figure 1. A Normal ECG Signal.

Table 1. Time intervals of ECG waves

Segment	Period
RR-Interval	0.6s to 1.2s
P-wave	80ms
PR-Interval	120ms to 200ms
PR-Segment	50ms to 120ms
QRS-Complex	80ms to 120ms
ST-Segment	80ms to120ms
ST-Interval	320ms
QT-Interval	420ms

3. System Model

The generalized system model for an ECG signal analysis is shown in Figure 2.

The developed system has signal conditioner, frequency analyzer, feature extraction unit, learning architecture, classifier, and decision logic unit. The signal conditioner preprocesses the input ECG, the frequency analyzer analyzes the frequency at which the signal is recorded and also checks whether the frequency of given ECG is at normal frequency or not. Further, the ECG signal is processed to feature extraction unit. The obtained features are given to learning architecture to create a feature data base. During testing, the extracted features of query signal are given to classifier. The classifier having two inputs, one from learning architecture and another from feature extraction unit. Finally, the decision logic unit declares the given testing signal into one of the heart disease categories to which it belongs based on decision logic.

4. Methodologies

4.1 De-noising

The ECG signal may be accumulated with different types of noises during its recording. Hence De-noising of an ECG is very important before the diagnosis. The noises added to normal ECG affects the diagnosing of the signal. Due to the presence of external noises, the characteristics of signal changes and thus affects diagnosing accuracy. For example, the range of RR-interval is 120ms to 200ms. For an ECG signal with RR-interval range beyond those limits reflects to the wrong diagnosis. Hence, there is a need to remove the external noise to increase the diagnosing accuracy. In[20] a de-nosing approach was proposed based on the normalization of features of signal, can be termed as Normalized Coefficient Coding (NCC).Initially, NCC decomposes a signal into Spectral Bands (SB). An SB is defined as a function that satisfies the following requirements:

- In the whole data set, the number of maxima and the number of zero-crossings must either be equal or differ at most by one.
- At any point, the mean value of the envelope defined by the local maxima and the envelope defined by the local minima is zero. The procedure of extracting an SB is called Sifting.

The sifting process is as follows:

- Identify all the local maxima in the test data.
- Connect all the local maxima by a cubic spline to produce upper envelope.
- Repeat the procedure for the local minima to produce the lower envelope.

The upper and lower envelopes should cover all the data between them. Their mean is m1. The difference between the data and m1 is the first component h1:

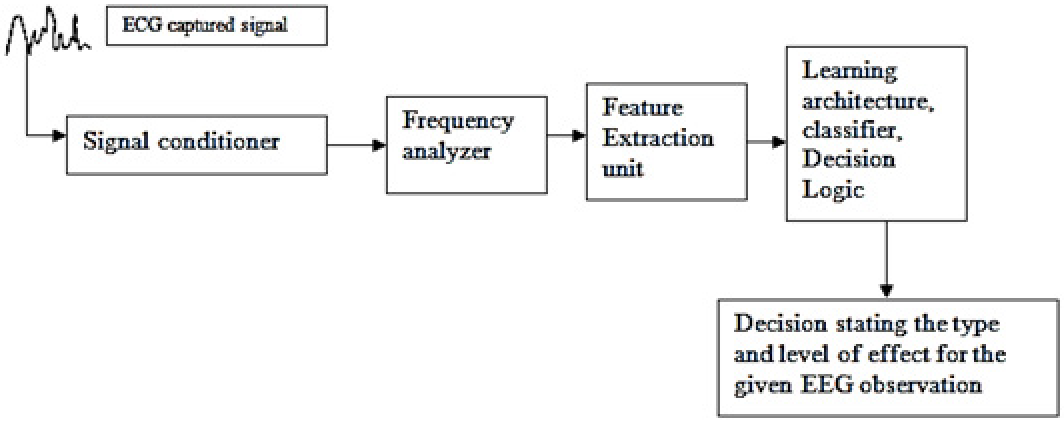

Figure 2. System Model for ECG Signal Analysis.

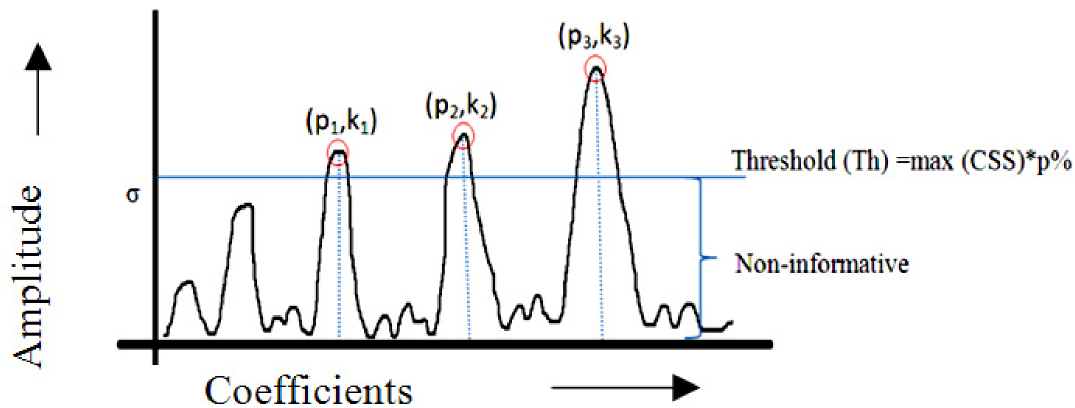

Figure 3. Noise Filtering through Thresholding.

$$X(t) - m_1 = h_1 \tag{1}$$

After the first round of sifting, a crest may become a local maximum. New maxima generated in this way actually reveal the proper modes lost in the initial examination. In the subsequent sifting process, h1 can only be treated as a proto-SB. In the next step, it is treated as the data, then

$$h_1 - m_{11} = h_{11} \tag{2}$$

After repeated sifting up to k times, h1 becomes an SB, that is

$$h_{1(k-1)} - m_{1k} = h_{1k} \tag{3}$$

Then, it is designated as the first SB component from the data:

$$c_1 = h_{1k} \tag{4}$$

At the end of the decomposition, the data s(t) will be represented as a sum of n SB signals plus a residue signal,

$$s(t) = \sum_{i=1}^{n} c_i(t) + r_n(t) \tag{5}$$

The finally obtained signal s(t) represents the partially reconstructed signal. It is reconstructed by summing the obtained SBs with the residue signal according to eq.(5).

In Figure3 the threshold is defined through Coefficient Scale Space (CSS). The threshold is obtained by multiplying the maximum value of CSS of an ECG with a constant value. However, in such process, information below the threshold is totally neglected. This elimination is based on the assumption that, only dominant coefficients exist for longer duration of smoothing and all the lower values are neglected treating as noise. For example, for a given plot for a query sample, the region below the threshold is considered to be non-informative and totally neglected. This consideration leads to following observations:

- Under semantic objects having similar representation, a false classification will appear.

- Information's at lower regions also reveals information of signals having shorter projections such as spines.
- Direct elimination of the entire coefficient leads to information loss as well, a random pickup will leads to higher noise density.

These problems are to be overcome to achieve higher level of retrieval accuracy in spatial semantic samples, or with sample having finer coefficients values.

In[21] a Multi-Scale Coding (MSC) approach for 12-lead ECG is proposed for detection and localization of MI. The work is carried out using a standard database to demonstrate the accuracy of the proposed method to classify the MI pathology. The complete implementation of MSC is carried out in three stages as pre-processing, multi-scale feature analysis and classification.The pre-processing involves filtering and frame based segmentation. In the filtering part, the artifacts such as base line wandering and drift are filtered out by a moving average filter[22] to remove high frequency noise, relative energies of wavelet sub bands and a noise variance based threshold are used[23]. The frame based processing of 12-lead ECG can capture the intra rhythm, inter-sample and inter-lead correlation information.This information can be used to diagnose various cardiac diseases. The multi-scale feature analysis involves wavelet transform of multi-lead ECG, evaluation of multi-scale energy features and multi-scale Eigen decomposition.

Wavelet analysis of an ECG signal with J level decomposition using suitable mother wavelet gives kth wavelet coefficient at jth level. The dyadic wavelet transform using a multi-resolution pyramidal decomposition technique based on a filter bank implementation gives J + 1 sub bands. For mth ECG lead, it results with anapproximation sub band coefficients, $cA_{J,k}^{m}$, atlevel J and with details sub-bands, $cD_{j,k}^{m}$, at level j, where j = 1; 2…..J . The approximation and the detail wavelet coefficients are obtained by the inner product of input ECG signal with scaling function

$$\phi_{J,k}(n) = 2^{\frac{-J}{2}}\phi\left(2^{-J}n - k\right) \tag{6}$$

and wavelet functions

$$\psi_{j,k}(n) = 2^{\frac{-j}{2}}\phi\left(2^{-J}n - k\right) \tag{7}$$

The approximation and detail wavelet coefficients for input signal Xm(n) are evaluated as

$$cA_{J,k}^{m} = \langle X^{m}(n)\phi_{J,k}(n)\rangle \tag{8}$$

and

$$cD_{j,k}^{m} = \langle X^{m}(n)\psi_{j,k}(n)\rangle \tag{9}$$

In case of six level wavelet decomposition is used. The diagnostic information of an ECG signal are distributed in different wavelet sub bands based upon their bandwidth or frequency content. It has been reported that the lower frequency sub bands contain most of the diagnostically significant information of the ECG signal. Then the energy due to the wavelet coefficients along each lead for approximation and detail sub bands are considered as multi-scale energy and it is given as

$$E_{cA_{J},k}^{m} = \frac{\Sigma_{k=1}^{N_J}\left[cA_{J,k}^{m}\right]^2}{N_J} \tag{10}$$

$$E_{cD_{j},k}^{m} = \frac{\Sigma_{k=1}^{N_J}\left[cD_{j,k}^{m}\right]^2}{N_j} \tag{11}$$

Where *NJ* and *Nj* are the number of coefficients in approximation and detail sub-bands. After obtaining energy values of sub bands, a thresholding technique was applied to extract the sub bans those having important features. After obtaining energies of sub bands, the multiscale energies are subjected to Eigen space analysis. The covariance matrices from mean removed data are evaluated as

$$C_{AJ} = \frac{1}{N_J - 1}\left([A_J][A_J]^T\right) \tag{12}$$

$$C_{Dj} = \frac{1}{N_j - 1}\left([D_j][D_j]^T\right) \tag{13}$$

Where CAJ the covariance matrix at Jth approximation level and is CDj is the covariance matrix at jth details scale. The Eigen decomposition of covariance matrices are

$$C_{AJ}V_{AJ} = V_{AJ}\Lambda_{AJ} \tag{14}$$

$$C_{Dj}V_{Dj} = V_{Dj}\Lambda_{Dj} \tag{15}$$

where V_{AJ}, V_{Dj} and Λ_{AJ}, Λ_{Dj} jare the eigenvectors and Eigen values for matrices of Approximation and

Detail sub band matrices respectively. Then the obtained featureset was given to classifier to perform MI detection. Support vector machine (SVM) isused for classification process.

4.2 Proposed Method

The method used for detecting the Myocardial Infraction (MI) is described in detailalong with the simulated results in this topic.

4.3 Multi Scale Spectral Coding (MSSC)

It could be observed that the obtained NCC plot represents the region variations over different band scaling. This representation appears as a 1-D signal with random variations. Taking this observation in consideration, a Multi Scale Spectral Coding (MSSC) for feature representation is proposed. For the process of coding, the MSSC bands are taken as a 1-D signal, and a linear wavelet decomposition using the approach of 1-D DWT coding is used. In the process of 1-D signal decomposition, banks of recursive filters are used to decompose the signal into finer bands. A pair of such filter bank is illustrated in Figure 4.

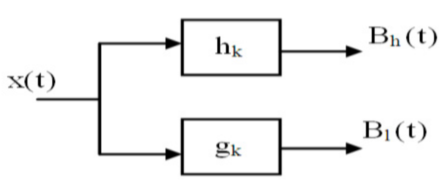

Figure 4. 1-D DWT Filter Bank Structure.

In the proposed approach of MSSC, a 1-D signal representation x(t), is taken as a variant of time-magnitude representation as shown in Figure 5.

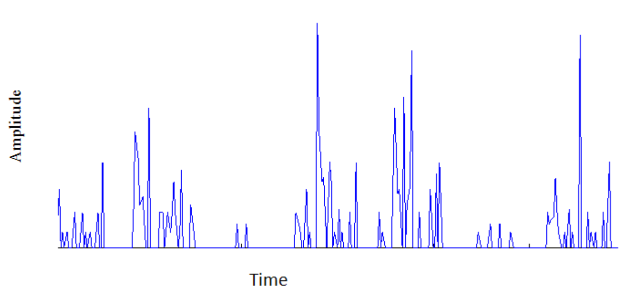

Figure 5. Representation ECG Signal.

To this 1-D signal x(t), a linear wavelet transformation is applied, to derive a bands of variant frequency contents. To perform wavelet decomposition, in this work, 'db4' and 'Morlet' wavelet transformation is carried out, for 4-scale levels. The 1-D signal x(t) is decomposed into components belonging to different frequency channels using a collection of filters defined by db4 coefficients, referred to as sub band filtering or sub band decomposition. In this process a two-channel sub band filtering is applied with a pair one low pass (gk) and one high pass (hk) filter, to bifurcate the signal x(t) into two sets of observations. An illustration to the band decomposition process is shown in Figure 6.

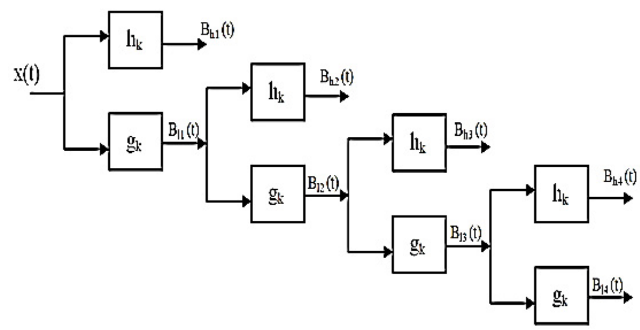

Figure 6.1-D Wavelet Decomposition in 4-scale Level.

The obtained bands {Bh1 – Bh4} are the decomposed detail bands reveling different frequency content at each level. {Bl1 – Bl4} are the low pass filter bands, which are decomposed in each successive band to obtain finer frequency information's. Each obtained high pass filter band, reveals a finer frequency content and based on the density of these frequency contents, then a decision of feature selection is made. This approach of feature selection, results in selection of feature details, at lower frequency resolutions also, which were discarded in the conventional MSC approach. To derive the spectral density of obtained bands, power spectral densities (PSD) to the obtained bands are computed. PSD is defined as a density operator which defines the variation of power over different content frequencies, in a given signal x(t). The Power Spectral Density (PSD) for a given signal x(t) is defined as,

$$PSD.P = \lim_{T \to \infty} \frac{1}{2T} \int_{-T}^{T} x(t)^2 \, dt \qquad (16)$$

Taking each band 'Bhi' as reference, a PSD for each band, 'PBi' is computed. The PSD features for the 4 obtained bands are then defined by,

$PB_i = PSD\,(B_{hi})$, for i = 1 to 4. (17)

The Band PSD's are derived as,

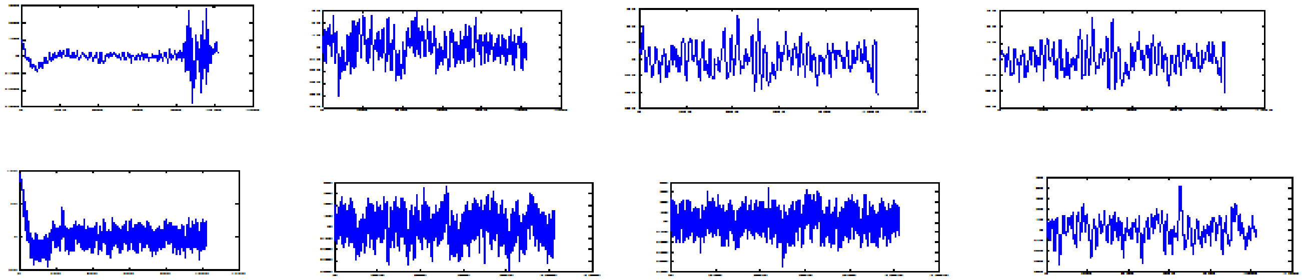

Figure 7. Training Samples.

$$PB_i = \lim_{T \to \infty} \frac{1}{2T} \int_{-T}^{T} B_{hi}(t)^2 \, dt \tag{18}$$

From these obtained energy values, bands are selected based on a defined selection criterion, as outlined,

For the obtained PBi, maximum PB is computed, defined by,

MPBi = max(PBi)

For i =1 to 4

if (PBi ≥ (MPBi / 2))

sel_Bi = Bi;

end

For these selected bands, 'Sel_Bi' features are then computed by the approach of peak picking, as carried. For each select band a maximum value is computed and all the coordinates above 60% of the peak value are taken as signal information. These approaches hence derive more informative feature information than MSC. To evaluate the developed approach a simulation model of the proposed approach is developed. The operation of the developed approach is carried out in two operation stages, training and testing. Wherein, training process set of recorded signals are processed in a sequence and the process of feature extraction is performed. For each of the training signal, the obtained features are buffered into an array termed as data base. To train the database the feature sextracted from the decomposed band sare, R_Amplitude, Q_Amplitude, S_Amplitude, P_location, Q_location, R_location, S_location, T_location, and ST deviation. During the process of querying the same process is repeated over the test sample and the obtained query feature is passed to a classifier to retrieve information's from the knowledge data base. For the process of classification, a SVM classifier is used. The classifier is designed with a Euclidian distance based approach to obtain the best set of matches from the knowledge data base. The decision 'D' for the retrieval is derived as the minimum value of the Euclidian distance defined as,

$$D = \min(Ed_i) \tag{19}$$

Where,

Euclidian Distance,

$$Ed_i = \sqrt{\sum_{i=1}^{n} Q - dbf_i}$$

Where, Q is the query feature and, dbf_i is the features trained in the data base.

5. Results and Discussions

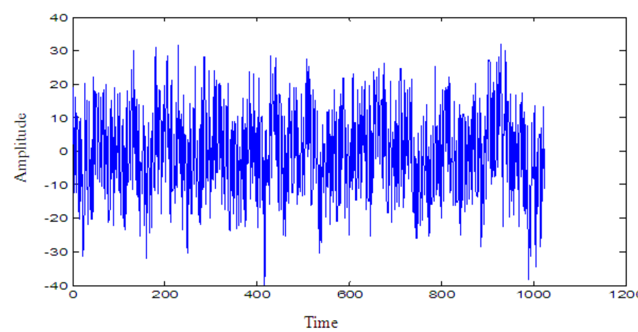

Figure 8. Query Sample.

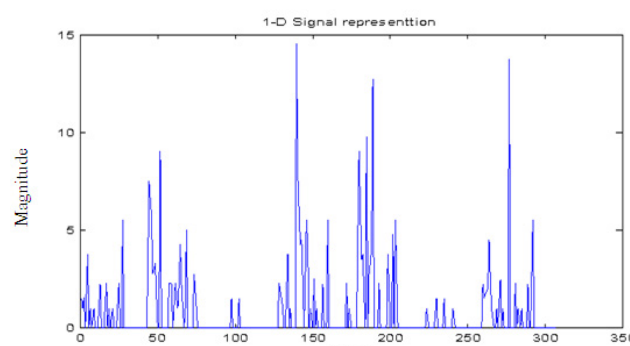

Figure 9. Detected Peak Signal for Given ECG Sample.

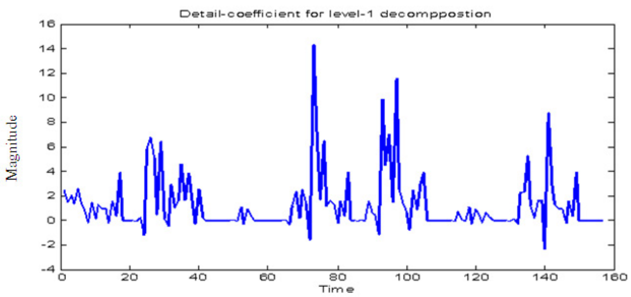

Figure 10. Detail Spectral Band at Level-1 Decomposition.

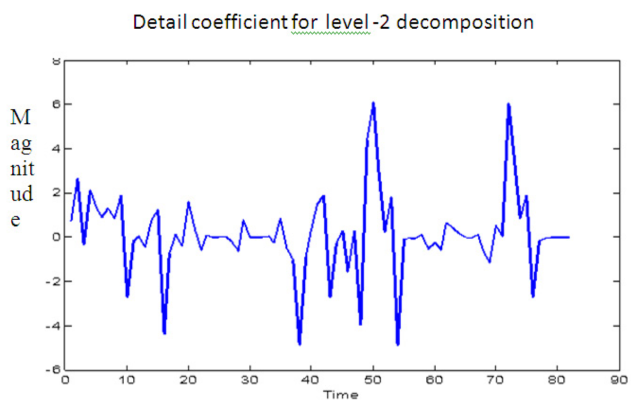

Figure 11. Detail Spectral Band at Level-2 Decomposition.

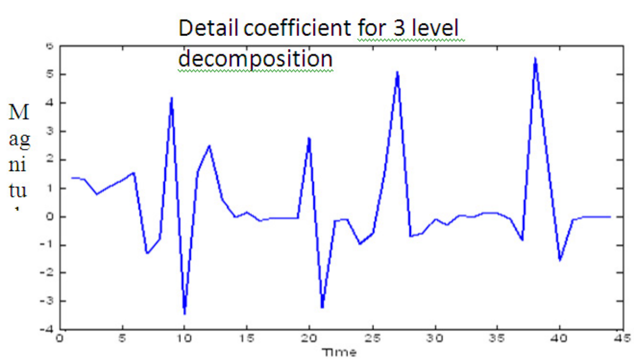

Figure 12. Detail Spectral Band at Level-3 Decomposition.

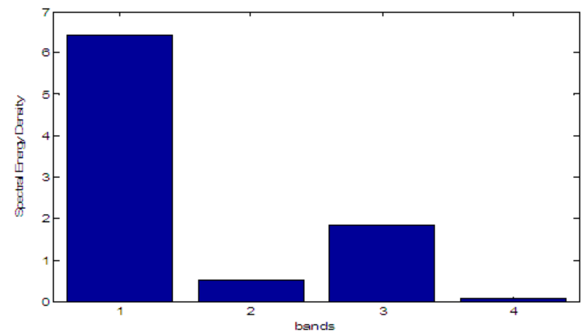

Figure 14. Spectral Energy Density for 4-Decomposed Bands.

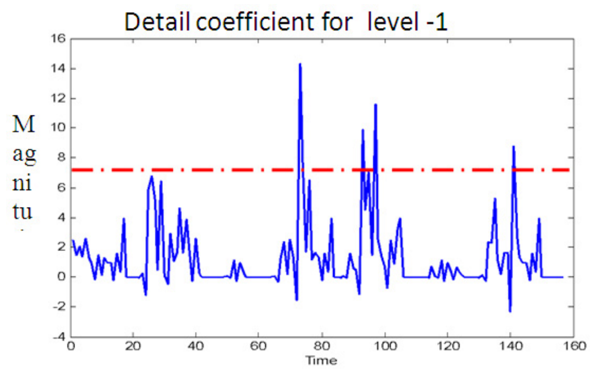

Figure 15. Extraction of Features from Selected Band 1.

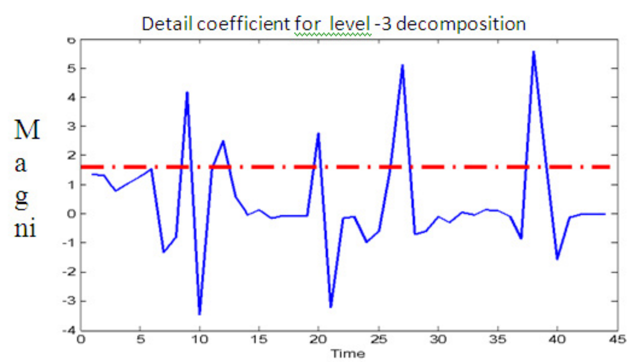

Figure 16. Extraction of Features from Selected Band -2.

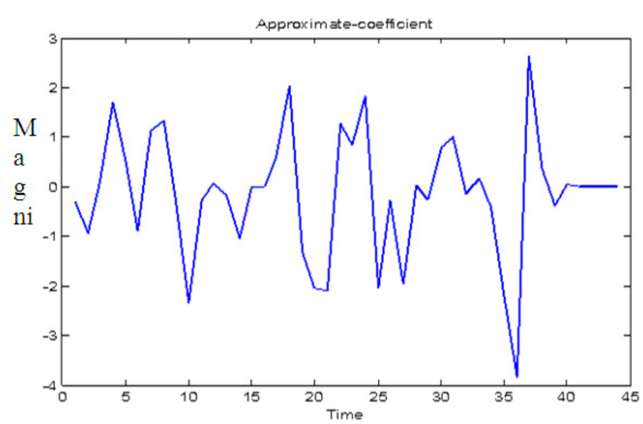

Figure 13. Approximate Coefficient for given Signal.

To evaluate the performance of the developed approach following parameters are used.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN};$$

$$Sensitivity = \frac{TP}{TP + FN};$$

$$Recall = \frac{TP}{TP + FN}; \quad Precision = \frac{TP}{TP + FP}$$

$$F - measure = \frac{2.Recall.Precision}{Recall + Precision}$$

For the simulation of the proposed approach, a set of ECG samples are taken for normal and effected case from MIT database for Myocardial infraction disease. Few samples from the database is shown in Figure 7. These test samples are passed to the processing algorithm for training, where each signal is read in a sequence and the computed features are buffered in an array. This buffered information is taken as the knowledge information for classification. The process of implementedtechnique is carried out for a selected query sample. The processing results obtained are illustrated below. For the evaluation of developed work, a test query ECG signal is passed. An ECG signal sample is shown in Figure 8. The test sample is tested for the extraction of similar test case sample from the database. The detected R-peaks for the given signal are shown in Figure 9. To derive the spectral band for the given test sample, the obtained coefficient information's are buffered into a linear array, and the coefficients are considered as a 1-D signal elements to perform spectral decomposition to compute multi-spectral band decomposition. To the obtained denoised ECG signal, a spectral decomposition is carried out using db4 wavelet transformation. The 3 detail bands and the approximate band obtained are shown in Figure 10-13 respectively. It is observed that band 1 and band 3 exhibits higher coefficients variation than the other two bands, hence more coefficient information are presented in these two bands. To select the required bands for feature extraction, a spectral density using power spectral density is used. The energy density for each band is as shown in Figure 14. The spectral energy density of each band is computed using, a power spectral density approach. Each band coefficients are averaged by the squared summation of its coefficients and energy is computed. From the obtained band energy, it can be concluded that, band 1 and 3 has comparatively higher energy density than the other two bands. This is observed to be synch with the observations made from the bands obtained as seen in above figures. Based on the energy derived, two highest energy density bands are selected, which is 1 and 3 in this case. Figure 15 and 16 shows the two selected bands for feature extraction. The features are selected based on the similar procedure of maximum thresholding approach as used in conventional MSC approach. For the two selected

Table 2. Parametric evaluation of the developed system for processing efficiency

Test sample	Method	Accuracy (%)	Sensitivity	Specificity	Recall	Precision	F-Measure	CT
S1	NCC [24]	55.670	0.220	0.608	0.220	0.680	0.478	0.545
	MSC[19]	62.500	0.315	0.752	0.315	0.740	0.523	0.348
	MSSC	**89.000**	**0.444**	**0.909**	**0.444**	**0.800**	**0.571**	**0.138**
S2	NCC[24]	49.484	0.432	0.712	0.432	0.508	0.542	0.273
	MSC[19]	58.1341	0.458	0.854	0.458	0.666	0. 621	0.143
	MSCC	**92.500**	**0.524**	**0.946**	**0.524**	**0.820**	**0.652**	**0.137**
S3	NCC[24]	55.670	0.420	0.762	0.420	0.650	0.569	0.310
	MSC[19]	63.824	0.452	0.886	0.452	0.720	0.688	0.1391
	MSSC	**94.840**	**0.484**	**0.924**	**0.484**	**0.795**	**0.690**	**0.132**
S4	NCC[24]	58.360	0.446	0.738	0.446	0.650	0.583	0.374
	MSC[19]	65.420	0.558	0.824	0.558	0.745	0.600	0.183
	MSSC	**96.820**	**0.582**	**0.908**	**0.582**	**0.810**	**0.680**	**0.132**

band, maximum peak values are found, and a threshold of 0.6 or the maximum peak is set as the threshold value. All the peaks falling above to this threshold is recorded as the feature magnitude with its corresponding coordinates, recording dominant coefficient peaks. With these extracted features, a retrieval process is carried out, by extracting the ECG features as defined prior. The developed system is evaluated under two samples of different types, called dissimilar case, and two samples of spatially similar case, where the samples are observe to be similar. This evaluation is carried out to analyze the performance of developed system retrieval performance. The obtained Analytical results for these developed systems are given in Table 2.

6. Conclusion

The approachfor ECG diagnosing is proposed to improve the diagnosing accuracy by using novel noise filtering technique. The ECG signal may be accumulated with different types of noises during its recording, affecting the diagnosing accuracy of the signal.The proposed approach uses a novel filtering technique and also a novel feature extraction technique. The proposed filtering technique decomposes the ECG signal into spectral bands which gives detailed information about the spectrum of both noise and desired signal. Based on the properties of noise spectrum,thresholding and feature extraction is carried-out. By using a novel pre-processing & filtering technique, the diagnosing accuracy is increased up to 96.82%.

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