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A knowledge-based technique for automated detection of ischaemic episodes in long duration electrocardiograms

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Abstract—*A novel method for the detection of ischaemic episodes in long duration ECGs is proposed. It includes noise handling, feature extraction, rule-based beat classification, sliding window classification and ischaemic episode identification, all integrated in a four-stage procedure. It can be executed in real time and is able to provide explanations for the diagnostic decisions obtained. The method was tested on the ESC ST-T database and high scores were obtained for both sensitivity and positive predictive accuracy (93.75% and 78.50% respectively using aggregate gross statistics, and 90.68% and 80.66% using aggregate average statistics).*

Keywords—*Ischaemic episodes detection, Knowledge-based method, ECG noise handling*

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1 Introduction

ISCHAEMIA IS the most common cardiac disease and its early diagnosis is very important. Techniques that automate the detection and help in the diagnosis of ischaemic episodes in long duration electrocardiograms (ECGs) have been proposed during the last two decades. These techniques can be grouped depending on the computational paradigm on which they are based (rule-based expert systems, artificial neural networks, fuzzy expert systems, pattern recognition, signal processing, etc.).

Rule-based methods exhibit certain advantages such as direct transformation of medical knowledge to rules, low computational load and explanation of the diagnostic decisions. However, their diagnostic value depends on the appropriate selection and combination of the rules and the method for the extraction of feature values used in the rules. Some rule-based techniques (LACHTERMAN *et al.*, 1990*a*, *b*; VELDKAMP *et al.*, 1994; ANSLEY *et al.*, 1996; YANG, 1996) used the ST deviation from the isoelectric line, while others (WATANABE *et al.*, 1980; WEISNER *et al.*, 1982; HSIA *et al.*, 1986) combined the ST deviation with ST segment slope and other parameters like the ST index, ST level and ST integral (or ST area). More specifically, if the slope is lower than a certain threshold and the ST deviation is higher than 0.1 mV then an ischaemic beat is detected. SILIPO *et al.* (1994) used such rules in ischaemic episode detection. Similar rules were adopted by AKSELROD *et al.* (1987), which could reach decisions for subclasses of ischaemic beats, and by SHOOK *et al.* (1989), but with feature values averaged on a 30-s window. CAIRNS *et al.* (1991) and LAKS *et al.* (1989) introduced a relation which has as input parameters age, sex, chest or left arm pain, Q wave amplitude, ST elevation and depression and T inversion, and as output the ischaemia probability. BADILINI *et al.* (1992), used ST segment frequency characteristics for ischaemic episodes detection.

Another class of techniques for ischaemia detection is based on artificial neural networks (ANN). BAXT (1991) proposed a four-layer ANN trained by back-propagation for ischaemic patient identification considering features from patient history, physical examination and ECG characteristics. STAMKOPOULOS *et al.* (1992) used a three-layer ANN trained by back-propagation using as input the raw signal corresponding to the ST segment. In other work (STAMKOPOULOS *et al.*, 1998), they used non-linear principal component analysis for ischaemic beat classification. SILIPO *et al.* (1994) adopted a three-layer ANN trained by back-propagation using as input the ST amplitude and slope. OUYANG *et al.* (1997) also developed a three-layer feed forward ANN trained by back-propagation, but for ischaemic patient identification. As input layer they used 40 nodes, five ECG characteristic values (Q, R, S and T waves amplitudes and ST deviation) for each one of the eight leads (I, II and V_{1-6}). SILIPO and MARCHESI (1998) compare various approaches for ischaemia detection based on ANNs: static ANNs, static ANNs combined with principal component analysis, recurrent ANNs and knowledge-learning networks.

There are also ischaemia detection techniques based upon different heuristic algorithms. OATES *et al.* (1989) used decision tree methods on three quasi-orthogonal leads. JAGER *et al.* (1992) used the Karhunen–Loève transform. TADDEI *et al.* (1995) developed a geometric method, while VILA *et al.* (1997) developed a monitoring system for coronary care units based on fuzzy logic.

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A knowledge-based approach is prepared to detect ischaemic episodes in long duration ECGs. The method is based on a four-stage schema. The first is used for noise handling, artefact characterisation and extraction of ECG features. The second stage is beat classification (ischaemic or not) using medical knowledge in the form of rules based on the features obtained in the first stage. The third stage is window classification (ischaemic or not). The fourth stage identifies and merges the sequences of ischaemic windows detecting the ischaemic episodes.

The proposed method is novel in several aspects; the whole detection process is structurally divided into four distinct stages. This division is made to naturally emulate the diagnostic steps followed by cardiologists and significantly facilitates the specification, adjustment and tuning of the overall method. Another important aspect of the approach is that it explicitly deals with noise problems. A noise handling procedure is proposed (applied in the pre-processing stage) that enables efficient treatment of most types of noise appearing in ECG recordings. Moreover, for ischaemic beat classification, medical knowledge is used in the form of three rules, one of which (T wave inversion or flattening) (ROWLANDS, 1982; GOLDMAN, 1982) is used for the first time for automated diagnosis. Also introduced is the notion of ischaemic window, which is a time window containing mostly (to allow tolerance in the decision) ischaemic beats. Also the method exhibits flexibility in the definition of an ischaemic episode as a sequence of ischaemic windows by allowing small intermediate intervals containing normal beats. These tolerance characteristics of the method allow on the one hand for the efficient treatment of artefacts, and on the other hand for dealing with problems related to the fact that strict rules (with certain threshold values) are used for beat classification. Finally, it is worth mentioning that the technique is real-time and exhibits the highly desirable characteristic that it is capable of providing explanations for each decision made at every stage of the method. Experimental results using the ESC ST-T database indicate that the proposed diagnostic procedure is effective and performs well both in terms of sensitivity and positive predictive accuracy.

2 Method

A four-stage procedure was developed for ischaemic episodes detection as shown in Fig. 1. The four stages correspond to noise handling and ECG feature extraction, beat classification, window classification and identification of ischaemic episodes duration. In the first stage, pre-processing of the ECG recording is performed to achieve noise removal and extraction of the signal features to be used for beat characterisation. In the second stage each beat is classified as normal, abnormal (ischaemic) or artefact. This information is used in the third stage (the window characterisation stage) where each 30-s ECG window is classified as ischaemic or not. In the fourth stage the identification of start and end points of each ischaemic episode is performed based on the concatenation of consecutive ischaemic windows. It is noted that the whole procedure described above is applied in each lead separately. At the last stage, a merging procedure is followed to identify the overall ischaemic episodes from the episodes detected in each available lead.

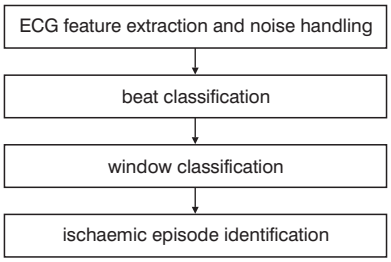

Fig. 1 *The four-stage technique*

2.1 *ECG feature extraction and noise handling*

2.1.1 *ECG feature extraction:* At this stage the beginning of the ST segment (J point) and the peak of the T wave are detected. We start with the detection of a point in the QRS complex (QRS point) for each beat using the HAMILTON and TOMPKINS (1986) algorithm. To make this algorithm faster some modifications have been made: specifically, after the detection of a QRS complex we ignore the next 300 ms. This means that the modified QRS detector will become 30% faster but it also means that in cases of tachycardia (with a heart rate higher than 200 beats min^{-1}) the QRS detection will fail. Nevertheless, these cases are rare and deserve special treatment by the cardiologist. The QRS detection continues as follows: first, the main wave of the QRS complex (not the R wave) is identified in the window [QRS − 280 ms, QRS + 120 ms] by locating the point with maximum absolute signal value. The next step is an initial estimation of the isoelectric line, which is defined as the mean value of the signal in the window [QRS − 100 ms, QRS − 80 ms], and is used for the location of the point in the QRS complex with maximum absolute deviation from that estimated isoelectric line. This point is the peak of the main wave in the QRS complex. It is used of as a reference point (RP) to continue the search for the final identification of the isoelectric line and the location of the start point (J point) of the ST segment.

The algorithm developed by DASKALOV *et al*. (1998) is applied to the window [RP − 100 ms, RP − 40 ms] and searches for an interval of 20 ms with signal slope (C_s) less than or equal to 2.5 μV ms^{-1}. This interval is used for the definition of the isoelectric line. The original algorithm (DASKALOV *et al*., 1998) uses a slope criterion of $C_s \leq 5$ μV ms^{-1}, but better results were obtained by using a stricter threshold of 2.5 μV ms^{-1}. The same algorithm is applied to the window [RP + 20 ms, RP + 120 ms] to locate the J point.

If all the above stages have been completed successfully, the algorithm continues to locate the peak of the T wave. Where no isoelectric line or J point has been detected, the current beat is classified as an artefact and the procedure starts again with the next beat. We locate the point T_{onset} at J80 + 0.0375* R-R, where J80 = J + 80 ms and R-R is the time interval between the current RP and the previous one. We search for the peak of the T wave in the window [T_{onset}, T_{onset} + 200 ms], which is defined as the point with maximum difference in amplitude with respect to the J80 point.

2.1.2 *Noise handling:* The procedure described above produces very good results only when the ECG recording has a high signal-to-noise ratio (SNR). If we attempt to define the isoelectric line and detect the J point in a noisy signal using the method described several problems will occur (middle row in Fig. 2). The presence of noise (top row in Fig. 2), such as power line interference (A/C), the electromyographic contamination (EMG) and the baseline wandering (BW), may lead the algorithm to ambiguous results. To overcome this problem we developed a technique that manages to remove BW and to accurately detect the isoelectric line and the J point in cases where the ECG is contaminated with A/C and/or EMG noise (bottom row in Fig. 2).

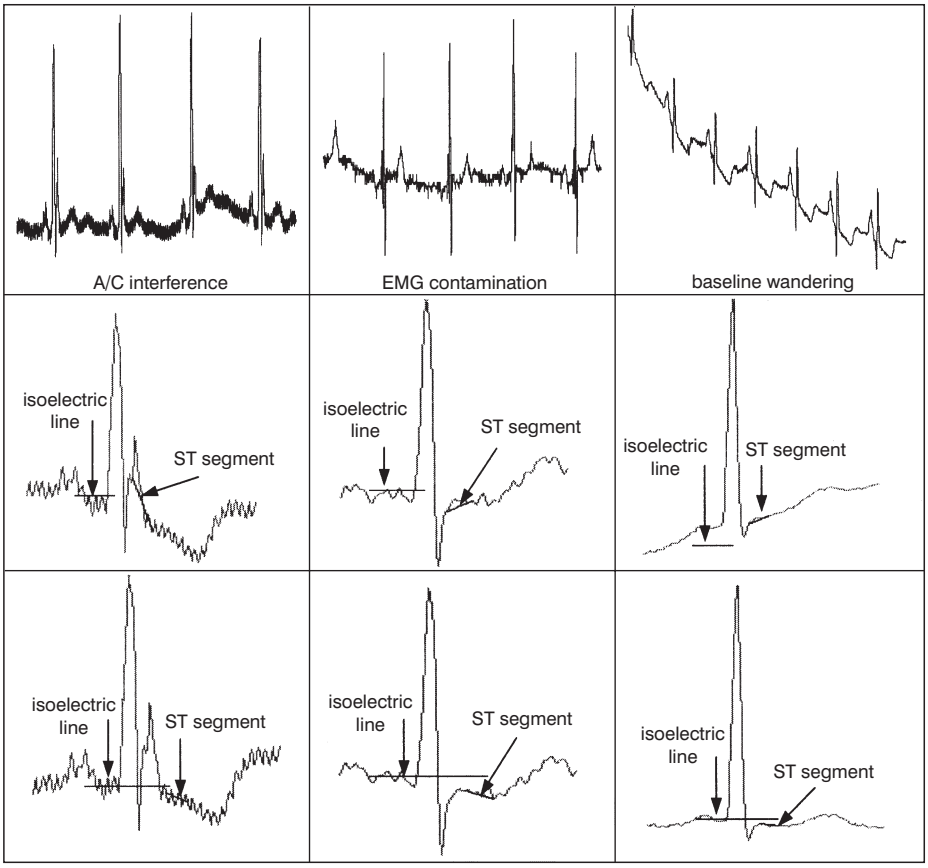

Fig. 2 *Detection of ECG characteristics in three types of noisy signals (top row), when the noise handling method is applied (bottom row) or not (middle row)*

The noise handling procedure starts by treating first the problem of baseline wandering. It is well known (BROCKWELL *et al*., 1991) that slow noise can be modelled successfully by low-order polynomials. This is the approach followed. Considering a small time interval in the ECG signal, for example one cardiac cycle, then the baseline shift can be modelled by a first-order polynomial (straight line). As a consequence, subtraction of the polynomial from the recorded signal reproduces the original ECG.

For each cardiac cycle, we consider the window [RP − [R-R/2.5] − 60 ms, RP + [R-R*0.6] − 60 ms], where [·] denotes the round-off operator. This window defines a time interval that starts approximately 60 ms before the P wave and ends approximately 60 ms after the T wave. Let $x(t),\ t = 1, 2, \ldots, N$ be the recorded ECG signal. Using a least squares procedure we can estimate the polynomial $\hat{x}(t)$ that best fits $x(t)$:

$$\hat{x}(t) = \hat{x}_1 t + \hat{x}_0, \quad \text{for } t = 1, 2, \ldots, N \tag{1}$$

The corrected ECG signal, $y(t)$ (without the baseline drift) is given by

$$y(t) = x(t) - \hat{x}t, \quad \text{for } t = 1, 2, \ldots, N \tag{2}$$

We have observed that the existence of the QRS complex slightly shifts the polynomial towards its main QRS polarity: if the QRS has a large R wave then the polynomial shifts upwards and the opposite happens when Q or S waves are large. Thus, a modified two-stage procedure has been adopted.

In the first stage, we estimate the polynomial corresponding to $x(t)$:

$$\hat{x}(t) = \hat{x}_1 t + \hat{x}_0 \tag{3}$$

As mentioned above, $x(t)$ may have a slightly diverted slope due to, for example, a large R wave. Let us assume that the QRS complex consists of the samples $x(t)$ for $t = t_1, \ldots, t_2$. In order to decrease the influence of the QRS complex on the estimated polynomial, in the second stage, we replace the QRS complex with the corresponding values of the polynomial $\hat{x}(t)$.

Thus we get a new signal, denoted $u(t)$, as follows:

$$\{u(t)\}_{t=1}^{N} = \{x(1), \ldots, x(t_1 - 1), \hat{x}(t_1), \ldots, \hat{x}(t_2), x(t_2 + 1), \ldots, x(N)\} \tag{4}$$

Then, we compute the fitting polynomial

$$\hat{u}(t) = \hat{u}_1 t + \hat{u}_0 \tag{5}$$

and we obtain the final ECG signal, $f(t)$, as

$$f(t) = x(t) - \hat{u}(t) \tag{6}$$

which is without BW noise and also translated around the zero voltage level.

It must be noted that in cases where no baseline wandering exists the influence of the above procedure on the original signal is very small; this becomes apparent from the high scores achieved by the proposed procedure.

After the baseline correction, we proceed with the isoelectric line and the J point identification. The isoelectric line is defined as the mean value of the signal $f(t)$ in the window [RP − 80 ms, RP − 60 ms]. We use a moving averaging window of 20 ms in the interval [RP + 20 ms, RP + 120 ms] to obtain the signal $g(t)$. The J point is detected using the DASKALOV *et al*. (1998) algorithm on the signal $g(t)$. This averaging technique does not remove the AC or the EMG noise from the ECG signal but is used as a rule of thumb for the definition of the isoelectric line and the J point.

Fig. 2 clearly illustrates the improvement of the proposed method in the detection of the isoelectric line and the J point. The top row shows the three types of noise distortion, the middle row displays the detected characteristics without use of our method and the bottom row the detected characteristics when our method is applied.

2.2 *Beat classification*

In the everyday medical practice when a cardiologist uses a long-term ECG to diagnose ischaemia, two features are examined in every available lead, the ST segment and the T wave. Our beat classification method is based on rules that take into account the above features. More specifically we consider three rules (ROWLANDS, 1982; GOLDMAN, 1982): the first one (top row in Fig. 3) classifies the beat as ischaemic when the ST deviation is more than 0.8 mm (0.08 mV) below the isoelectric line and has a slope (angle) larger than 65° measured from the vertical line. The ST deviation is measured at the point J80 (J + 80 ms) when the cardiac rhythm is less than 120 beats min^{-1} or at the point J60 (J + 60 ms) when the heart rate is higher than the previous threshold. The ST slope is measured considering the line segment from J to J80 (or J60). The second rule (middle row in Fig. 3) refers to positive ST segment deviations: when the point J80 (or J60) is more than 0.8 mm above the isoelectric line then this beat is characterised as ischaemic. The third rule (bottom row in Fig. 3) refers to the T wave inversion or flattening: if, at the initial beats of the ECG recording, the T wave has positive (negative) voltage (we use the first 30 s to extract the polarity) then all beats with negative (positive) T wave voltage are classified as ischaemic—also, beats with T waves of very low voltage, compared to the T waves voltage of initial beats, are classified as ischaemic.

It must be noted that this method of beat classification is unreliable when the SNR is very low. In such cases it is risky to perform beat classification due to the lack of reliable definition of the isoelectric line and the J point. In noisy cases, even an expert doctor cannot decide safely if a beat is ischaemic or not. When our algorithm encounters artefacts (as an output of the first stage) it ignores them and behaves as if these artefacts had never been met.

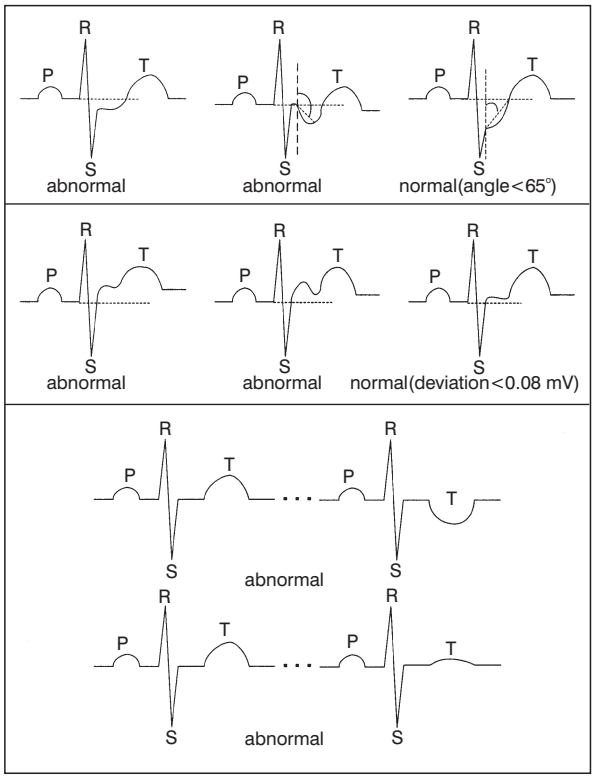

Fig. 3 *Negative (top row) and positive (middle row) ST deviations and T wave inversion and flattening (bottom row)*

The beat classification method is summarised below:

Detection of ischaemic beats

IF (J80 (or J60) $\leq$ 0.08 AND slope $\geq$ 65°) **OR** {rule 1}
(J80 (or J60) $\geq$ 0.08) **OR** {rule 2}
(T is inverted OR T $\rightarrow$ 0) {rule 3}
THEN The beat is ischaemic
ELSE The beat is normal

2.3 *Window classification*

Once every beat in each lead has been classified as ischaemic or normal, the next stage is to decide whether a sequence of beats belongs to an ischaemic window. According to ESC recommendations (TADDEI *et al.*, 1988), an ischaemic episode is defined as a time period of no less than 30 s containing ischaemic beats. For this reason we have implemented a sliding adaptive window that examines whether there exists a sequence of ischaemic beats lasting more than 30 s. The window is classified as ischaemic if the same rule is valid for all ischaemic beats in the window. If for example, there exist 15 s with positive ST deviation which are followed by 15 s with T inversion, the window is not ischaemic. The first window of the recording includes the initial 30 s of the ECG signal and the sliding technique proceeds, moving the window one beat at the time, while always keeping its duration equal to 30 s. This means that we will not have the same number of beats in all the windows but this number is adapted to the heart rate. To make window classification less strict we use a threshold in the percentage of the ischaemic beats appearing in a window. If a window has more than 75% of ischaemic beats, we consider that it belongs to an ischaemic episode. This percentage threshold is applied to avoid situations in probable ischaemic intervals where noise worsens the reliability of feature extraction or to handle cases where some beats in the window are close to being characterised as ischaemic but are not triggering any of the rules we use.

The sliding window classification algorithm is summarised below:

Detection of ischaemic windows

IF [(number of ischaemic beats from rule k)/(all beats)] $\geq$ 0.75
THEN Window$_{[k]}$ is ischaemic
ELSE Window$_{[k]}$ is normal
(where $k = 1, 2, 3$)

2.4 *Identification of ischaemic episodes*

If a series of consecutive ischaemic windows is identified then the left boundary of the ischaemic episode corresponds to the beginning of the first window in the series and the right boundary to the end of the last window. However, to increase the flexibility of the algorithm, the existence of time intervals of less than 30 s with beats that do not constitute an ischaemic window is permitted in the above counting. Once all the episodes for each lead are detected, then a merging technique is realised to define the overall episodes in the ECG recording.

The algorithm for identification of ischaemic episodes is summarised below:

Definition of ischaemic episodes in each lead

IF Window$^{j}_{[k]}$ is ischaemic
THEN Start of Ischaemic Episode^{i} = Start of Window$^{j}_{[k]}$
WHILE Window$^{j}_{[k]}$ is ischaemic **OR** (End of Window$^{j}_{[k]}$ − End of Ischaemic episode^{i}) < 30 s
DO
IF Window$^{j}_{[k]}$ belongs to an ischaemic area
THEN End of Ischaemic Episode^{i} = End of Window$^{j}_{[k]}$
ENDDO

(where $k = 1, 2, 3$; $i = 1, 2, \ldots$, number of ischaemic episodes in each lead and $j = 1, 2, \ldots$, number of windows)

The complete flowchart of our method is shown in Fig. 4.

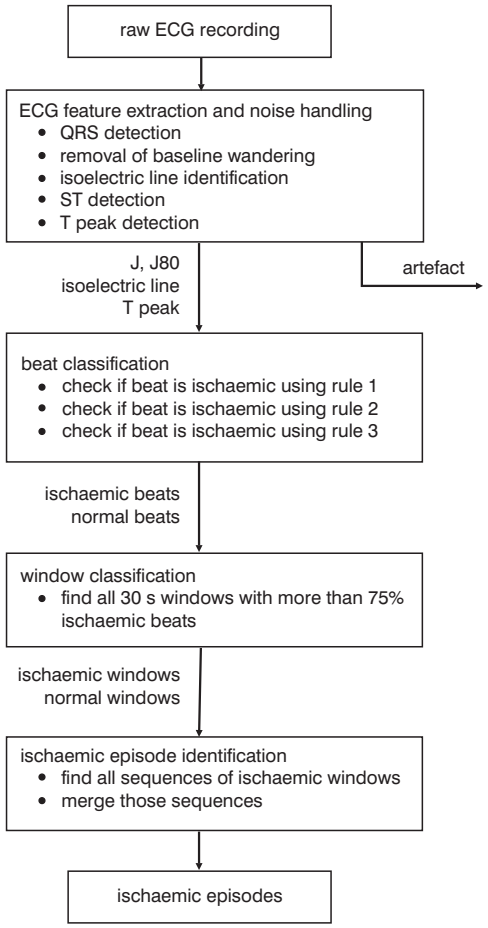

Fig. 4 *Flowchart of the overall technique*

3 Results

The proposed method was tested using the European ST-T database. This database contains ECG recordings with annotated ischaemic episodes. To evaluate the performance of the method two common measures were used for ischaemia detectors (JAGER, 1998). The first is the sensitivity (Se), which measures the ability to detect ischaemic episodes, and the second is the positive predictive accuracy (PPA), which gives an estimation of the likelihood that a detected episode is a true ischaemic episode.

Following the description of the method the main parameters are:

- ischaemic ST deviation (≥ 0.08 mm);
- ischaemic ST slope ($\geq 65°$);
- percentage of ischaemic beats in a window in order to characterise it as ischaemic ($\geq 75\%$);
- window duration ($= 30$ s);
- maximum time interval to differentiate two consecutive ischaemic episodes ($= 30$ s).

There are also secondary parameters involved in our method such as:

- the time at the beginning of each ECG used to extract T wave polarity ($= 30$ s);
- the maximum allowed time interval between two consecutive ischaemic episodes in order to merge them to one ($= 30$ s);
- the minimum number of non-artefact beats in a window to proceed with the window characterisation ($=$ [window duration$/3$] $= 10$ beats);
- the slope criterion in detecting the J-point [30] ($\leq 2.5\ \mu V\ ms^{-1}$).

The performance of the technique was tested using different parameter values. The performance of the method is primarily affected by the main parameters: best results were obtained for the values indicated in parentheses above. Table 1 shows how the sensitivity and the positive predictive accuracy vary when the main parameter values are modified. The first 10 records of the ESC ST-T database were used for the evaluation (records: e0103–e0113).

From the episodes in the ESC ST-T database, those episodes annotated as ischaemic those showing more than 0.2 mV increase in the amplitude of already positive T waves were excluded as medical experts thought that such episodes refer to myocardial infarction rather than to ischaemia (ROWLANDS, 1982; GOLDMAN, 1982). Moreover, the ischaemic episodes in the database were annotated separately for each lead and were pre-processed in order to obtain an overall annotation (lead independent) of ischaemic episodes. It was also found that in some cases the method produced ischaemic episodes, mainly short in duration, that were not annotated as ischaemic in the database. Three cardiologists were consulted to evaluate those

Table 1 Sensitivity and positive predictive accuracy variation when modifying the main parameters' values of the proposed method (records e0103–e0113 are used)

	Se			PPA		
	Gross		Average	Gross		Average
Main parameter values	%	episodes	%	%	episodes	%
0.08 mm, 65°, 75%, 30 s, 30 s	91.76	78/85	86.67	91.76	78/85	91.29
0.1 mm, 65°, 75%, 30 s, 30 s	92.55	87/94	91.32	89.69	87/97	89.25
0.08 mm, 45°, 75%, 30 s, 30 s	92.94	79/85	87.67	87.78	79/90	88.43
0.08 mm, 65°, 60%, 30 s, 30 s	90.16	55/61	83.09	74.32	55/74	71.99
0.08 mm, 65°, 75%, 60 s, 60 s	87.69	57/65	84.67	95.00	57/60	94.64

episodes and their evaluation was taken into account in the assessment of the method. This is not unusual, as similar practice has been reported previously for the proposed method (TADDEI *et al*., 1995; VILA *et al*., 1997).

Using the 90 ECG recordings (592 ischaemic episodes) and aggregate gross statistics the sensitivity obtained is 93.75% and the positive predictive accuracy 78.50%. Using aggregate average statistics the sensitivity and positive predictive accuracy become 90.68% and 80.66% respectively. The 90 ECG recordings can be separated into two groups (A and B) based on the amount of noise. Group A (64 recordings) contains those ECGs with at most 10% of noisy beats (noisy beats ranging from 0.67% to 9.56%), while group B contains the remaining recordings, where the amount of noisy beats ranges from 10.69% to 99.82% (see Table 2). The noise information is provided by the ESC ST-T database.

The performance of the method on clean (Group A) and noisy (Group B) recordings is shown in Table 3, while the results per recording are given in the Appendix.

4 Discussion

As Table 3 indicates, the method provides good detection results in terms of both sensitivity and positive predictive accuracy. It is worth mentioning that the sensitivity is not influenced by the presence of noise. This indicates the efficiency of the noise handling method employed. Our findings, when compared with those of other researchers, show the superiority of the proposed approach. More specifically, the reported sensitivity for the ESC ST-T database set ranges from 71% to 85.2% and the reported PPA ranges from 66% to 90%. It must be noted that most previous work refers to a subset of ECG recordings of the database (STAMKOPOULOS *et al*., 1992; SILIPO *et al*., 1994; TADDEI *et al*., 1995; VILA *et al*., 1997; STAMKOPOULOS *et al*., 1998), and these do not use the whole database for evaluation, as do JAGER *et al*. (1992) and SILIPO and MARCHESI (1998). It is also worth mentioning that the techniques used in the above references are based mainly on neural and statistical approaches. Such methods exhibit a serious drawback compared with our knowledge-based approach, due to their inability to provide explanations for their classification decisions. This is a serious disadvantage from the point of view of the user (doctor), who expects the decision system to supply explanations for each classification decision it makes. It is well known that neural and statistical approaches do not provide this highly desirable feature (unless tedious further post-processing is performed in the form of rule extraction).

Table 2 ECG recordings groups

Group A	e0103, e0104, e0105, e0106, e0108, e0110, e0111, e0112, e0113, e0114, e0116, e0122, e0123, e0124, e0125, e0126, e0127, e0129, e0136, e0147, e0151, e0154, e0161, e0162, e0163, e0166, e0202, e0203, e0204, e0206, e0207, e0208, e0210, e0211, e0212, e0302, e0303, e0304, e0305, e0306, e0403, e0404, e0405, e0408, e0409, e0410, e0411, e0413, e0417, e0418, e0501, e0509, e0602, e0603, e0604, e0605, e0606, e0609, e0610, e0615, e0704, e1301, e1302, e1304
Group B	e0107, e0115, e0118, e0119, e0121, e0133, e0139, e0148, e0155, e0159, e0170, e0205, e0213, e0406, e0415, e0515, e0601, e0607, e0611, e0612, e0613, e0614, e0801, e0808, e0817, e0818

Table 3 Overall performance of the proposed technique for 'clean' and noisy ECGs

	Se			PPA		
	Gross		Average	Gross		Average
ECG type	%	Episodes	%	%	Episodes	%
Clean	94.26	394/418	92.55	80.74	394/488	82.70
Noisy	92.53	161/174	86.08	73.52	161/219	75.43
Total	93.75	555/592	90.68	78.50	555/707	80.66

In contrast, due to the knowledge-based nature of every decision module in our system, the proposed method satisfies this important requirement, and it is able to provide for each ischaemic episode, the reason (rule) that led to that decision. The method also exhibits the additional desirable features of simplicity and easy and rapid implementation. This final feature is of particular importance, because the proposed method can operate in real-time mode providing on-line decision support to medical personnel (using a 450 MHz processor, approximately 6 min are needed (depending on the number of cardiac beats) to detect ischaemic episodes in each database record—roughly speaking, 25 ms are needed for each recorded second in each lead).

The set of rules used for beat characterisation is based on the modern understanding of ECGs (ROWLANDS, 1982; GOLDMAN, 1982). The set includes rules based on T inversion or flattening and ST slope from the vertical. The T wave is used in a novel way, compared to previous usages (AKSELROD *et al*., 1987; LAKS *et al*., 1989; CAIRNS *et al*., 1991; BAXT, 1991; BADILINI *et al*., 1992; OUYANG *et al*., 1997), to distinguish between the gradual change in the wave's polarity (T inversion) and the gradual weakening of the wave's amplitude (T flattening); however, we cannot assess the previous algorithms since they use their own datasets. The proposed set of rules works better than previous approaches, even in the case of two-phase T waves, which are difficult to classify. When the dominant phase of a two-phase T wave has the opposite polarity to the one defined using the first 30 s of the recording, then the T inversion rule is triggered and this beat is classified as ischaemic. The proposed rules are less effective in cases where the dominant phase of a two-phase T wave has the same polarity as the predefined one.

The performance of the method can be further improved in terms of positive predictive accuracy by refinement of the noise handling procedure. Difficulties were encountered in recordings with very low SNR in the J point, the isoelectric line and T peak detection. In the last case severe problems arise when incorrect T peak detection occurs at the beginning of the ECG recordings (e0122, e0139, e0163, e0170, e0204, e0205, e0411, e0601, e0604 and e0605) since the sign of the T wave is determined incorrectly. Exclusion of these ten recordings leads to a significant improvement in the PPA (gross Se 95.32% and PPA 87.31%; average Se 93.55% and PPA 87.94%). It must be noted that modern ECG recorders and Holter devices include filtering modules so the output ECG signal has better SNR than signals contained in the database. It is obvious that our method will perform better with such equipment.

5 Conclusions and future work

We have proposed a novel technique for the detection of ischaemic episodes in long duration ECGs, which has shown good diagnostic performance in the ESC ST-T database.

The good performance is a result of effective noise handling, beat classification using up-to-date medical knowledge, and flexibility in the definition of ischaemic windows and ischaemic episodes. The method is simple, easily implemented and can be executed in real time, and is capable of providing explanations for the diagnostic decisions made. The performance of the method compares well with previously reported results using the ESC ST-T database.

Future work will focus on further improvement of the noise handling procedure and in the development of a database with annotated ECG recordings based on updated medical knowledge. The possibility of transferring the method to clinical practice and evaluating its performance in real conditions is of great interest. A hybrid intelligent system that appropriately combines the proposed method with artificial neural networks to enhance diagnostic reliability is under development.

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Appendix

Performance of the proposed technique for all ECG recordings of the ESC ST-T database

SNR	ECG	Se (%)		PPA (%)		SNR	ECG	Se (%)		PPA (%)	
99.33	e0103	100	7/7	100	7/7	95.4	e0211	100	1/1	50	1/2
97.14	e0104	100	14/14	100	14/14	94.64	e0212	100	1/1	100	1/1
99.06	e0105	100	6/6	100	6/6	82.35	e0213	50	2/4	100	2/2
99.42	e0106	90	9/10	100	9/9	96.32	e0302	100	10/10	100	10/10
80.44	e0107	60	3/5	42.86	3/7	97.6	e0303	100	2/2	100	2/2
98.54	e0108	100	15/15	100	15/15	98.72	e0304	100	7/7	100	7/7
93.72	e0110	33.33	1/3	100	1/1	94.18	e0305	100	1/1	100	1/1
96.4	e0111	100	6/6	100	6/6	92.83	e0306	25	1/4	16.67	1/6
95.42	e0112	100	7/7	70	7/10	99.44	e0403	100	17/17	94.44	17/18
90.44	e0113	83.33	10/12	100	10/10	98.75	e0404	100	3/3	100	3/3
98.04	e0114	100	15/15	100	15/15	96.76	e0405	100	6/6	100	6/6
83.5	e0115	92.31	12/13	100	12/12	85.64	e0406	100	2/2	50	2/4
92.35	e0116	66.67	2/3	50	2/4	97.43	e0408	100	1/1	50	1/2
80.82	e0118	100	7/7	63.64	7/11	99.53	e0409	100	2/2	100	2/2
78.73	e0119	100	9/9	75	9/12	96.53	e0410	50	1/2	100	1/1
89.19	e0121	100	3/3	60	3/5	95.68	e0411	71.43	5/7	41.67	5/12
98.97	e0122	100	1/1	7.69	1/13	99.78	e0413	100	4/4	40	4/10
98.92	e0123	100	3/3	100	3/3	74.08	e0415	100	9/9	100	9/9
92.64	e0124	88.89	8/9	100	8/8	100	e0417	100	4/4	100	4/4
97.14	e0125	100	4/4	66.67	4/6	99.35	e0418	85	17/20	94.44	17/18
97.04	e0126	80	4/5	44.44	4/9	92.22	e0501	100	3/3	100	3/3
94.65	e0127	100	8/8	88.89	8/9	98.22	e0509	100	2/2	100	2/2
95.07	e0129	100	12/12	100	12/12	83.35	e0515	85.71	6/7	85.71	6/7
78.06	e0133	100	1/1	100	1/1	89.31	e0601	50	2/4	16.67	2/12
94.18	e0136	100	8/8	100	8/8	97.4	e0602	100	11/11	68.75	11/16
86.89	e0139	100	2/2	11.76	2/17	99.96	e0603	100	3/3	100	3/3
96.22	e0147	100	5/5	100	5/5	94.9	e0604	55.56	5/9	41.67	5/12
0.18	e0148	100	18/18	90	18/20	99.36	e0605	100	1/1	33.33	1/3
93.46	e0151	94.12	16/17	100	16/16	97.44	e0606	100	5/5	83.33	5/6
94.26	e0154	100	11/11	100	11/11	88.5	e0607	100	9/9	100	9/9
52.49	e0155	100	5/5	100	5/5	97.1	e0609	100	3/3	100	3/3
51.53	e0159	100	2/2	100	2/2	97.85	e0610	100	5/5	100	5/5
92.92	e0161	100	4/4	26.67	4/15	88.74	e0611	100	5/5	100	5/5
91.68	e0162	100	2/2	66.67	2/3	75.68	e0612	100	4/4	50	4/8
94.68	e0163	100	5/5	38.46	5/13	60.26	e0613	100	5/5	100	5/5
98	e0166	100	12/12	80	12/15	85.81	e0614	100	7/7	100	7/7
71.71	e0170	0	0/1	0	0/5	93.38	e0615	100	8/8	100	8/8
93.58	e0202	100	9/9	64.29	9/14	94.86	e0704	100	7/7	100	7/7
98.94	e0203	100	9/9	100	9/9	75.96	e0801	0	0/4		
95.39	e0204	0	0/2	0	0/3	36.9	e0808	100	14/14	100	14/14
85.63	e0205	100	4/4	40	4/10	43.78	e0817	100	16/16	100	16/16
97.89	e0206	100	9/9	100	9/9	77.94	e0818	100	14/14	100	14/14
98.06	e0207	100	4/4	100	4/4	98.89	e1301	100	4/4	100	4/4
92.89	e0208	100	9/9	100	9/9	94.28	e1302	100	15/15	100	15/15
95.25	e0210	100	3/3	75	3/4	97.07	e1304	100	1/1	100	1/1

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