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ECG HEARTBEAT CLASSIFICATION USING WAVELET PACKETENTROPY AND RANDOM FOREST

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Abstract

ECG or electrocardiogram is an electrical signal which is generated by our heart. It is the cardiac electrical activity that provides important information about heart conditions [2]. ECG is very popular to identify heart illnesses like arrhythmia, chest pain, heart abnormalities, measuring heart rate, etc. In the past, till now ECG is the primary technique to detect heart illness in medical. ECG is a non-invasive technique. A survey World Health Organization says that heart diseases are the main reason for most deaths worldwide. In most cardiovascular diseases, arrhythmia is the most common. For thisECG is very much famous in medical studies. The study of an individual ECG beat can provide meaningfully correlated clinical information for the automatic ECG recognition of an ECG signal but it is difficult to investigate more ECG signals of different patients because of their different physical conditions. So here the main problem to investigating an ECG signal is that it can be different in every person. Suppose two different types of diseases have the same type of properties in an ECG signal. Even sometimes different patients have the same type of ECG pattern graph. These are the main difficulties in diagnosing an ECG signal. Many methods of feature extraction and classification have been proposed but some of the techniques remain to be improved. In this paper first of all we make our database with the help of the MIT-BIH database. After preprocessing and segmentation we decompose the signal by wavelet packet decomposition. Then calculate the entropy from the decomposed coefficients and extract the features.

Keywords: ECG Beat classification; RF-based classifier; wavelet packet entropy; feature extraction; MIT-BIH

I. Introduction

In an ECG signal, different beats are there. AAMI categorized 16 different types of beats into 5 beat classes. They are Normal beat(N), Supraventricular Ectopic beat (S), Ventricular ectopic beat (V), Fusion beat (F), and Unknown beat (Q). To the detection of these beats, many scientists approach different methods. In the year 2014, Manab Kumar Das et al. proposed a system with two different feature extraction methods. They are S-transform-based features with temporal features and a mixture of ST and WT-based features with temporal features. The average sensitivity for N, S, V, F, and Q is 95.70%, 78.05%, 49.60%, 89.68%,and 33.89%. In the year 2020 Soroj Kumar Panday, Rekh Ram Janghel et al. proposed a method with a new deep learning-based Restricted Boltzmann machine (RBM) model with a SoftMax activation function for classification. They got the overall accuracy of 99.61%. In the same year Jaya Prakash Allam et al. proposed a system SpEc is proposed based on Stockwell transform and two-dimensional residual network (2D-ResNet). They got the overall accuracy (acc) of 99.73%. Although more work is proposed on ECG beat classification. Some work remains to be improved. The remainder of this paper is to classify the heartbeats with an RF classifier with different numbers of features. To detect heart disease by ECG it is very much needed to observe each and every heartbeat. In the case of long-term ECG records, it is more difficult [III].In this paper, the MIT-BIH database is used as a source. The database has 48 numbers of recordings and each recording is 30 min long. The database has different types of arrhythmias. A total of 16 numbers of heartbeats are there. These 16 numbers of heartbeats are categorized into five classes as AAMI recommendations. The five classes are normal beat (N), supraventricular ectopic beat (S), ventricular ectopic beat (V), fusion of a V and an N (F), and unknown beat type (Q). The MIT-BIH database contains 48 records of heartbeats. All MIT-BIH database beats are sampled at 360 Hz [I] and have a time duration of approximately 30 min for 47 different patients [I]. The record has two leads. Lead A and lead B. Here lead A is used for detecting the heartbeats, since the QRS complex is more prominent in this lead. Lead B is used for classifying arrhythmias SVEB and VEB.

As early mentioned in the paper the MIT-BIH database is used as a source. Here an additional database is designed for this paper.Because in the main database, the number of normal beats is so huge. So that they can affect the result of performance. So with the help of an annotation file (available on physionet.com) which is needed for Segmentation, a limited number of beats are selected. Here is a table shown below with the number of beats contained in the database which is used in this paper.

II. Research Objective

The main objective of this paper is the development of an automated computer-based ECG classification model. The MIT-BIH database is used here but not directly. With the help of the segmentation, a total 17207 number of beats are selected for work.

Then filter the ECG signal. Then decompose the signal up to 3-level decomposition. After 3-level decomposition, we got eight signals. Now calculate the entropy of every signal then we got 32 features. Then determine the segmented beat class and calculate the performance.

III. Literature survey

ECG beat classification plays a fundamental role in the detection of numerous cardiac diseases by classifying the data into normal and abnormal beats. Several authors proposed various algorithms for extracting the features in the ECG signals and further classifying the ECG beats that are discussed in **Table 1**.

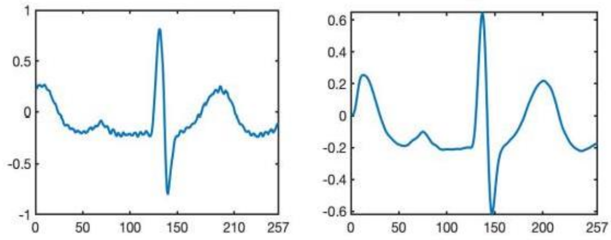
Table 1: Literature Survey

Work	Feature	Classifier	Effectiveness
De Chazal et al., 2004[2]	ECG intervals, Morphological	Weighted LD	Acc=83%
Escalona-Moran etal.,2015 [4]	Raw Wave	RC	Acc=98%
Bazi et al.,2013 [4]	Morphological, Wavelet	SVM IWKLR, DTSVM	Acc=97%Acc=92%
Ye et al.,2012 [4]	Morphological, Wavelet, RR interval,ICA PCA	SVM	Acc=84.4%
Jiang and Kong [2]	Heremite Transform coefficients and time intervals	Block-based NN	Acc=96.6%
Lin and Yang, 2014 [4]	Normalized RR-interval	Weighted LD	Acc=85%
Zhang and Luo, 2014[4]	RR intervals, Morphological features, ECG-intervals and segments, wavelets coefficients	Combined SVM	Acc=87%
Soria and Martinez,2009 [4]	RR-intervals, VGC, +FFS	Weighted LD	Acc=90%

IV. Proposed Framework

a. ECG filtering

In general, filters try to remove unwanted noise from a signal. In the case of ECG, the signal levels are very small. All are in the mV unit. But there are many noises present in an ECG signal. They are Muscle noise, power line interference, baseline wander, electrode contact noise, etc. So this kind of noise should be removed before analyzing an ECG signal. In this paper, a finite impulse response filter is used with 12 taps and sampled at 35 Hz. Here 35 Hz is selected because the R peak has the highest frequency which is in the range of 30-35Hz.



before filtering after filtering

Fig. 1. Before and after filtering diagram

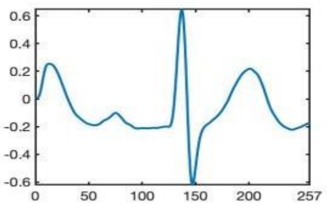
b. ECG beat Segmentation

The heartbeat segmentation is the task of segmenting numerous beats in one signal based on the provided R-peak location from the MIT BIH database [VI]. In this paper, the task is to classify the ECG beats. The Standard MIT-BIH database gives thetotal ECG signal. One ECG record contains multiple numbers of ECG beats. One ECG beat means P-QRS-T. So here is the first task to segment the ECG into beats. For this task, R Peak detection is needed. By detecting the R peak and taking a proper window the segmentation can be done. For R-peak detection, the annotation file is used which is available on the MIT-BIHwebsite. Based on the R-peak location, every individual beat is segmented from the ECG signal by taking 128 samples on oneside and 128 samples on the other side. A total of 256 samples are selected in the segmentation stage for deep information on every ECG beat.

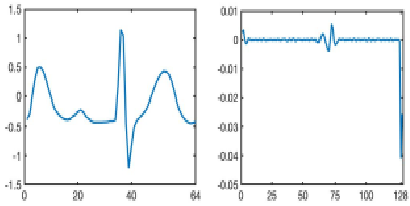
V. Wavelet packet Entropy Based Heartbeat classification

a. Wavelet packet decomposition

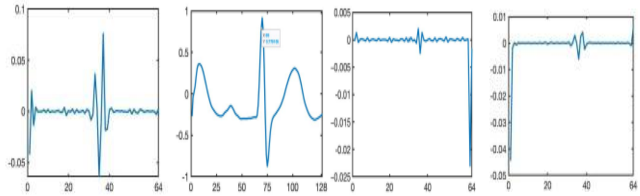
Discrete Wavelet Transform is a popular method because it has a more powerful time-frequency transformation than other methods like discrete Fourier transform [V]. DWT mainly decomposes the signal into two components. They are approximationcoefficients and detail coefficients. Then in the next step, the detail coefficients remain unchanged, and Approximation coefficients are decomposed into new detail coefficients and Approximation coefficients. This process repeats until the decomposition level reaches. It is widely used in ECG signal processing, diagnosis, and classification. It is mainly used for featureextraction. But DWT decomposes the approximation coefficients only. So it is hard to extract information from detail coefficients. So in this paper wavelet packet decomposition is used for feature extraction. It is an extraction of DWT [V]. The main difference is that the DWT decomposes the approximation coefficients only but the WPT decomposes both detail coefficients and Approximation coefficients. So information can be extracted from here.



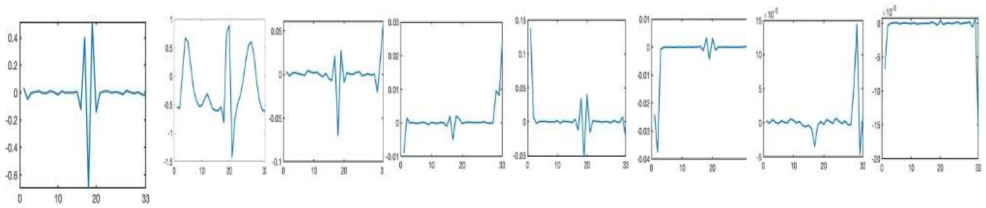
Main signal



1st level decomposition



2nd level decomposition



3rd level decomposition

Fig. 2. shows a wavelet packet tree for three-level wavelet packet decomposition.

b. All Entropy feature Calculation

The coefficients by DWT or WPD can reveal the local characteristics of an ECG signal, the number of such coefficients is usually so huge that it is hard to use them as features for classification directly. Therefore, some high-level features may derive from these coefficients for better classification. Here 4 WPT features are used. They are Shannon entropy (SE), Log energy entropy (LEE), Renyi Entropy (RE), and Tsallis entropy (TE). Entropy can be calculated based on energy [V].

c. Calculation formulas of Entropy

The information of the k-th coefficient of the j-th node at i-th level can be measured by wavelet energy [5] which is defined as

$$E_{i,j,k} = \| d_{i,j,k} \| \quad (1)$$

The total energy for the j-th node at i-th level can be calculated by

$$E_{i,j} = \sum_{k=1}^{N} E_{i,j,k} \quad (2)$$

N is the number of the corresponding coefficients in the node. The probability of the k-th coefficient at its corresponding nodecan be calculated by

$$p_{i,j,k} = E_{i,j,k} / E_{i,j} \quad (3)$$

SE is a measure of uncertainty associated with random variables in information theory, and it can be calculated as

$$SE_{i,j} = \sum_{k=1}^{N} P_{i,j,k} * \log(P_{i,j,k}) \quad (4)$$

LEE is defined as

$$LEE_{i,j} = \sum_{k=1}^{N} \log(P^2_{ijk}) \quad (5)$$

RE defiened as

$$RE_{i,j,k} = \frac{1}{1-q} \log(\sum_{i=1}^{N} p^q_{i,j,k}) \quad (6)$$

TE is another type of entropy that is defined at various q values as.

$$TE_{i,j,q} = \frac{1}{q-1} (1 - \sum_{k=1}^{N} P^q_{i,j,k}) \quad (7)$$

The q value for RE and TE is 4.7 and 3.5.

d. Statistical features

In this paper, another four statistical features are used for better classification results. The features are 1. AC power, 2. Kurtosis, 3. Skewness, 4. Sample Entropy. These four entropies are applied before decomposition and after filtering.

AC power: It indicates the total power content of the QRS complex signal [VIII]

$$P = E(x[n]^2) \tag{8}$$

Kurtosis: It indicates the peakedness of the QRS complex signal [VIII].

$$\mathrm{Kurt}(x) = \frac{E[(X-\mu)^2]}{\sigma^4} \tag{9}$$

Skewness: It is a measure of the symmetry of the distribution of the signal [VIII].

$$\mathrm{Skew}(x) = \frac{E[(X-\mu)^3]}{\sigma^3} \tag{10}$$

Sample entropy: Sample entropy is a useful tool for investigating the dynamics of heart rate. Sample entropy values arecalculated by

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$$\mathrm{sampEn}_{k,r,n} = -\ln\left(\frac{A(k)}{B(k-1)}\right) \tag{11}$$

VII. Machine Learning based classifier (RF)

Random Forest (RF) is a machine learning-based classifier. It was first proposed by Breiman [5]. The process of random forestis to build many classification trees based on some randomly selected features from randomly selected samples. Then for the classification task, the output of the random forest is that class that is selected by most of the trees. Random forest is constructedwith many base learners. Every base learner is an independent binary tree. For building a binary tree, a bootstrap sample withN objects is drawn from the training data. By selecting the feature subset the tree fits to the bootstrap sample. Then it splits each terminal node into two child nodes with the best-selected features. RF has many advantages. The random forest has higher accuracy than other methods. It is efficient for large amounts of data. It can be used for both numeric and categorical variables. It can be used for classification. It can be used for multi-class problems.

VIII. Performance measures

To check the performance of the classification, four statistical indices are proposed here. They are sensitivity (SE), positive predictively (+P), false positive rate (FPR), and accuracy (ACC). These are derived from the true positive (TP), false negative(FN), true negative (TN), and false positive (FP) [V].

True positive (TP): True positive is an outcome where the model correctly predicts the positive class.

$$SE = \frac{TP}{TP+TN} \text{ X } 100\% \tag{12}$$

True negative (TN): True negative is an outcome where the model correctly predicts the negative class.

$$+P= \frac{TP}{TP+FN} X\,100\ \% \tag{13}$$

False positive (FP): False positive is an outcome where the model incorrectly predicts the positive class.

$$FPR = \frac{FP}{TN+FP} X100\% \tag{14}$$

False negative (FN): False negative is an outcome where the model incorrectly predicts the negative class

$$ACC = \frac{TP+TN}{TP+TN+FP+FN} X100\% \tag{15}$$

IX. Simulation Study and analysis

In this paper, all the experimental data and modeling are done on Matlab software. Here uses a standard MIT-BIH database for data sources. In the first stage, the R- peaks are detected by the annotation file which is freely available on the MIT-BIH site. With this data beats are separated by selecting 128 samples on both sides of R Peak. A limited number of beats (17207 beats) are selected for experiment purposes. Because the number of N-type beats is so huge in the total dataset. So that they can effect the result of performance. The mother wavelet is selected as Doubechies 4 wavelet (db4) with the 3 decompositionlevel for wavelet packet decomposition (WPD).

a. Case study 1: 32 features

In this paper, after decomposing the signal with 3 level db4 wavelet we get total 8 signals. The Sannon Entropy, Log energy Entropy, Renye Entropy, and Tsallis Entropy are applied in every signal. So a total of 32 features are extracted from here. With this data, now the trees of RF have to be selected. Here 100, 200, 400, 800,1200 trees are applied in the data for selecting the bestresults. The results (in %) are shown in **Table 2.**

Table 2: Results with 32 features

No of Trees	Over all Acc	N SE/+P/FPR	S SE/+P/FPR	V SE/+P/FPR	F SE/+P/FPR	Q SE/+P/FPR
100	90.51	95.4/93.5/15.9	80.5/89.2/24.4	97.3/88.7/44.1	49.2/87.6/12.5	2.56/99.9/0
200	91.25	95.5/93.8/12.3	81.8/90.7/21.5	97.6/89.6/8.57	50.1/91.1/2.5	25.6/21.2/.007
400	91.43	96.4/93.9/10.4	81.8/91.8/19.1	97.289.7/8.5	51.3/86.1/3.7	3.7/66.6/.0018
800	91.87	97.3/93.9/22.7	80.7/93.5/14.3	97.8/90.1/9.15	54.3/93.1/2.1	25.5/100/0
1200	91.54	96.5/94.2/21.2	81.9/91.1/15.9	97.5/89.5/8.5	55.2/91.8/2.5	7.6/7.5/.0016

Table 2 shows the results of applying 100, 200, 400, 800, and 1200 trees in Random forest. Respectively the results are 90.51%,
91.25%, 91.43%, 91.81%, 91.54%. With four Entropies a total of 32 features are extracted. With these features and 800 base learners of RF showing the best results here with 91.87% accuracy.

b. Case study 2: 36 features

In this paper, to improve the performance of the result another 4 statistical features are applied before the decomposition process. After applying the features in the main signal and decomposition total of 4+32=36 features are extracted here. The mainaim of adding new 4 features is to get more information from the signal. With this data, now again 100, 200, 400, 800, and 1200 trees are applied for selecting the best results. The results are shown in **Table 3.**

Table 3: Results with 36 features

No of trees	OverallAcc	N SE/+P/FPR	S SE/+P/FPR	V SE/+P/FPR	F SE/+P/FPR	Q SE/+P/FPR
100	93.85	97.4/96.5/12.2	89.1/93.1/17.3	98.6/91.9/4.26	59.2/93.8/1.9	5.12/100/00
200	94.39	97.6/97.1/15.1	89.8/92.4/18.2	98.7/93.3/5.55	64.4/91.7/3.1	2.04/100/00
400	94.63	97.8/96.5/11.4	91.4/94.3/13.9	98.6/93.5/5.32	56.7/91.4/2.5	5.13/66.6/.0018
800	94.72	96.7/97.3/14.6	92.2/92.3/18.2	98.7/93.4/5.16	64.3/91.3/2.5	4.17/66.7/.0018
1200	94.59	97.5/97.1/15.4	92.3/92.8/17.4	98.5/93.4/5.26	61.8/90.4/3.1	5.36/100/00

Table **3** shows the results of applying another four statistical features. So now a total of 36 features are extracted for this stage. Again in the same way for finding the best results, different numbers of trees are applied. Again 100, 200, 400, 800, and 1200 trees are applied in RF. Respectively the results are 93.85%, 94.39%, 94.63%, 94.72%, 94.59%. With these 36 features and 800 base learners showing the best result here with 94.72% accuracy.

X. Summary

Here first the four entropy features are applied after decomposing. With 32 features and 800 base learners showing the result of 91.87% accuracy. Next another four features are applied before decomposition. Then after decomposition, the four entropy features are applied. So now with 36 features and 800 base learners showing the result of 94.72% accuracy. So by increasing the feature set, the results are improved. The 36 feature sets have more information than the 32 feature sets. The first time with 32 features showing the best results in that stage. But for classification for unknown beats(Q) the false positive rate (FPR) is 0. So here the unknown beat cannot detect property. But next time when another 4 statistical features are applied then with 36 features and 800 base learners show the result of 94.72% accuracy. Here the FPR of Q beat class is .0018. So here an unknown class is detected quite better.

XI. Conclusion and Future Work

This paper is mainly focused on feature extraction and finding the best result for ECG beat classification. For classification, a limited amount of data sets are used. The main reason is to reduce the normal type class from huge data sets. In the feature extraction phase first, the four Entropies are applied. For classification, the Random Forest classifier is used. All experiments are conducted on the MIT-BIH arrhythmia database. From the experimental results, it can be concluded that: by increasing the feature sets the result can be improved. Also, the 800 tree shows a better result than less number of trees. When the information is more in data sets than the RF shows the best result.

In the future, the work can be extended as changing in the q value of RE and TE. Here the value is fixed. Another work can beapplying other wavelets like coif1, demy, and bior 4.4. Here the 3-level decomposition is done. In the future different decomposition levels can be applied here.

Conflicts of Interest:

There is no conflict of interest regarding the paper.

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