SPECTRAL CORRELATIVE CODING FOR MEDICAL IMAGE RETRIEVAL

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Abstract: *The medical experts study the electromechanical association of the human heart in order to detect heart diseases from the of the heart patients. A myocardial infarction or heart attack is a heart disease that occurs when there is a block (blood clot) in the pathway of one or more coronary blood vessels (arteries) that carry oxygenated blood away from the heart to the tissues. The quality (or)state of being abnormal in the heart can be recognized by the changes in the medical signal. The conventional approaches require too much time for medical analysis. This paper proposed an efficient medical diagnosing system that detects the MI within less time period. This paper also proposed a novel sift technique to detach the environmental stimulus present in medical. The proposed approach decomposes the patients signal into some bands in which when the number of atoms is large, one gets a continuum of energy levels. These obtained bands are filtered and then process for feature extraction. The proposed approach evaluates the measure of signal's power content versus frequency is finded out of noise filtered bands and then process for classifier. A person (or) thing that classifies something performs the comparison between the features of query and database sample features and reveals the type of heart disease it belongs.*

Keywords: medical diagnosis, myocardial infarction (MI), spectral bands, PSD.

I.INTRODUCTION

An 1-D contour is a signal generated by the electromechanical association of heart to demonstrate the functioning of heart. It is another way of analyzing numerical data. An medical can provide very much useful information for cardiologists about the functioning and rhythm of the heart. The specialists can discover different type of abnormalities through the medical recordings. However, as the medical recording time increases, the time required for the analysis also increases. Thus there is a requirement of automated tools to accurately analyze the vast amount of medical data collected by monitoring devices. Automated medical classification of long-term medical recordings is becoming a universal need inclinical applications.Myocardial infarction (MI), commonly known as heart attack, occurs when blood flow decreases (or) stops to a part of the heart causing damage to the heart muscle. The detection of MI can be done by analyzing the levels of enzymes in blood serum only after 6 to 9 hours. This time delay can be avoided by detecting MI through the analysis of MEDICAL of the suspected patient. This can be done within ten minutes. The medical signal of a suspected patient can be analyzed through digital processing techniques with in very less time. For this purpose, there is a requirement of preprocessing and feature extraction of an medical. Various techniques were proposed in earlier to perform medical classification. An R-peak detection [1] approach extracts the all R-peaks present in the medical data. To restrict to a particular place, QRS regions, the difference of two squares is a squared number subtracted from another squared number of the medical signal is used. The complete process of R-peak detection is finished out in three phases: sorting and thresholding of squared double difference of medical 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 medical classification through R-peak detection give better performance, the medical signal consists of external noise which Needs to be removed to further analyze.In [2], an MEDICAL signal denoising approach was proposed through soft thresholding criterion to filter PLI noise [17]. According to the distribution of spectral energy, there may be difference between the normal medical and abnormal medical. To analyze this difference effectively, there is aneed to filter all noises present in medical signal. Hence, [2] proposed a wavelet base soft thresholding technique to filter the unwanted noise from an medical 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 solve this problem, K-nearest neighbor (KNN)algorithm was proposed in [3] to classify the QRS complex in medical. [3] Applies a band-pass filter to reduce the noise and interference present in medical further to reduce false detection. This approach considered the gradient of the medical signal as a characteristic 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 medical, an appropriate band-pass FIR filter was proposed in [4]. [4] Evaluates totally six features for QRS complex detection and delineation by sliding a rectangular window has a value of one over its length sample by sample. They are curve length, sum of absolute second order demarcation, sum of absolute first order demarcation, 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 medical 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 neyman Pearson classifier was used which is a simple (False-Alarm Probability) FAP tester. The complexity of [4] is observed to be high due to the extraction of six features. In [5] a simple segmentation approach was proposed based on information optimized decision static. In this approach, a uniform length sliding window slide on the preprocessed medical 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 both orthogonal and normalized projection on the preprocessed data. After the feature extraction, the neyman 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 medical data information along with less size, the classifier will give correct results within the less time. So, to enhance the performance of any medical classification system, there is a requirement 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 medical classification system by extracting the features in in adaptive way. The obtained characteristics can be used for Arrhythmia detection. The proposed approach in [6] not only considers the waves as features, but also considers the relation between the temporal sequences as long as they observed. [6] Used wavelet transform for effective feature detection. Initially, QRS complexes were detected. Further, each QRS was defined by the diagnosis of peaks of single 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 [7] tries to enhance the MEDICAL classification accuracy by differentiating different heart diseases, such as, Atrial Flutter, Atrial Fibrillation, Myocardial Infraction and Branch Bundle Block. [7] Tries to give perfect results about the patient, that is whether he/her is suffering from single or multiple heart diseases. 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 medical signal. In [8], 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 [9] based on wavelet features and SVM classifier. The features of medical were obtained through the morphology of medical 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 [10] 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 medical 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. [11] Aims to process and classify an medical signal as healthy subject or subject diagnosed with Myocardial Infarction (MI) using Artificial Neural Networks (ANN) and SVM (Support Vector Machine).The direct application of DWT on medical gives the information of that particular signal only. Along with feature information, if the relation among the medical feature were found, it will give more accuracy compared to conventional DWT. The cross wavelet transform (XWT) based MEDICAL classification was proposed in [12]. The XWT gives the measure of similarity between two time domain signals. The application of XWT on the pair of medical data yields wavelet coherence (WCOH) and wavelet cross spectrum (WCS).In [13], wavelet entropy (WE) based atrial fibrillation detection was proposed for medical 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 medical classification approach proposed in [14] considered the frequency description of P, T, QRS segments as a signature and processed for medical classification. This approach is for high resolution medical (HR-medical) for Arrhythmia detection. This is a two-step wavelet analysis and synthesis performed in the medical dataset with Myocardial Infarction (MI). In [15], a novel approach for generating the wavelet that best represents the medical beats in terms of discrimination capability is proposed. Based

on the property of bats, an medical classification approach was proposed in [16]. In this approach, the feature is extracted based on the rhythm of heart beats. The loudness and pulse emission rate of sample are considered as features for classification. The features are obtained through bat algorithm and the obtained features were given to NN classifier.

II.MEDICAL ANALYSIS

An medical signal is graph produced by an electrocardiograph, measured through the electrical activity of heart. The primal objective of an medical is to represent the rhythm and functioning of heart. The construction of an medical signal is through the electrical potential measured at various points of body using a galvanometer. To obtain the useful and diagnostic information from an medical, the knowledge of normal vectors of repolarization and depolarization and various waves information is important. medical signals have wide variety of applications overall the medical field in measuring and in diagnosing the abnormalities in the functioning of heart. For a normal healthy persons medical, 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) or may be depressed (cardiac ischemia) with respect to the isoelectric line due to the injury currents when the ventricles are at rest and during PR and TP intervals. The entire analysis of medical is present in the deflections such as P, QRS, T and U [18]. 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 [19]. The complete time period details of all segments of a normal medical is shown in table.1.

III. SYSTEM MODEL &MEDICAL DENOISING

A. System Model

The generalized system model for an MEDICAL signal analysis is shown in figure 1.

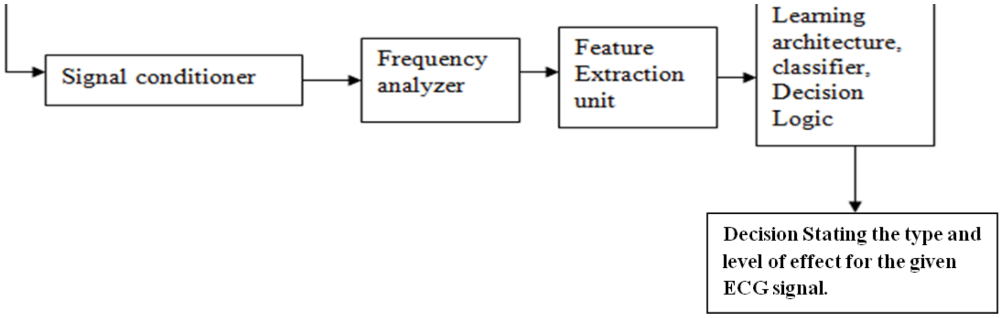

Figure 1: System model for MEDICAL signal analysis

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

B. Denoising

Denoising of an medical is very important before the diagnosis, since the medical signal may accumulate with so many types of noises during its recording. The noises added to normal medical affects the diagnosis. Due to the presence of external noises, the characteristics of signal will change intern affects to diagnosis accuracy. For example, the range of RR-interval is 120ms to 200ms. For an medical 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 diagnosis accuracy. This approach proposed a non-stationary filter called as Multiscale spectral coding (MSSC) to remove the external noises accumulated in the medical. The MSSC is a non-stationary in nature.Initially, the MSSC decomposes a signal into spectral bands (SB).

The procedure of extracting an SB is called sifting.

The upper and lower envelopes should cover all the data between them. Their mean is m_1. The difference between the data and m_1 is the first component h_1:

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

After the first round of sifting, a crest may become a local maximum. New extrema generated in this way actually reveal the proper modes lost in the initial examination. In the subsequent sifting process, h_1 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, h_1 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).

This elimination is made based on the assumption that, only dominant edges exist for longer duration of smoothing and all the lower values are neglected treating as noise. For example, for a given MSSC bands for a query sample, the region below the threshold is considered to be non-informative and totally neglected. This consideration leads to following observations;

1) Under semantic features having similar region representation, a false classification will appear.
2) Information's at lower regions also reveals information of signals having shorter projections such as spines.
3) 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 variation regions. To achieve the objective of efficient retrieval in semantic observations, a selective normalized coefficient coding is proposed.

IV. NORMALIZED COEFFICIENT CODING

It could be observed that the obtained MSSC 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 normalized coefficient coding for feature representation is proposed. For the process of normalization, 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 proposed approach of Normalized coefficient coding (NCC), for the obtained MSSC, a 1-D signal representation x(t), is taken as a variant of time-magnitude representation as shown in figure 2.

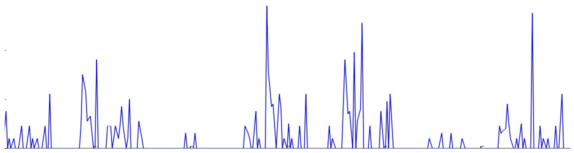

Figure 2: 1-D representation of a MSSC plot

The obtained bands $\{B_{h1} - B_{h4}\}$ are the decomposed detail bands reveling different frequency content at each level. $\{B_{l1} - B_{l4}\}$ 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 MSSC approach. To derive the spectral density of these 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,

$$PSD, P = \lim_{T \to \infty} \frac{1}{2T} \int_{-T}^{T} x(t)^2 \, dt \qquad (6)$$

Taking each band 'B_{hi}' as reference, a PSD for each band, 'PB_i' is computed. The PSD features for the 4 obtained bands are then defined by,

$$PB_i = PSD\,(B_{hi}), \text{ for } i = 1 \text{ to } 4. \qquad (7)$$

The Band PSD's are derived as,

$$PB_i = \lim_{T \to \infty} \frac{1}{2T} \int_{-T}^{T} B_{hi}(t)^2 \, dt \qquad (8)$$

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

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

$MPB_i = \max(PB_i)$

For $i = 1$ to 4
if $(PB_i \geq (MPB_i / 2))$
$sel\_B_i = B_i$;
end

For these selected bands, 'Sel_B_i' features are then computed by the approach of peak picking, as carried out in MSSC approach. 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 MSSC. To evaluate the developed approach a simulation model of the proposed approach is developed.
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,

$$D = \min(Ed_i) \qquad (9)$$

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.

To analyze the performance of this developed system an experimental analysis is carried out as presented below.

V. EXPERIMENTAL RESULTS

For the simulation of the proposed approach, a set of medical samples are taken for normal and effected case from MIT database for Myocardial infraction disease. Few samples from the database is shown in figure 3.

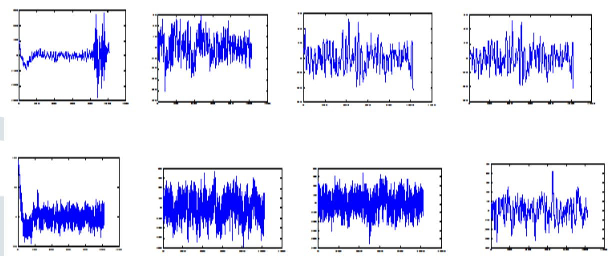

Figure 3: Training samples

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 proposed approach is carried out for a selected query sample. The processing results obtained are illustrated below.

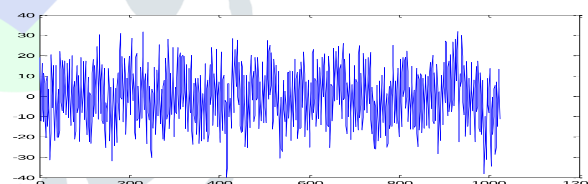

Figure 4: Query sample

For the evaluation of developed work, a test query MEDICAL signal is passed. An medical signal sample is shown in figure 4. The test sample is tested for the extraction of similar test case sample from the database.
The detected R-peaks for the given signal is shown in figure 5.

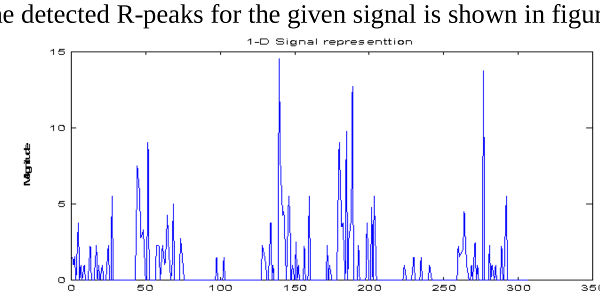

Figure 5: detected peak signal for the given medical sample

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. The obtained bands for the given medical signal is outlined in figure below.

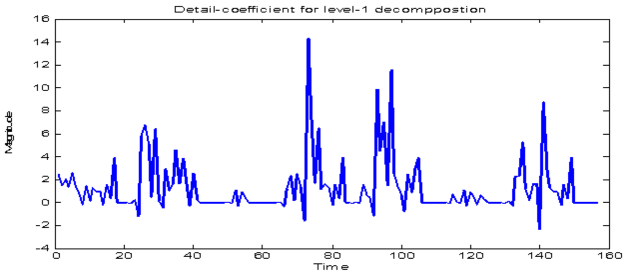

Figure 6: Detail Spectral band at level-1 decomposition

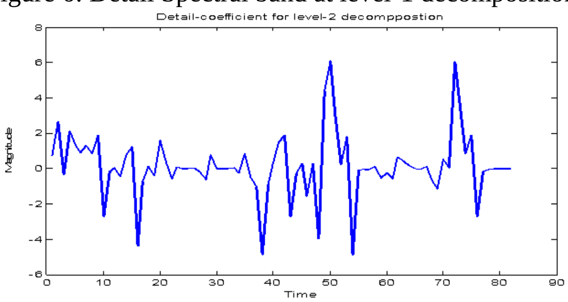

Figure 7: Detail Spectral band at level-2 decomposition

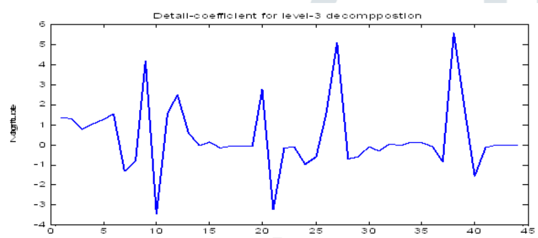

Figure 8: Detail Spectral band at level-3 decomposition

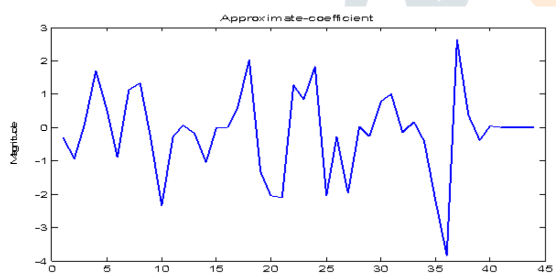

Figure 9: Approximate coefficient for given signal

To the obtained denoised medical signal, a spectral decomposition is carried out using db4 wavelet transformation. The 3 detail bands and the approximate band obtained are shown in figure 6-9 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 10.

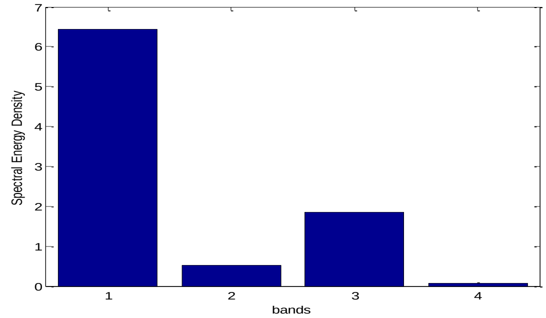

Figure 10: spectral Energy Density for 4-Decomposed Bands

The spectral energy density for 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 band energy obtained, it is observed 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.

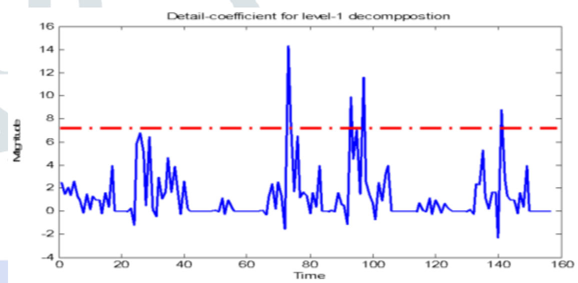

Figure 11: Extraction of Features from selected band -1

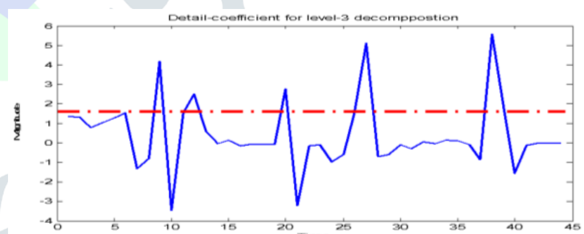

Figure 12: Extraction of Features from selected band -2

Figure 11 and 12 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 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 medical 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 as shown below.The obtained mean feature count for various cycles of medical is represented as,

Table 1: Observation for the Derived band decomposed values with its density value and mean energy for 5-cycles

Sample	Time	F1	F2	F3	F4	Mean-f
S1	1.357ms	0.34	0.37	0.375	0.41	0.373
S2	1.348ms	0.42	0.45	0.47	0.52	0.465
S3	1.362ms	0.56	0.51	0.52	047	0.554
S4	1.365ms	0.55	0.53	0.44	0.49	0.502
S5	1.370ms	0.56	0.57	0.62	0.66	0.602
S6	1.380ms	0.61	0.62	0.64	0.66	0.632
S7	1.385ms	0.67	0.69	0.70	0.72	0.695
S1	1.40ms	0.70	0.71	0.73	0.74	0.725
S2	1.42ms	0.73	0.71	0.74	0.76	0.735
S3	1.45ms	0.72	0.73	0.76	0.80	0.752
S4	1.46ms	0.77	0.74	0.73	0.79	0.757
S5	1.48ms	0.78	0.76	0.79	0.82	0.787
S6	1.50ms	0.82	0.85	0.86	0.88	0.852
S7	1.55ms	0.86	0.87	0.88	0.90	0.877
S1	1.60ms	0.867	0.867	0.87	0.872	0.869
S2	1.65ms	0.91	0.89	0.92	0.95	0.917
S3	1.66ms	0.92	0.93	0.898	0.92	0.917
S4	1.75ms	0.94	0.93	0.93	0.92	0.934
S5	1.80ms	0.965	0.93	0.934	0.95	0.944
S6	1.85ms	0.97	0.92	0.94	0.96	0.947
S7	1.90ms	0.98	0.97	0.96	0.99	0.975

Table 2: Observation for the Derived band decomposed values with its density value and mean energy for 10-cycles

Sample	Time	F1	F2	F3	F4	Mean-f
S1	1.35ms	0.38	0.36	0.35	0.42	0.3775
S2	1.348ms	0.392	0.36	0.48	0.55	0.4455
S3	1.36ms	0.47	0.51	0.47	0.49	0.485
S4	1.35ms	0.495	0.54	0.46	0.49	0.491
S5	1.370ms	0.56	0.57	0.62	0.66	0.602
S6	1.38ms	0.61	0.59	0.63	0.65	0.62
S7	1.35ms	0.67	0.70	0.69	0.71	0.692
S1	1.41ms	0.70	0.69	0.71	0.69	0.697
S2	1.42ms	0.73	0.72	0.76	0.79	0.75
S3	1.45ms	0.75	0.71	0.66	0.83	0.737
S4	1.48ms	0.78	0.68	0.75	0.79	0.75
S5	1.46ms	0.78	0.78	0.80	0.82	0.795
S6	1.50ms	0.81	0.85	0.82	0.86	0.835
S7	1.54ms	0.85	0.88	0.86	0.90	0.872
S1	1.60ms	0.86	0.857	0.86	0.872	0.869
S2	1.63ms	0.90	0.88	0.91	0.95	0.91
S3	1.66ms	0.91	0.94	0.88	0.95	0.92
S4	1.75ms	0.93	0.95	0.96	0.92	0.94
S5	1.81ms	0.96	0.94	0.924	0.94	0.941
S6	1.84ms	0.95	0.91	0.95	0.93	0.935
S7	1.90ms	0.97	0.96	0.95	0.99	0.9675

In the proposed approach, the feature is extracted after decomposing the medical signal using wavelets. To evaluate the proposed approach a analysis is carried out for Haar, Dabuchie and morlet wavelets. The obtained mean feature count at Haar, Dabuchie and Morlet wavelets for the 5, 10 and 15 cycles are shown in figure 13, figure 14 and figure 15 respectively.

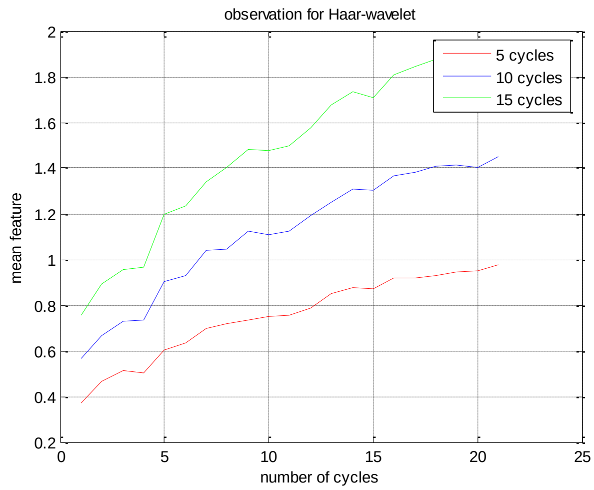

Figure 13: observation of obtained mean feature count through Haar wavelet

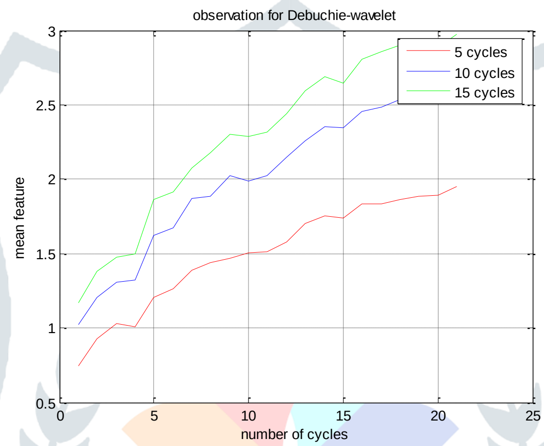

Figure 14:observation of obtained mean feature count through Dabuchie wavelet

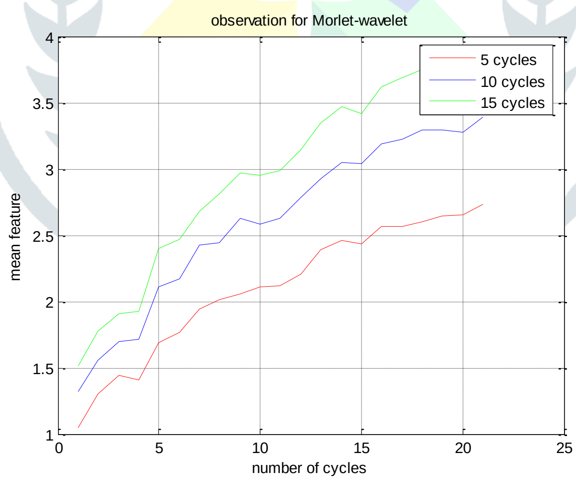

Figure 15: observation of obtained mean feature count through Morlet wavelet

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

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \qquad (1)$$

Where,
TP =True Positive = correctly identified
FP=False positive = incorrectly identified
TN=True negative = correctly rejected
FN=False negative = incorrectly rejected
Along with accuracy, to show the enhancement of propose approach and also to compare the proposed approach with earlier approaches, few more metrics such as sensitivity, specificity, Recall, precision and F-measure was evaluated with following mathematic expressions.

Sensitivity measures the proportion of positives that are correctly identified as such.

$$Sensitivity = \frac{TP}{TP+FN} \qquad (2)$$

Specificity measures the proportion of negatives that are correctly identified as such.

$$Specificity = \frac{TN}{TN+FP} \qquad (12)$$

Precision is the fraction of identified instances that are correct, while recall is the fraction of correct instances that are identified.

$$Recall = \frac{TP}{TP+FN} \quad (3)$$

$$Precision = \frac{TP}{TP+FP} \quad (4)$$

F-measure or balanced F-score is a measure that combines precision and recall is the harmonic mean of precision and recall.

$$F - measure = \frac{2.Recall.Precision}{Recall+Precision} \quad (5)$$

Table 3: Parametric evaluation of the developed system for processing efficiency.

Test sample	DR-method	Accuracy (%)	Sensitivity	Specificity	Recall	Precision	F-Measure	CT
	NCC	55.670	0.220	0.608	0.220	0.680	0.478	0.545
	MSC	62.500	0.315	0.752	0.315	0.740	0.523	0.348
S1	**MSSC**	**70.000**	**0.444**	**0.909**	**0.444**	**0.800**	**0.571**	**0.138**
	NCC	49.484	0.432	0.712	0.432	0.508	0.542	0.273
	MSC	58.1341	0.458	0.854	0.458	0.666	0. 621	0.143
S2	MSCC	69.500	0.524	0.946	0.524	0.820	0.652	0.137
	NCC	55.670	0.420	0.762	0.420	0.650	0.569	0.310
	MSC	63.824	0.452	0.886	0.452	0.720	0.688	0.1391
S3	MSSC	70.840	0.484	0.924	0.484	0.795	0.690	0.132
	NCC	58.360	0.446	0.738	0.446	0.650	0.583	0.374
	MSC	65.420	0.558	0.824	0.558	0.745	0.600	0.183
S4	MSSC	72.820	0.582	0.908	0.582	0.810	0.680	0.132

VI.CONSLUSION

This paper proposed a new MEDICAL diagnosing approach to improve the diagnosis accuracy by noise filtering. The medical signal will be accumulated with so many types of noised during its recording, affects the diagnosis accuracy. This approach proposed a filtering technique and also a novel feature extraction technique. The proposed filtering technique decomposes the medical signal into spectral bands which gives details information about the spectrum of both noise and desired signal. Based on the properties of noise spectrum it will be threshold and then processed for feature extraction. Since the proposed system having a preprocessing filter, the diagnosis accuracy is increased.

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