Transient ST-Segment Episode Detection for ECG Beat Classification

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***Abstract*— Sudden Cardiac Death (SCD) is an unexpected death caused by loss of heart function when the electrical impulses fired from the ventricles become irregular. Most common SCDs are caused by cardiac arrhythmias and coronary heart disease. They are mainly due to Acute Myocardial Infarction (AMI), myocardial ischaemia and cardiac arrhythmia. This paper aims at automating the recognition of ST-segment deviations and transient ST episodes which helps in the diagnosis of myocardial ischaemia and also classifying major cardiac arrhythmia. Our approach is based on the application of signal processing and artificial intelligence to the heart signal known as the ECG (Electrocardiogram). We propose an improved morphological feature vector including ST-segment information for heart beat classification by supervised learning using the support vector machine approach. Our system has been tested and yielded an accuracy of 93.33% for the ST episode detection on the European ST-T Database and 96.35% on MIT-BIH Arrhythmia Database for classifying six major groups, i.e. Normal, Ventricular, Atrial, Fusion, Right Bundle and Left Bundle Branch Block beats.**

I. Introduction

Coronary Heart Disease (CHD) (also known as ischemic heart disease) is caused when the coronary arteries cannot supply enough blood to the heart due to clogging. It can become catastrophic resulting in myocardial ischemia and infraction with affected myocardium that is reflected in the occurrence of lethal arrhythmias.

The Electrocardiogram (ECG) is an electrical recording of the heart behavior and is crucial to investigating cardiac abnormalities in a human. The ambulatory ECG recordings are typically examined visually by a physician for important features. Figure 1 shows a two cycle ECG recording with the fiducial points of importance; P wave, QRS complex and T wave.

The heart diseases are clinically diagnosed by the study of ST-T complex [1]. The changes in amplitudes, times and duration on the ST-T can indicate an electrical instability due to increased susceptibility to ventricular fibrillation and thus leading to sudden cardiac death. In particular, the ST-segment is the most diagnostic parameter as it represents a state of unchanged polarization. It begins at the offset of depolarization (QRS) and ends at the onset of depolarization (T wave), in the ECG. Any significant change of this ST-segment level from the isoelectric line indicates an ischemic or infracted heart condition [2].

In view of the length of each recording and the number of recordings in real time clinical cardiology, manual intervention is very time consuming. Automated analysis of the ECG could therefore be a useful technology, especially when performed in real time [3]. In this paper, we focus on automated ST-segment analysis and automated arrhythmia classification.

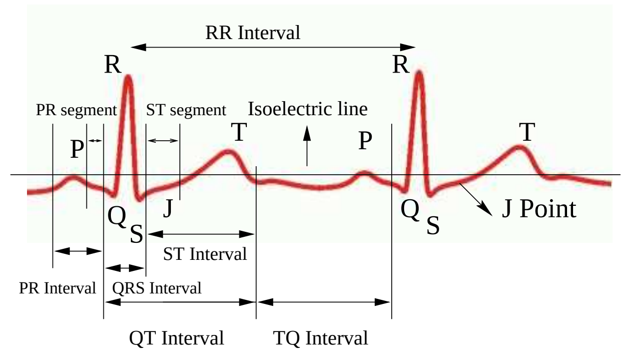

Figure 1. Sample two cycle ECG recording with fiducial points marked.

Our contribution towards diagnosis of cardiac abnormalities is two-fold. First, we propose a simplified real time algorithm based on wavelet processing for the detection of ST-segments and ST-deviation changes, which further help in identifying transient ST-episodes. This would give an immediate evaluation of the patient's condition in emergency, independent of the patient history. Second, we introduce a novel approach of using the ST-analysis features and correlation matrix between heart beats for classifying each beat by supervised learning. Our classifier distinguishes six classes, i.e. the Normal Sinus rhythm and five most common arrhythmia categories. Every heart beat/ training instance of the classifier is represented with a total of 203 features (morphological features and discrete wavelet coefficients). Our contribution is in employing additional morphological features of ST-segment and correlation coefficients for each arrhythmia class template. In terms of practical use of our approach, our automated detection system can help in indicating any possibility of SCD, much ahead of time. Thus facilitating with wider time-frame for relevant treatment and effectively reduce the SCDs.

II. Prior Work

Several techniques have been introduced for ECG beat classification in general, and ST-segment analysis of ECG waves in particular. Authors in [4] developed a ST-segment recognition system based on neural networks with large data sets for training and obtained an average accuracy of 95.7% within a 10ms error. However, a large amount of memory is needed for their learning phase. The work in [5] described a hardware configuration for an ECG monitoring device and the detection of ST pattern change. A small dataset of four records from the European ST-T database are used for pattern matching and for evaluating their system. Authors in [6] also proposed an algorithm for ST-segment analysis using the multi-resolution wavelet approach, achieving an accuracy of 97.3% within an error margin of 8ms. Our system indicated a better accuracy using the discrete wavelet transformation.

As for beat classification, the approach described in [7] classified only four types of arrhythmia, with a hierarchical decision tree by grouping similar classes together and branching down to finer granularity of classification. A knowledge-based method was proposed in [3] for arrhythmic beat classification, arrhythmic episode detection and classification using only the RR-interval signal. It classified only four classes based on only RR features. In [8], the authors proposed a learning algorithm for analyzing the gray relations between templates and test data set. The database of templates used in this work was large and the system only classified two classes. De Chazal et al. classified the beats by analyzing the RR intervals and ECG morphology features along with heart beat segmentation information [9]. They combined two linear discriminant classifiers to make the final decision. The work presented in [10] uses a hybrid of fuzzy clustering and artificial neural networks to discriminate between different classes of beats.

III. ST-Segment Analysis

The analysis of the ECG ST-segment involves three major parts which we describe in the following subsections.

A. ST-segment Detection

To identify the ST-segment in an ECG signal, accurate detection of the isoelectric line, the J point and the heart rate are required. The *isoelectric line* is the baseline of the electrocardiogram, typically measured between the T wave offset and the preceding P wave onset. It indicates no muscular activity in the heart at a particular point of time. This line is used as a reference to measure ST-segment deviation. The J point is the inflection point at which the QRS complex changes its direction of propagation. It occurs after the offset of the QRS point within a window of 20-50 samples at the rate of 250 Hz of sampling, as shown in Figure 1. Our recognition algorithm involves applying three major functions; Discrete Wavelet Transformation (DWT), Windowing Technique, and Slope Detection; on each ECG cycle.

Discrete Wavelet Transform (DWT) which is of great importance in analyzing biomedical signals, represents the ECG signal in both time and frequency domains through time windowing function. The length of the window indicates a constant time and frequency resolution. The wavelet transform decomposes the ECG signal into different scales with different levels of resolution by scaling it to a single prototype which has a zero net area, called the mother wavelet. DWT makes use of multiresolution analysis which enables the signal to be analyzed in different frequency bands by passing the signal into cascaded levels of high-pass and low-pass filters, resulting in detailed and approximate coefficients. The level at which the coefficients are obtained is called scale, represented as 2^n for *n*-stage/level filtering.

In this work, a single UWLT (Undecimated) Decomposition is implemented with Db4 (Daubechies) as the mother wavelet.

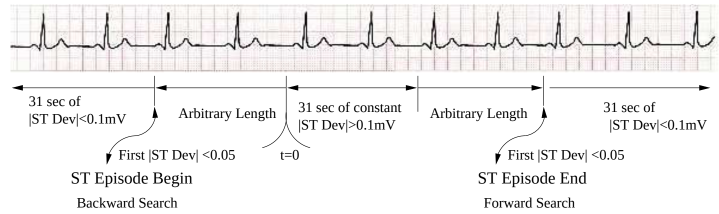

Figure 2. ST-Episode Detection

The level is determined based on the frequency sub-band to be extracted from the ECG signal. The transform is applied at the scales of 2^3 and 2^1. The isoelectric line is determined by approximating each beat with the 2^3 scale transform. A search method is used to find the most stable zero crossings between the P and T waves. This is obtained by using the windowing and backward search algorithms for the signal before the QRS complex. This is repeated for 20 beats and the average is determined as the isoelectric line.

The J point is detected from the 2^1 scale transformation. This point corresponds to the peak after the S point. On estimating the J point, the ECG inflection point is determined on the denoised signal before applying transformation.

The ST-segment is defined as the part of the ECG signal between the J point and the onset of the T wave. This is achieved by the Windowing Technique. On the 2^1 scale, a windowed search is implemented from the S point. The region where the slope of the signal is maximum is determined and a backward search starts from the local maximum till the point where the signal is minimal. This point is fixed as the T onset. If there is no local maximum or minimum in the windowing technique, the T onset is estimated to be at the J+80 point.

B. ST-Segment Deviation Measurement

From the detected J point and the ST-segment, the ST-deviation is measured. The ST-deviation is relative to a reference waveform for each subject. This reference level is computed from the first 30 seconds of the ECG data. The equation for the measurement is as follows:

$$ST\ Deviation = [ST\ Level - Reference\ ST\ level] \quad (1)$$

ST level function is the measured difference between the isoelectric line and the ECG amplitude during the ST-segment at a given time. Reference ST level is the average ST level function during the first 30 seconds of the ECG. The equation calculates the ST-Deviation as the difference of the ST level and the Reference ST level. This ensures that any changes in the ST level due to unwanted factors such as noise, movement of the electrodes or patient, electrical axis shift and more importantly, non-ischemic ST changes are excluded. In the above formulation, if the ST deviation for a beat is greater than +0.1mv then *ST-Elevation* is said to occur. If the ST deviation is less than -0.1mv then *ST-Depression* is said to occur.

C. ST-Episode Detection

Once the absolute value of the ST-deviation is found to be no less than 0.1mv, the ST Episode detection begins. It involves a series of backward searches and forward searches from the critical point (see Figure 2). The algorithm involves the following steps:

- *Interval Verification*: Each episode lasts at least 30 seconds for which the absolute deviation is greater than 0.1mv. A forward search for 30 seconds verifies this condition.
- *Episode Begin Annotation*: A backward search takes place for the first beat occurrence with absolute deviation less than 0.05mv and for which the previous 30 seconds have a absolute deviation less than 0.1mv. This beat is annotated as 'Begin'.
- *Episode End Annotation*: A forward search takes place for which the absolute ST deviation first exhibits less than 0.05 mv and for which the absolute deviation for next 30 seconds is less than 0.1mv. This beat is annotated as 'End'.

Transient ST-segment episodes are the few time intervals during which an abnormal/crucial ST deviation is observed. As they occur as only a few bursts in time, they are called episodes. These episodes vary anywhere between one minute to several minutes and do not persist for hours together; hence they are termed as transient.

IV. Beat Classification

Our heart beat classification system is implemented by the Support Vector Machine (SVM) approach. It is a supervised learning framework which performs classification by constructing an N dimensional hyper-plane that optimally separates the data into two categories [11]. It is one of the best learning algorithms that gives the flexibility for the choice of the kernel and performs training in less time when compared to other learning algorithms like neural networks. Every heart beat is represented as a row in the data set with its feature values and its class label. SVM aims to find the optimal separating plane and the data points that determine the position and the orientation of the plane are called the support vectors.

The system was designed to classify six major arrhythmia most commonly observed by the cardiologists. The classes include Normal (N), Premature Ventricular Contraction (V), Premature Atrial Contraction (A), Fusion (F), Right Bundle Branch Block (R), and Left Bundle Branch Block (L). We use two types of features to describe each heart beat or one cardiac cycle, i.e. Morphological Features, and DWT Features.

We use 12 morphological features, which give the timing, area, energy and correlation information of the signal. Our method uses the ST-segment features, i.e. the slope of the ST-segment, the ST-deviation measurement and the correlation coefficients of the signal with the templates of each class. Each class is represented by a template manually chosen from the MIT-BIH database [12]. The correlation coefficient lies between 0 and 1; the higher the coefficient is, the more likely it is for the signal to belong to that class.

Twelve morphological features used here are: (*i*) QS Width, (*ii*) Pre RR Interval, (*iii*) Post RR Interval, (*iv*) QR Width, (*v*) RS Width, (*vi*) Mean Power Spectral Density, (*vii*) Area Under QR, (*viii*) Area Under RS, (*ix*) Autocorrelation Value, (*x*) ST-segment Deviation, (*xi*) Slope of ST, (*xii*) Correlation coefficient with class template.

We use 191 DWT (Discrete Wavelet Transform) coefficients, which are obtained by a 4 level decomposition of the signal with the db2 mother wavelet. These coefficients are based on the 180 samples taken to represent each heart beat. We train six classifiers, each for identifying one arrhythmia type and using all the heart beats in our databank for training and testing. The six single beat classifiers are: N vs. All, V vs. All, A vs. All, L vs. All, R vs. All and F vs. All.

Each data sample (heart beat) is represented by its class label and all 191+12=203 feature values, including the morphological and DWT features. Since we perform five-fold cross validation experiments, we use four folds of the data for training the classification system. In particular, we train six classifiers, one for identifying a particular type of beat using the one-versus-all scheme, resulting in six binary beat classifiers. After training, the test data set from the remaining fold (i.e., the fold not used for training) is given to the classification system.

The classification is a two stage process. During the first stage, the training data is generated with the features selected. We have divided the ECG beats into five sets of equal number of beats. One out of the five sets is randomly selected and labeled as *Test Data Set*. The remaining four sets are labeled as *Training Data Sets* and are passed into the feature extraction module where each beat is represented with the 203 features. The sets thus obtained are used to train the learning algorithm, SVM, which results in a SVM model file containing all the beats which form the hyper plane for classification. In the second stage, the SVM model file and the Test Data Set are given as the input to the SVM classifier tuned to the selected parameters. The output of the classifier gives the prediction of the class for each beat in the Test Data Set.

TABLE I

Overall Results of ST-Analysis for European ST-T Database

Parameter	**Accuracy in %**
ST-segment Detection	98.57
ST-Deviation Measurement	97.34
ST-Episode Detection	93.33

V. Experimental Setup and Results

The European ST-T database, an open-source database in the MIT Physionet databank, was used for evaluating our ST-analysis system. Each record in the database has the annotations of ST-change and maximum ST-deviation observed in an episode. The ECG recordings were first down sampled to 250 Hz and passed through a signal processing module which performs the QRS extraction [13]. The resulting signal has the baseline wandering excluded and denoised using wavelet transforms [14]. The QRS fiducial features thus obtained are used for further processing of the ST-segment and beat classification. The results presented below are for 27 records containing 75 episodes.

A. ST Extractor and Episode Detector

We have conducted several experiments for ST-segment analysis by first detecting the ST-segment and measuring the deviation for each record of the European ST-T database. Table I shows the overall accuracies obtained for all e0103-e0147 records.

TABLE II

OUR CLASSIFIER PERFORMANCE

Arrhythmia Type	Total No. of Beats	TP	TN	FP	FN	(S_e) %	(S_p) %	$(Acc.)$ %
Normal: N	67932	66492	17276	1730	1440	97.88	90.89	96.35
Ventricular: V	2848	2319	75214	8876	529	81.43	89.44	89.18
Atrial: A	2394	1925	80573	3971	469	80.41	95.3	94.89
Fusion: F	385	169	72615	13938	216	43.89	83.89	83.71
RBBB: R	7136	6919	71272	8530	217	96.96	89.31	89.94
LBBB: L	6243	6074	16621	2385	169	97.29	87.45	89.88

B. Beat Classification

We evaluated our classification system on the MIT-BIH arrhythmia database, involving 48 records of 30 minutes. We have used Thorsten Joachim's SVM^{light} software, which is a C implementation of the Support Vector Machines (SVM) [15], for the training and classification of the data.

In the experiments, we have used the Radial Basis Function kernel with different width g-gamma and different trade-off values between training error and margin C. C ranges from 0.1 to 10 and gamma ranges from 0.1 to 1. To evaluate the performance of the classification system, two statistical indicators, Sensitivity (Se) and Specificity (Sp) in addition to the Accuracy (Acc.) have been used [1].

The Five-fold cross validation technique was implemented for training and testing the classification system. The best results were obtained for **C=7** and **gamma=0.65**, when both the morphological features and DWT coefficients were used. Table II describes the results of our classifier on the MIT-BIH arrhythmia database with respect to each of the six classes. We observe that the low accuracies are due to the fact that Fusion beats are a series of Normal and Ventricular. So these beats were more likely to be classified as N or V.

We also performed a comparison with other beat classifiers as well as a commercially available software Monebo [16]. Table III represents comparative results. As can be seen, our scheme has achieved a comparable or better performance.

TABLE III

COMPARISON OF BEAT CLASSIFICATION APPROACHES ON MIT-BIH ARRHYTHMIA DATABASE.

Method	Ref.	# of Classes	# of Records	*Performance [%]*		
				Se	*Sp*	*Acc.*
de Chazal et. al	[9]	4	22	77.7	98.8	NA
Monebo	[16]	2	48	NA	NA	NA
Haseena et. al	[10]	8	48	NA	NA	97.54
Proposed	-	6	48	97.88	90.89	96.35

VI. CONCLUSION

In this work, we presented a two-fold contribution towards ECG signal analysis for arrhythmia detection. We first analyzed the ST-segment in ECG signals, which is of major significance in ischemia detection. Second, we implemented a Support Vector Machine approach for classifying heart beats into six major categories. The ST-segment analyzer gave an accuracy of 98.57% in ST-recognition, 97.34% in ST-deviation measurement and 93.33% in ST-episode detection, which are indicative of higher accuracies as compared to the prior work in this field. The beat classifier gave an overall high accuracy of 96.35% in classifying the six classes; Normal, Ventricular, Atrial, Fusion, Right Bundle and Left Bundle Branch Block beats.

[1] $S_e = \frac{TP}{TP+FN}$, $S_p = \frac{TN}{TN+FP}$ and $Acc. = \frac{TP+TN}{TN+TP+FP+FN}$, where **TN** (True Negatives) is the number of beats correctly classified as abnormal, **TP** (True Positives) is the number of beats correctly classified as normal, **FN** (False Negatives) is the number of beats incorrectly classified as abnormal when actually normal, and **FP** (False Positives) is the number of beats incorrectly classified as normal when actually abnormal.

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