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DETECTION AND EXTRACTION OF THE ECG SIGNAL PARAMETERS

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Abstract: **This work investigates a set of efficient techniques to extract important features from the ECG data applicable in automatic cardiac arrhythmia classification. The selected parameters are divided into two main categories namely morphological and statistical features. Extraction of morphological features were achieved using signal processing techniques and detection of statistical features were performed by employing mathematical methods. Each specific method was applied to a pre-selected data segment of the MIT-BIH database. The classification of different heart beats were performed based upon the extracted features. The morphological features were found as the most efficient for further ECG signal analysis. However, because of ECG signal variability in different patients, the mathematical approach is preferred for a precise and robust feature extraction. As a result of the extracted features, an efficient computer based ECG signal classifier could be developed for detection of a vast range of cardiac arrhythmias.**

Keywords: ECG feature extraction, ECG signal parameters, ECG signal detection, Cardiac arrhythmia classification.

***I.* Introduction:** Extraction of various parameters or *features* is of paramount importance in automatic ECG beat classification [1]. In this work the term *parameter* or *feature* refers to the ECG waveform characteristics in an all encompassing sense. The goal of this paper is to introduce some important parameters derived from stochastic information and morphometric analysis of normal and pathological ECG signals included in a database to distinguish between different types of abnormalities.

The ECG signal parameters are extracted from the QRS complex, the ST segment, and the statistical characteristics of the signal. The ECG features can be divided into two main categories namely morphological and statistical features as described in the following sections.

A. The morphological features

Fig. 1 illustrates a general indication of the P-wave, QRS complex, T-wave, and U-wave as well as the P-R, Q-T, ST, and QRS interval in a normal ECG beat. A group of important morphological parameters such as: the QRS complex duration, R-R interval, P-R interval, Q-T interval, ST segment, and the R-wave amplitude (Fig. 1) can be detected by applying different signal processing techniques such as the QRS detection and ST segment analysis.

A.1 Features extracted from the QRS complex

The R-R interval is the distance between two subsequent QRS complexes and represents the Heart Rate (HR). Normal HR is between 60 to 100 bpm. A high HR means the possibility of tachycardia, and a low HR indicates sinus bradycardia.

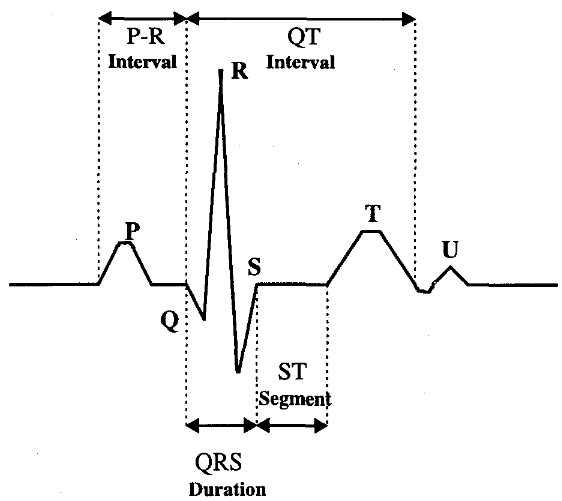

Fig. 1 ECG components .

The QRS complex duration is another important parameter employed in the analysis and classification of the ECG signal. This parameter is defined as the time it takes for depolarisation of the ventricles. Normal depolarisation requires normal functioning of the right and left bundle branches and it varies from 0.04 to 0.09 seconds. Any block in either the right or left bundle branch delays depolarisation of the ventricle due to the blocked bundle. In abnormal cases the QRS interval is 0.1 seconds or more. There is an intraventricular conduction delay when the QRS interval is between 0.1 to 0.12 seconds. QRS intervals greater than 0.12 seconds indicate bundle branch block [2].

The P-R interval as another useful feature, represents the time lag from the start of atrial depolarisation to the start of ventricular depolarisation and allows atrial systole to occur. The P-R interval is the time necessary for the SA node impulse to spread over the atria and through the AV node. The P-R interval between 0.12 to 0.20 is normal. When the P-R interval is less than 0.11 seconds, accelerated AV

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conduction has occurred. There is 1st degree AV block and impaired AV conduction, when the P-R interval is greater than 0.2 seconds. Careful attention should be paid to the P-wave and P-R interval when assessing ECG rhythm.

***A.2* ST segment**

The S point is identified as the first inflection after the R-wave. In normal ECG, the S point can be recognised as a relative minimum after the R-wave. Generally, it can be recognised by a change in the slope of the ECG signal. The T-wave is the inflection after the S point and within 0.75 of the *RR* interval.

Ischaemia is caused by insufficient blood supply to the heart muscle. Elevation and depression of the ST segment together with the T-wave changes indicate the zone of ischaemia around the applied lead. Therefore, the ST slope is the most important feature of the ECG for investigating myocardial ischaemia [3].

***B.* Statistical features of the ECG signal**

The most basic but confident way to extract useful information contained in the statistical characteristics of the ECG signal is to take the n pre-aligned time-sampled values $a(t_1),...,a(t_n)$ and form a vector A.

$$A = [a_1, a_2, \ldots, a_n] = [A(t_1), A(t_2), \ldots, A(t_n)] \, . \qquad (1)$$

Due to the ECG signal characteristics, $a(t_i)$ is a random vector variable.

A large number of statistical parameters can be defined for a random vector A. Specially, it is fully characterised by its distribution or density function. It is preferable to adopt a less complete but more practical set of parameters instead of using its distribution or density function. These parameters will be discussed and the result of a testing procedure will be shown in the following sections.

***B.1* Expectation vector**

One of the most important parameters in statistical feature extraction process, is the expectation vector or mean of a random vector A. The expectation of a random variable is also called the first moment of the variable. Two distinct types of mean are used [4].

First one is long-term time averages taken by calculations on an actual physical realisation of a random process. For this method, mean of a time series with data values $x(n)$, $n = 0, 1, \ldots, N-1$, is defined by:

$$E[x(n)] = M = N^{-1} \sum_{n=0}^{N-1} x_n \, . \qquad (2)$$

where E denotes expectation and N is the number of data points.

Second one is the theoretical averages calculation by using the probability density function (PDF) at some given instant of time. For this method, mean of $x(n)$ is defined by:

$$E[x(n)] = M = \int xp(x)dx. \qquad (3)$$

where $p(x)$ is PDF of data (ECG) vector [5].

***B.2* Covariance matrix**

Another important parameter is covariance matrix which indicates the dispersion of the distribution. The Wiener-Khinchin relationships express that, there is also a frequency equivalence feature for the time-domain autocovariance function. This frequency-domain equivalence is called power spectrum of the original signal and can be applied to the classification of cardiac arrhythmia problem. In other words, the operation of convolution in the time domain is similar to that of correlation, or more specifically the calculation of cross covariance and hence, the autocorrelation function and the power density spectrum are Fourier transforms of each other [6].

***II.* Methods**

The above mentioned parameter extraction techniques have been implemented on the pre-selected ECG signal from different records of the MIT/BIH arrhythmia data base for classification purposes [7].

A. The morphological features

***A.1* Features extracted from the QRS complex**

The modified Balda algorithm [8] proposed for QRS complex detection was applied to pre-selected ECG signals to detect the R-wave (the R-waves are marked with 'o' in Fig. 2-(a)). The R-R interval of the consequent beats can be calculated by finding the difference between the sample numbers associated with each R-wave.

To measure the QRS duration, two steps were taken. First, the area under the QRS complex was calculated, then by assuming this area has a triangular shape, the QRS duration was obtained using the following equation (Fig. 1).

QRS duration = **(4)**

2x(Area under the QRS complex) / (R-wave amplitude).

More parameters are detectable from the QRS complex for classification purposes.

Normally, the R-wave amplitude and the area under the QRS complex are in direct relationship. It means for small R-wave amplitude the area gets smaller. Therefore, the product of the R-wave amplitude and the area under the QRS complex was selected as a powerful feature for the cardiac arrhythmia classification.

A.2 Features extracted from the ST segment

After detecting the QRS complex and the position of the R-wave, two important features can be extracted from the ST segment. These features are: level and slope of the ST segment. The ST level is the maximum deviation from the isoelectric level. The isoelectric level is determined between the offset of the P-wave and the onset of the Q-wave. The J-point is defined as the offset point of the S-wave. The slope of the ST segment is determined by the difference between the amplitude of the starting point of the ST segment (J-point) and its ending point (J80), located at *80ms* interval from J-pont. An alternative method for determining this slope is using the R104 point instead of the J80. The R104 is an additional point located at *104ms* interval from the R-peak [9].

B. Statistical feature extraction methods

Pre-aligned time-sampled ECG signals with 196 samples per beat were selected as test waveforms for these methods.

B.1 Expectation vector

Based on the *ergodic theorems* or *laws of large numbers* both computations of mean as expressed in Equations 2, and 3 often give the same answer. Assuming that ECG behaves like a uniform random variable on the selected interval, the first definition was applied to the ECG vector.

To distinguish between three different classes of ECG signals, two thresholds were selected as follows:

$$THRSH_1 = 0.18MAX(M). \tag{5}$$

$$THRSH_2 = 0.69MAX(M). \tag{6}$$

where M is the mean vector of the classifier input data.

The ECG beats with a mean value less than $THRSH_1$ belong to class one, similarly, class two, includes those ECG beats with mean values greater than $THRSH_1$ and less than $THRSH_2$, and finally, ECG beats belong to class three if they have a mean value greater than $THRSH_2$.

B.2 Covariance matrix

The classification and categorisation aspects of the ECG signal recognition can be immediately obtained by simply identifying the highest cross correlations between a set of stored templates and an unknown ECG signal and determining which template has given the maximum cross correlation.

The variance of the time series $x(n)$ is defined by:

$$var[x(n)] = \Sigma = E\{[x(n)-M]^2\}. \tag{7}$$

The autocovariance of x(n) is given by:

$$C(m) = \Sigma_a = E\{[x(n)-M][x(n+m)-M]\}. \tag{8}$$

or

$$C(m) = \Sigma_a = E\{[x(n)-M][x(n)-M]^T\}. \tag{9}$$

where m denotes the lag in the data points and $[x(n)-M]^T$ is the transpose of $[x(n)-M]$.

Autocorrelation matrix of $x(n)$ is related to the covariance matrix and contains the same amount of information. The autocorrelation matrix of the n-dimensional vector $x(n)$ is defined by

$$S = E\{x(n)x(n)^T\}. \tag{10}$$

The correlation coefficients can be used in place of the autocorrelation to classify the selected ECG beats. If C is the covariance matrix, then correlation coefficients form a matrix whose (i,j) 'th element is as follows [10]:

$$CC(i, j) = C(i, j) / \sqrt{C(i, i)C(j, j)} \tag{11}$$

***III.* Results**

Fig. 2 shows the result of applying the QRS duration feature extraction procedure to the ECG signal. The circle on the ECG signal in part (a) indicates the position and the value of the detected R-waves. The star on the ECG signal in part (b) indicates the value of the measured QRS complex area. The product of the R-wave amplitude and the area under the QRS complex was selected as a powerful feature. This feature is not only important in the analysis of the ECG signal, but also it is a good parameter for classifying ECG abnormalities.

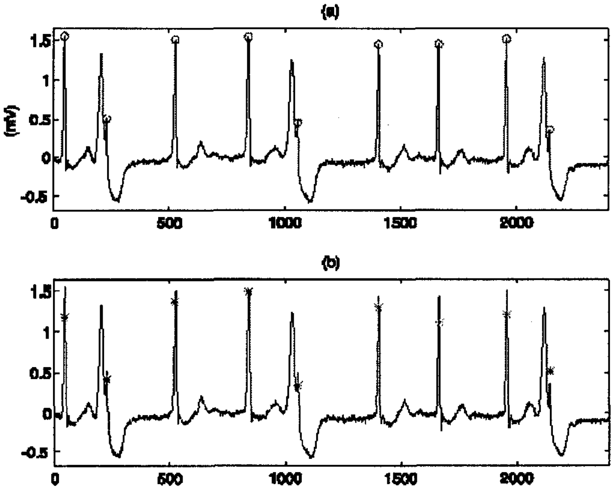

Fig. 2 Features extracted from the QRS complex. (a) The detected R-waves (o). (b) The measured QRS complex duration (*).

To detect the ischaemia, the ST segment analysis was performed by finding the position of the ST segment and its slope related to the isoelectric line. The isoelectric level is measured as a period of at least *80ms* before the R-wave with almost zero slope. By testing this method on the ECG records including ischaemia *90%* of this cardiac abnormality was detected.

Another test was performed (on record 119) for classifying 157 ECG beats into normal and PVC (premature ventricular contraction) using the mean feature (MF) classifier. The percentage of correct detection of normal beats was *99.1%* and the PVC beats was *97.8%*. The same procedure with another feature extracted from the R-wave position had *100%* correct classification.

For improving the performance of the MF classifier, a general boundary function $g(n)$ can be defined as

$$g(n+1) = \sqrt{M(n+1)g(n)} \quad (n = 1,2,3\cdots, N-1)$$

$$g(1) = M(1). \tag{12}$$

The result of classifying 83 ECG beats into three different classes using the covariant feature was quiet successful. This feature is more powerful than the mean feature in classifying a larger group of ECG beats.

Using the correlation coefficients feature, four different classes of ECG signals were correctly recognised (Fig. 3).

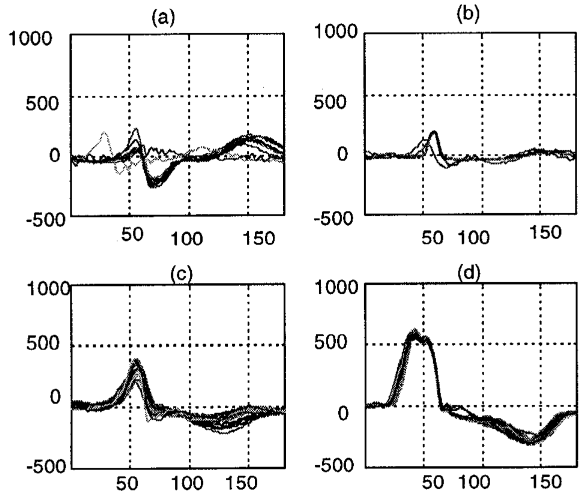

Fig. 3 Classification of ECG signal by the correlation coefficients feature. a) Class one. b) Class two. c) Class three. d) Class four.

IV. Discussion

The extracted morphological features are devised to automatically detect and classify the ECG signal abnormalities. Thus the product of the R-wave amplitude and the QRS area is effective in classifying the cardiac abnormalities that are reflected in the QRS complex. With the extracted features from the ST segment, ischaemia can be recognised. In fact, pre-processing steps are necessary for removing noise from the ECG signal before extracting the morphological parameters.

The accuracy of the ECG data classifiers using the statistical features is highly dependent on the number of classes in the data. With only two classes, each feature is able to provide correct classification. However, as the number of classes increases more features should be employed.

The advantage of the MF classifier is its simplicity and ease of implementation. However, the mechanism of decision making of this classifier is not automatic and a threshold should be selected for each record.

The cross covariance can be obtained by taking the inverse FFT (IFFT) of the cross spectra. The advantage of computing this parameter using IFFT is the considerable saving in computation time. The extracted features from the correlation coefficients of the data matrix were used in place of the autocorrelation to classify the selected ECG beats. Four different classes of ECG signals were correctly recognised by this feature. This feature can be one of the most attractive features among the statistical ones.

V. Conclusions

A number of methods for detecting and extracting a group of ECG parameters applicable to ECG signal analysis and classification are presented. This work shows that the important features can be extracted both from the morphological and statistical characteristics of the ECG signal. The principle problems addressed when extracting statistical features were: pre-processing and temporal alignment of the QRS complex at the centre of each beat, collecting sufficient testing data, and choosing an appropriate threshold for each data record. The basic problems during extracting morphological parameters were: extracting features from the noisy ECG signals, variability of the signal characteristics in different patients, and implementation of sufficiently powerful algorithms to achieve a reasonable real-time parameter extraction outcome. By employing both types of features and using advanced software and hardware computer systems none of these problems present seriously. The morphological features are found most effective method for further ECG signal analysis and the mathematical approach is preferred for a precise and robust feature extraction. A computer based ECG signal classifier can be developed by employing the extracted features for detection of a vast range of cardiac arrhythmias.

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