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Detection of ST segment deviation episodes in ECG using KLT with an ensemble neural classifier

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Abstract
In this paper, we describe a technique for automatic detection of ST segment deviations that can be used in the diagnosis of coronary heart disease (CHD) using ambulatory electrocardiogram (ECG) recordings. Preprocessing is carried out prior to the extraction of the ST segment which involves noise and artifact filtering using a digital bandpass filter, baseline removal and application of a discrete wavelet transform (DWT) based technique for detection and delineation of the QRS complex in ECG. Lead-dependent Karhunen–Loève transform (KLT) bases are used for dimensionality reduction of the ST segment data. ST deviation episodes are detected by a classifier ensemble comprising backpropagation neural networks. Results obtained through the use of our proposed method (sensitivity/positive predictive value = 90.75%/89.2%) compare well with those given in the existing research. Hence, the proposed method exhibits the potential to be adopted in the design of a practical ischemia detection system.

Keywords: ECG, myocardial ischemia, Karhunen–Loève transform (KLT), neural networks, classifier ensemble

(Some figures in this article are in colour only in the electronic version)

1. Introduction

Heart disease is one of the leading causes of death all over the world with myocardial ischemia and infarction (collectively called coronary heart disease or CHD) being the most common among these cardiac disorders. Myocardial ischemia and infarction stem from the insufficient supply of blood to the heart muscle (myocardium) due to blockages in the coronary artery, which is responsible for providing blood to the heart. The development of plaque within the coronary artery that blocks more than 70% of the lumen of the vessel can cause symptoms of myocardial ischemia, such as decreased exercise tolerance and exertional angina, to appear. At times, this may be the first instance where the subject begins to experience effects of the suboptimal operation of the heart due to decreased blood supply. As large areas of the heart muscle become ischemic, its relaxation and contraction patterns are affected, which cause variations in the ST level and T-wave in electrocardiogram (ECG) due to the development of an injury current (Gettes and Cascio 1991) between the ischemic and non-ischemic regions of the heart. If the blood supply to the heart muscle is restored, myocardial ischemia can be reversed, thus making the early and correct diagnosis of myocardial ischemia an imperative task. Myocardial infarction, however, is not reversible and represents the death of heart muscle due to prolonged lack of blood supply to the heart.

CHD causes the elevation or depression of the normally isoelectric ST level and variations of the T-wave in ECG and thus makes the use of ECG one of the easiest, least costly, reliable and most readily available forms of diagnostic test for the detection of CHD. Automatic detection of CHD with ECG using machine learning techniques is one of the leading areas of research in the field of biomedical engineering through artificial intelligence. A large number of techniques exist in the literature for the automatic detection of myocardial ischemia through the identification of ST deviations and T-wave variations in ECG. These include the use of time-domain approaches (Garcia *et al* 2000, Taddei *et al* 1995), artificial neural networks (Maglaveras *et al* 1998, Frenkel and Nadal 1999), principal component analysis (PCA) (Stamkopoulos *et al* 1998, Tasoulis *et al* 2004), wavelet transform (Senhadji *et al* 1995) and fuzzy and neuro-fuzzy systems (Exarchos *et al* 2007b, Pang *et al* 2005). Ischemia detection methods detect either individual ischemic beats or ischemic episodes. The performance of ischemic beat detectors is given by the classification accuracy, whereas the latter methods use sensitivity and positive predictive values (PPV) for presenting the accuracy of episode detection.

Maglaveras *et al* (1998) have presented a three-layer adaptive backpropagation neural network for detection of ischemic episodes and achieve a sensitivity/PPV of 88.62%/78.38% for episode detection using average statistics and 85%/68.69% using gross statistics of the European Society of Cardiology Database (ESC-ST-T DB) (Taddei *et al* 1992). The neural network proposed operates on an estimate of the deviation of the baseline-corrected ST segment that starts 40 ms after the R-peak with a duration of 160 ms which is down-sampled by a factor of 2 for further processing as a means of dimensionality reduction. Jager *et al* (1998) have presented a technique based on lead-independent Karhunen–Loève transform (KLT) components for the detection of ST segment episodes with a sensitivity/PPV of 87.1%/87.7% (average), 85.2%/86.2% (gross) over the ESC-ST-T DB. Principal component bases are obtained by first dividing the input database into a number of pattern classes and then applying KLT regardless of the lead to which the input signal belongs. Frenkel and Nadal (1999) have proposed an artificial neural network based approach for ST-T segment classification with a sensitivity/PPV of 84.15%/72.63%. Garcia *et al* (2000) have proposed a method which applies a detection algorithm to the filtered root mean square (RMS) series of differences between the beat segment (ST segment or ST-T complex) and an average pattern segment. This method gives a (average) sensitivity/PPV of 85%/86% and 85%/76%, for ST segment deviations and ST-T complex changes respectively over the ESC-ST-T DB. Papaloukas *et al* (2002a) have proposed a technique for the detection of myocardial ischemia with a neural network trained using Bayesian regularization. They used a 400 ms long estimate of the ST segment. Five lead-independent principal components of the ST segment estimates are obtained for the entire database for dimensionality reduction. This method gives a sensitivity/PPV of 90%/89% for aggregate gross statistics and 86%/87% for average statistics using the ESC-ST-T DB. Bezeianos *et al* (2000) proposed a network self-organizing map (NetSOM) model for the detection of ST-T episodes. The sensitivity/PPV of ischemic beats for this method over the ESC-ST-T DB is given as 77.7%/74.1%. Papadimitriou *et al* (2001) have reported an episode detection sensitivity/PPV of 82.8%/82.4% over the ESC-ST-T DB with a self-organizing map and support vector machines employing a radial basis function kernel. Papaloukas *et al* (2002b) have presented a rule-based approach for ST segment and T-wave abnormality detection using the J + 60/80 ms (dependent upon the heart rate) point as an estimate of the ST segment and application of a set of rules over the slope and level of the ST segment and T-wave, followed by window characterization for episode detection. The accuracies presented in the paper in terms of sensitivity/PPV for ST segment deviation and T-wave episode detection are 92.02%/93.77% and 91.09%/80.09% on the ESC-ST-T DB respectively. Zimmerman *et al* (2003) have proposed a reconstructed phase-space approach for distinguishing ischemic from non-ischemic ST changes through Gaussian mixture models. The sensitivity/specificity of this method is given as 81%/88.1% over the Long-Term ST Database (LTST DB) (Jager 2000). Langley *et al* (2003) have employed ST segment deviations and their principal components for detection of ischemic beats. The sensitivity/specificity of this technique is given as 99%/88.8% with an accuracy of 91.1% over the LTST DB. Smrdel and Jager (2004) have used ST deviation time series for the detection of ST episodes. Sensitivity/PPV of this method over the ESC-ST-T DB is 81.3%/89.2%. An ischemia detection method using genetic algorithms and multi-criterion decision analysis has been proposed by Goletsis *et al* (2004). This method uses ST deviation defined at the J + 60/80 ms point, ST segment slope, T-wave amplitude, T-wave normal amplitude and polarity along with age. The sensitivity/specificity of this algorithm for ischemic beat classification over the ESC-ST-T DB is 91%/91%. A technique using nonlinear PCA and neural networks for ischemia detection was proposed by Stamkopoulos *et al* (1998) giving a correct classification rate of approximately 80% for the normal beats and higher than 90% for the ischemic beats for ST segment deviations on the ESC-ST-T DB.

Another method using PCA and artificial neural networks for episode detection has been proposed by Tasoulis *et al* (2004) which gives an episode detection accuracy of 80.4% over the ESC-ST-T DB. A hidden Markov model (HMM) based approach is given by Andreao *et al* (2004) with a sensitivity/PPV of 83%/85% over 48 freely available files out of 90 from the ESC-ST-T DB. A real time ischemia detection system is presented by Pang *et al* (2005), which employs a real-time R-peak detector and combined time domain and KLT features along with an adaptive neuro-fuzzy system for classification. This method achieves a sensitivity/PPV of 81.29%/74.65% over the ESC-ST-T DB. A method using decision trees for detection of ischemic beats was proposed by Dranca *et al* (2006) and it has achieved a sensitivity/PPV of 89.89%/70.03% over the LTST DB. Exarchos *et al* (2007a) have proposed a method using a rule mining approach for ischemia detection. This method uses ECG features such as ST segment deviation, slope, area, T-wave deviation (from a normal template) amplitude along with a patient's age. This method then uses specially mined rules for detection of ischemia. The sensitivity/specificity of this method for ischemic beat classification over the ESC-ST-T DB is 87%/93%. Exarchos *et al* (2007b) give a fuzzy expert system based technique for ischemic beat classification that relies on the extraction and application of fuzzy rules and optimization of membership function parameters. The ischemic beat detection accuracy of this method is given by a sensitivity/specificity of 91%/92%.

For the purpose of detection of ST segment deviation episodes, an estimate of the ST segment from the ECG signal can be obtained which can then be subtracted from the isoelectric level for the beat to result in a deviation signal. The ST deviations thus obtained are severely

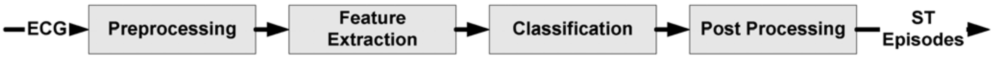

Figure 1. Different stages in ST segment episode detection.

affected by noise, and their use for detection of ST episodes can lead to high intra-class and low inter-class variabilities making the classification task intricate. Another issue is the appearance of the curse of dimensionality (Duda *et al* 2007) in classification stemming from the use of the whole ST deviation signal which contains redundant information. A solution to this problem is to reduce the dimensionality of the ST deviation signal through the PCA (Duda *et al* 2007), also known as the KLT. The KLT can also help minimize the effects of noise since the signal is projected along orthogonal bases obtained as the eigenvectors corresponding to maximal eigenvalues of the covariance matrix for the ST deviation data. The subspace created by these bases (corresponding to maximal eigenvalues) represents the non-noisy component of the ST deviation signal (Kantz and Schreiber 2004). A large amount of training data is required for obtaining a generalized classifier. However, applying the PCA on a large amount of data is computationally not feasible. Therefore, the existing methods using the KLT for the detection of ST episodes usually select a number of representative training patterns through *a priori* clustering as discussed in Jager *et al* (1998). These methods used the same KLT bases for all ECG leads. In this paper, we conjecture that the application of a classical PCA with bases specific to each ECG lead coupled with an ensemble of lead-specific classifiers can give better results in classifying ischemic and non-ischemic ST deviations. The notion of having separate bases for different leads allows data reduction without *a priori* clustering as the training set is divided into lead-specific groups upon which the KLT can directly be applied without *a priori* clustering. Moreover, it opens up an avenue of having lead-specific classifiers which, due to a reduction in the variability of the training data, can offer better generalization.

The rest of the paper is organized as follows. Section 2 describes in detail the proposed technique along with a description of the dataset used for performance evaluation. Section 3 provides the results and discussion.

2. Materials and methods

For performance evaluation of algorithms designed for the detection of CHD using ECG, two standard databases are available through Physionet (Goldberger *et al* 2000), i.e. The European Society of Cardiology Database (ESC-ST-T DB) (Taddei *et al* 1992) and the Long-Term ST-T Database (LTST-T DB) (Jager *et al* 2000). In this work, we have used the ESC-ST-T DB which originally contains two-channel, 2 h recordings for 90 records sampled at 250 Hz with expert annotation of ST deviation and T-wave episodes. However, data for only 48 of these 90 records are available freely and have been used in this research.

Automated ST deviation episode detection is based upon the following major steps (see figure 1).

(i) Preprocessing
(ii) Feature extraction
(iii) Classification
(iv) Post-processing

These steps are explained in detail henceforth.

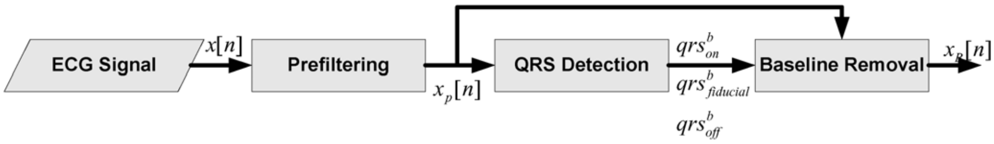

Figure 2. Different stages in preprocessing.

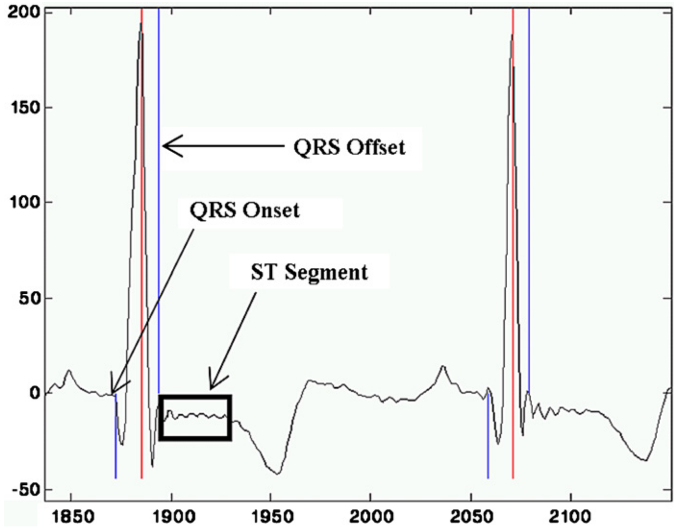

Figure 3. Detection of QRS onsets and offsets and the associated ST segment.

2.1. Preprocessing

Preprocessing involves removal of noise and baseline artifacts from the input ECG signal. It also includes detection of the QRS reference points for the extraction of features for ST segment deviation detection, which appears as the next stage in the system. Here we describe, in detail, the preprocessing stage (see figure 2) for use with the subsequent stages.

A given input ECG signal $x[n]$, $n = 1, \ldots, N$, with a sampling frequency of f_s (250 Hz for the ESC-ST-T DB) belonging to lead l is taken as input and is passed through a pre-filtering stage, which is responsible for the removal of high-frequency noise and minimization of the effects of baseline variation. This is done by passing $x[n]$ through the cascade of a high-pass and a low-pass filter to obtain $x_p[n]$. A sixth-order Butterworth IIR high-pass filter with cutoff frequencies of $f_{\text{pass}} = 0.6$ Hz and $f_{\text{stop}} = 0.4$ Hz for the pass and stop bands respectively is employed through zero-phase (forward–backward) filtering to reduce the effects of baseline variation which lies up to ~0.5 Hz while minimizing distortion in the ST segment. Effects of high-frequency noise are reduced by the use of zero-phase filtering through a 12th-order Butterworth IIR low-pass filter with a cutoff frequency of $f_c = 45$ Hz.

The pre-filtered signal $x_p[n]$ is used for QRS detection using a genetic algorithm optimized wavelet transform based QRS detection and delineation system (Afsar and Arif 2007) that gives a triple $\{qrs^b_{\text{on}}, qrs^b_{\text{fiducial}}, qrs^b_{\text{off}}\}$ (see figure 3) corresponding to the onset, fiducial point and offset for each beat $b = 1, \ldots, N_b$ (number of beats).

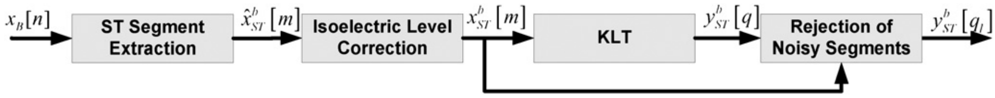

Figure 4. Feature extraction.

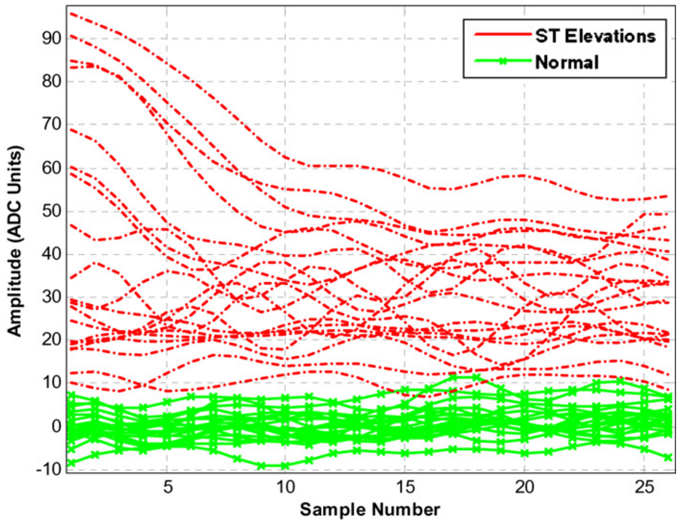

Figure 5. ST segment amplitudes for selected ST elevated and normal beats for MLIII.

The QRS delineation information and the pre-filtered signal $x_p[n]$ are used for baseline removal using a two-stage linear-interpolation-based technique proposed in Papaloukas *et al* (2000) to obtain the baseline-removed signal $x_B[n]$. This baseline removal methodology works in conjunction with the high-pass filter used during pre-filtering to remove baseline variations while introducing minimum distortion in the ST segment. This baseline-removed ECG signal is used in subsequent processing.

2.2. *Feature extraction*

For feature extraction, we have used lead-specific principal component analysis for the detection of ST segment episodes as shown in figure 4.

An estimate of the ST segment, $\hat{x}^b_{\mathrm{ST}}[m]$, $m = 1, \ldots, M$, starting from $\mathrm{QRS}^b_{\mathrm{off}}$ and ending at $\mathrm{QRS}^b_{\mathrm{off}}$ + 100 ms is extracted for each beat b, from the baseline-removed signal. The isoelectric level is then estimated by finding the average value of the flattest 20 ms long region starting 80 ms before $\mathrm{QRS}^b_{\mathrm{on}}$ and ending at $\mathrm{QRS}^b_{\mathrm{on}}$ for each beat. This value for each beat is subtracted from the corresponding $\hat{x}^b_{\mathrm{ST}}[m]$ to obtain a more precise estimate of the true ST deviation $x^b_{\mathrm{ST}}[m]$. These ST segment estimates for a collection of normal and ST-elevated beats are shown in figure 5.

The ST deviation estimate $x^b_{\mathrm{ST}}[m]$ is projected onto lead-specific KLT bases Φ^q_l, $q = 1, \ldots, Q$, where Q is 5, to obtain the principal coefficients $y^b_{\mathrm{ST}}[q]$ corresponding to ST deviation for each beat. These bases are not patient specific as they are obtained by using a training set of ST deviations of the corresponding lead from different patients in the database.

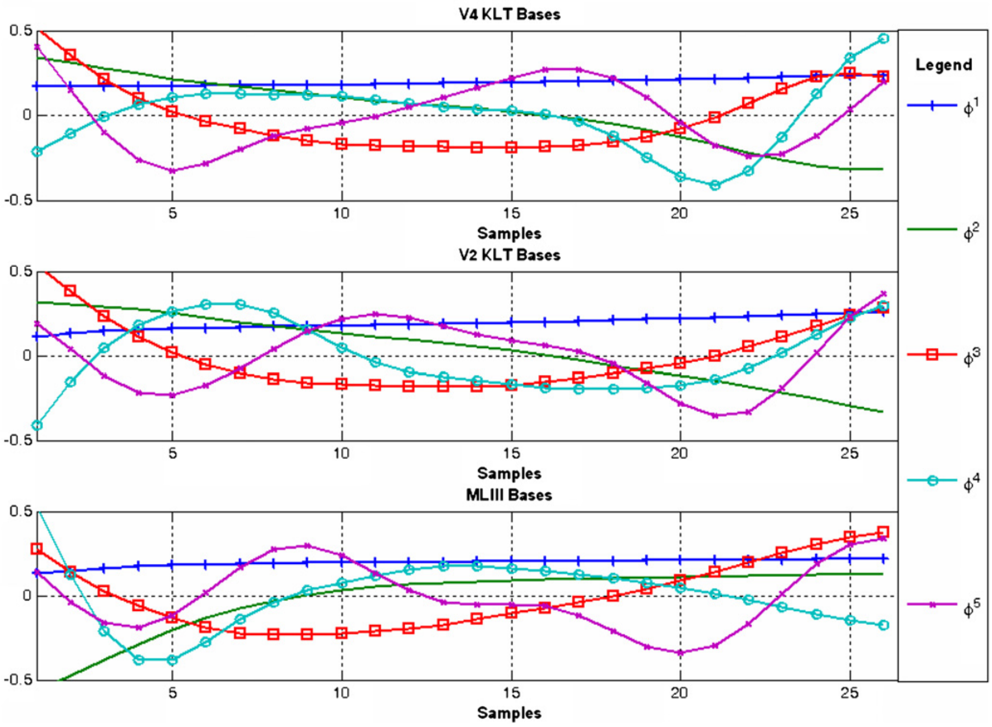

Figure 6. KLT bases for different leads.

Only non-noisy beats are used for the calculation of the lead-specific basis, and for this purpose manual noise level annotations available with the database are utilized. The covariance (or dispersion) matrix R_l formed by these non-noisy beat ST segments is calculated as follows:

$$R_l = \frac{1}{N_t^l} \sum_{n_t=1}^{N_t^l} \left(x_{\mathrm{ST}}^{n_t} - \mu_l\right)\left(x_{\mathrm{ST}}^{n_t} - \mu_l\right)^T, \tag{1}$$

where $N_t^{l_i}$ is the number of ST segments chosen (randomly) from the non-noisy beats for l_i for determining KLT bases and $\mu_{l_i}[m]$ is the mean of these beats given by

$$\mu_{l_i}[m] = \frac{1}{N_t^{l_i}} \sum_{n_t=1}^{N_t^{l_i}} \left(x_{\mathrm{ST}}^{n_t}[m]\right), \qquad m = 1, \ldots, M. \tag{2}$$

The eigenvalues and eigenvectors are obtained by solving the eigenvalue problem:

$$R_l \Phi_l^q = \lambda_l^q \Phi_l^q, \qquad q = 1, \ldots, M. \tag{3}$$

The eigenvalues λ_l^q are sorted in a descending order $\lambda_l^1 \geqslant \lambda_l^2 \geqslant \cdots \geqslant \lambda_l^M$ and eigenvectors corresponding to the top five eigenvalues are selected. These five eigenvectors contribute maximum variance (energy) (Jager 2006a). KLT bases for different leads are shown in figure 6 and they turn out to be different for different leads.

Let Φ_l be the matrix of the eigenvectors as follows:

$$\Phi_l = \begin{bmatrix} \Phi_l^1 & \Phi_l^2 & \cdots & \Phi_l^Q \end{bmatrix}. \tag{4}$$

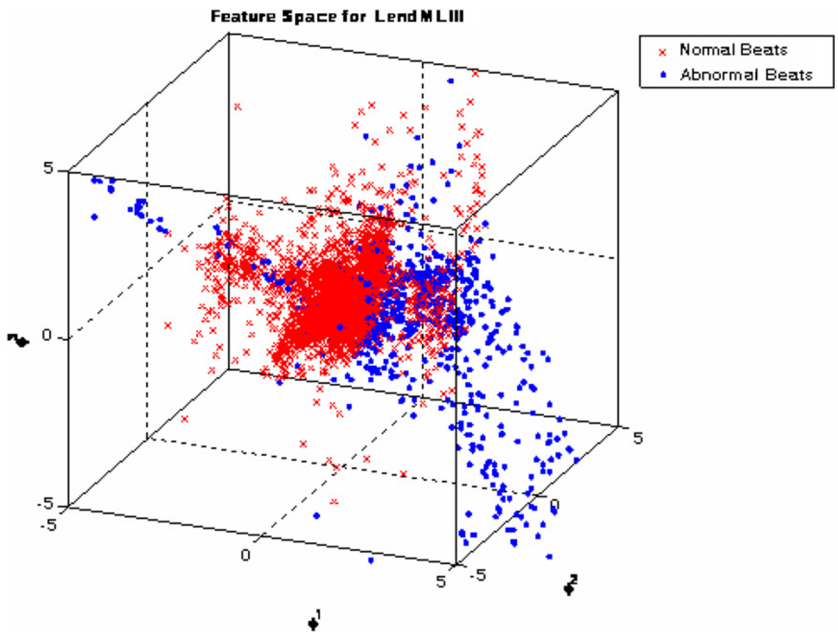

Figure 7. Features space (only three out of five dimensions shown).

This matrix is used to obtain y_{ST}^{b} for each beat as follows:

$$y_{\mathrm{ST}}^{b} = \Phi_{l}^{T}\left(x_{\mathrm{ST}}^{b} - \mu_{l}\right). \tag{5}$$

A scatter plot of these features for normal and elevated ST segment beats is shown in figure 7, which exhibits the discrimination power of these features in distinguishing normal and abnormal beats. The reconstruction of the ST segment deviation of a beat is given by

$$\underline{x}_{\mathrm{ST}}^{b} = \left(\sum_{q=1}^{Q} y_{\mathrm{ST}}^{b}[q]\Phi_{l}^{q}\right) + \mu_{l}. \tag{6}$$

This reconstruction is used to find the normalized reconstruction error as follows:

$$r(b) = \frac{\left\|\underline{x}_{\mathrm{ST}}^{b} - x_{\mathrm{ST}}^{b}\right\|}{x_{\mathrm{ST}}^{b}}. \tag{7}$$

The normalized reconstruction error is used to detect noisy beats. ST segments having $r(b) > 0.3$ are taken as noisy and rejected in further processing (Jager 2006a). The total number of beats rejected on the basis of this criterion during the test phase of the algorithm corresponds to about 7% over all leads.

2.3. Classification

In this method, we have used an ensemble of neural networks with k-fold training and majority voting for classification as shown below (see figure 8).

Non-noisy ST segment deviations $y_{ST}^{b}[q_l]$ $(q_l = 1, \ldots, Q_l)$ with $b = 1, \ldots, N_{\mathrm{nnb}}$ (number of non-noisy beats) and Q_l being the number of principal components used in the classification of ST episodes for lead l are applied at the input of two sets of neural

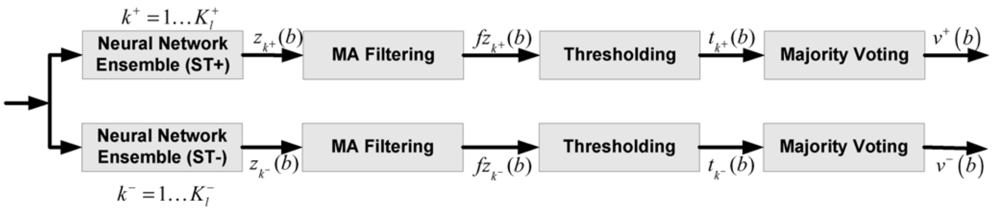

Figure 8. Classification of ST segment episodes using the ensemble of neural networks.

Table 1. Parameters for the classifier used.

l	K_l^+	K_l^-	Q_l	S_l	Θ_l^+	Θ_l^-
MLI	5	5	5	10,12,1	0.65	0.7
MLIII	5	5	5	10,12,1	0.65	0.7
D3	5	0	5	10,12,1	0.725	NA
V1	5	5	5	8,8,1	0.8	0.825
V2	5	5	5	8,8,1	0.8	0.8
V3	0	5	5	8,8,1	NA	0.785
V4	5	5	5	8,8,1	0.8	0.8
V5	7	7	5	10,12,1	0.8	0.725

networks: one each for the detection of ST elevation (ST^+) (having K_l^+ neural networks) and ST depression (ST^-) episodes (having K_l^- neural networks). The output of these neural networks for a beat is given by $z_{k^+}(b), k^+ = 1, \ldots, K_l^+$, and $z_{k^-}(b), k^- = 1, \ldots, K_l^-$. A moving average filter of length $L = 40$ is applied (through zero-phase filtering) to all of $z_{k^+}(b)$ and $z_{k^-}(b)$ separately to obtain $f z_{k^+}(b)$ and $f z_{k^-}(b)$ to introduce temporal linking in the output of the neural networks. Thresholding is then performed on each of $f z_{k^+}(b)$ and $f z_{k^-}(b)$ as follows:

$$t_{k^+}(b) = \begin{cases} 1 & \text{if} \quad f z_{k^+}(b) > \Theta_l^+ \\ 0 & \text{if} \quad f z_{k^+}(b) \leqslant \Theta_l^+, \end{cases} \tag{8}$$

$$t_{k^-}(b) = \begin{cases} 1 & \text{if} \quad f z_{k^-}(b) > \Theta_l^- \\ 0 & \text{if} \quad f z_{k^-}(b) \leqslant \Theta_l^-. \end{cases} \tag{9}$$

Thus, $t_{k^+}(b) = 1$ implies that the neural network classifier number k^+ has conjectured the input ST segment as a (ST^+) segment. $t_{k^+}(b) = 0$ implies that this classifier has classified the input ST segment as a non-elevated ST segment. Similarly, $t_{k^-}(b)$ labels the input ST segment as depressed or non-depressed ST segments. The thresholds Θ_l^+ and Θ_l^- are lead specific and are given in table 1. Majority voting is then used to combine the results of different neural-network-based classifiers for detecting ST elevation versus non-elevated ST segments and ST depressions versus non-depressed ST segments. For a given beat, $v^+(b)$is taken as the label for which the maximum number of classifiers, out of K_l^+ classifiers used for discerning ST elevations and normal ST segments, has voted. Similarly, $v^-(b)$ is taken as the label for which the maximum number of classifiers, out of the K_l^- classifiers used for classifying ST depressions and normal ST segments, has voted.

The training of these neural networks is carried out using *k-fold training* (Polikar 2006) (see figure 9). For each lead, a training set of approximately an equal number of ST-elevated (if present) and normal beats is selected (<6% of the total number of beats in the database for

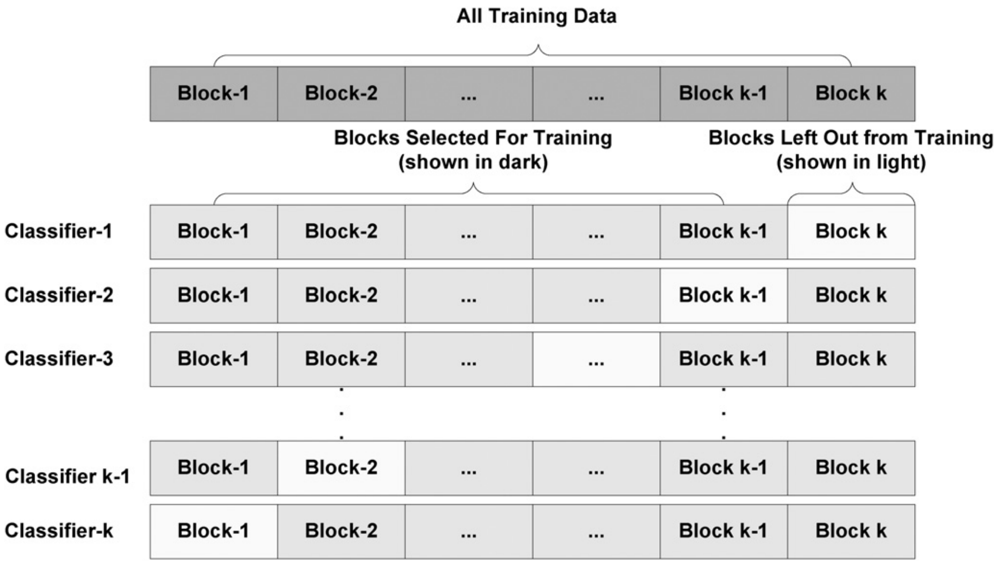

Figure 9. Data sets for *k*-fold training (Polikar 2006).

that lead) and is used to train K_l^+ backpropagation neural networks. The training class labels are given as $C_t^+(b)$ with

$$C_t^+(b) = \begin{cases} 1 & \text{for ST}^+ \\ 0 & \text{else.} \end{cases} \tag{10}$$

Some of these beats form the cross validation set over which different parameters of this system, such as the neural network architecture and different thresholds used, are optimized empirically.

The same holds for the set of neural network detecting ST depressions where we train the neural networks with an equal number of ST-depressed (if present) and normal beats with class labels given by

$$C_t^-(b) = \begin{cases} 1 & \text{for ST}^- \\ 0 & \text{else.} \end{cases} \tag{11}$$

The structure of all the three-layered neural networks is the same for a lead and is represented by S_l as given in table 1. Tangent sigmoid activation functions are used in all the layers of neural networks.

ST depression data for lead D3 and ST elevation data for lead V3 were not available, so the ensemble for these leads consisted only for the ST elevation and ST depression detection neural networks respectively.

2.4. Post-processing

This procedure takes the outputs of the classifier for a number ($N_{\text{episode}} = 35$) of beats and assigned it as a ST deviation episode if a certain percentage ($P_{\min} = 75\%$) of these beats are marked as ST deviations. Episodes smaller then a specific length ($L_{\min} = 15$) are removed and episodes that are spaced by a normal duration less than ($D_{\min} = 40$) are combined. The

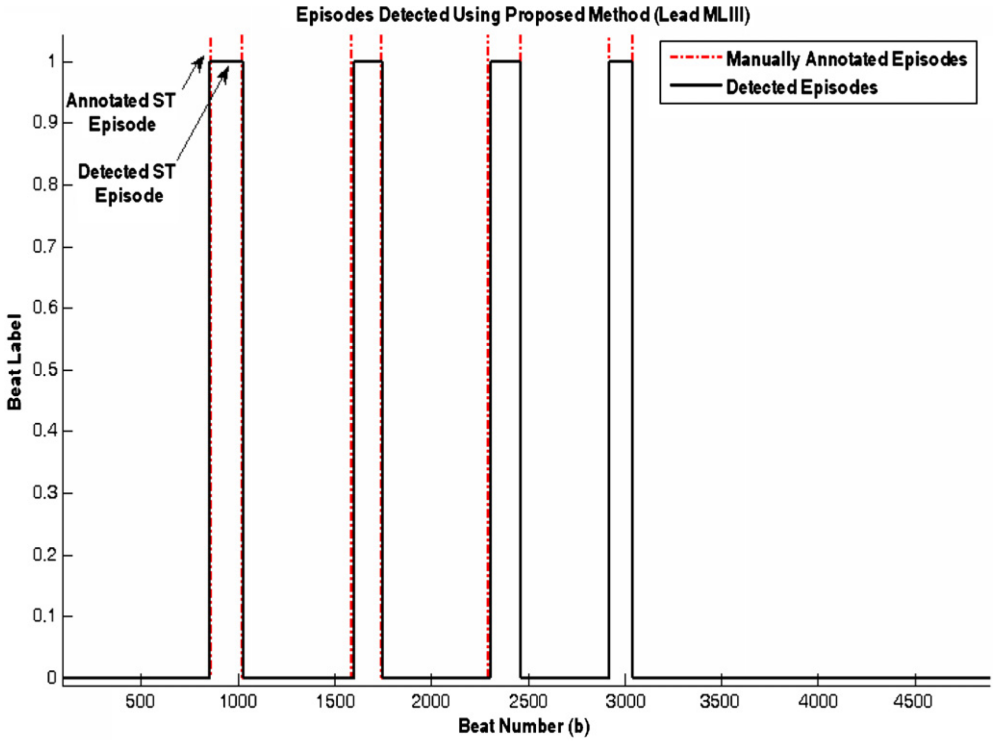

Figure 10. Some of the detected ST deviation episodes.

Table 2. Results for each lead.

Lead (l)	Number of ST episodes	PPV (%)	Se (%)
MLI	6	100	100
MLIII	45	93.02	88.89
D3	2	100	100
V1	9	90	100
V2	10	83.3	100
V3	4	100	100
V4	44	92.86	88.64
V5	53	82.46	88.68
All	173	89.20	90.75

output of the window characterization stage is taken as $C(b)$. $C(b) = 1$ employs that the beat has been labeled as ST depressed or elevated, otherwise it is taken to be normal.

3. Results and discussion

A typical result of ST deviation episode detection using this method is shown in figure 10. Detected episodes exhibit perfect overlap with the annotated episodes, indicating the degree of accuracy of the proposed algorithm.

In order to quantify these results, sensitivity (Se) and PPV of the ST episode detection are given in table 2. These accuracy measures are defined as

Table 3. Comparison with existing methods.

Reference	Sensitivity/PPV	Detection type	Data size and annotations used
ESC-ST-T DB cardiologists (Taddei *et al* 1992)	(70–83)%/(85–93)%	Ischemic episodes	All 90 records
Maglaveras *et al* (1998)	88.6%/78.4%	Ischemic episodes	All records, original annotations
Jager *et al* (1998)	87.1%/87.7%	ST segment episodes	As above
Smrdel and Jager (2004)	81.3%/89.2%	ST segment episodes	As above
Pang *et al* (2005)	81.3%/74.6%	Ischemia episode	As above
Frenkel and Nadal (1999)	84.2%/72.6%	ST segment episodes	Reduced records, original annotations
Andreao *et al* (2004)	83.0%/85.0%	ST segment episodes	As above
Papadimitriou *et al* (2001)	82.8%/82.4%	Ischemic episodes	As above
Garcia *et al* (2000)	85.0%/86.0%	ST segment episodes	All records, revised annotations
Papaloukas *et al* (2002a)	86.0%/87.0%	Ischemic episodes	As above
Papaloukas *et al* (2002b)	92.1%/93.8%	ST segment episodes	As above
	82%/86% (our implementation)	As above	48 records, original annotations
This work	90.75%/89.2%	ST segment episodes	48 records, original annotations

$$\text{Se} = \frac{TP_s}{TP_s + FN}, \tag{12}$$

$$\text{PPV} = \frac{TP_p}{TP_p + FP}. \tag{13}$$

In equation (12), TP_s is the number of annotated episodes detected by the algorithm whereas FN is the number of annotated episodes missed by the algorithm (false negatives). For the definition of PPV in equation (13), TP_p is the number of detected episodes that match with annotated episodes and FP is the number of episodes detected by the algorithm that do not have matching episodes in the annotation file (false positives). The matching criterion is based on the degree of temporal overlap between the two episodes under consideration as reported in Jager (2006b).

The proposed method exhibits a total sensitivity/PPV of 89.20%/90.75%. A comparison of the proposed method with other techniques in the literature is given in table 3. Reported methods have been evaluated on different data sets, different amounts of training and testing data and some of them have used revised annotations, e.g. Papaloukas *et al* (2002b). Therefore, this fact must be kept in mind while comparing the reported results. We have performed our evaluation on 48 freely available records of the ESC DB using original annotation files. Furthermore, in the results given by the proposed method, we do not consider combining episode annotations for two leads as in Papaloukas *et al* (2002b). In a practical application, it may be possible that only single ECG lead is used for processing or localization of the blockage causing ST segment deviation. Table 3 shows that the proposed method outperforms all the existing techniques for ST deviation except Papaloukas *et al* (2002b). Our own implementation of Papaloukas *et al* (2002b) and its evaluation on the 48 files of the ESC-ST-T DB without combining lead annotations resulted in an accuracy of sensitivity/PPV of 82%/86%, which is lower than the accuracy of our proposed method. Our method gives the highest error on lead V5. If this lead is not considered, the results are improved to 91.67%/92.44% (sensitivity/PPV). These results can be improved further, but caution must be taken to evaluate the accuracies of the database annotations themselves as it can affect the generalization of the system performance on other databases or in practical system implementation. For the purpose of comparison, we have used a single backpropagation neural network for ST segment classification in lead MLIII and sensitivity/PPV comes out to be 96%/81% that is much lower that that of the classifier ensemble, and it effectively illustrates the advantages brought in by the use of multiple classifiers in detecting ST segment episodes.

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