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A patient adaptable ECG beat classifier based on neural networks

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A R T I C L E I N F O

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A B S T R A C T

A novel supervised neural network-based algorithm is designed to reliably distinguish in electrocardiographic (ECG) records between normal and ischemic beats of the same patient. The basic idea behind this paper is to consider an ECG digital recording of two consecutive R-wave segments (RRR interval) as a noisy sample of an underlying function to be approximated by a fixed number of Radial Basis Functions (RBF). The linear expansion coefficients of the RRR interval represent the input signal of a feed-forward neural network which classifies a single beat as normal or ischemic. The system has been evaluated using several patient records taken from the European ST-T database. Experimental results show that the proposed beat classifier is very reliable, and that it may be a useful practical tool for the automatic detection of ischemic episodes.

1. Introduction

The electrocardiogram (ECG) is a graphic recording of the electrical activities in human heart and provides diagnostically significant information. Its shape, size and duration reflect the heart rhythm over time. The waves related to electrical impulses occurring at each beat of the heart are shown in Fig. 1. The P-wave represents the beginning of the cardiac cycle and is followed by the QRS complex, which is generally the most recognizable feature of an ECG waveform. At the end of the cardiac cycle is the T-wave. The varied sources of heart diseases provide a wide range of alterations in the shape of the electrocardiogram. For instance, inverted T waves (Fig. 2) are seen during the evolution of myocardial infarction, while ST-segment depression (Fig. 3) can be caused by ischemia. In recent years, many researches concerning automated processing of ECG signals have been conducted ([1,4,5,7,10,11,13,14]). A difficult problem in computer-aided ECG analysis is related to the large variation in the morphology of ECG waveforms, not only among different patients, but even within the same patient. This makes the detection of ECG features (ST-segment, T-wave, QRS-area) a tough task.

The aim of the present work is to design an ECG beat recognition method to distinguish normal and ischemic patterns of the same patient without requiring the extraction of ECG features. The method is a supervised neural network-based algorithm, and hence its applicability requires the availability of recordings of both normal beats and annotated ischemic episodes. Once trained, the system should be capable of detecting new ischemic beats similar to those previously observed in the patient. This objective is relevant because of the observed tendency of patients discharged after an acute myocardial ischemic attack to repeat a similar ischemic episode within a short period of time (up to 30% within one month). The possibility of automatically monitoring such patients would then translate directly into reduced morbidity and mortality.

In the proposed method, the pattern under classification is defined to be the ECG signal from an RRR interval, i.e. the ECG signal from two successive heart beats, marked by three successive R peaks. We remark that RRR intervals can be easily detected and contain enough information for pattern recognition. The patterns of the RRR intervals can be represented as

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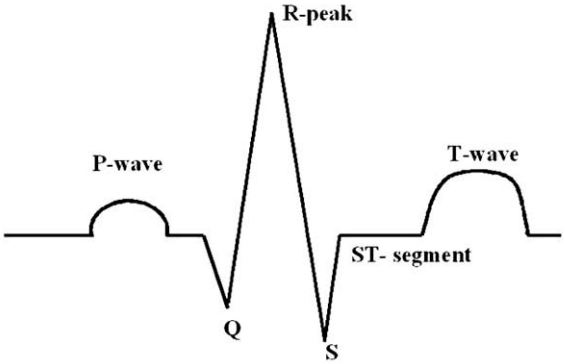

Fig. 1. ECG features of a cardiac beat.

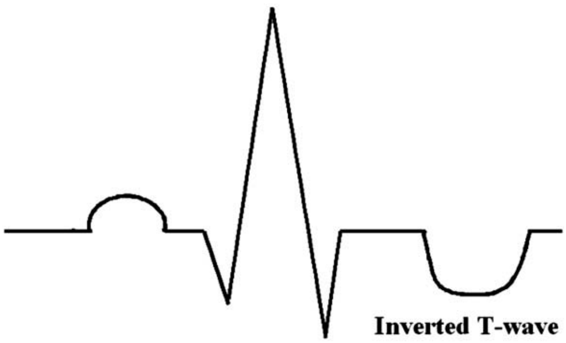

Fig. 2. Abnormal ECG beat seen during the infarction.

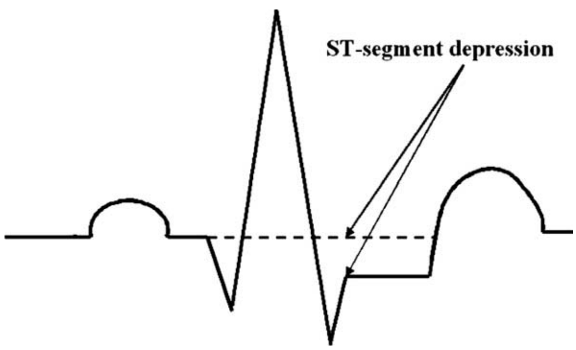

Fig. 3. Ischemic ECG beat.

vectors lying in relatively high dimensional spaces. However, due to the variation of the ECG waveform, to variations in heart rate and to the presence of noise, vectors may be very different from each other and actually lie in different dimensional spaces. This makes it difficult to train a neural network for beat recognition. The proposed strategy is that of considering the ECG data from an RRR interval as a noisy sample of an underlying function. The function is approximated by means of a linear combination of a fixed number of suitable basis functions. The coefficients of the linear expansion can be easily computed by solving a linear least-squares problem, and constitute the extracted features of the RRR interval. The transformed patterns, i.e. the coefficients of the linear expansions, become the input signals of a feed-forward neural network classifier, which provides an output of zero for the normal and one for the ischemic case. The adopted technique merges all the patterns to be classified in the same lower dimensional space and reduces the influence of ECG morphology and noise.

In Section 2 we describe the approximation technique of RRR interval and the neural network ECG beat classifier. In Section 3 we present the results of the tests that were carried out in order to evaluate the designed system as beat classifier. Finally, Section 4 contains some concluding remarks.

2. Approximation of RRR interval and beat classification using neural networks

The pattern under classification is the ECG digital recording of two consecutive RR-segments (hereafter defined RRR interval). Note that

(i) R peaks can be easily detected in the digitized signal, since they are local maxima that can be exactly determined once known the period of the heart cycle and the sampling frequency.
(ii) The RRR interval contains two complete heart cycles and hence it constitutes suitably informative input of a pattern recognition system.
(iii) Sampled ECG over an RRR interval is a vector lying on a high dimensional space whose dimension depends on cardiac frequency and sampling frequency.
(iv) The presence of noise affects the measurements made in the recorded RRR intervals.

From observations (iii) and (iv) it follows that the "direct" use of RRR intervals for classifying heart beat may not be suitable. The proposed strategy is then that of considering the RRR interval recording as a noisy sample of an underlying function $y : R \to R$, which can be approximated by means of an a-priori defined number of basis functions. In particular, the approximating function $\tilde{y} : R \to R$ can defined as

$$\tilde{y}(t) = \sum_{j=1}^{m} a_j \phi_j(t), \tag{1}$$

where $\phi_j(t)$, for $j = 1, \dots, m$ are smooth functions from a suitable family, and the coefficients of the linear expansion $a_1, \dots, a_m$ have to be determined using the ECG values corresponding to the given RRR interval. In this way the RRR interval is mapped onto the vector $a = (a_1, \dots, a_m)^T$ belonging to a space of lower dimensionality (*approximation of* RRR *interval*, see Fig. 4). A sufficient degree of smoothness of the basis functions ϕ_j and a suitable choice of the number m permit to reduce the influence of the noise. The components $a_1, \dots, a_m$ can be viewed as "implicit features" of the RRR pattern to be classified (in the sense that they are not interpretable by cardiologists) and represent the input to a classifier implemented by a supervisioned feed-forward neural network, which provides an output of zero for the normal and on for the ischemic case. Before being approximated, the RRR vector is translated in such a way that its minimum value is set to zero in order to take into account the ECG baseline (*baseline correction*). Let $t_1, \dots, t_P$ be sampling instants within a given RRR interval, and let

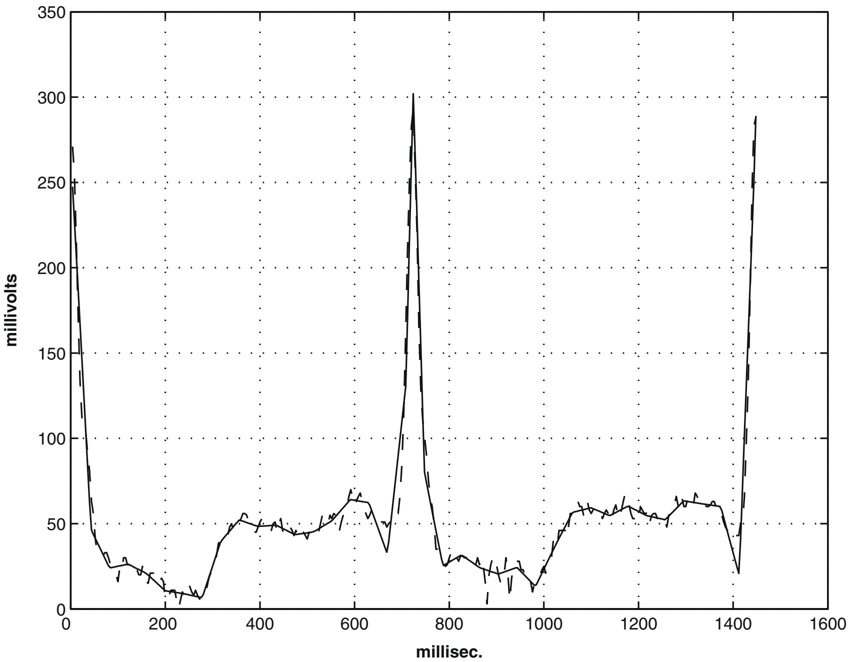

Fig. 4. Approximation of RRR interval. The dashed line represents the RRR interval, the continuous line is the approximating function $\tilde{y}(t) = \sum_{j=1}^{m} a_j \phi_j(t)$.

$y(t_1), \ldots, y(t_P)$ be the corresponding ECG values, which can be viewed as noisy samples of an underlying smooth function $y : R \to R$. The problem (regression problem) is that of approximating y, represented by the observed pairs $(t_i, y(t_i))$, by means of a suitable function $\tilde{y}(t)$. This is a well-studied problem in the context of regularization theory [16], which leads to an approximating function expressed as linear combinations of basis functions (see (1)). A possible choice is taking basis functions of the form

$$\phi_j(t) = \phi(|t - c_j|),$$

where $\phi : R^+ \to R^+$ is a *radial basis function* [15], and c_j is the *centre* of basis function ϕ_j. Several forms of radial basis functions have been defined, the most common being

$$\begin{aligned}
&\phi(r) = e^{-\frac{r^2}{2\sigma^2}} \quad \text{Gaussian}\\
&\phi(r) = (r^2 + \sigma^2)^{-1/2} \quad \text{inverse multiquadric}\\
&\phi(r) = (r^2 + \sigma^2)^{1/2} \quad \text{direct multiquadric}
\end{aligned}$$

where $r \geqslant 0$ and σ is a positive parameter. With reference to (1), where the basis functions are radial basis functions, once fixed the number m of basis functions and their form (which implies a choice of the centres c_j for $j = 1, \ldots, m$) the regression problem leads to the following linear least-squares problem

$$\min_{a_1,\ldots,a_m} \sum_{i=1}^{P} \left(y(t_i) - \sum_{j=1}^{m} a_j \phi(|t_j - c_j|) \right)^2. \tag{2}$$

Problem (2) can be solved by using a direct method based on the *singular value decomposition* or by employing an iterative method such as the *conjugate gradient method* (see, e.g. [3]). The components of the obtained solution represent the implicit features of the RRR interval considered. With reference to the classification task, it is desirable that "similar" RRR intervals will be represented by vectors close to each other in the space of implicit features, and viceversa. Therefore, continuity of the operator mapping the underlying function y into the approximating function $\tilde{y}$ is required. This aspect deserves attention and theoretical analysis, but it is not the object of the present work. According to the described strategy, each beat is represented by a vector $a \in R^m$ obtained using the ECG values of a RRR interval and the procedure previously defined.

For the classification of the cardiac beats a feed-forward neural network (with m input units, N_h hidden nodes, and an output layer with one unit) is used. The availability of the training set

$$TS = \{(a^\ell, d^\ell), a^\ell \in R^m, d^\ell \in \{0,1\}, \ell = 1, \ldots, T\}$$

is assumed, where the value 0 of the label d^ℓ indicates a normal beat, while $d^\ell = 1$ for ischemic beats. Let $w \in R^N$ be the vector of adjustable parameters in the network, and let $z(., w) : R^m \to R$ be the input–output mapping realized by the network. The training process is aimed to design a network that learns the mapping represented by the given training set. The problem of training is formulated in terms of the minimization of a nonlinear least-squares error function, i.e.

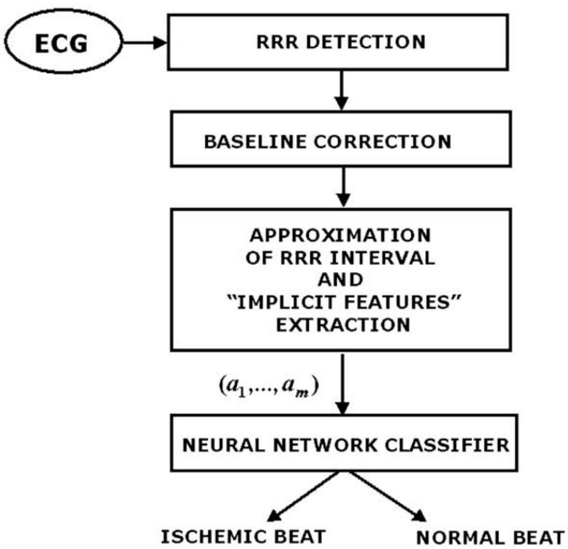

Fig. 5. Neural network-based system for beat recognition.

$$\min_{w \in R^N} E(w) = \sum_{\ell=1}^{T} \left(d^\ell - z(a^\ell; w) \right)^2.$$

Several conventional optimization algorithms can be applied for the minimization of $E(w)$, such as gradient methods, conjugate gradient methods, quasi-Newton methods [12]. The general configuration of the proposed ECG beat classifier is shown in Fig. 5.

The method described above extracts information used for beat classification directly from ECG signal, which is strongly nonlinear and may be corrupted by the noise. The choice of providing the approximation coefficients as inputs to the classifier, instead of using a linear dimensionality reduction technique (e.g., Principal Component Analysis), is made in order to better describe existing nonlinear relationships in ECG signal.

3. Experimental results and discussion

The described pattern recognition system is targeted to a single patient, in the sense that it is trained using the ECG of that patient in order to correctly distinguish his/her normal and ischemic beats. The European ST-T Database [6] was used as source of experimental ECG's. Among the records having dominant R peaks (the method requires extraction of RRR intervals), we randomly selected a subset of 20 records. For each considered record (i.e. for each considered patient), a set of 400 RRR intervals (200 ischemic, 200 normal) was extracted.

Each RRR interval is represented by the pairs $\{(t_i, y(t_i))\}$, $i = 1, \dots, N$. We recall that the integer N depends on heart rate, which is not constant. The N pairs were mapped onto a vector of $m = 20$ components by means of the approximating procedure described in Section 2: the instances of the linear least-squares problem (2) were solved by a direct method. The number $m = 20$ of basis functions was heuristically determined through a standard cross-validation technique [2]. We used the direct multiquadric as radial basis function ϕ, with $\sigma = 0.1$. The centres c_j, for $j = 1, \dots, 20$, were chosen in such a way that $c_1 = t_1$, and $c_{j+1} = c_j + (t_N - t_1)/20$ (equal spaced centres). For each patient, a data set of 400 pairs $(a^k, d^k) \in R^{20} \times \{0, 1\}$ was thus generated, where a^k is the vector of the implicit features (i.e. the coefficients of the linear expansion (1)) related to the kth RRR interval. In order to obtain bootstrap estimates of classification performance indicators, 10,000 training, validation and test subsets, with 200, 100 and 100 RRR intervals respectively, were randomly generated by resampling the original 400 RRR intervals. Each generated subset contained the same number of normal and ischemic RRR intervals. For the classification of RRR intervals, represented by vectors $a^k \in R^{20}$, a multi-layer neural network was used. The input layer was made of $m = 20$ input units, the hidden layer had $N_h = 20$ nodes with hyperbolic tangent as activation function, and the output unit was linear. Training was performed using a nonmonotone version of the Barzilai-Borwein gradient method (proposed in the optimization literature [9]) with *early stopping* [2]. Thus for each patient a trained neural network for RRR classification was obtained.

Classification performance in each one of the 10,000 artificial samples was expressed as

–Sensitivity (Se), that is

$$\mathrm{Se} = \frac{TruePositive}{TruePositive + FalseNegative};$$

–Specificity (Sp), that is

$$\mathrm{Sp} = \frac{TrueNegative}{TrueNegative + FalsePositive};$$

of the classifier (trained and validated on 200 and 100 RRR intervals, respectively) acting on the test set of 100 RRR intervals. The empirical distributions of both sensitivity and specificity were used to derive 95% highest density confidence regions for the respective bootstrap estimates.

Computations were carried out on an AMD Athlon personal computer at 1.54 GHz with 512 MB of RAM, and the training procedure required, for each run, a few CPU seconds. In Table 1 we report, for each patient, the ECG lead used and the statistics relative to the empirical distribution of ten thousand sensitivity (Se) and specificity (Sp) values from artificial test sets. For both sensitivity and specificity the average, the median and the lower and upper limits of the 95% highest density confidence intervals are reported. It can be appreciated that sensitivity and specificity are both very high for all evaluated patients, medians lying always above 96%. As a general measure of the reliability of the proposed method in the studied patient population, the grand averages of sensitivity and specificity are respectively 98.64% and 99.23%.

From the reported results it appears that the novel approach suggested in the present paper attains sensitivity and specificity of detection of ischemic heart beats in the 95% to 100% range. Even though very good results have been obtained by considering only one lead (typically V4, V5, V6) for any single patient (the lead where ischemia was noted in the ST-T database), better results would in all likelihood be obtained by pooling information from all available derivations. Moreover, for each patient, in correspondence to the run where the test accuracy attained the lowest value, the area under the ROC curve (AUC) was computed and reported in Table 1.

Table 1
Experimental results for patients extracted from the European ST-T database. For each patient, the ECG used lead, the average and the median sensitivity (Se) and specificity (Sp), together with the 95% confidence lower and upper limits, and the area under the ROC curve (AUC), computed in correspondence to the run where the test accuracy attained the lowest value, are reported.

Patient	Lead	$\overline{\mathrm{Se}}$(%)	Median Se (%)	L_{Se}(%)	U_{Se}(%)	$\overline{\mathrm{Sp}}$(%)	Median Sp (%)	L_{Sp}(%)	U_{Sp}(%)	AUC
e0105	V4	95.44	96	90	100	96.74	98	90	100	0.9838
e0123	V4	99.93	100	100	100	99.99	100	100	100	0.9998
e0211	V5	98.54	100	96	100	99.13	100	96	100	0.9952
e0415	V5	95.98	98	88	100	96.37	98	90	100	0.9794
e0607	V5	98.09	100	94	100	98.47	100	96	100	0.9800
e0107	V4	99.32	100	96	100	99.47	100	96	100	0.9996
e0113	V4	99.81	100	98	100	99.94	100	100	100	0.9992
e0115	V5	97.03	100	90	100	97.64	100	92	100	0.9964
e0121	V4	99.95	100	100	100	100	100	100	100	0.9938
e0125	V4	99.99	100	100	100	100	100	100	100	0.9998
e0127	V4	99.33	100	98	100	99.99	100	100	100	0.9996
e0139	V4	98.80	100	96	100	99.96	100	100	100	0.9996
e0147	V4	95.96	96	90	100	99.62	100	98	100	0.9988
e0159	V4	98.89	100	96	100	99.21	100	96	100	0.9966
e0161	V4	98.68	100	96	100	100	100	100	100	0.9908
e0203	V5	98.31	100	94	100	99.25	100	96	100	0.9864
e0205	MLI	100	100	100	100	99.99	100	100	100	0.9880
e0207	V5	99.57	100	98	100	99.33	100	96	100	0.9944
e0305	V5	100	100	100	100	100	100	100	100	0.9966
e0409	V5	99.12	100	96	100	99.54	100	98	100	0.9874

Table 2
Performance comparison of different methods for beat classification using the European ST-T database. For each method sensitivity (Se) and specificity (Sp) are reported.

Method	$\overline{\mathrm{Se}}$ (%)	$\overline{\mathrm{Sp}}$ (%)
ANN and PCA [13]	90	90
Multicriteria decision analysis [7]	90	89
Genetic algorithms and multicriteria decision analysis [8]	91	91
Association rule mining [5]	87	93
SVM [10]	92	90
Current Work	98	99

The Area Under the ROC Curve (AUC) is a measure of the classifier accuracy. The ROC curve is a two-dimensional graph in which *sensitivity* is plotted on the *Y* axis and (*1-specificity*) is plotted on the *X* axis. ROC analysis is widely used in medicine, and it has recently been introduced in machine learning and data mining. The obtained AUC values are all greater than 0.97, and this shows a good robustness of the predictive model. Experiments not reported here show that the choice of the particular RBF does not greatly influence the performance of the method.

In Table 2 the performances of the proposed method are compared with those of other algorithms of the literature. Comparison clearly shows the effectiveness of the proposed pattern recognition method (specifically targeted to a single patient) which can be advantageously employed whenever recordings of annotated ischemic episodes for a given patient are available.

Finally, the possibility of using several heart beats (instead of two) may deserve attention in order to improve the system performance, but this has not been investigated in the present work.

4. Conclusion

In this work we have presented a supervised neural network-based algorithm for ECG ischemic beat recognition of the same patient. The obtained results show that the proposed algorithm offers a good combination of sensitivity and specificity, making the design of a practical automatic ischemia detector feasible. The proposed approach leads to a dedicated model for each patient, so that, its applicability requires the availability of recordings of annotated ischemic episodes. Therefore, it could be used, for instance, on patients coming from Coronary Care Units, for which continuous ECG monitoring is available.

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