A KNOWLEDGE-BASED TECHNIQUE FOR AUTOMATED DETECTION OF ISCHEMIC EPISODES IN LONG DURATION ECGs

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A Knowledge-Based Technique for Automated Detection of Ischemic Episodes in Long Duration ECGs

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Abstract–A novel method for the detection of ischemic episodes in long duration ECGs is proposed. It includes noise handling, feature extraction, rule-based beat classification, sliding window classification and ischemic 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. We tested the method on the ESC ST-T database and high scores were obtained for both sensitivity and positive predictivity (93.75% and 78.50% respectively).

Keywords–Ischemic Episodes Detection, Knowledge–Based Method, ECG Noise Handling.

1 Introduction

ISCHEMIA IS the most common cardiac disease (CAIRNS *et al.*, 1991; BADILINI *et al.*, 1992; SILIPO *et al.*, 1994), and its early diagnosis is very important. Several techniques that automate the detection and diagnosis of ischemic 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 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 some 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 ischemic beat is detected. SILIPO *et al.* (1994) used such rules in ischemic episode detection. Similar rules were adopted by AKSELROD *et al.* (1987), which could reach decisions for subclasses of ischemic beats and by SHOOK *et al.* (1989), but with feature values averaged on a 30 seconds window. CAIRNS *et al.* (1991) and LAKS *et al.* (1989) introduced a relation which has as input parameters the age, sex, chest or left arm pain, Q wave amplitude, ST elevation and depression and T inversion, and as output the ischemia probability. BADILINI *et al.* (1992), used ST segment frequency characteristics for ischemic episodes detection.

Another class of techniques for ischemia detection is based on artificial neural networks (ANN). BAXT (1991) proposed a four-layer ANN trained by back-propagation for ischemic 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 with input the raw signal corresponding to the ST segment. In another work (STAMKOPOULOS *et al.*, 1998), they used non-linear principal component analysis for ischemic beat classification. SILIPO *et al.* (1994) adopted the 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 ischemic patient identification. As input layer they used 40 nodes, 5 ECG characteristic values (Q, R, S and T waves amplitudes and ST deviation) for each one of the 8 leads (I, II and $V_{1\text{-}6}$). SILIPO and MARCHESI (1998) compare various approaches for ischemia detection based on ANNs: static ANNs, static ANNs combined with principal component analysis, recurrent ANNs and knowledge-learning networks.

There are also ischemia detection techniques based upon different principles. 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.

Currently we propose a knowledge – based approach to detect ischemic episodes in long duration ECGs. The method is based on a four – stages schema. The first is used for noise handling, artefact characterisation and extraction of ECG features. The second stage is beat classification (ischemic 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 (ischemic or not). The fourth stage identifies and merges the sequences of ischemic windows detecting the ischemic 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 our approach is that we explicitly deal with noise problems. We propose a noise handling procedure (applied in the pre-processing stage) that enables efficient treatment of most types of noise appearing in ECG recordings. Moreover, for ischemic beat classification, we use medical knowledge 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. We also introduce the notion of ischemic window, which is a time window containing mostly (to allow tolerance in the decision) ischemic beats. Also the method exhibits flexibility in the definition of an ischemic episode as a sequence of ischemic 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 is capable of providing explanations for each decision made in 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 predictivity.

2 Method

We developed a four-stage procedure for ischemic episodes detection shown in Fig. 1. The four stages correspond to ECG processing and analysis, beat classification, window classification and identification of ischemic episodes duration. In the first stage the pre-processing of 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 (ischemic) or artefact. This information is used in the third stage (the window characterisation stage) where each 30-second ECG window is classified as ischemic or not. In the fourth stage the identification of start and end points of each ischemic episode is performed based on the concatenation of consecutive ischemic windows. We note that the whole procedure described above is applied in each lead separately. At the last stage, also, a merging procedure is followed to identify the overall ischemic episodes from the episodes detected in each available lead.

2.1 *ECG Signal Processing and Analysis*

At this stage we detect the beginning of the ST segment (J point) and the peak of the T wave. We start with the detection of a point in the QRS complex (QRS point) for each beat using the algorithm by HAMILTON and TOMPKINS (1986). To make this algorithm faster we have made some modifications. More specifically, after the detection of a QRS complex we ignore the next 300 msec. 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) 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 msec, QRS + 120 msec] by locating the point with maximum signal absolute 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 msec, QRS – 80 msec], 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. We use it 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 msec, RP– 40 msec] and searches for an interval of 20 msec with signal slope (C_s) less than or equal to 2.5 μV/msec. The original algorithm (DASKALOV *et al.*, 1998) uses a slope criterion of $C_s \leq 5$ μV/msec, but we obtained better results by using a stricter threshold of 2.5 μV/msec. The same algorithm is applied to the window [RP + 20 msec, RP +120 msec] to locate the J point.

In the case that all the above stages have been completed successfully, our algorithm continues in order to locate the peak of the T wave. In the opposite case the current beat is classified as artefact and the procedure starts over again with the next beat. We locate the point T_{onset} at J80 + 0.0375* R-R, where J80 = J + 80 msec and R-R is the time interval between the current RP and the previous one. We search for the peak of the T wave on the window [T_{onset}, T_{onset} + 200 msec], which is defined as the point with maximum difference in amplitude with respect to the J80 point.

2.1.1 *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 described method several problems will occur. The presence of noise (top row in Fig. 2), such as the 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.

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

For each cardiac cycle, we consider a time interval that starts 60 msec before the P wave and ends 60 msec after the T wave. Let $x(t)$, $t = 1,2,...,N$ be the recorded ECG signal. Using a least squares procedure we can estimate the polynomial $\hat{x}(t)$ that best fits $x(t)$:

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

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

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

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 we 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 $t = t_1,...,t_2$. 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:

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

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 our 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 msec, RP – 60 msec]. We use a moving averaging window of 20 msec in the interval [RP + 20 msec, RP + 120 msec] to obtain the signal $g(t)$. The J point is detected using the DASKALOV *et al.* (1998) algorithm on the signal $g(t)$.

Fig. 2 clearly illustrates the improvement of the described 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 every day medical practice when a cardiologist uses a long-term ECG to diagnose ischemia, he examines two features 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 (Fig. 3) classifies the beat as ischemic 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 msec) when the cardiac rhythm is less than 120 beats/min or at the point J60 (J + 60 msec) 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 (Fig. 4) 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 characterized as ischemic. The third rule (Fig. 5) refers to the T wave inversion or flattening, *eg*: if at the initial beats of the ECG recording the T wave has positive (negative) voltage (we use the first 30 seconds to extract the polarity) then all beats with

negative (positive) T wave voltage are classified as ischemic – also, beats with T waves of very low voltage, compared to the T waves voltage of the initial beats, are classified as ischemic.

It must be noted that this method for 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 ischemic 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.

The beat classification method is summarised below:

Detection of ischemic beats

IF	(J80 (or J60) $\leq$ 0.08 AND slope $\geq 65^{\circ}$)	**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 ischemic		
ELSE	The beat is normal		

2.3 *Window Classification*

Once every beat in each lead has been classified as ischemic or normal, the next stage is to decide whether a sequence of beats belongs to an ischemic window. According to ESC recommendations (TADDEI *et al.*, 1988), an ischemic episode is defined as a time period of no less than 30 seconds containing ischemic beats. For this reason we have implemented a sliding adaptive window that examines whether there exists a sequence of ischemic beats lasting more than 30 seconds. The window is classified as ischemic if the same rule is valid for all ischemic beats in the window. If

for example, there exist 15 seconds with positive ST deviation which are followed by 15 seconds with T inversion, the window is not ischemic. The first window of the recording includes the initial 30 seconds 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 seconds. 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 ischemic beats appearing in a window. If a window has more than 75% of ischemic beats, we consider that it belongs to an ischemic episode. This percentage threshold is applied to avoid situations in probable ischemic intervals where noise deteriorates the reliability of the feature extraction or to handle cases where some beats in the window are close to be characterized as ischemic but are not triggering any of the rules we use.

The sliding window classification algorithm is summarised below:

Detection of ischemic windows

IF [(number of ischemic beats from rule k) / (all beats)] ≥ 0.75

THEN Window$_{[k]}$ is ischemic

ELSE Window$_{[k]}$ is normal

(where $k = 1, 2, 3$)

2.4 *Identification of Ischemic Episodes*

If a series of consecutive ischemic windows is identified then the left boundary of the ischemic episode corresponds to the beginning of the first window in the series and the right boundary to the end of the last window. However, in order to increase the flexibility of our algorithm, the existence of time intervals of less than 30 seconds with beats that do not constitute an ischemic

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 identification of ischemic episodes algorithm is summarised below:

Definition of ischemic episodes in each lead

IF $\text{Window}^{j}_{[k]}$ is ischemic

THEN Start of Ischemic Episode^{i} = Start of $\text{Window}^{j}_{[k]}$

WHILE $\text{Window}^{j}_{[k]}$ is ischemic **OR**

(End of $\text{Window}^{j}_{[k]}$ – End of Ischemic episode^{i}) < 30 sec

DO

IF $\text{Window}^{j}_{[k]}$ belongs to an ischemic area

THEN End of Ischemic Episode^{i} = End of $\text{Window}^{j}_{[k]}$

ENDDO

(where $k = 1, 2, 3$

$i = 1, 2, \ldots,$ number of ischemic episodes in each lead and

$j = 1, 2, \ldots,$ number of windows)

The complete flow – chart of our method is shown in Fig. 6.

3 Results and Discussion

We tested the proposed method using the European ST-T database. This database contains ECG recordings with annotated ischemic episodes. To evaluate the performance of our method we use

two common measures for ischemia detectors (JAGER, 1998). The first is the sensitivity (Se), which measures the ability in detecting ischemic episodes, and the second is the positive predictivity (PPA), which gives an estimation of how well ischemic and non-ischemic episodes are differentiated.

Following the description of our method the main parameters are:

- Ischemic ST deviation (≥ 0.08 mm)
- Ischemic ST slope ($\geq 65°$)
- Percentage of ischemic episodes in a window in order to characterise it as ischemic (≥ 75 %)
- Window duration (= 30 sec)
- Maximum time interval to differentiate two consecutive ischemic windows (= 30 sec).

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

- The time at the beginning of each ECG used to extract the T wave polarity (= 30 sec)
- The maximum allowed time interval between two consecutive ischemic episodes in order to merge them to one (= 30 sec)
- The minimum number of non-artefact beats in a window to proceed with the window characterisation (= 10 beats)
- The slope criterion in detecting the J-point [30] (≤ 2.5 μV/msec).

We tested the performance of our technique using different parameter values. The performance of our method is mainly affected by the main parameters. The best results were obtained for the values indicated in the parentheses above.

From the episodes in the ESC ST-T database we excluded those annotated ischemic episodes that refer to alterations of more than 0.2 mV between the T wave amplitudes, since our medical experts disagreed with this rule (ROWLANDS, 1982; GOLDMAN, 1982). Moreover, the ischemic episodes were annotated separately for each lead and we performed a pre-processing in order to

obtain an overall annotation (lead independent) of the ischemic episodes. We also found that in some cases our method produced ischemic episodes, mainly short in duration, that were not annotated as ischemic in the database. We consulted three cardiologists who evaluated those episodes and their evaluation was taken into account in the assessment of our method. This is not unusual, as similar practice has been reported previously of the proposed method (TADDEI *et al.*, 1995; VILA *et al.*, 1997).

Using the 90 ECG recordings (592 ischemic episodes) the obtained sensitivity is 93.75% and the positive predictivity 78.50%. The 90 ECG recordings can be separated in two groups (A and B) based on the amount of noise. Group A (64 recordings) contains the ECGs with at most 10% of noisy beats, the amount of noisy beats ranges from 0.67% to 9.56%, while group B the remaining recordings, where the amount of noisy beats ranges from 10.69% to 99.82% (see Table 1). The noise information is provided by the ESC ST-T database.

The performance of our method on clean (Group A) and noisy (Group B) recordings is shown in Table 2, while the results per recording are given in the Appendix.

As Table 2 indicates, our method provides good detection results concerning both sensitivity and positive predictivity. It is worth mentioning that the sensitivity is not essentially influenced by the presence of noise. This indicates the efficiency of the employed noise handling method. Our findings compared with other researchers results 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 of the works refer to a subset of ECG recordings of the database (JAGER *et al.*, 1992; STAMKOPOULOS *et al.*, 1992; SILIPO *et al.*, 1994; TADDEI *et al.*, 1995; VILA *et al.*, 1997; STAMKOPOULOS *et al.*, 1998; SILIPO and MARCHESI, 1998). Also, it is 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 inability constitutes a serious disadvantage from the user's (doctor's) point of view, which expects from the decision system to supply him with 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). On the contrary, 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 ischemic episode, the reason (rule) that led to that decision. Also, our method exhibits additional desirable features, since it is simple, easily implemented and fast. The last feature is of particular importance, because the proposed method can operate in real-time mode providing on line decision support to the medical personnel.

The set of rules we use for beat characterisation is based on the modern understanding of ECGs (ROWLANDS, 1982; GOLDMAN, 1982). We include rules based on T inversion or flattening and ST slope from the vertical. We use T inversion in a novel way compared to others (AKSELROD *et al.*, 1987; LAKS *et al.*, 1989; CAIRNS *et al.*, 1991; BAXT, 1991; BADILINI *et al.*, 1992; OUYANG *et al.*, 1997), but we cannot assess their method since they use their own datasets.

The performance of our method can be further improved in terms of positive predictivity by further refinement of the noise handling procedure. We noticed that we had difficulties in recordings with very low SNR in the J point, the isoelectric line and T peak detection. In the last case severe problems will occur when incorrect T peak detection happens 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. The exclusion of those ten recordings leads to a significant improvement of the PPA (Se: 95.32% and PPA: 87.31%). It must be noted that modern ECG recorders and Holter devices include filtering modules so the output ECG signal has better SNR than the signals contained in the database. It is obvious that our method will perform better with such equipment.

4 Conclusions and Future Work

We have proposed a novel technique for the detection of ischemic episodes in long duration ECGs, which has shown good diagnostic performance in the ESC ST – T database. This is due to several characteristics of the method such as: effective noise handling, beat classification using up-to-date medical knowledge and flexibility in the definition of ischemic windows and ischemic episodes. The method exhibits desirable features, since it is simple, easily implemented and can be executed in real time. Also, the method is capable of providing explanations for the diagnostic decision made. The performance of our method compares well with previous 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. We are also highly interested in transferring the method to the clinical practice and evaluate its performance in real conditions. Furthermore, we are in the process of developing a hybrid intelligent system that appropriately combines the proposed method with artificial neural networks to enhance diagnostic reliability.

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Appendix

Performance of our 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	½	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

Table 1 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 2 Overall performance of our technique for "clean" and noisy ECGs

	Se		PPA	
	%	Episodes	%	episodes
Clean	94.26	394/418	80.74	394/488
Noisy	92.53	161/174	73.52	161/219
TOTAL	93.75	555/592	78.50	555/707

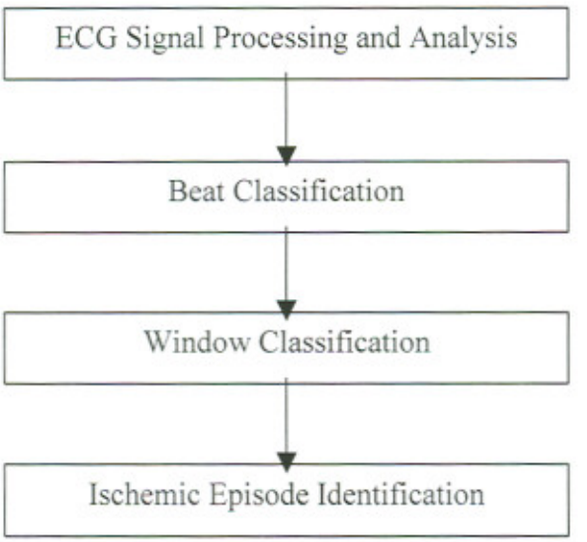
ECG Signal Processing and Analysis
Beat Classification
Window Classification
Ischemic Episode Identification

Fig. 1

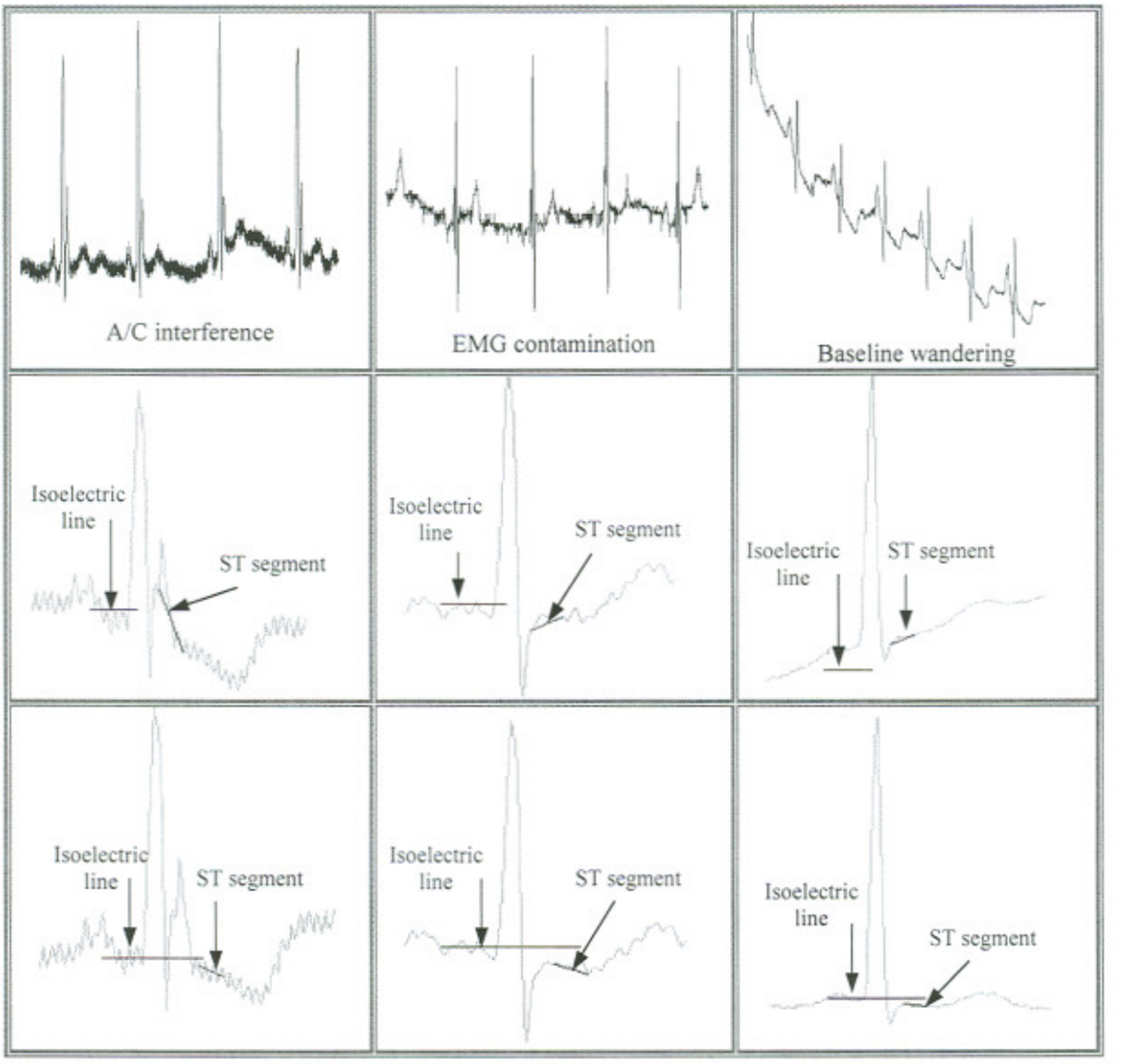
A/C interference
EMG contamination
Baseline wandering
Isoelectric line
ST segment
Isoelectric line
ST segment
Isoelectric line
ST segment
Isoelectric line
ST segment
Isoelectric line
ST segment
Isoelectric line
ST segment

Fig. 2

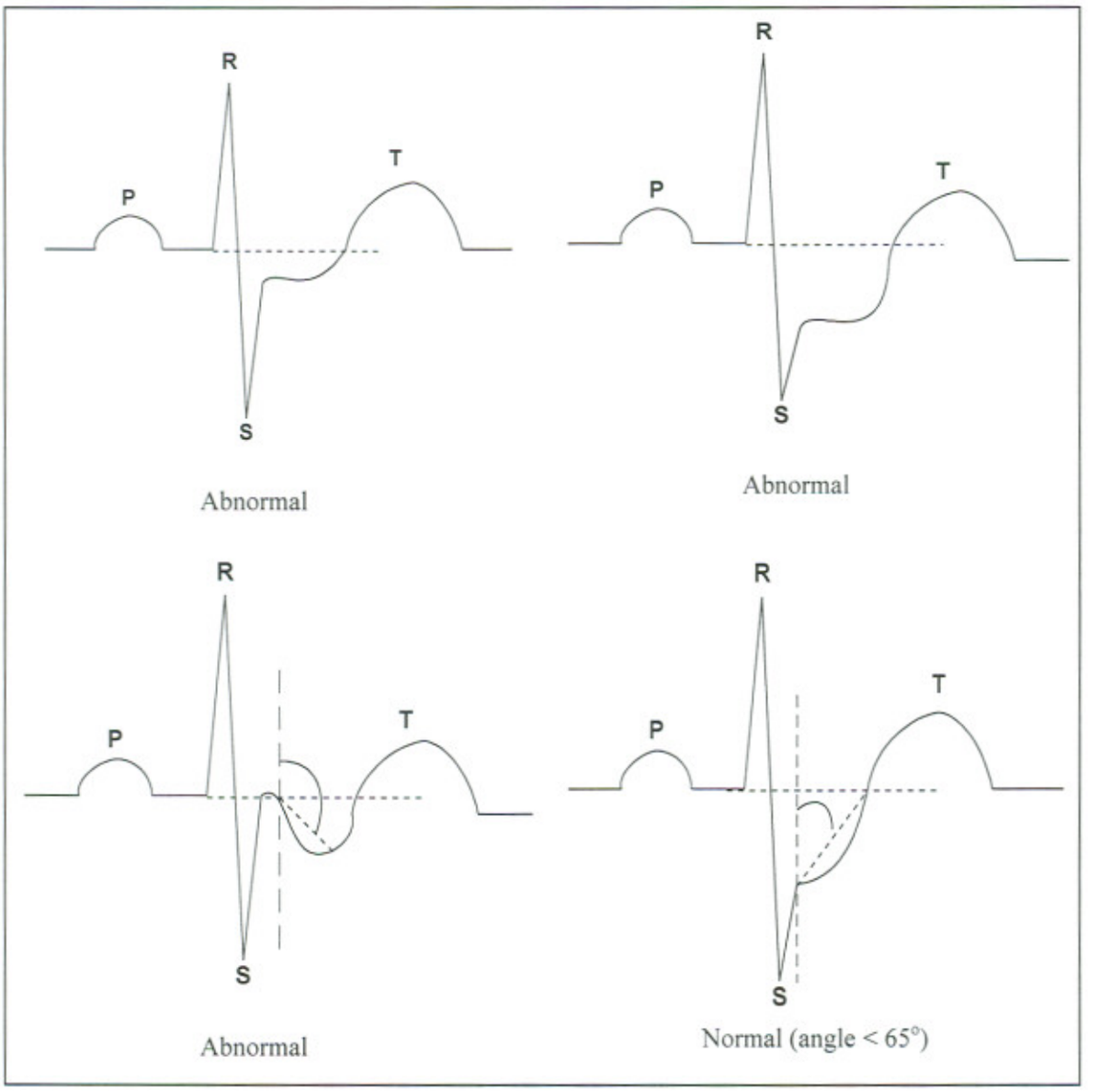
R
P
T
S
Abnormal
R
P
T
S
Abnormal
R
P
T
S
Abnormal
R
P
T
S
Normal (angle < 65°)

Fig. 3

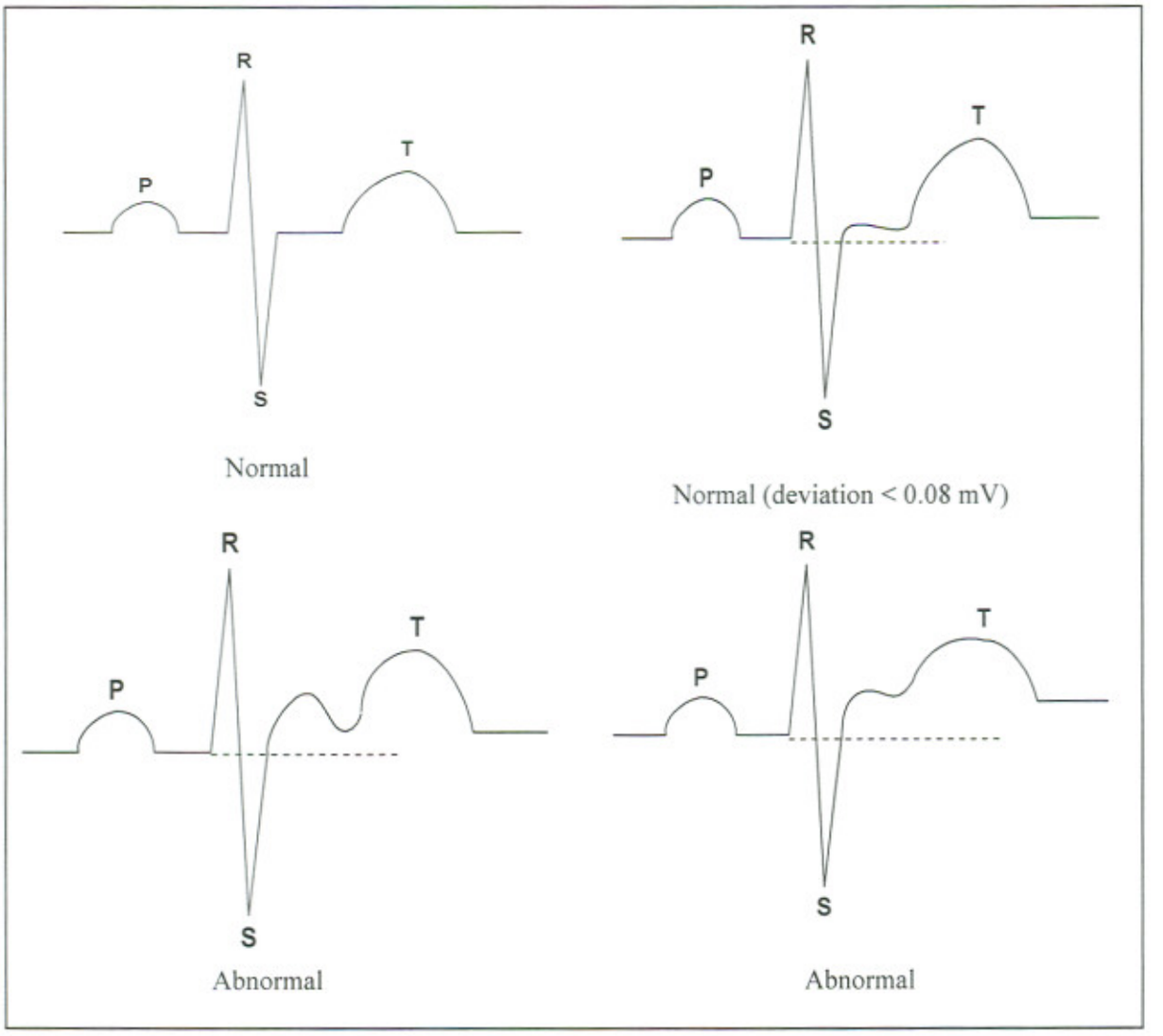
R
P
T
S
Normal
R
P
T
S
Normal (deviation < 0.08 mV)
R
P
T
S
Abnormal
R
P
T
S
Abnormal

Fig. 4

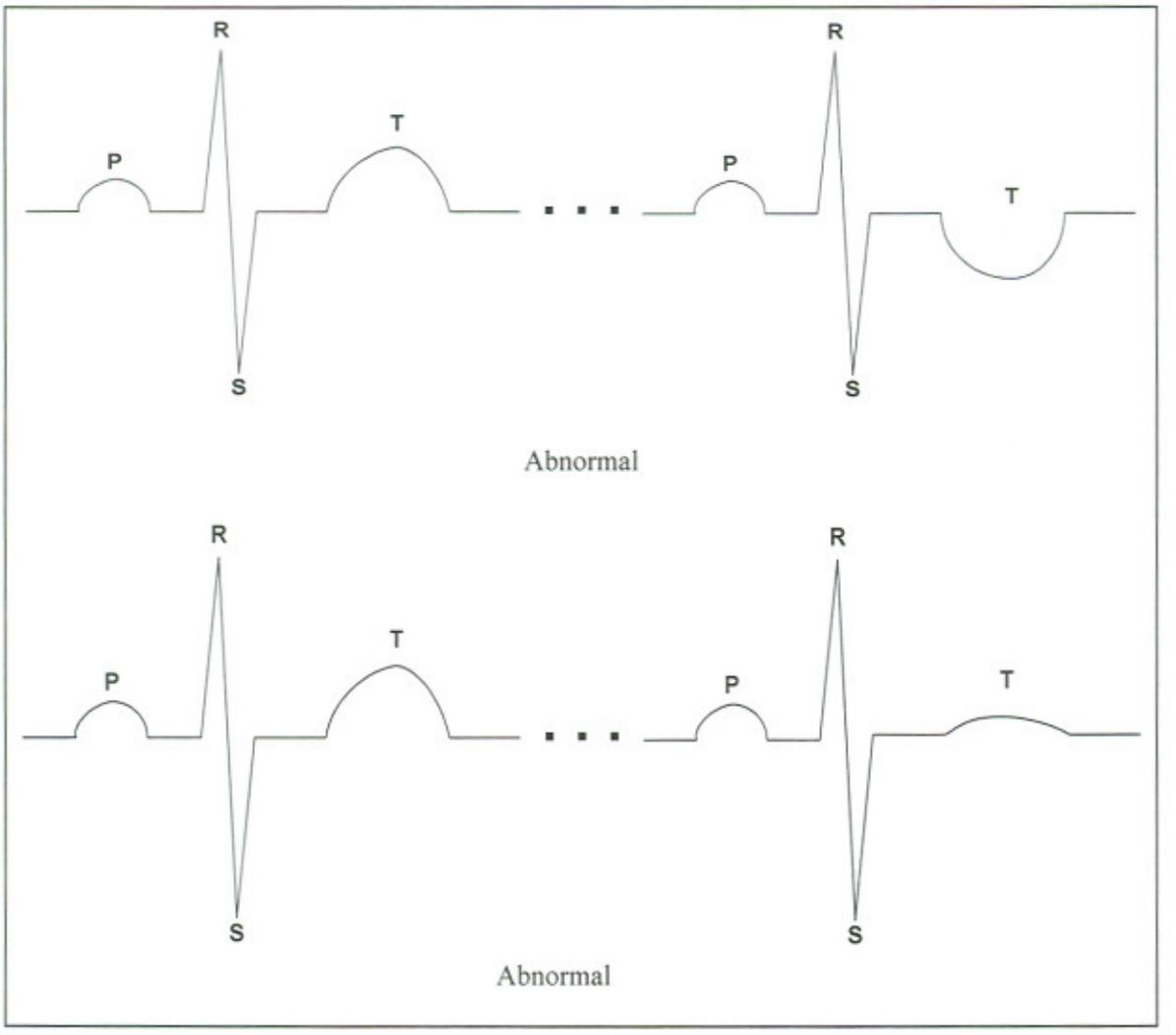

Fig. 5

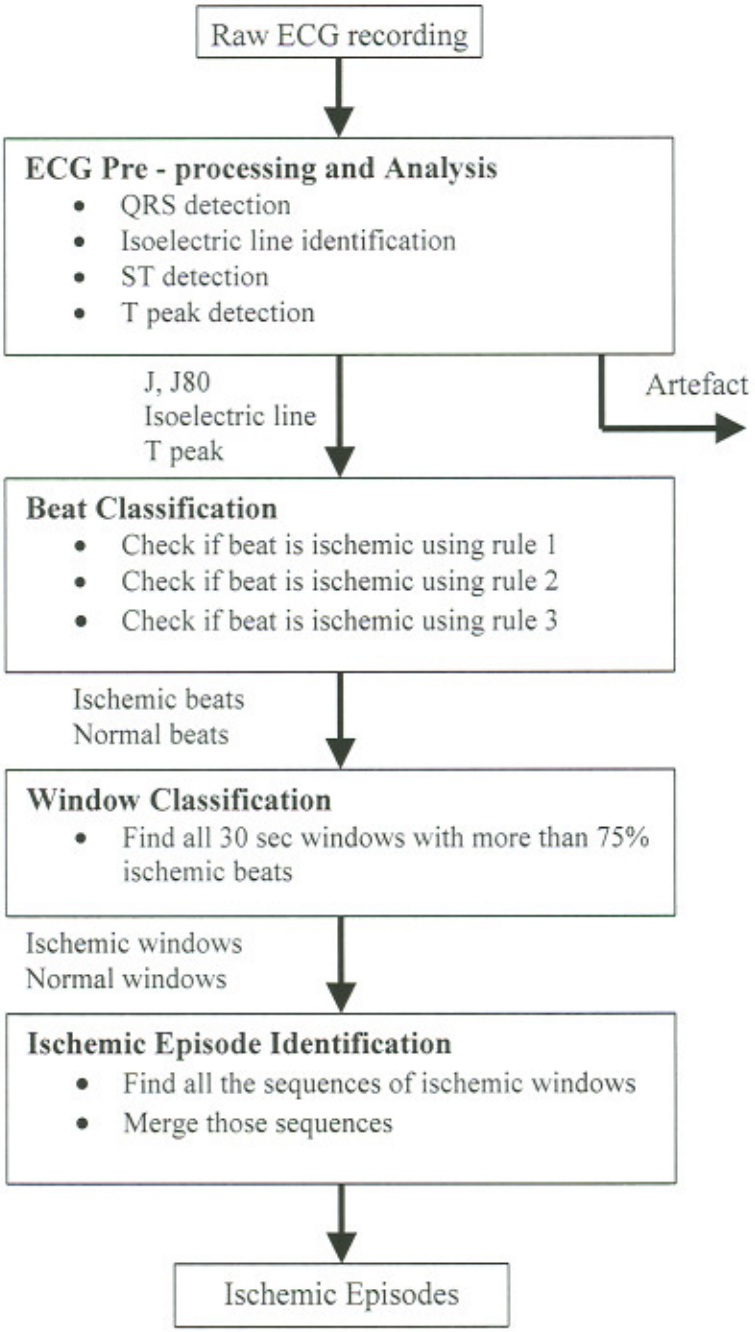
Raw ECG recording
ECG Pre - processing and Analysis
QRS detection
Isoelectric line identification
ST detection
T peak detection
J, J80
Isoelectric line
T peak
Artefact
Beat Classification
Check if beat is ischemic using rule 1
Check if beat is ischemic using rule 2
Check if beat is ischemic using rule 3
Ischemic beats
Normal beats
Window Classification
Find all 30 sec windows with more than 75% ischemic beats
Ischemic windows
Normal windows
Ischemic Episode Identification
Find all the sequences of ischemic windows
Merge those sequences
Ischemic Episodes

Fig. 6