Ischemia Detection in the Context of a Cardiovascular Status Assessment Tool

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Abstract – **In this work a new strategy for automatic ischemic episodes detection is proposed, considering ST segment deviation, T wave and QRS morphology characteristics. A new measure of ST deviation based on time-frequency analysis, and the use of the expansion in Hermite functions technique for T wave and QRS complex morphologies, are the key points of the proposed methodology.**

HeartCycle is a European project that aims to improve life quality of coronary artery disease (CAD) and heart failure (HF) patients. Within this project, the *Medical Risk Assessment* module is responsible for develop models to assess cardiovascular (CV) risk and status of referred patients. The present work was performed under the context of CV status models, where myocardial ischemia plays a central role.

For algorithms validation purposes, the European Society of Cardiology ST-T database was used. A sensitivity of 99.6% and a positive predictivity of 90.2% reveal the capacity of the proposed strategy to perform ischemic episodes identification.

I. Introduction

The World Health Organization estimates that 17.5 million people died of cardiovascular diseases in 2005, representing 30% of all global deaths. Out of these, 7.6 million were due to coronary artery disease [1]. As one of the leading causes of death worldwide, this cardiovascular condition represents a focus of international interest.

HeartCycle European project aims to improve the quality of life for patients with coronary artery disease or heart failure, by monitoring their condition and involving them in the daily management of their disease [2]. Integrated in the third workpackage (*Multi-parameter Analysis and Decision Support System*) *Medical Risk Assessment* module is responsible for develop models to assess CV risk and status of the referred patients. This work was performed under the development of models for CV status assessment. Basically, these models assume that CV status *i*) is continually updated using measurements, parameters and symptoms, collected during daily home monitoring process, and *ii*) that may be characterized based on specific cardiovascular conditions. Examples of these are myocardial ischemia, hypertension, arrhythmias, pulmonary edema, etc, which are themselves very well defined through literature or by clinical expertise. Concluding, CV status is derived from the combination of those specific cardiovascular conditions. Given its relevance for CAD patient status assessment, myocardial ischemia is the condition addressed in this work.

In CAD, coronary arteries become narrowed by atherosclerosis, restricting the supply of blood and oxygen to the heart. Ischemia can be silent, without evidence of symptoms, or characterized by chest pain also known as angina pectoris. A severe and sudden blockage of coronary arteries causing a prolonged lack of blood supply to the heart, may lead to a myocardial infarction (heart attack) due to cellular necrosis. Moreover, myocardial ischemia is the pathological substrate to originate serious abnormal heart rhythms (arrhythmias), which can cause fainting or frequently sudden death. For the exposed reasons, its early diagnosis and treatment is of great importance to improve patient's health. In effect, if blood supply of heart muscle is timely reestablished, myocardial ischemia can be reversed, cellular necrosis limited and all complications avoided.

Usually, ischemia is expressed in the ECG signal as ST segment deviations and/or T wave changes [3]. Long term ECG recording (Holter technique) is a simple and non-invasive method that makes it possible to detect and to assess such alterations. The automatic diagnosis of myocardial ischemia, based on ECG signal, usually involves two phases: ischemic beat classification and ischemic episode identification. In the first, each cardiac beat is labeled as normal or ischemic and, in the second, sequential ischemic beats are appropriately grouped in order to identify ischemic episodes. In this context, several methodologies have been developed, such as: time and/or frequency domain analysis techniques [4][5], wavelet transform [6][7], artificial neural networks [8][9][10], principal component analysis/ Karhunen-Loève transform [11][12][13], discrete Hermite functions [14], rule based systems [15][16] and fuzzy systems [17][18]. In the present work a new methodology for automatic ischemic episodes detection is proposed, considering ST segment deviation, T wave and QRS morphology variations. In effect, it is known that variations in the ST segment are not always associated with ischemia. For example, sudden changes in QRS morphology parameters can reflect shifts in the electrical axis and ventricular depolarization of the heart, which usually causes considerable alterations in ST segment level [11]. Thus, taking into account QRS morphology, it is expected to improve the detection of true ischemic beats. A new measure of ST deviation based on time-frequency analysis, and the use of the expansion in Hermite functions technique for T wave and QRS complex morphologies, are the key points of the proposed strategy.

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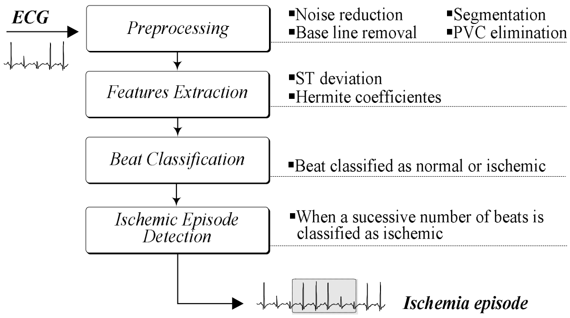
The paper is organized as follows: in the next section the proposed methodology is described, in section III validation results using the ESC ST-T database are presented and, finally, in section IV, some conclusions are drawn.

II. PROPOSED METHODOLOGY

A. Scheme

Figure 1 depicts the schematic diagram of the strategy followed in this work.



The input consisted of a discrete ECG signal, which passed through a set of pre-processing techniques such as, noise reduction, signal segmentation, premature ventricular contractions (PVCs) detection and elimination, and baseline removal. Following this, the algorithm involved two steps. Firstly, each individual beat was classified as normal or ischemic, considering features based on ST deviation, T wave and QRS complex morphologies. Secondly, ischemic episodes detection took place, using a sliding window procedure.

B. Preprocessing

The first stage of preprocessing was noise reduction, which was achieved by applying a low-pass filter to the ECG signal. Then, a segmentation algorithm was employed in order to identify the beginning, the peak and the end of each ECG wave (P, Q, R, S and T). Following, PVCs were detected and eliminated from the signal. Both algorithms (segmentation and PVCs detection), were developed under HeartCycle project [2]. Finally, a baseline removal procedure was applied to each cardiac beat, using Wolf's method [22]. Basically, in this technique baseline shift is approximated by a first order polynomial that, subsequently, is subtracted from the original signal.

C. Features Extraction

The main goal of this work is to develop algorithms to automatically detect ischemia episodes. For this purpose, features based on ST segment deviation, T wave and QRS complex morphology changes, were extracted.

1. <u>ST segment deviation</u>

The ST segment deviation was assessed by two different approaches. In the first, deviation was evaluated in a point that depended on Heart Rate and R peak location [12] (Table I). The second approach was based on time-frequency analysis, in particular, using the Wigner-Ville transform. By evaluating the minimum of high frequency components, in relevant time regions, it was possible to identify two points (WV and isoelectric point), being ST deviation calculated using the difference between them (Figure 2).

TABLE I
ST DEVIATION – MEASURING POINT

Heart Rate (bpm)	*Measuring point*
< 100	R + 120 ms
100 ~ 110	R + 112 ms
110 ~ 120	R + 104 ms
>120	R + 100 ms

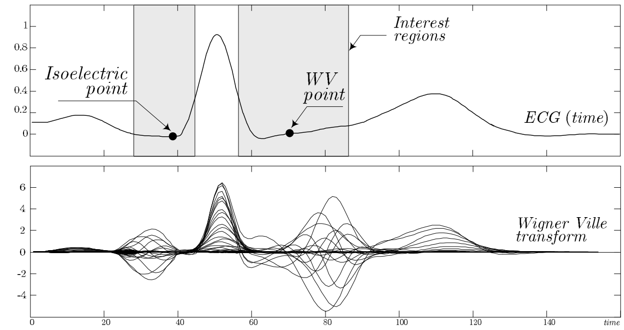


Figure 2- Wigner Ville transform of a cardiac beat.

2. <u>Coefficients of expansion in Hermite functions</u>

In order to capture changes in T wave and QRS morphologies, each cardiac beat was approximated using expansion in Hermite functions [23]. Moreover, to simplify this process, cardiac beat was divided in two segments: the first from the end of P wave until WV point (*Segment 1*) and the second from WV point until the end of T wave (*Segment 2*). Thus, for each beat, two expansions in Hermite functions were carried out. Essentially, using the expansion in Hermite functions, a signal is expressed as a linear combination of basis functions, as with Principal Component Analysis (PCA) technique [11]. However, the first method has the advantage to be patient independent and not to require any previous set of data.

The Hermite functions form an orthonormal basis of $L^2(\mathbf{R})$, the space of integrable functions. They can be determined as the product of a Gaussian by the Hermite polynomials with some normalization constants:

$$H^n(t,l) = \frac{1}{\sqrt{n!2^n\sqrt{\pi}l}} e^{\frac{-t^2}{2l^2}} P^n(\frac{t}{l}) \tag{1}$$

In previous equation, $P^n(t/l)$ is the Hermite polynomial of order n, with l as a scaling factor. Hermite polynomials can be determined by the following recursive relations:

$$P^o(x) = 1;\ P^1(x) = 2x$$
$$P^n(x) = 2xP^{n-1}(x) - 2(n-1)P^{n-2}(x) \tag{2}$$

Each segment of ECG beat can be expanded as a linear combination of orthonormal Hermite basis functions by the following equation:

$$y(t) = \sum_{j=0}^{m-1} c_j H^j(t,l) \tag{3}$$

In previous equation, $y(t)$ is the signal to be expanded, m is the number of basis functions and c_j correspond to the expansion coefficients. The last ones can be obtained by minimizing the sum squared error, as follows:

$$E = \sum_i \left[y(t_i) - \sum_{j=0}^{m-1} c_j H^j(t_i, l) \right]^2 \quad (4)$$

In matrix notation, given a signal Y ($N\times 1$), the coefficients matrix C ($m\times 1$) is obtained by:

$$C = (H^T H)^{-1} H^T Y \quad (5)$$

In previous equation H is a ($N\times m$) matrix formed by the Hermite functions $H=[H^o, H^1,\ldots, H^{m-1}]$. The expansion coefficients C, represent the second set of features used in beat classification process.

D. Beat Classification

For classifier selection, several experiments were made with different types and number of neural networks. Based on sensitivity and positive predictivity values, the chosen solution was a lead dependent classification scheme. In fact, two independent Feed-Forward Neural Networks (FFNNs) where used for each lead: the first classifying beats as having ST elevation or not, and the second distinguishing beats with ST depression from others. After beat classification, a sliding window with size of 20 beats is applied to each FFNN output signal, in order to eliminate isolated misclassified beats. At the end, the outputs from both networks (elevation and depression) are combined by an OR operation.

E. Episodes Detection

Ischemia episodes detection involved two steps. Firstly, a sliding window procedure was applied to the entire ECG signal. The window's length was of 35 beats, and they were considered as an episode if more than 50% had been classified as ischemic. Secondly, the classification done in previous step was reviewed, and episodes with less than 30 beats separating them were merged.

III. RESULTS

Following, the main topics of validation results will be presented. All the implementations done in this work (regarding database access, signal processing, classification, training and validation) were carried out using Matlab [19].

A. European ST-T database and validation parameters

For algorithms validation purposes, the European Society of Cardiology ST-T database was used [20][21]. To estimate the quality of these algorithms, sensitivity (SE) and positive predictivity (PP) have been evaluated.

B. Features extraction

Features extracted were related with ST segment deviation as well as with QRS and T wave morphologies changes. In effect, ST deviation was evaluated using two different approaches described before in this document, while each cardiac beat segment (*Segment 1* and *Segment 2*) was approximated by a linear combination of the first six Hermite functions (order 0 to 5) (Figure 3), originating 6 expansion coefficients.

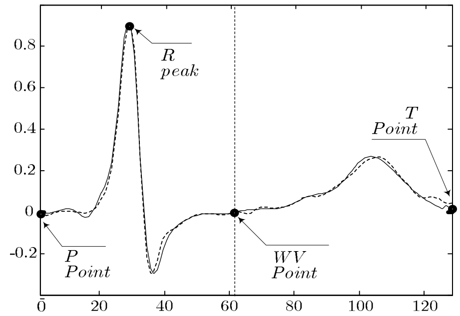


Figure 3- Hermite expansion.

Therefore, a total of fourteen features, 2 from ST deviation and 12 from Hermite expansions, were determined for each cardiac beat.

C. Training and validation

As referred before, beat classification was lead dependent and was carried out by means of two FFNNs per lead. Considering the 8 different leads (V1, V2, V3, V4, V5, MLI, MLIII and D3) present in ESC ST-T database signals, a total of 16 neural networks were utilized. The number of hidden neurons was experimentally determined and the parameters (weights and bias) that characterize all the FFNNs were trained using the Levenberg Marquardt algorithm.

Regarding training, data subsets (based on the 48 freely available signals of the ESC ST-T database) were selected according to each lead. In fact, each ECG signal was split in two (one from channel 1 and other from channel 2), originating 96 signals for training and validation purposes. For each lead, only signals acquired through it, were considered. Moreover, only a small portion of representative signals (30 beats before and after the annotated episodes transitions) were considered.

To validate beat classification, only 81 of the 96 referred signals were used (rejected signals contained some annotations that were not very clear to the present work authors). In terms of ischemic episodes validation, beat sequences of annotated and identified episodes, were compared. If the beginning and the end of them matched within a defined tolerance, then episode detection was considered as successful. Otherwise, was considered as unsuccessful.

D. Results and discussion

Concerning ischemic beat classification and ischemic episodes detection, results are presented in tables II and III. As can be observed, sensitivity and positive predictivity values reveal the method's capacity to perform the intended detection task.

Despite the difficulty in comparing existing methods performances, as they were evaluated based on different data sets, some undertaken studies [13] allow us to conclude that our results are significant, when compared with similar works.

TABLE II

BEAT CLASSIFICATION PERFORMANCE

Lead	Nº of Signals	Nº of Beats	FFNN Neg.		FFNN Pos.	
			SE	*PP*	*SE*	*PP*
V1	4	30636	100%	99,7%	100%	100%
V2	6	35139	99,9%	99,6%	100%	100%
V3	3	15213	100%	100%	100%	100%
V4	16	108363	83,8%	88,5%	99,6%	96,6%
V5	23	158605	86,6%	92,6%	75,1%	87,8%
D3	1	1504	100%	100%	100%	100%
MLI	7	48625	97,8%	96,4%	92,8%	99,5%
MLIII	21	133705	97,5%	90,3%	92,8%	84,1%

TABLE III

EPISODES DETECTION PERFORMANCE

Lead	Episodes	TP	FP	FN	SE	PP
V1	5	5	0	0	100%	100%
V2	5	5	0	0	100%	100%
V3	2	2	0	0	100%	100%
V4	41	41	16	0	100%	71,9%
V5	38	37	7	1	97,4%	84,1%
D3	1	1	0	0	100%	100%
MLI	5	5	1	0	100%	83,3%
MLIII	34	34	7	0	100%	82,9%
Total	**131**	**130**	**31**	**1**	**99,6%**	**90,2%**

IV. CONCLUSIONS

In this paper a strategy for ischemic episodes detection was proposed. Basically, two main steps were carried out. First, each individual beat was classified as normal or ischemic, considering features based on ST deviation, T wave and QRS complex morphologies. Classification process was lead dependent and, for this purpose, two FFNNs were used (one dealing with ST elevation and other with ST depression). After that, ischemic episodes detection took place, based on a sliding window procedure. The methodology potential was confirmed by using the European Society of Cardiology ST-T database.

As referred in the introduction, the proposed strategy will be part of a cardiovascular status assessment tool that is being developed under HeartCycle European Project. Myocardial ischemia, recognized as the most relevant condition in CAD, was addressed in this paper. As future work, all the other cardiovascular conditions (such as tachycardia and hypertension) should be studied and characterized (e.g. based on trends analysis), in order to derive a complete model which output will be the aimed cardiovascular status.

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