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Real time heart ischemia detection in the smart home care system

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***Abstract*— In this paper, a novel real-time algorithm for detecting ischemia in the ECG signal is proposed. The goal of this research is to meet the requirements of some smart cardiac home care devices, which can automatically diagnose the ECG and detect the heart risks outside the hospital, especially heart ischemia without symptoms in their early stages. The algorithm is developed based on a real time R peak detector, time domain traditional ECG parameters, the advanced morphologic parameters from Karhunen-Loève transform, and the adaptive neuro-fuzzy logic classification. Besides, in order to improve the reliability of our algorithm, several significant constraints of the ECG signal are considered. As a result, the ischemia episodes can be detected if the ischemic alteration persists longer than one minute in the ECG signal.**

I. Introduction

Nearly 20% of all heart pathologies are largely due to the ischemia - interrupted arterial blood flow of the heart, which is especially characteristic for myocardial infarction. Ischemia reflects the unbalance between the oxygen supply and the oxygen demand in the cardiac muscle. The unbalance is developed normally during a long period before the patients begin to feel uncomfortable in their breast (angina pectoris). However, it may happen even without symptoms, which is called silent ischemia. If the patients are not treated in the early stage, the affected heart tissue will die and such damage will become irreversible.

As another statistic points out that, among 4 million cardiac risk patients in Europe, 80% of the fatalities happen at home. Therefore, we have proposed a new concept of home monitoring system that can detect the cardiac risk of the patients at home, and at the same time automatically generate an alarm [3]. For such a system, the heart ischemia identification is considered to be one of the significant features.

As to the detection of heart ischemia in the ECG signal, the efforts started at the beginning of the 1990s. Different approaches were applied to analyze the typical ischemic changes (ST segment, ST-T complex) in the long-term ECG signal. These approaches are based on time-domain threshold method, frequency-domain spectrum analysis, wavelet transform, principal component analysis, fuzzy logic, artificial neural network [1]. Most of the algorithms are developed to meet the clinical requirements that help the physicians diagnose the patients in the hospital.

In our study, we propose a real-time ischemia detection algorithm for the automatic ischemia detection, which can be embedded in the home monitoring system. This application requires more reliability and accuracy in the detection. The system structure is shown in Fig. 1. : ECG pre-processing, real-time R peak detector, parameter extraction, classification, signal qualities assessment. The ischemia alarm will be set if the detected ischemic alteration in the ECG persists longer than one minute. The entire system is simulated in MATLAB/SIMULINK, where a dynamic environment is provided. As the primary evaluation, the European ST-T databases that include many typical ischemic episodes were used.

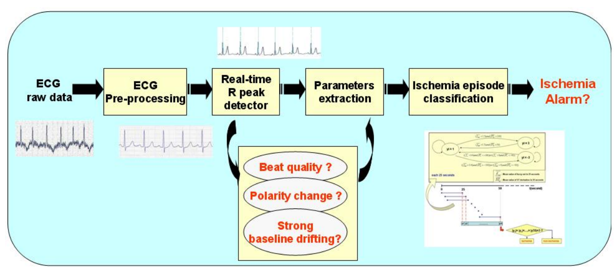

Fig. 1. System structure

II. REAL-TIME R PEAK DETECTOR

When ischemia occurs, the ECG signal usually displays a series of temporary changes in the ST-segment and T wave [10]. These signal parts can be observed after detecting the R peak, which is the most striking point in the ECG.

Before R peak detection, the raw ECG data is preprocessed to reduce some artifacts. A 50 Hz notch filter is used to eliminate the power line interference, a band-pass filter (1 - 100 Hz) is employed to limit the bandwidth of the ECG signal.

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The R peak should be fast and accurately labelled and the calculation should be as simple as possible to meet the computational complexity and memory capacity of battery-driven devices. In order to satisfy these requirements, a modified real time QRS detection algorithm - maximum slope detection is developed based on the algorithm in [4]. The QRS detector needs two input signals: the derivative of the pre-processed ECG signal and its derivative. The onset of a QRS complex is detected by the following rule: after 200 ms of flat segment in the ECG, the first sample, where the slop becomes steeper than the higher slope threshold, is the QRS onset. The lower slope threshold is used to detect the 200 ms flat segment. Both thresholds are updated every 4 seconds. After finding the QRS onset, the R peak is labelled by keeping on with searching for the maximal value of the ECG samples in the following 36 milliseconds after the QRS onset. (Fig. 2.)

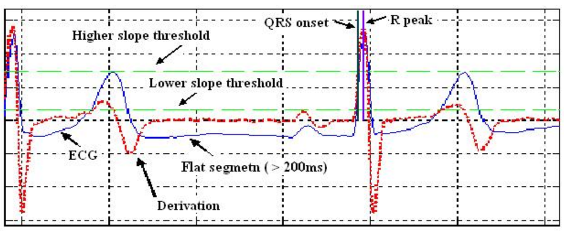

Fig. 2. QRS detection

III. PARAMETER EXTRACTION

Five parameters are extracted from the ST-T complex and ST-segment. Four of them are obtained from the Karhunen-Loève transform (KLT) of the ST-T complex. Another parameter is the deviation of the ST-segment, which is measured as the elevation or the depression in respect to the ECG baseline.

KLT is one of the orthogonal transforms, the optimal transform with the best statistical characteristic because it is the most suitable to absolutely decorrelate the signal [5]. In this case, KLT is applied to model the ST-T complex, concentrating the signal information to the minimum number of parameters. In order to compute the eigenvectors of the KLT transform, 77193 ST-T complexes are collected four databases from PhysioBank [2] – the most widespread online bio-signal database: the European ST-T database, the MIT-BIH arrhythmia database, the MIT-BIH ST change database and MIT-BIH supraventricular arrhythmia database (Table I). The onset of the ST-T complex depends on the averaged RR interval (interval between two R peaks) [6].

$$\mathrm{STT_{onset}} := \mathrm{R_{peak}} + \Big(40(ms) + 1.3\sqrt{\mathrm{RR(ms)}}\Big) \quad (1)$$

TABLE I

KLT TRAINING SET COLLECTION.

Database name	number of ST-T complexes	record name
European ST-T DB	47919	e0103, e0111, e0113, e0115, e0121, e0123, e0125, e0129, e0133, e0139, e0149, e0151, e0155, e0159, e0161, e0163, e0203, e0205, e0207, e0403, e0405, e0415, e0501, e0515, e0601, e0603, e0605, e0607, e0609, e0611, e0613, e0801, e1301
MIT-BIH Arrhythmia DB	17204	103, 113, 114, 115, 117, 121, 122 202, 230, 234
MIT-BIH ST change DB	7558	300, 304, 306, 307, 309, 310, 311, 327
MIT-BIH Supraventricular Arrhythmia DB	4512	811, 827, 840, 844, 873, 877, 886

The length of the ST-T length is chosen as 300 ms, which contains 91 samples at 300 Hz sample rate (STT(1), STT(2), $\cdots$ STT(N), N=91). It includes the whole ST-segment and most of the T wave. These ST-T complexes are organized into a signal matrix, from which the eigenvalues and eigenvectors are derived. Ranking the eigenvalues in decreasing order, we observe that the first four eigenvalues contain more than 95% of the whole energy (Fig. 3.). Therefore, the four corresponding eigenvectors [e1, e2, e3, e4] are applied in the KLT transform as basis vectors (Fig. 4.). Fig. 5 shows an example of ST-T complex recovery with m KLT basis vectors (m=1$\cdots$4).

$$STT^k = \sum_{i=1}^{m} \mathbf{e}_i \cdot STT_{KL}(i)^k \quad (2)$$

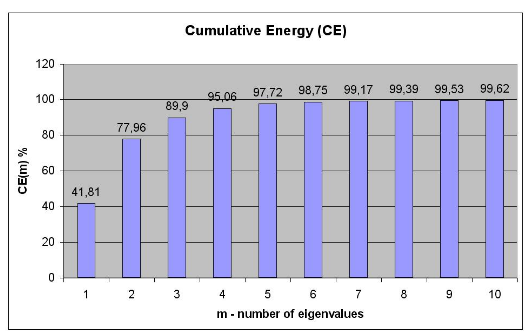

Fig. 3. Cumulative energy distribution

For each ECG beat, four KLT parameters are calculated as the inner-product between the ST-T complex

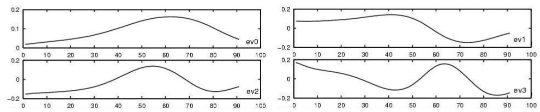

Fig. 4. Four KLT basis vectors with the largest eigenvalues

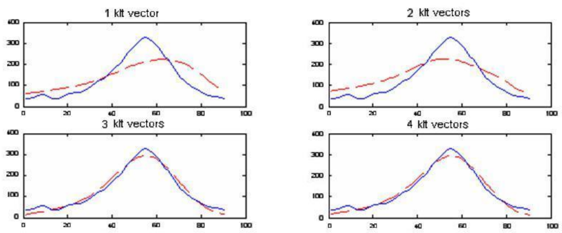

Fig. 5. ST-T complex recovery using 1 to 4 KLT basis vectors

vector and each KLT basis vector individually (3), where k is the index of consecutive beats.

$$klt_i^k = \mathbf{e}_i \cdot STT^k \quad (i = 1 \cdots 4) \tag{3}$$

The LMS algorithm is applied to further smooth the KLT parameters. Afterwards, these parameters are observed using ECG records, e.g., "e0113" in the European ST-T database that includes several ischemic episodes (Fig. 6). It shows that KLT parameters can sensitively reflect the ischemic changes.

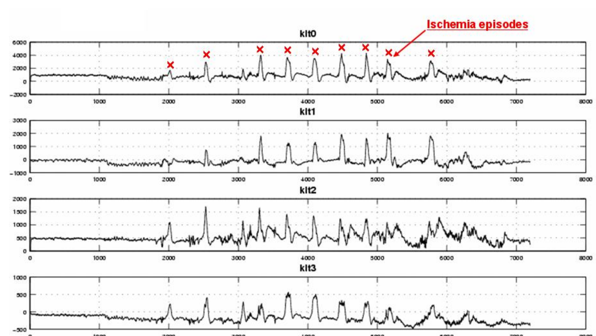

Fig. 6. KLT parameters - "e0113 lead V4"

From the medical point of view, the most significant ischemic change is the elevation and depression of the ST-segment. This important information is included in our algorithm as the fifth parameter. The measure point of the ST-segment deviation depends also on the heart rate (Table II).

IV. CLASSIFICATION

In the previous steps, five parameters are available for each ECG beat (4 KLT parameters, 1 ST-segment

TABLE II

MEASURING POINT OF THE ST-SEGMENT DEVIATION

Heart rate	ST-segment deviation measuring point
< 100	R + 120 ms
$100 \sim 110$	R + 112 ms
$110 \sim 120$	R + 104 ms
> 120	R + 100 ms

deviation). Afterwards, each beat should be classified as ischemic or not. These parameters occupy different numerical ranges, so it is not obvious to define some simple thresholds directly. An ANFIS (adaptive neuro-fuzzy inference system) is trained in the purpose of the classification. The training-set and the checking-set of the ANFIS have the same format, which contain the desired input data (the five parameters) and the output data (diagnosed result). The output can assume three values: '3' (positive ischemic changes), '-3' (negative ischemic changes), and '1' (normal). Each training-set and checking-set contains 500 beats with or without ischemic changes from different signals. Subtractive clustering [9] is used, which is based on the clustering algorithm and can provide some dimension reduction of the ANFIS.

After training the ANFIS, the rules of the system can be obtained. The numerical coefficients of these rules are stored in a table, so that a floating point fuzzy output can be calculated by addition and multiplication operations with each input data and the coefficients. This floating point fuzzy output is between -3 and 3

V. POST-PROCESSING

The necessary post-processing – decider module is designed that combines the fuzzy output from the ANFIS and the ST-segment deviation to identify the ischemic episode. A 25-second moving window is applied to calculate the average value of the fuzzy output and the ST-segment deviation. Based on the states of the two averaged values, the output is recalculated every second by a state machine. Considering the real-time implementation, the first output is obtained after the first 25 seconds. Afterwards, if the outputs in the following 35 seconds indicate the characteristic alterations of ischemia, the alarm will be activated (Fig. 7.). In whole, a ischemia episode needs to be longer than one minute.

VI. ROBUSTNESS OF THE ALGORITHM

In this paper, three conditions of the ECG signal are checked in order to improve the reliability and robustness of the ischemia detection algorithm.

- Beat quality

In the real system, there are a lot of artifacts that impair the ECG signal [8]: poor contact of the electrodes or leads, motion artifacts, muscle contraction, and others.

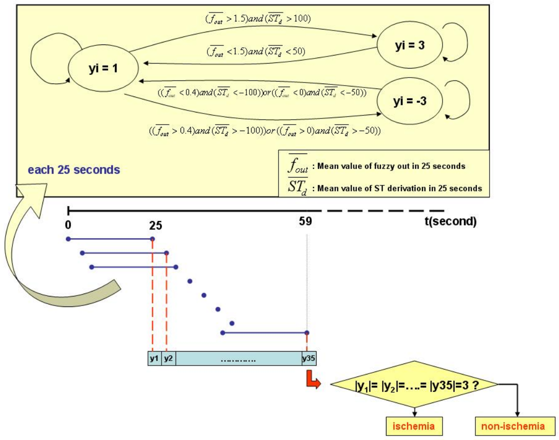

Fig. 7. Post-processing: Ischemia Decider

In order to avoid wrong update of the parameters for ischemia detection, the RR interval variability is measured to check the beat quality. It is defined as the difference between two consecutive RR intervals. If the variability becomes larger than 500 ms, then such a beat is regarded as ectopic beat and the parameters extraction will not be performed.

- Sudden polarity change

Some extrasystoles (especially the ventricular extrasystole) beats lead to sudden polarity change. These beats should also be excluded in the subsequent steps. The polarity of the ECG beats is always checked in parallel with the threshold adaptation for the R peak detection. If the polarity of the new beat suddenly changes, then its parameters will not be extracted.

- Strong baseline drifting

After the ECG pre-processing, the slight baseline drifting is eliminated by a band-pass filter. However, a strong baseline drifting, which overlaps with the ECG signal in the frequency spectrum, can not be avoided. Such drifting can even destroy the ST-T complex. Therefore, the baseline of each beat is estimated by measuring the TP segment: an isoline window, which starts at the middle of two R peaks and has the length of 1/20 of the RR interval, is applied; within the window, the ECG samples, which have derivative values lower than a threshold, are averaged as the baseline. The estimated baseline value of the current beat will be compared to that of the previous beat. If the difference is larger than 400 microvolt, the parameters of the beat will be ignored.

VII. RESULT AND DISCUSSION

It is hard to find a suitable database to test the performance of the ischemia detector. Most of the previous efforts used the European ST-T database [2][7] to test the algorithms. It consists of 90 annotated excerpts of ambulatory ECG records from 79 subjects. Myocardial ischemia was diagnosed or suspected for each subject. Additional selection criteria were established in order to obtain a representative selection of ECG abnormalities in the database, including baseline ST segment displacement resulting from conditions such as hypertension, ventricular dyskinesia and effects of medication. These annotations of the abnormal ST segment are made according to whether deviation is over 100 microvolt.

As the first evaluation of our algorithm, all the records in the European ST-T database are tested. The episode is identified as ischemic, if it contains the abnormal ST-segments and its duration is longer than one minute. The sensitivity and the positive predictivity are 81.29% and 74.65%, respectively. Due to the different test methods and the implementations of the real-time system.

However, one issue should be discussed: the European ST-T database is annotated relating to a reference level established from the first 30 seconds of each ECG record, which can be regarded as the 'normal ST displacement' for each patient individually. Such 'normal ST displacement' can be larger than 100 microvolt. Therefore, the actual ischemia episode should be confirmed using the relative parameters instead of the absolute parameters. That is, in home care devices, the 'normal ST displacement' of the patients could be firstly recorded as the reference value.

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