Biomedical Signal Processing and Control 5 (2010) 271–281

Contents lists available at ScienceDirect

Biomedical Signal Processing and Control

journal homepage: www.elsevier.com/locate/bspc

A lead dependent ischemic episodes detection strategy using Hermite functions

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ARTICLE INFO

Article history:
Received 23 November 2009
Received in revised form 22 June 2010
Accepted 1 July 2010
Available online 26 August 2010

Keywords:
ECG analysis
Ischemic episodes detection
Hermite functions
Wigner–Ville transform
Neural networks classifier

ABSTRACT

In this work a new strategy for automatic detection of ischemic episodes is proposed. A new measure for ST deviation based on the time–frequency analysis of the ECG and the use of a reduced set of Hermite basis functions for T wave and QRS complex morphology characterization, are the key points of the proposed methodology.

Usually, ischemia manifests itself in the ECG signal by ST segment deviation or by QRS complex and T wave changes in morphology. These effects might occur simultaneously. Time–frequency methods are especially adequate for the detection of small transient characteristics hidden in the ECG, such as ST segment alterations. A Wigner–Ville transform-based approach is proposed to estimate the ST shift. To characterize the alterations in the T wave and the QRS morphologies, each cardiac beat is described by expansions in Hermite functions. These demonstrated to be suitable to capture the most relevant morphologic characteristics of the signal. A lead dependent neural network classifier considers, as inputs, the ST segment deviation and the Hermite expansion coefficients. The ability of the proposed method in ischemia episodes detection is evaluated using the European Society of Cardiology ST–T database. A sensitivity of 96.7% and a positive predictivity of 96.2% reveal the capacity of the proposed strategy to perform ischemic episodes identification.

1. 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 (CAD) [1]. As one of the leading causes of death worldwide, this cardiovascular condition represents a focus of international interest. On the other hand, the use of new monitoring technologies and specialized processing based on wearable and information technologies, provide professionals with adequate information that allows the evaluation of cardiovascular conditions and symptoms progression, enabling the early detection of forthcoming clinical severe conditions [2]. In this context, personal Health systems (pHealth) are a new and fast growing concept. The patient is at the center of the health delivery process and, through remote monitoring and management applications, pHealth systems aim the continuity of care at all levels of health care delivery. Following this perspective, several research projects have been developed over the past few years [3].

This work focuses coronary artery disease and, in particular, the development of algorithms for myocardial ischemia detection. Moreover, the feasibility of incorporating the designed algorithms into pHealth monitoring systems (e.g. personal data assistant) is also a fundamental aspect and, therefore, the computational efficiency of the algorithms is essential.

In CAD, coronary arteries become narrowed by atherosclerosis, restricting the supply of blood and oxygen to the heart. This deprivation may originate a cardiac disorder called myocardial ischemia, which can be silent, without evidence of symptoms, or it might be 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 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. Hence, it is observed that early diagnosis and treatment of CAD is of primary importance to avoid serious consequences for patient's health, treatment success and quality of life. In effect, if blood supply of the heart muscle is timely reestablished, myocar-

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doi:10.1016/j.bspc.2010.07.001

dial ischemia can be reversed, cellular necrosis limited and severe complications avoided.

The analysis of the electrocardiogram's (ECG) characteristics, namely the ST segment deviation as well as the QRS complex and the T wave morphologies, are determinant for accurate detection of ischemic episodes [4]. The automatic diagnosis of myocardial ischemia based on the ECG signal usually involves two phases: ischemic beat classification and ischemic episode identification. In the first phase, each cardiac beat is labeled as normal or ischemic and, in the second phase, sequential ischemic beats are appropriately grouped in order to identify ischemic episodes.

In the context of ischemic beat detection and ischemic episodes identification using the ECG, several methodologies have been developed. Time, frequency and time–frequency domain analysis techniques [5–10] have been successfully applied for feature extraction and analysis. Some authors have explored the projection onto different sets of basis functions for feature extraction. In this context, principal component analysis (PCA) and Karhunen–Loève transform (KLT) [11–13] have been extensively utilized, while a few number of works have used discrete Hermite functions [14]. The classification stage has been tackled using different approaches. For instance, artificial neural networks-based methods [15–17] have been proposed. Other authors favor rule-based [18,19] and fuzzy rule [20,21] approaches.

In terms of time and frequency domain analysis techniques, Akselrod et al. [5] proposed the first method for direct analysis of the ST segment. It is based on a single measure of the magnitude of the point located 104 ms after the R peak. Another method was proposed by Benhorim et al. [6], in which two points, considered as the start and end points of the ST segment, are calculated depending on the RR interval of each beat. Badilini et al. [7] presented an algorithm that uses statistic variables, extracted from the frequency distributions of ST displacements, to discriminate between normal and ischemic ambulatory ECG recordings. Furthermore, ischemic episodes are identified by using a cluster technique. Garcia et al. [8], applied an adaptive amplitude threshold method to the *root mean square* series of differences between ST–T complex (or ST segment) and an average pattern segment, to detect ischemic episodes. Ranjith et al. [9] employed a wavelet transform to determine ECG characteristic points from which ST segment deviation and T wave amplitude measures are obtained and used to detect ischemic episodes. Milosavljevic and Petrovic [10] proposed the use of wavelets for extracting myocardial ischemia characteristic patterns, which are obtained through different decomposition scales. ST deviation is calculated for each beat and the number of ST deviations is correlated with the time of consecutive appearances in order to distinguish normal from ischemic ECGs.

Regarding methods based on neural networks, Maglaveras et al. [15] introduced an adaptive backpropagation neural network to identify ischemic beats. In this approach, ischemic episodes classification is achieved by analyzing a sequence of classified beats. Mohebbi and Moghadam [17] also proposed a beat classification method based on an adaptive backpropagation neural network. In [16], Papaloukas et al. employed a feed-forward neural network (trained using a Bayesian regularization method) as a beat classifier, which was integrated into a four-stage procedure for the detection of ischemic episodes.

With respect to PCA and KLT approaches, Castells et al. [11] reviewed the application of principal component analysis techniques for the detection of myocardial ischemia and abnormalities in ventricular repolarization. Pang et al. [12] utilized Karhunen–Loève transform parameters extracted from ST–T complex and a measure of the ST segment deviation to detect ischemia by means of an adaptive neuro-fuzzy logic classifier. In turn, Afsar et al. [13] used Karhunen–Loève transform to reduce ST segment data together with an ensemble of lead-specific neural networks classifiers to detect ST segment deviation episodes. In terms of Hermite functions based methods, Gopalakrishnan et al. [14] used ECG expansion in discrete Hermite functions for a real-time monitoring of ischemic changes. Namely, the first fifty Hermite coefficients are applied as inputs to a committee neural network classifier, trained to identify ischemic beats.

Regarding rule-based systems methods, Papaloukas et al. [18] proposed a strategy to detect ECG changes suggestive of ischemia using a rule-based expert system. Specifically, the system is able to distinguish between episodes of ST segment deviation and T wave changes. Andreao et al. [19] presented an ischemia detection system that uses a hidden Markov model approach for online beat detection and segmentation, and a rule-based classifier for ischemic episodes detection, derived from some heuristic rules defined by cardiologists.

Vila et al. [20] developed an intelligent monitoring system supported on fuzzy set theory, which uses three electrocardiographic leads and one invasive cardiovascular pressure signal in real-time to detect ischemic episodes. Exarchos et al. [21] proposed a methodology to create fuzzy expert systems for ischemic beats detection that involves a set of rules extraction using a decision three.

Despite of the many works that have been developed in the context of ischemia automatic detection, the results achieved in terms of sensitivity and positive predictivity can yet be improved. Thus, the search for better results is an incentive for further investigation.

In the present paper a new methodology for automatic detection of ischemic episodes is proposed considering the ST segment deviation, the T wave and the 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 can reflect shifts in the electrical axis and ventricular depolarization of the heart, which usually causes considerable alterations in the ST segment level [11]. Thus, taking into account the QRS morphology, it is expected to improve the detection of true ischemic beats. A new measure of ST deviation based on the time–frequency analysis of the signal and the expansion onto Hermite basis functions to capture the T wave and the QRS complex morphologies are the key points of the proposed strategy.

The paper is organized as follows: in the next section the proposed methodology is described, in Section 3 validation results, using the European Society of Cardiology (ESC) ST–T database, are presented and, finally, in Section 4 some conclusions are drawn.

2. Proposed methodology

Fig. 1 depicts the schematic diagram of the methodology followed in this work. The input consists of a discrete ECG signal, which is passed through a set of preprocessing stages for noise

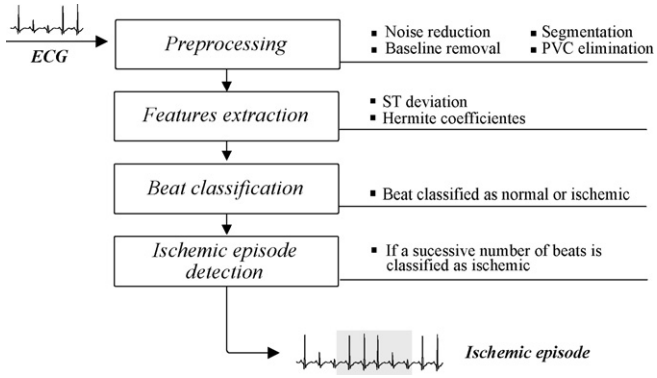


Fig. 1. Proposed ischemic episode detection methodology.

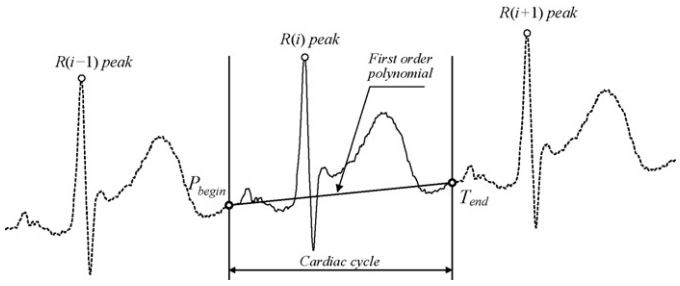


Fig. 2. Baseline removal.

reduction, fiducial points identification, premature ventricular contractions (PVCs) elimination and baseline removal. Following this, the algorithm involves two processing steps: firstly, each individual beat is classified as normal or ischemic. For this end, features based on the ST deviation, the T wave and the QRS complex morphologies are considered. Secondly, ischemic episodes detection is performed using a sliding window procedure. The detailed algorithms are introduced in the next subsections.

2.1. Preprocessing

The first stage of preprocessing is concerned with noise reduction. This is achieved by applying a low-pass filter to the ECG signal. In particular, a 4th order Butterworth low-pass filter, with a cut off frequency of 40 Hz, is employed for this purpose.

Afterwards, a segmentation algorithm is used in order to identify the beginning, the peak and the end of each ECG characteristic wave (P, Q, R, S and T). The applied algorithm is based on the work introduced by Sun [22]. After the segmentation stage, PVCs are detected and removed from the signal. The algorithm implemented for this task is adapted from Couceiro et al. [23].

The final preprocessing stage consists of baseline wander removal. Baseline wander presence increases the difficulty of the ECG analysis, especially while assessing ST segment deviation. Since the spectrum of baseline wander and the low frequency components of the ECG usually overlap, baseline removal using filtering can cause significant distortion of important clinical information, particularly, ST segment alterations. An effective baseline removal approach has been proposed by Wolf [24]. This method does not require isoelectric level determination and preserves the low frequency ECG information. Originally, the method considered the average of the distances between consecutive R peaks to split the signal into cardiac cycles. As it is illustrated in Fig. 2, based on the segmentation procedure previously mentioned, Wolf's method is modified to consider as starting and ending points the start of the P wave (P_{begin}) and the end of the T wave (T_{end}), respectively. The average of the first and last N cardiac cycle samples (in this work $N = 5$) is used to define a first order polynomial. Fundamentally, baseline shift is approximated by this first order polynomial being the baseline removal procedure completed by subtracting this baseline shift from the original cardiac cycle signal.

2.2. Features extraction

The approach followed here, assumes that variations in the T wave and QRS complex morphologies, and the ST segment shift estimation, can be used to discriminate ischemic from non-ischemic episodes.

2.2.1. ST segment deviation

The ST segment deviation is assessed considering two different approaches. In the first, the ST deviation is evaluated based on the heart rate and on the R peak location. This information can be easily obtained by means of any ECG segmentation algorithm. Mainly for this reason, this is a very simple and practical method, guarantying robustness, even in the presence of noise and artifacts. However, since it basically depends on the R peak location and not on the ECG waves morphology, this method does not guarantee accurate results. On the other hand, the second approach, based on the time frequency analysis is able to explicitly capture the transient characteristics of the ECG waves. Given these properties, this method is ideal to estimate the ST deviation being, however, more sensitive to noise and artifacts. The strategy followed in this work aims to take advantage of both approaches by providing accurate ST estimation in the case of noise free signals, while ensuring satisfactory results in the presence of artifacts.

Table 1
ST deviation—measuring point.

Heart rate (bpm)	Measuring point
<100	R_{peak} + 120 ms
100–110	R_{peak} + 112 ms
110–120	R_{peak} + 104 ms
>120	R_{peak} + 100 ms

2.2.1.1. ST segment deviation based on R peak location. Through a correlation analysis procedure, three algorithms for ST shift estimation ([5,12,25]) have been implemented, compared and validated using the ESC ST–T database. In view of the obtained results, the method proposed by Pang et al. [12] was chosen for this task. In this method, the ST segment deviation is evaluated in a point that depends on the heart rate and on the R peak location, according to Table 1.

2.2.1.2. ST segment based on time–frequency analysis. In general, time–frequency methods are applied to provide a more detailed view of the time distribution of the spectral components that constitute a signal. In particular, it is recognized that time–frequency methods are especially adequate for the detection of small transient characteristics hidden in the ECG, such as ST segment alterations. Thus, this work proposes a new approach for the estimation of ST deviation based on a time–frequency analysis, in particular using the Wigner–Ville transform, since it offers a good balance between time and frequency resolution.

The Wigner–Ville distribution (WVD) $W_x(t,f)$ for a complex continuous time signal $x(t)$ is defined in the time domain as:

$$W_x(t,f) = \int_{-\infty}^{\infty} x\left(t+\frac{\tau}{2}\right) x^*\left(t-\frac{\tau}{2}\right) e^{-j2\pi f\tau} d\tau \quad (1)$$

where $r(\tau) = x(t+(\tau/2))x^*(t-(\tau/2))$ is the instantaneous autocorrelation function and the operator (*) indicates the conjugate operation. The correspondent discrete time transform $W_x(nT, f)$ is given by Eq. (2).

$$W_x(nT,f) = 2T\sum_{p=-L}^{L} x(n+p)x^*(n-p)w(p)w^*(-p)e^{-j4\pi fp} \quad (2)$$

In this equation, T represents the sampling period and w is a sliding window, symmetrical and with finite-length duration, verifying $w(pT) = 0$ for $abs(p) > L$. This relationship defines the discrete WVD at the time origin. At any other point in time, the discrete WVD can be obtained by shifting the signal $x(t)$, so that time t is mapped on the time origin. To avoid interference between the negative and positive regions of the spectrum, the equivalent analytic signal of the real ECG time-series has to be used. In effect, it can be obtained by adding to the real signal its Hilbert transform as the

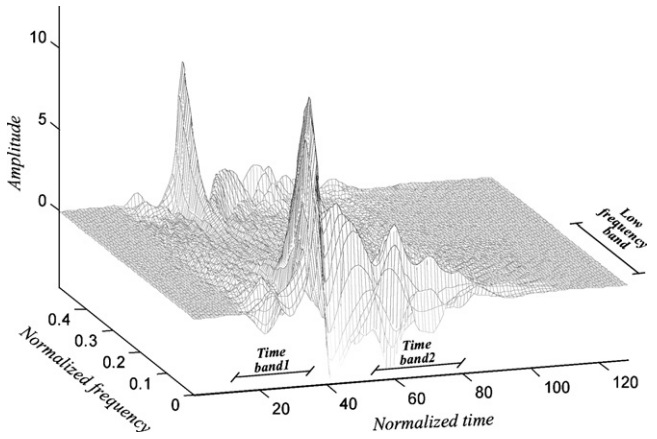


Fig. 3. WVD transform of a cardiac beat.

imaginary part, as shown by Eq. (3).

$$Y(k) = X(k) + jH[X(k)] \tag{3}$$

In the previous equation $X(k), k = 1, \ldots N$, represents the real ECG signal (being N the number of samples), $Y(k)$ denotes the equivalent analytic one and H[.] corresponds to the Hilbert transform.

The Wigner–Ville transform presents a constant resolution. Thus, specifically in the low frequencies, which are prevalent in the ST segment, WV transform preserves a good time–frequency resolution, while not presenting serious artifacts, as in higher frequencies.

Fig. 3 illustrates the WV transform, corresponding to the cardiac cycle shown in Fig. 4a.

Using this time frequency map, particular characteristics of a specific region can be analyzed. With respect to the ST shift estimation, two time bands and one frequency band were taken into account. Regarding the time bands, the regions considered were those on the left and on the right of the R peak, as seen in and Figs. 3 and 4a. In each of these time bands (Time band 1 and Time band 2) the purpose is to determine the sections where there is no signal activity. These points correspond, respectively, to the isoelectric line and to the ST segment deviation point. Regarding the frequency band, the low frequency regions where the ST segment is prevalent is considered. Fig. 4b shows the low frequency components (corresponding to the frequency content below 0.2 in the normalized frequency range). The isoelectric and J' points are identified by the minimums of the sum of the low frequency components' absolute value in each of the above mentioned time bands. Having determined these points, the ST deviation value is measured as the difference between the ECG's amplitudes at the J' and isoelectric points.

2.2.2. QRS complex and T wave characterization

As already mentioned, ischemia may induce morphology alterations in the T wave and in the QRS complex. In order to characterize changes in the T wave and in the QRS morphologies, each cardiac beat is represented in a space spanned by a limited number of Hermite basis functions. Basically, using the expansion in Hermite functions method, the signal of interest is decomposed into a linear combination of orthonormal basis functions, which coefficients can be used as features in the classification process, just as with the principal component analysis technique [11]. However, the former has the advantage to be patient independent, since the set of basis functions are predefined (Fig. 5) and do not require any prior knowledge of the data set. This reason, coupled with its ability in capturing the relevant morphology changes using a low number of basis functions led to the choice of the expansion in Hermite functions methodology for the present work.

2.2.2.1. Expansion in Hermite functions. The Hermite functions form an orthonormal basis of L2(R), the space of integrable functions. They can be determined as the product of a Gaussian by the Hermite polynomials with some normalization constants [27], i.e.

$$H^n(t, l) = \frac{1}{\sqrt{n!2^n\sqrt{\pi}l}} e^{-t^2/2l^2} P^n\left(\frac{t}{l}\right) \tag{4}$$

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

$$\begin{aligned} P^0(x) &= 1 \\ P^1(x) &= 2x \\ P^n(x) &= 2xP^{n-1}(x) - 2(n-1)P^{n-2}(x) \end{aligned} \tag{5}$$

Fig. 5 shows the first six Hermite functions ($n = 0, 1, \ldots, 5$), considering the scaling factor $l = 3$.

In order to approximate as closely as possible the shape of each beat to the shape of the Hermite functions, while using a reduced number of coefficients, each cardiac cycle was divided into two segments: *Segment1* is defined from the end point of the P wave until the J' point and *Segment2* is defined from the J' point until the end of the T wave. Thus, two expansions in Hermite functions were actually carried out for each cardiac beat. The goal was to describe

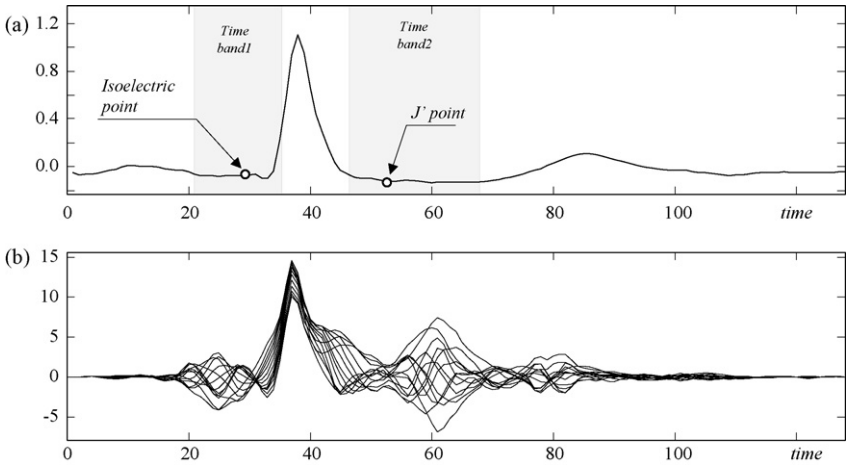


Fig. 4. (a) Cardiac cycle and (b) respective low frequency components.

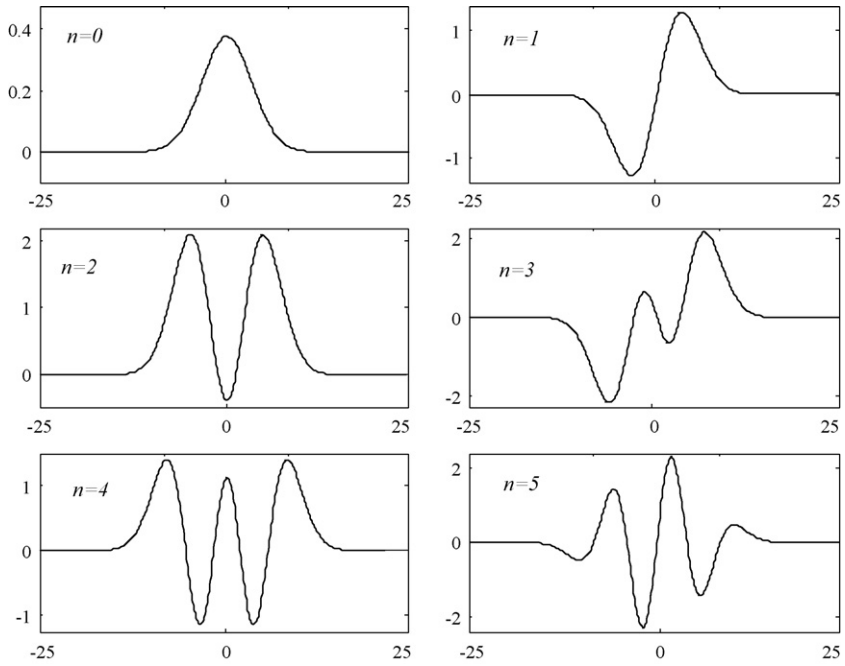


Fig. 5. First six Hermite functions (order $n = 0$ to $n = 5$).

each discrete signal segment $y(k)$ as

$$\hat{y}(k) = \sum_{j=0}^{m-1} c_j H^j(k, l) \tag{6}$$

In the previous equation, $\hat{y}(k)$ stands for the estimated signal segment, m defines 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:

$$E(c_j) = \sum_{k} \left[y(k) - \sum_{j=0}^{m-1} c_j H^j(k, l) \right]^2 \tag{7}$$

In matrix notation, given a signal $Y\,(N \times 1)$ and being H a $(N \times m)$ matrix formed by the Hermite functions

$$H = [H^0,\ H^1,\ \ldots,\ H^{m-1}] \tag{8}$$

the vector of coefficients $C\,(m \times 1)$

$$C = [c_0,\ c_1,\ \ldots,\ c_{m-1}] \tag{9}$$

is obtained by using a pseudo inverse formulation:

$$C = (H^T H)^{-1} H^T Y = H^+ Y \tag{10}$$

2.2.2.2. Number of Hermite basis functions, scaling factors and expansion coefficients. One of the main assumptions in this work is that the expansion coefficients C can reflect the changes in the ECG's morphology induced by ischemia and, therefore, be able to represent the second set of features used in beat classification process. It is important to highlight that it is not fundamental to obtain very low approximation errors. In fact, the underlying idea is that the approximated signal and, indirectly, the Hermite coefficients have the capacity to capture the most relevant morphologic characteristics of the signal.

In order to determine the adequate number of Hermite basis functions several experiments were carried out, which results are summarized in Fig. 6. In effect, for a selected set of representative cardiac beats, several expansions were done considering different

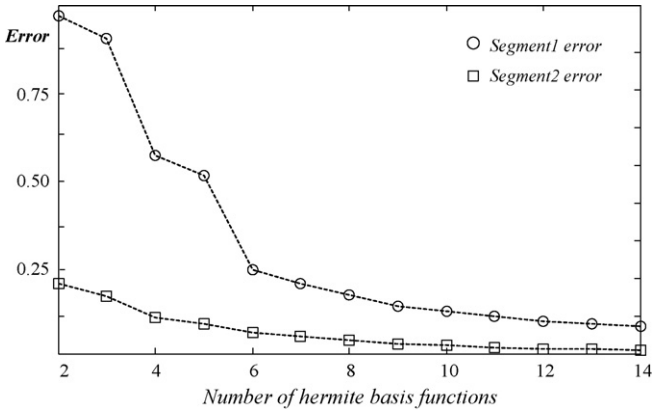


Fig. 6. Approximation of Segment1 and Segment2 using Hermite functions.

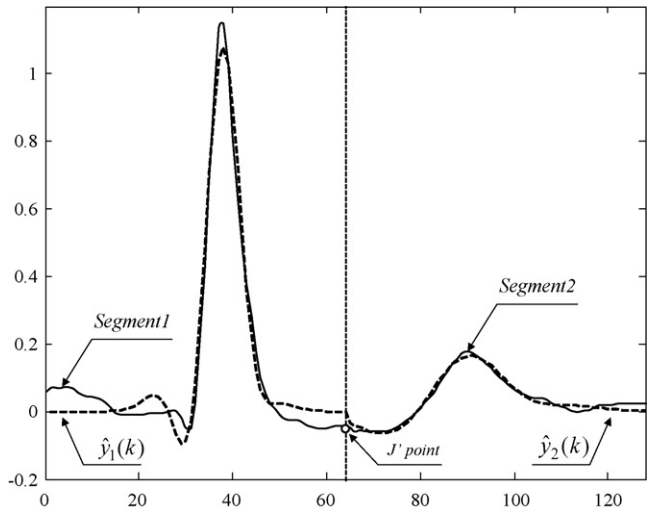


Fig. 7. Approximation of a cardiac beat using expansion in Hermite functions.

numbers of basis functions and the respective errors calculated (as the difference between the real signal and the estimated one). Fig. 6 presents the mean error obtained from the selected set of signals, which is separately indicated for Segment1 and Segment2. From the analysis of both error curves it can be concluded that a total of six Hermite basis functions is a choice that leads to an acceptable error at the same time that guaranties a number of coefficients sufficiently low for both segments.

Regarding, the scaling factors, a similar strategy was followed. The estimation of the adequate scaling factors resulted from experiments in which the values of these parameters were varied in a given range [2–15]. The scaling factors for each segment (*Segment1* and *Segment2*) were independently obtained by the minimization of the error between the real and the estimated signals. These values were of $l = 5$ and $l = 8$, respectively for *Segment1* and *Segment2*.

The number of Hermite basis functions, as well as the values of the scaling factors, were considered constants for all the signals. Actually, as referred above, it was not fundamental to obtain very low approximation errors for each specific case, but to capture the most relevant morphologic characteristics of each cardiac beat. With the selected values this goal was achieved.

Fig. 7 depicts a real cardiac beat and the correspondent approximation using its expansion in Hermite functions. The Hermite coefficients were evaluated for each segment (each one resampled to 64 samples) using $m = 6$, and $l = 5$ and $l = 8$, for *Segment1* and *Segment2*, respectively. For each segment, the resulting coefficients were C1 and C2, presented below.

$$C1 = \begin{bmatrix} 0.9835 & -0.1700 & -0.2926 & 0.1298 & 0.0595 & -0.0840 \end{bmatrix}$$
$$C2 = \begin{bmatrix} 0.1631 & -0.0041 & -0.0451 & 0.0294 & -0.0107 & 0.0188 \end{bmatrix} \quad (11)$$

To analyze how changes in the ECG morphology are reflected in the Hermite coefficients, a simulated cardiac beat was created: the first segment presenting a deep Q wave and the second segment exhibiting an inverted T wave. Fig. 8 shows this simulated cardiac beat and the respective Hermite approximation. The correspondent Hermite coefficients are C1 and C2 presented below, with the same scaling factors as before.

$$C1 = \begin{bmatrix} 0.8561 & 0.3626 & -0.2008 & 0.0496 & -0.1550 & 0.1959 \end{bmatrix}$$
$$C2 = \begin{bmatrix} -0.3369 & -0.2261 & 0.0349 & 0.0955 & -0.0562 & -0.0092 \end{bmatrix} \quad (12)$$

For these two particular situations, the coefficients revealed the morphology changes in the ECG. In fact, for the first segment, the major variation occurred in the second coefficient that assumed a value of −0.1700 for the original signal and of 0.3626 for the simulated one. This disparity reflects the Q wave variation, mainly corresponding to the Hermite function observed in Fig. 5 with $n = 1$.

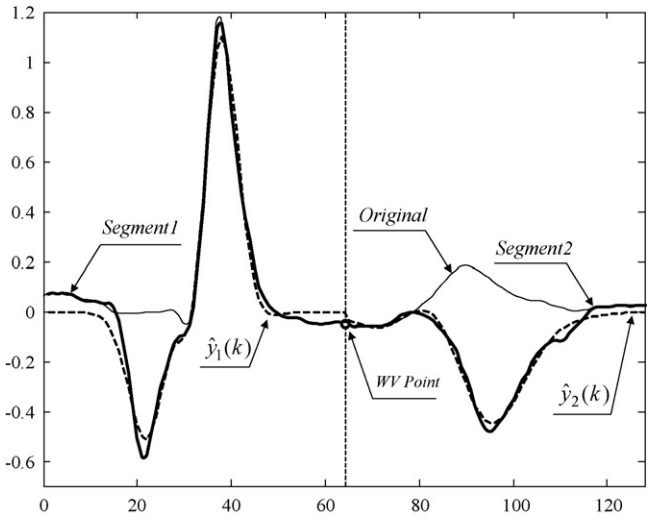


Fig. 8. Approximation of a cardiac beat using Hermite expansion.

For the second segment, the major variation was verified in the first coefficient, which took a value of 0.1631 in the case of the original segment and of −0.3369 in the case of the simulated one. Clearly, this difference is related to the T wave inversion, as observed in Fig. 5 with $n = 0$. These results confirm that the QRS complex and the T wave morphologies can be characterized by a relatively small number of Hermite functions and that the correspondent coefficients have the potential to be used as features for ischemic beats identification.

2.3. Classification

The first classification strategy considered two classifiers: one to deal with ST elevation and other to manage ST depression. However, since the morphology of the ECG waves depends on the specific ECG acquisition lead, the results achieved with this approach were not significant when compared to the ones presented in literature. Therefore, to deal with the particularities of each lead configuration, a lead dependent classification system was the chosen solution. As a result, a specific classifier is implemented for each lead.

Given their properties, neural networks have been recognized as a powerful tool for pattern classification problems, especially when applied to numeric data classification. In the context of ischemic beats classification, neural networks have been extensively applied with significant performances results [15,16]. Due to their universal approximation nature, low complexity and excellent results

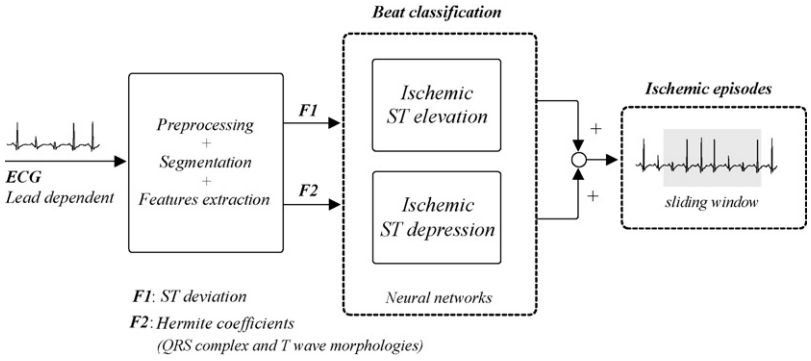


Fig. 9. Proposed classification scheme.

achieved in similar classification tasks, neural networks are used in this work.

Fig. 9 depicts the main modules of the classification scheme.

2.3.1. Beat classification

For classifier selection several experiments were carried out with different types of neural networks. The chosen strategy consists of two independent feed-forward neural networks (FFNNs) for each lead: the first classifies the nature of the ST elevation of each beat and the second distinguishes beats with ST depression from others. After beat classification a sliding window with size of 40 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.

2.3.2. Episode detection

Ischemia episodes detection involves two steps: first a sliding window procedure is applied to the entire ECG signal. The window's length is set to 40 beats. It is considered as an ischemic episode if more than 50% of the beats are classified as ischemic. In a second phase, the classification done in the previous step is reviewed and episodes with a separation of less than 40 beats are merged.

3. Results

For algorithm validation purposes the European Society of Cardiology ST–T database was used [25,26]. This database consists of 90 annotated excerpts of ambulatory ECG recordings from 79 subjects for which myocardial ischemia was diagnosed or suspected. Each record is 2 h in duration and contains two signals from 8 different leads (V1, V2, V3, V4, V5, MLI, MLIII and D3). These signals are sampled at 250 Hz. From the 90 complete records of this database, 48 records are freely available and were used in this work.

To assess the quality of the proposed algorithms, sensitivity (SE) and positive predictivity (PP) have been evaluated, according to Eqs. (11) and (12), respectively.

$$\mathrm{SE} = \frac{TP}{TP + FN} \tag{13}$$

$$\mathrm{PP} = \frac{TP}{TP + FP} \tag{14}$$

In the equations above, *TP* (true positives) represents the annotated beats/episodes in the database that were identified by the algorithms, *FN* (false negatives) corresponds to the annotated beats/episodes that were not detected and, finally, *FP* (false positives) denotes the number of beats/episodes that were not annotated in the database, but that were incorrectly identified by the algorithms.

3.1. Features extraction

The extracted features in each cardiac cycle were related with ST segment deviation as well as with the QRS and the T wave morphology changes. ST deviation has been evaluated using both approaches described in Section 2.2.1. In turn, each cardiac beat segment (Segment1 and Segment2) was approximated by a linear combination of the first six Hermite functions (orders 0–5). Taking into account that the expansion of each segment originated 6 coefficients, a total of 14 features were determined for each cardiac beat: 2 features related to the ST deviation and 12 Hermite coefficients. Subsequently, a moving average filter of order 10 was applied to all the features.

To validate the potential of the referred features in discriminating normal from ischemic beats, a linear correlation analysis procedure took place. In effect, the correlation coefficients between the computed Hermite coefficients and the beat classification according to ESC ST–T database were assessed. Table 2 presents the average correlation coefficients and the respective standard deviations computed from all the beats considered in this study. The ST1 and ST2 labels represent the ST deviation calculated using the two different approaches mentioned before (Section 2.2.1) and the H_j $j = 0, \ldots, 5$, denote the Hermite coefficients from orders 0 to 5. The values presented in Table 2 confirm the potential of the features in question.

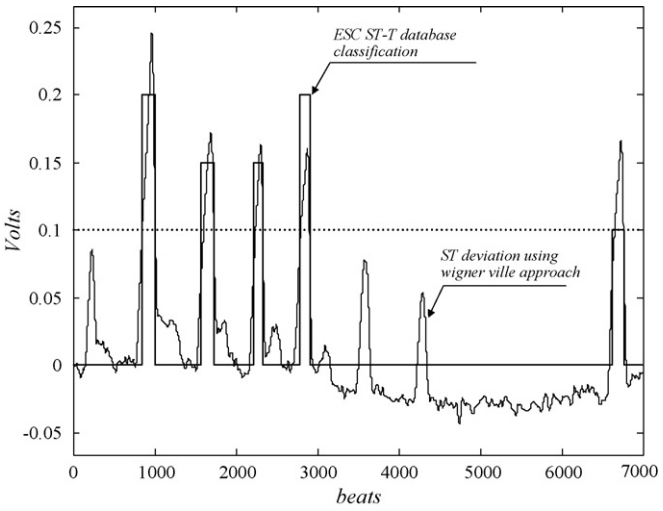


Fig. 10. ST deviation.

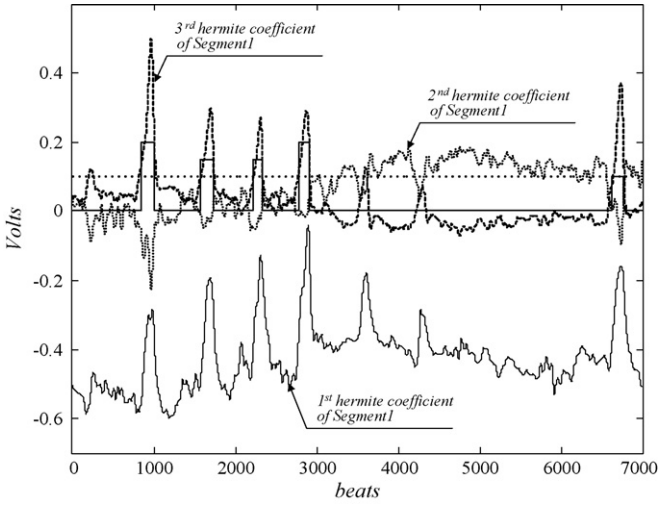


Fig. 11. First three coefficients of Hermite expansion—Segment1.

Figs. 10–12, illustrate this correlation analysis performed on the e0103 record, channel 2, lead MLIII, which is composed of 6997 beats. In order to simplify the visualization, only some of the features are depicted. Thus, Fig. 10 depicts the ST deviation obtained using the Wigner–Ville approach. Fig. 11 shows the first three Hermite coefficients corresponding to *Segment1* and Fig. 12 presents the first three Hermite coefficients corresponding to *Segment2*. For this particular example, the correlation coefficients obtained are presented in Table 3.

The correlation coefficients presented in Table 3, as well as the respective visualization in Figs. 10–12, demonstrate the discrimination effectiveness of the selected features.

Table 2
Features correlation analysis.

Correlation coefficient	ST deviation		Hermite coefficients for Segment1						Hermite coefficients for Segment2					
	ST1	*ST2*	*H0*	*H1*	*H2*	*H3*	*H4*	*H5*	*H0*	*H1*	*H2*	*H3*	*H4*	*H5*
Average	0.63	0.64	0.30	0.34	0.41	0.40	0.37	0.35	0.35	0.41	0.28	0.46	0.48	0.63
Standard deviation	0.21	0.23	0.25	0.22	0.27	0.26	0.24	0.26	0.26	0.26	0.20	0.24	0.23	0.22

Table 3
Correlation analysis for the e0103 record.

	ST deviation	Hermite coefficients for Segment1			Hermite coefficients for Segment2		
	ST2	*H0*	*H1*	*H2*	*H0*	*H1*	*H2*
Correlation coefficient	0.82	0.53	0.49	0.79	0.83	0.11	0.44

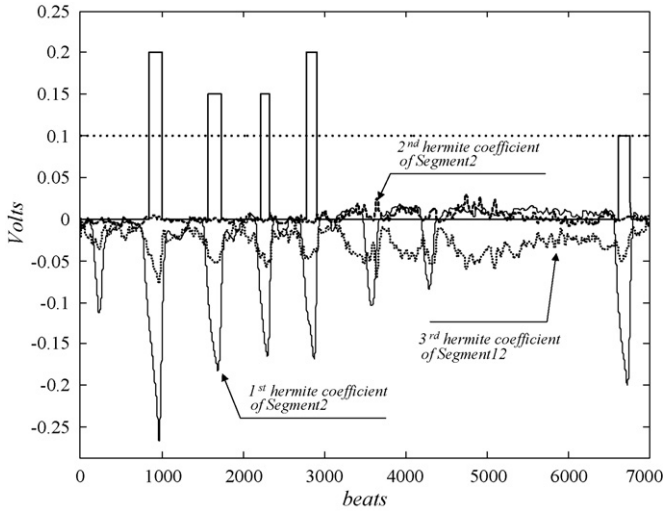


Fig. 12. First three coefficients of Hermite expansion—Segment2.

3.2. Training and validation

3.2.1. DataSet

Regarding training and validation, data subsets from the 48 freely available signals of the ESC ST–T database were selected according to each lead. Each ECG record was split into two sub-records, i.e. one from channel 1 and another one from channel 2, originating 96 signals for training and validation. Each specific classifier for each lead was trained and validated using signals contained in the database for that lead type. Moreover, after the preprocessing phase, some of the cardiac cycles were removed and were considered neither for training nor for validation purposes. In this category are PVCs and noisy beats.

To validate beat classification, 81 of the 96 available signals were utilized. In effect, some signals containing annotations that were not considered consistent were discarded. An example of an ambiguous situation is illustrated in Fig. 13. The figure on the left (Fig. 13a) shows a 4 s section of the e0207 record, channel 1, lead V5, starting at index 1620900. The figure on the right (Fig. 13b) shows a 4 s section of the e0303 record, channel 2, lead V5, starting at index 1107300.

According to the ESC ST–T database classification, the signal on the right has been annotated as normal, while the one on the left has been considered as having ST depression. However, as can be observed, this classification contradicts what one might expect.

Table 4 presents the exact number of cardiac cycles used for each lead (after PVCs, noisy and non-consistent beat elimination). The discarded signals, for each lead, were: e0207 for lead MLI, e0109, e0121, e0609 and e0613 for lead MLIII, e0403 for lead V1, e0415 and e0603 for lead V2, e0119, e012 and e0161 for lead V4, and e0207, e0213, e0303 and e0405 for leadV5.

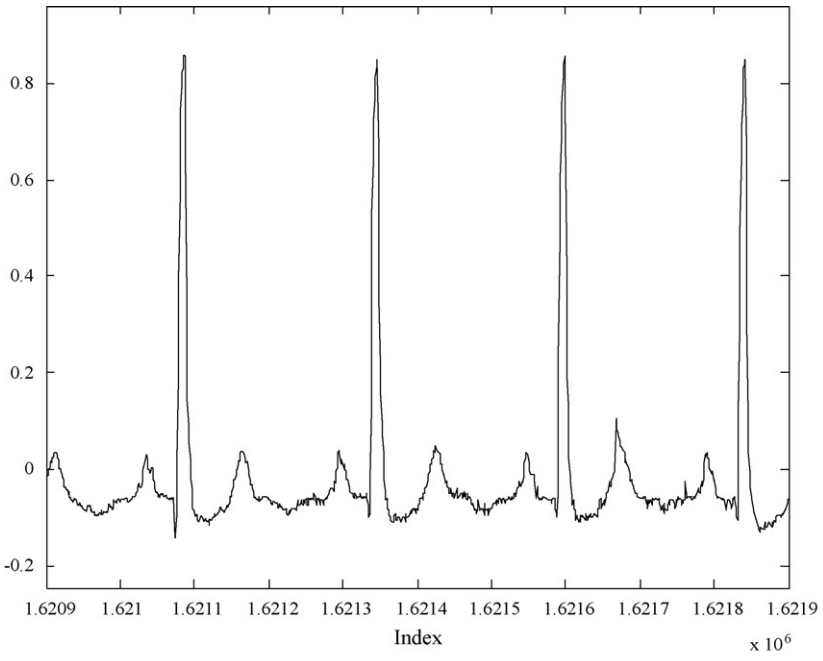
3.2.2. Training and validation

For training purposes only a small portion of representative signals (30 beats before and after the annotated episodes transitions) were applied. As already mentioned, 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 the ESC ST–T database, a total of 16 neural networks were utilized. A neural architecture composed by two hidden layers (sigmoid tangent activation functions) was considered. 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. Table 5 presents, for each lead, the architecture applied for each classifier. The notation used is the number of neurons corresponding to [*inputs*, *first layer*, *second layer*, *output*].

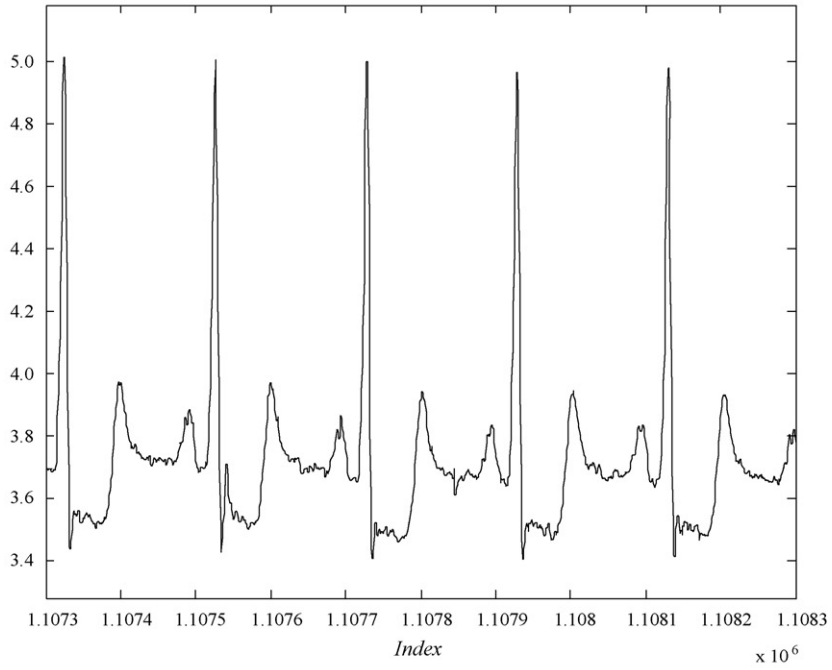
For ischemic episode validation, beat sequences of annotated and identified episodes were compared. If the beginning and the end of them matched within a defined tolerance (40 beats) then episode detection was considered as successful. Otherwise, it was considered as unsuccessful. In Fig. 14, a representative example of ischemic episodes identification by the proposed algorithms is presented using the e0103 record. In fact, the manifest overlap

Table 4
Training and validation dataset.

Lead	No. of signals in database	Cardiac cycles in database	No. of signals considered	Cardiac cycles considered
V1	5	33,554	4	30,548
V2	8	49,704	6	35,110
V3	3	14,487	3	14,487
V4	19	1,34,872	16	1,08,107
V5	27	1,92,249	23	1,62,747
MLI	8	63,851	7	56,990
MLIII	25	1,59,142	21	1,33,477
D3	1	1465	1	1465
Total	96	6,49,324	81	5,42,931



(a) *ESC ST-T depression beats*



(b) *ESC ST-T normal beats*

Fig. 13. Non-consistent beat classification examples. (a) ESC ST–T depression beats and (b) ESC ST–T normal beats.

between the annotated episodes and the ones identified by the algorithms, testifies the ability of the methodology to perform the intended detection task.

4. Results and discussion

The results achieved by the proposed algorithms for ischemic beat classification and ischemic episode detection are presented in Tables 6 and 7.

As can be observed in the tables above, the global sensitivity and positive predictivity reached average values of 96.7% and 96.2%, respectively.

Despite the importance of evaluating the performance of the proposed algorithms with respect to other state of the art methods, it is observed that this is a very difficult task due to the fact that different data sets are applied to derive the reported results in many of these papers. Badilini et al. [7] uses a private database. Although many authors use the ESC ST–T database to evaluate their algorithms, it is observed that some (e.g. [10,14]) do not specify the number of records (although the latter refers the number of ischemic/normal beats used). Others (e.g. [16]) use all the available records of the database but with reviewed annotations. In other studies, as those reported in [17,21], only a small set of records are utilized (5 and 10, respectively) for validation purposes. On the

Table 5
Lead NN structure.

Lead	NN structure
V1	[14,5,3,1]
V2	[14,5,3,1]
V3	[14,5,3,1]
V4	[14,6,4,1]
V5	[14,7,3,1]
MLI	[14,3,3,1]
MLIII	[14,5,3,1]
D3	[14,5,3,1]

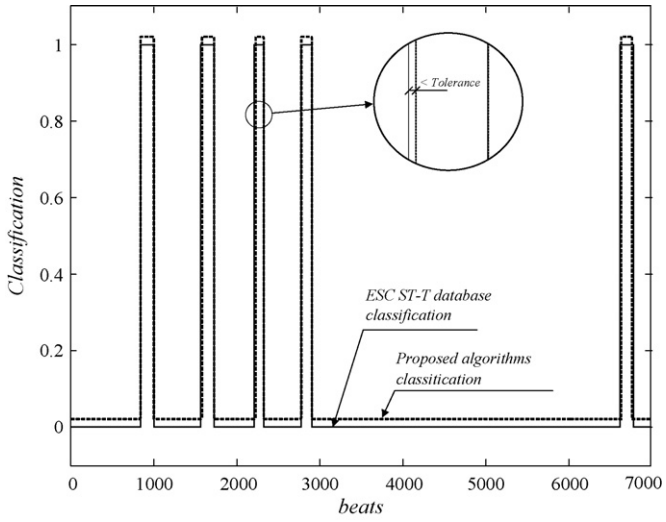


Fig. 14. Ischemic episodes validation (e0103 record).

other hand, some authors evaluate their methods using all database records with the original annotations. This is the case of Pang [15] and Vila et al. [20] (ischemic episodes detection), where SE varies from 81.3% to 83.0% and PP ranges from 74.7% to 75.0%. For ST segment deviation episodes, Garcia et al. [8] and Papaloukas et al. [18] report for SE between 84.7% and 92.0%, while PP ranges from 86.1% to 93.8%. Another group of authors base their evaluation on the 48 records freely available. This is the case of the method for ischemic episodes detection introduced by Andreao et al. [19] that achieves a SE of 83.0% and a PP of 85.0%. The algorithm reported by Afsar et al. [16] for ST segment deviation episodes achieves a SE of 90.8% and a PP of 89.2%. For obvious reasons, it would be unfair to compare the current work with the group that used the entire records of the database as they would be in disadvantage. In fact, the most suitable studies for comparison are actually those reported by Andreao et al. and by Afsar et al., since the data set used for their evaluation is basically the same as the one applied in the present study. Consequently, it can be concluded that the results presented in Table 7 significantly improve the results achieved by the methods reported by these authors, both in terms of sensitivity (96.7%) as well as in terms of positive predictivity (96.2%).

Table 7
Episodes detection performance.

Lead	Episodes	*TP*	*FP*	*FN*	SE	PP
V1	5	5	0	0	100.0%	100.0%
V2	5	5	0	0	100.0%	100.0%
V3	2	2	0	0	100.0%	100.0%
V4	34	32	2	4	88.9%	94.1%
V5	38	35	3	6	85.4%	92.1%
MLI	5	5	1	0	100.0%	83.3%
MLIII	32	32	0	0	100.0%	100.0%
D3	1	1	0	0	100.0%	100.0%
Total	122	117	6	10	96.7%	96.2%

It should be stressed that all modules of the algorithm have been designed to operate on short signal windows (40 beats). This is an important aspect, since it does not require significant durations of ECG to perform ischemia characterization. Since the proposed detection scheme is based on neural network models, the classification process is very fast. Thus, this methodology has the potential to be used in home monitoring pHealth applications.

5. Conclusions

In this paper a strategy for ischemic episode detection was proposed. The methodology consists of two main steps: first, each individual beat is classified as normal or ischemic, considering features based on the ST deviation, the T wave and the QRS complex morphologies. To deal with the particularities of each lead configuration, a lead dependent classification scheme is implemented using two FFNNs per lead, specifically designed to deal with ST elevation and ST depression, respectively. In the second stage of the algorithm, ischemic episodes detection is performed based on a sliding window procedure.

The most innovative aspects are the new approach for accurate ST shift and isoelectric point estimation based on the time–frequency analysis, and the ECG beat morphology effective characterization using the expansion in Hermite functions.

The methodology's potential was confirmed by using the European Society of Cardiology ST–T database. In fact, the achieved results (sensitivity of 96.7% and positive predictivity of 96.2%) are relevant when compared with similar works reported in literature.

Given the relative simplicity of the algorithm it will be straightforward to incorporate it into pHeath systems. In particular, the developed solution will be part of a cardiovascular status assessment tool that is being developed under HeartCycle European Project.

Table 6
Beat classification performance.

Lead	No. of signals	No. of beats	FFNN neg.		FFNN pos.	
			SE	PP	SE	PP
V1	4	30,548	100.0%	100.0%	–	–
V2	6	35,110	99.6%	99.9%	100.0%	100.0%
V3	3	14,487	100.0%	99.3%	–	–
V4	16	1,08,107	94.6%	92.8%	100.0%	100.0%
V5	23	1,62,747	95.7%	97.5%	100.0%	100.0%
MLI	7	56,990	99.2%	98.7%	99.6%	99.3%
MLIII	21	1,33,477	100.0%	100.0%	96.4%	97.0%
D3	1	1465	–	–	100.0%	100.0%
Total	81	5,42,931	98.4%	98.3%	99.3%	99.3%

Acknowledgements

This work was supported by HeartCycle, a project partly funded by the European Community's Seventh Framework Programme under grant agreement no. FP7-216695, and by CISUC—Center for Informatics and Systems of University of Coimbra, Portugal.

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