AN ISCHEMIA DETECTION METHOD BASED ON ARTIFICIAL NEURAL NETWORKS

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An ischemia detection method based on artificial neural networks

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Abstract

An automated technique was developed for the detection of ischemic episodes in long duration ECG recordings that employs an artificial neural network. In order to train the network for beat classification, a cardiac beat dataset was constructed based on recordings from ESC ST-T database. The network was trained using a Bayesian regularization method. The raw ECG signal containing the ST segment and the T wave of each beat were the inputs to the beat classification system and the output was the classification of the beat. The input to the network was produced through a principal component analysis to achieve dimensionality reduction. The network performance in beat classification was tested on the cardiac beat database providing 89.62% sensitivity and 89.65% specificity. The neural beat classifier is integrated in a four-stage procedure for ischemic episode detection. The whole system was evaluated on the ESC ST-T database. When aggregate gross statistics was used the sensitivity was 89.55% and the positive predictive accuracy 88.61%. When aggregate average statistics was used the sensitivity became 86.21% and the positive predictive accuracy 87.23%. These results are better than other reported.

Keywords: Ischemic episode detection; Cardiac beat classification; Artificial neural networks; Bayesian regularization

1. Introduction

Myocardial ischemia is caused by insufficient blood supply to the heart muscle. As a result alterations are observed in the electrocardiographic (ECG) signal like deviations in the ST segment or/and changes in the T wave [9,21]. The detection and assessment of those alterations in long duration ECGs is a simple and non-invasive method for the diagnosis of ischemia [6].

Diagnosis of myocardial ischemia is based upon two tasks: ischemic beat classification and ischemic episode definition. The first is related to the classification of beats as normal or ischemic. The accuracy of beat classification influences ischemic episode definition where sequences of ischemic beats need to be identified. Various methods have been proposed for ischemia detection based on set of rules [1,4,13,17,22-24], artificial neural networks [3,18,23-26], fuzzy logic [28,29] or other signal analysis techniques [2,10,12,14,27].

In a previous work [20] a four-stage knowledge-based method was proposed for ischemic episode detection. This method was based on a set of medical rules for beat classification. This method performed quite well, but in the case of noisy ECG recordings its positive predictive accuracy was rather low due to the lack of flexibility that characterises rule – based systems.

Currently an improvement of the previous method is proposed that employs artificial neural networks for beat classification. In order to perform the neural network training an appropriate data set containing characterised beats was developed. This data set contains normal, ischemic and artefact beats annotated by three medical experts that correspond to 11 hours of two-channel ECG recordings, extracted from the ESC ST-T database. The cardiac beat data set was developed since the ESC ST-T database contains annotations for ischemic episodes and usually not all beats in an episode can be characterised as ischemic. Using the above data set and principal component analysis a feed-forward neural network was trained to provide beat classification. Various neural network architectures were tested with different training algorithms in order to develop a more effective beat classification system compared to the rule based technique. The neural network method was integrated in the four-stage approach and the resulted system exhibited very good performance in the detection of ischemic episodes in long duration ECGs.

2.1. *Beat Classification using ANN*

2.1.1. *Network Architecture and Training Method*

For the classification of the cardiac beats a feed-forward neural network is used. The network has an input layer with four input units, one hidden layer with 10 sigmoid units (with hyperbolic tangent as activation function) and an output layer with one linear unit. The architecture of the network is shown in Fig. 2. Normally, the network could be trained to accept as input the cardiac beat and provide an output of zero for normal and one for ischemic case. The input pattern to the network could be the interval $[J, J+400ms]$ (100 data points), which includes both the ST segment and the T wave. However, in order to reduce the dimensionality of the input pattern a principal component analysis (PCA) is employed that eliminates those components which contribute only a small amount (less than 5%) to the total variance in the training set. Thus the input dimension is reduced to four.

Training is performed using the Bayesian regularization technique [8,15]. Within this framework the following objective function is minimised:

$$E = a_1 \sum_{i=1}^{N} (t_i - o_i)^2 + a_2 \sum_{i=1}^{M} \mathbf{w}_i^{\,2}, \tag{1}$$

where t_i are the desired network outputs, o_i are the network outputs during training, $\mathbf{w}_i$ are the network parameters (weights and biases), M is the number of those parameters and N is the number of the training patterns. The hyperparameters a_i are estimated at each iteration as follows:

$$a_1 = \frac{N - \gamma}{2\sum_{i=1}^{N} (t_i - o_i)^2}, \tag{2}$$

$$a_2 = \frac{\gamma}{2\sum_{i=1}^{M} \mathbf{w}_i^{\,2}}, \tag{3}$$

performance of the network. It must be noted that the training set corresponds to 2.5% of the total dataset and is constructed by selecting the first out of a sequence of 40 beats.

3. Results

In order to apply the proposed beat classification method the number of units in the hidden layer of the neural network must be determined. Several experiments with different numbers of hidden units were performed and the results are shown in Table 1. Table 1 also displays experimental results obtained from the use of other training algorithms, besides Bayesian regularisation. The network performance was evaluated using the cardiac beat test set in terms of sensitivity (Se) and specificity (Sp), which are defined as:

$$Se = \frac{TP}{TP + FN} \tag{3}$$

$$Sp = \frac{TN}{TN + FP} \tag{4}$$

where TP is the number of the ischemic beats correctly classified, FN is the number of the normal beats falsely classified, TN is the number of the normal beats correctly classified and FP is the number of the ischemic beats falsely classified. The Bayesian regularization method, described in the previous section, was found to be the most effective. In addition, when the number of nodes in the hidden layer was increased, the network training was very slow without significant improvement in performance. Therefore, the use of 10 hidden units was considered sufficient. For comparison, when the rule-based approach [20] was used for beat classification, the sensitivity and the specificity were 70.13% and 62.98%, respectively, while for the ANN method the results were 89.62% and 89.65% for both measures.

The ANN method for beat classification was integrated into the four-stage technique for ishaemic episode detection [20], replacing the rule-based classification stage. To assess the

4. Discussion

Several methods for automated detection of ischemic episodes have been reported in the literature. Signal analysis techniques [2,10,12,14,27] transform the original signal in order to define features appropriate for differentiation. Rule-based approaches [1,4,13,17,20,22-24] exhibit the highly desirable feature of interpreting their decisions. Fuzzy expert systems [28,29] manage to keep this feature without applying strict threshold values. Artificial neural networks [3,18,23-26] due to their non-linear characteristics and learning capabilities have provided good performance results. The above methods when tested with the ESC ST-T database demonstrated a sensitivity that ranged from 71% to 93.75% and a positive predictive accuracy from 66% to 90%. Some works [2,3,4,13,17,18,22,29] report better results which are not comparable since they refer to their own datasets. In [25] a nonlinear PCA neural network is proposed for ischemic beat classification instead of episode detection. Using 34 out of the 90 recordings of the ESC ST-T database, a sensitivity of 79.32% and a specificity of 75.19% are reported.

The proposed method was evaluated using all the 90 recordings of the ESC ST-T database and exhibited very high sensitivity and positive predictive accuracy (Table 3). It must be noted that the majority of the results reported in Table 3 refer to subsets of ECG recordings of the ESC ST-T database [24, 26-28] and only some have used all the ESC ST-T database recordings [12,20,23]. Also, the currently evaluated beat classification network performs better than similar approaches [25], as indicated in Table 1.

The high performance of the proposed beat classification schema can be attributed to several factors. A new cardiac beat database, based on a subset of the ESC ST-T database, was developed in collaboration with three medical experts. This database was used to train a feed-forward neural network for beat classification. During the training process as input to the network were used signal values extracted from both the ST segment and the T wave. The exclusion of artefacts from the training process helped in a proper adjustment of the network's weights. In addition, a state-of-the-art neural network training algorithm based on Bayesian regularization was employed, providing very good generalisation performance. Finally, the dimensionality reduction obtained using PCA contributed to a more effective training since the number of the network's input units was essentially decreased.

Several improvements are possible. The cardiac beat database can be expanded and include beat patterns that are not represented in the current version. Moreover, the quality of the data set can be enhanced through the improvement of the J point detection method. Inaccurate J point detection results in a shift of the network's input interval that partly contains either the ST segment (the J point is detected after its true location) or the T wave (the J point is detected before its true location). The early detection of the J point is not so decisive since we mainly need the peak of the T wave. If the J point is detected after its true position then the ST segment is not fully included in the network's input vector. This obviously affects the performance of the episode detection method. For more accurate detection of the J point, more advanced noise removal techniques may be examined.

5. Conclusions and future work

We have presented a novel method that employs artificial neural networks for the automated detection of ischemic episodes in long duration ECG recordings. In this system a feed-forward neural network ischemic beat classifier has been implemented. In order to train the network a cardiac beat database was constructed containing beats that are annotated as ischemic, normal or artefact. The neural beat classifier was integrated into a four-stage procedure for the detection of ischemic episodes. The performance of the system was better than other reported when tested with the ESC ST-T database.

A disadvantage of the proposed method is that it cannot provide any interpretation for the decisions made due to the employment of the neural network model. Proper combination of the knowledge-based approach [20] with the neural network model can eliminate this drawback. The potential of our method will be further assessed in recordings from ambulatory patients and patients undergoing continuous ECG monitoring in the coronary care unit.

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Appendix

Performance of the episode detection method for all the recordings of the ESC ST-T database

	Se[1]		PPA[2]			Se		PPA	
ECG	%	episodes	%	episodes	ECG	%	episodes	%	episodes
e0103	100	10/10	90.91	10/11	e0211	100	1/1	100	1/1
e0104	87.5	7/8	100	7/7	e0212	100	1/1	100	1/1
e0105	100	7/7	100	7/7	e0213	100	5/5	100	5/5
e0106	80	4/5	100	4/4	e0302	100	2/2	100	2/2
e0107	66.67	4/6	66.67	4/6	e0303	66.67	2/3	100	2/2
e0108	93.33	14/15	100	14/14	e0304	66.67	2/3	100	2/2
e0110	100	2/2	100	2/2	e0305	75	3/4	100	3/3
e0111	100	3/3	100	3/3	e0306	83.33	5/6	100	5/5
e0112	87.5	7/8	100	7/7	e0403	100	1/1	100	1/1
e0113	88.89	8/9	100	8/8	e0404	100	6/6	100	6/6
e0114	100	11/11	100	11/11	e0405	33.33	2/6	100	2/2
e0115	100	1/1	100	1/1	e0406	100	3/3	42.86	3/7
e0116	100	6/6	60	6/10	e0408	0	0/1	0	0/5
e0118	87.5	7/8	100	7/7	e0409	100	3/3	100	3/3
e0119	85.71	6/7	60	6/10	e0410	100	7/7	100	7/7
e0121	90.91	10/11	100	10/10	e0411	100	5/5	83.33	5/6
e0122	100	6/6	75	6/8	e0413	0	0/1		0/0
e0123	100	2/2	100	2/2	e0415	100	4/4	100	4/4
e0124	20	1/5	100	1/1	e0417	100	5/5	100	5/5
e0125	71.43	5/7	100	5/5	e0418	88.89	8/9	100	8/8
e0126	66.67	2/3	100	2/2	e0501	90.91	10/11	100	10/10
e0127	100	3/3	50	3/6	e0509	100	1/1	100	1/1
e0129	75	3/4	100	3/3	e0515	100	16/16	100	16/16
e0133	100	2/2	100	2/2	e0601	83.33	5/6	83.33	5/6
e0136	100	11/11	84.62	11/13	e0602	50	1/2	100	1/1
e0139	100	1/1	100	1/1	e0603	50	1/2	100	1/1
e0147	100	10/10	100	10/10	e0604	100	7/7	100	7/7
e0148	87.5	7/8	100	7/7	e0605	100	2/2	100	2/2
e0151	100	5/5	100	5/5	e0606	66.67	2/3	100	2/2
e0154	100	1/1	100	1/1	e0607	100	1/1	100	1/1
e0155	80	4/5	100	4/4	e0609	88.89	8/9	100	8/8
e0159	0	0/1		0/0	e0610	100	6/6	66.67	6/9
e0161	100	2/2	100	2/2	e0611	100	3/3	75	3/4
e0162	100	3/3	100	3/3	e0612	100	6/6	100	6/6
e0163	100	5/5	100	5/5	e0613	75	3/4	75	3/4
e0166	100	3/3	50	3/6	e0614	100	1/1	100	1/1
e0170	100	4/4	80	4/5	e0615	100	7/7	100	7/7
e0202	100	8/8	66.67	8/12	e0704	0	0/3		0/0
e0203	100	7/7	100	7/7	e0801	100	9/9	81.82	9/11
e0204	100	8/8	80	8/10	e0808	0	0/5		0/0
e0205	71.43	5/7	100	5/5	e0817	100	3/3	100	3/3
e0206	100	10/10	100	10/10	e0818	100	7/7	100	7/7
e0207	100	6/6	100	6/6	e1301	100	5/5	71.43	5/7
e0208	100	10/10	90.91	10/11	e1302	100	7/7	100	7/7
e0210	100	1/1	16.67	1/6	e1304	100	2/2	100	2/2

[1]Se: Sensitivity
[2]PPA: Positive Predictive Accuracy

Table 1

Test set sensitivity and specificity of the neural network model in classifying cardiac beats for various training algorithms and number of units in the hidden layer

Training algorithm	Number of hidden units	Se[1] (%)	Sp[2] (%)
Bayesian Regularization	10	89.62	89.65
Bayesian Regularization	25	90.54	89.76
Bayesian Regularization	50	91.03	90.47
Bayesian Regularization	100	91.21	90.25
Levenberg-Marquardt	10	89.60	89.15
Levenberg-Marquardt & use of validation set for early stopping	10	88.91	88.20
Levenberg-Marquardt	50	90.63	90.05
BFGS	10	90.21	89.06
BFGS	25	89.59	89.25
Scaled Conjugate Gradient	10	88.44	88.20
Scaled Conjugate Gradient	25	90.42	90.23
Resilient backpropagation	10	88.82	87.64

[1]Se: Sensitivity
[2]PPA: Positive Predictive Accuracy

Table 2

Overall performance of the episode detection method on the ESC ST-T database

Statistics		**Se**[1]	**PPA**[2]
Gross	**episodes**	420/469	420/474
	%	89.55	88.61
Average	%	86.21	87.23

[1]Se: Sensitivity
[2]PPA: Positive Predictive Accuracy

Table 3

Comparison of the performance of several methods for ischemic episode detection in the ESC ST-T database

Method	Se[1] (%)	PPA[2] (%)
Jager [12]	85.2	86.2
Papaloukas [20]	93.75	78.50
Silipo and Marchesi [23]	77	82
Silipo and Marchesi [23]	77	83
Silipo and Marchesi [23]	77	85
Silipo and Marchesi [23]	71	66
Silipo and Marchesi [23]	77	86
Silipo [24]	85	88
Silipo [24]	78	90
Stamkopoulos [26]	84.4	78.8
Taddei [27]	84	85
Vila [28]	83	75
Present Work	**89.55**	**88.61**

[1]Se: Sensitivity
[2]PPA: Positive Predictive Accuracy

Fig. 1. The four-stage ischemic episode detection method

Fig. 2. The artificial neural network architecture

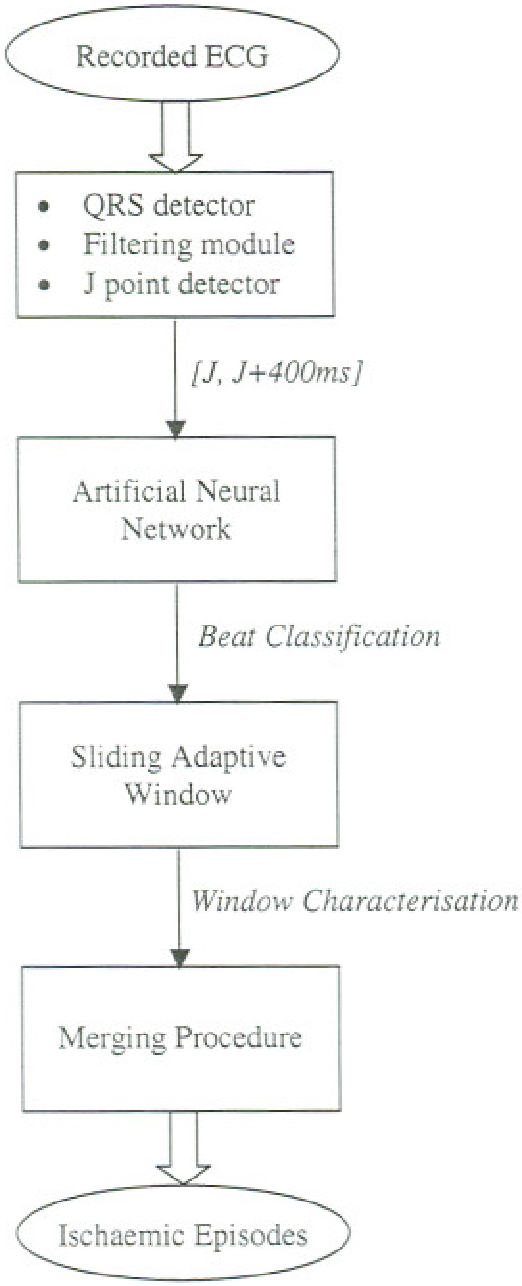

Fig. 1

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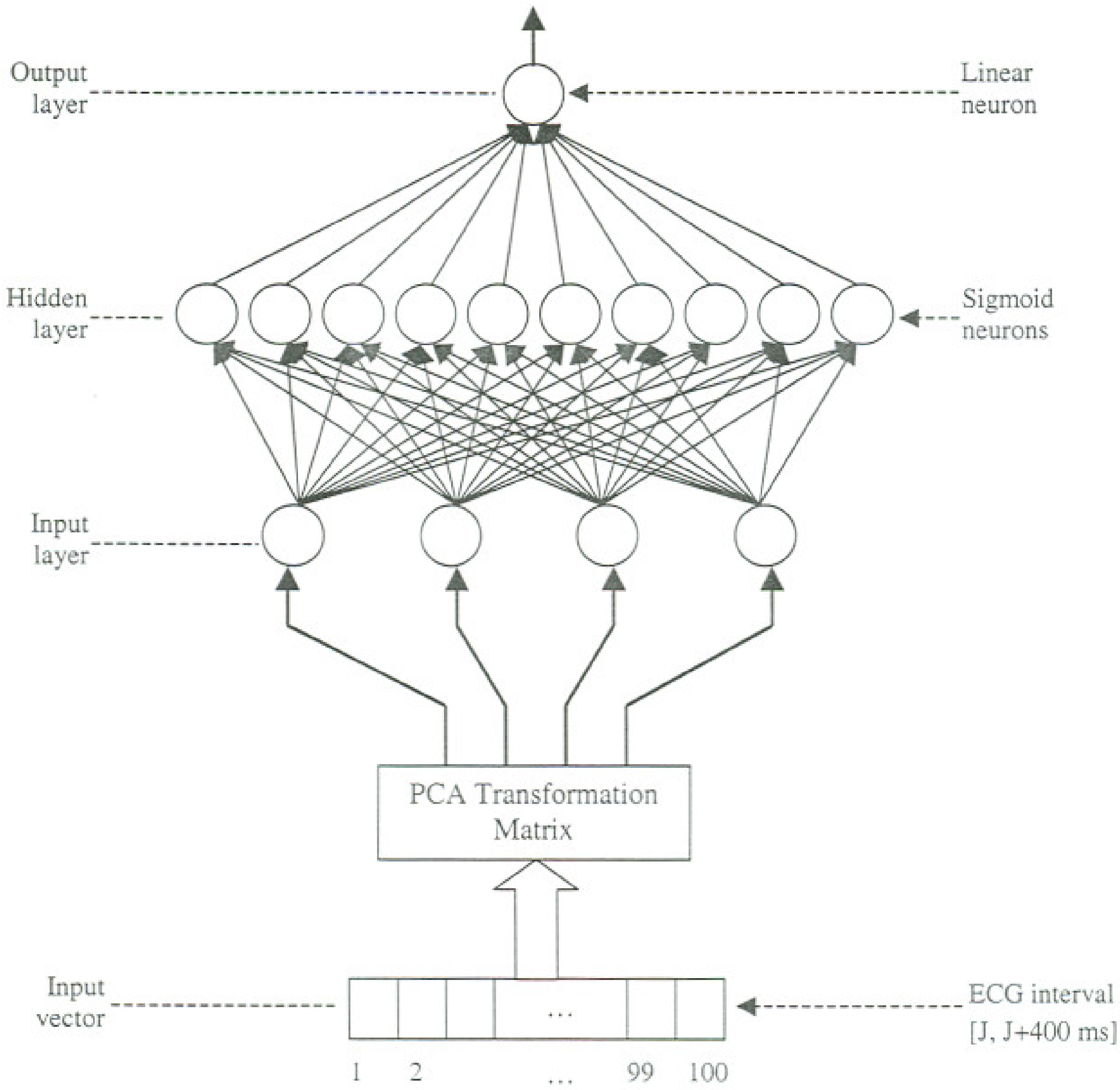

Fig. 2

(C. Papaloukas et al.)