33rd Annual International Conference of the IEEE EMBS
Boston, Massachusetts USA, August 30 - September 3, 2011

An Efficient Method for Ectopic Beats Cancellation Based on Radial Basis Function

Jorge Mateo*, Ana Torres and José J. Rieta, *Member, IEEE*

Abstract— **The analysis of the surface Electrocardiogram (ECG) is the most extended noninvasive technique in cardiological diagnosis. In order to properly use the ECG, we need to cancel out ectopic beats. These beats may occur in both normal subjects and patients with heart disease, and their presence represents an important source of error which must be handled before any other analysis. This paper presents a method for electrocardiogram ectopic beat cancellation based on Radial Basis Function Neural Network (RBFNN). A trainable neural network ensemble approach to develop customized electrocardiogram beat classifier in an effort to further improve the performance of ECG processing and to offer individualized health care is presented. Six types of beats including: Normal Beats (NB) ; Premature Ventricular Contractions (PVC) ; Left Bundle Branch Blocks (LBBB) ; Right Bundle Branch Blocks (RBBB) ; Paced Beats (PB) and Ectopic Beats (EB) are obtained from the MIT-BIH arrhythmia database. Four morphological features are extracted from each beat after the preprocessing of the selected records. Average Results for the RBFNN based method provided an ectopic beat reduction (*EBR*) of $(mean \pm std)$ $EBR = 7,23 \pm 2.18$ in contrast to traditional compared methods that, for the best case, yielded $EBR = 4.05 \pm 2.13$. The results prove that RBFNN based methods are able to obtain a very accurate reduction of ectopic beats together with low distortion of the QRST complex.**

I. INTRODUCTION

The presence of ectopic beats in the electrocardiogram perturbs the impulse pattern initiated by the sinoatrial node, and implies that RR intervals adjacent to an ectopic beat cannot be used for Heart Rate Variability (HRV) analysis. In such cases, autonomic modulation of the sinoatrial node is temporarily lost, and an ectopic focus instead initiates the next beat prematurely. The location of the ectopic focus gives rise to different types of RR interval perturbation; a beat of ventricular origin inhibits the next sinus beat so that a compensatory pause is introduced after the ectopic beat, whereas a beat of supraventricular origin discharges the sinoatrial node ahead of schedule and causes the following sinus beat to also occur ahead of schedule. Other perturbations of physiological origin are those related to an interpolated ectopic beat, manifested by two short RR intervals adjacent to the ectopic beat, or an escape beat, manifested by a prolonged RR interval [1], [2].

In the last decades, the application of mathematical models and statistical analyses for better interpretation of the physiologic cardiac events has offered many advantageous solutions for fast automatic recognition of ventricular ectopic beats. ECG recording is also used as a tool for the analysis of Atrial Fibrillation (AF), where it is need to separate the Atrial Activity (AA) from other cardioelectric signals and the ectopic beats are one common problem for that extraction. In respect to this, some of the most popular methods are based on assessment of the QRS complex as the most characteristic wave in ECG. Classical techniques extract heuristic ECG descriptors, such as the QRS morphology [3], [4] and interbeat RR intervals [4], [5]. Other ECG descriptors rely on QRS frequency components calculated either by Fourier transform [6] or by computationally efficient algorithms with filter banks [7]. More sophisticated methods apply QRS template matching procedures, based on different transforms, e.g., Karhunen-Loève transform [8], techniques based in Template Matching and Subtraction (TMS) [9], Hermite functions [10], method based on Integral Pulse Frequency Modulation (IPFM) [2], [11] and Matching Pursuits [12], to approximate the variety of temporal and frequency characteristics of the QRS complex waveforms. Other techniques for computerized arrhythmia detection employ cross-correlation with predefined ECG templates to identify markers for the individual wave components in one cardiac cycle [13]. Although, some of the cited studies have proved the individual advantage of using ECG templates based mainly on sophisticated mathematical transforms, other studies have emphasized the particular benefit of a number of heuristic QRS features [14]. One of the common approaches in ECG beat classification is Artificial Neural Networks (ANNs) that have shown accurate performance in different classification tasks. Among ANNs, Multi-Layer Perceptrons (MLPs) [15], [16] and Radial Basis Function (RBF) [5], [17] networks have been of considerable interest.

In this paper, we present a method for ectopic beat classification and suppression using a Radial Basis Function Neural Network (RBFNN). This RBF network has been developed like hierarchically layered structure. It starts with a small number of RBFNN and then adds new RBFNN if the approximation error is larger than some predetermined threshold. They were applied on the large collection of morphological QRS descriptors used by Christov [3]. We have tested the performance of the defined classification methods for two classes, which feature with particular QRS behavior (class 1: NB, PVC, LBBB, RBBB, PB and class 2: EB), as well as in dependence of the content and the size of the learning set. Although EB cancellation may remove relevant medical information, this work is focused on the analysis of atrial fibrillation recordings, where the target

*J. Mateo and A. Torres are with the Innovation in Bioengineering Research Group, University of Castilla-La Mancha, Campus Universitario, 16071, Cuenca, Spain (email: jorge.mateo@uclm.es).

J. J. Rieta is with the Biomedical Synergy, Electronic Engineering Department, Universidad Politécnica de Valencia, Spain (email: jjrieta@ieee.org).

signal is the atrial activity. As a consequence, normal and ectopic ventricular activity will be sooner of later removed.

II. MATERIALS

The study involved all ECG recordings from PhysioNet Database (MIT-BIH Atrial Fibrillation Database, Long-Term AF Database, MIT-BIH Arrhythmia Database, AF Termination Challenge Database, etc) [18]. The sampling frequency is 360 Hz and the resolution is 200 samples per mV. All heartbeats were recognized by the fiducial points in the databases and the original databases' annotations were accepted. We defined two groups of heartbeats: (i) Group 1 'NVBs' for beats NB, PVC, LBBB, RBBB and PB, (ii) Group 2 'EVBs' for ectopic beats.

Before the ECG analysis we applied some preprocessing filters to the input ECG signal in order to prevent against artifacts that might impede the accurate measurements and classification of the heartbeats. All these signals have been classified in three groups. 50% random signals have been chosen to integrate the first group, which have been employed to network training. The second group (20%) has helped to validate the proper neural working. And the third group (30%) has helped to compare ANN.

III. METHOD

The performance of a radial basis function neural network depends on the number and centers of the radial basis functions, their shapes, and the method used for learning the input–output mapping [19], [20]. One characteristic of these functions is that any function can be approximated by a linear combination of radial basis functions (i.e. $f(x) \approx \sum w_i \xi_j(x)$). Then, it's possible to do a linear combination of this type of data that approximates the function that generated these data. To achieve this approach, this study uses a regression where several radial basis functions have been used [21], [22].

In this section we present the RBFNN initialization and training strategies used in this paper. In the classification scenario a neural network performs a mapping from a continuous input space $X(= \mathbb{R}^d)$ into a finite set of classes $Y = \{p_1, ...p_t\}$. In the training phase the parameters of the network are determined from a finite training set: $S = \{(x^\mu, p^\mu)\ \mu = 1, ...N\}$, each feature vector $x^\mu \in \mathbb{R}^d$ is labeled with its class membership $p^\mu \in Y$. In the recall phase further unlabeled observations $x \in \mathbb{R}^d$ are presented to the network which estimates their class membership p.

Here, we restrict ourselves to Gaussian basis functions [23] of the type:

$$\phi_j(x) = \exp\left(-\frac{\|x - c_j\|^2}{2\sigma_j^2}\right) \tag{1}$$

where x is the d–dimensional input vector with elements $x_i \in \mathbb{R}$, and $c_j \in \mathbb{R}^d$ is the vector determining the center of the basis function ϕ_j and has elements $c_{ji} \in \mathbb{R}$, $\|.\|$ denotes the Euclidean norm. The radial basis function neural network mapping with M basis functions is then:

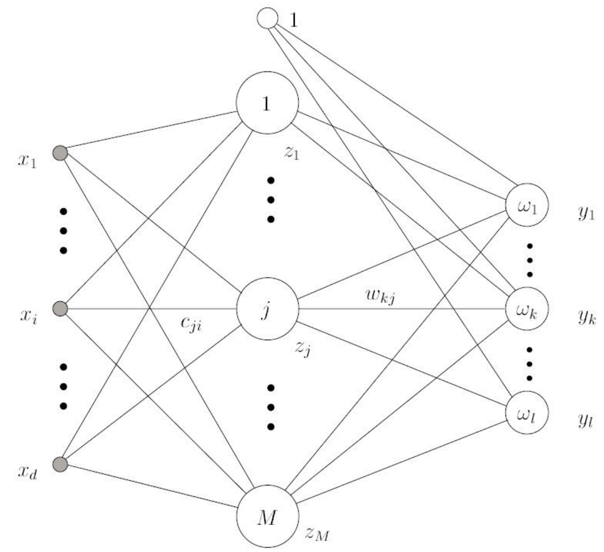

Fig. 1. Architecture of the radial basis function neural network

$$y_k(x) = \sum_{j=1}^{M} w_{kj}\phi_j(x) + w_{k0} \tag{2}$$

where the w_{k0} denote the bias, which may be absorbed into the summation by including an extra basis function ϕ_0 whose activation is set equal to 1. This mapping can be represented as the network diagram of figure 1 with the radial basis functions in the hidden layer and linear summation on the output layer. In our classification scenario the number of output units corresponds to the number of classes (1 of coding). Categorization is performed by assigning the input vector x the class of the output unit with maximum activation.

Data classification is conducted with the RBF networks constructed with the proposed learning algorithm. Assume that the objects of concern are distributed in an m-dimensional vector space and let f_t denote the probability density function that corresponds to the distribution of class-t objects in the m-dimensional vector space. The proposed learning algorithm constructs one RBF subnetwork for approximating the probability density function of one class of objects in the training data set. In the construction of the RBF network, the learning algorithm places one RBF at each training sample [24]. The general form of the RBF network-based function approximators is as follows:

$$\widehat{f}_t(x) = \sum_{c_j \in S\mu} w_j \exp\left(-\frac{\|x - c_j\|^2}{2\sigma_j^2}\right) \tag{3}$$

With the RBF network-based function approximators, a new object located at with an unknown class x is predicted to belong to the class that gives the maximum value of the likelihood functions defined in the following:

$$Lj(x) = \frac{|S_\mu|}{|S|}\widehat{f}_t(x) \quad (4)$$

where S_μ is the set of class-training samples and S is the set of training samples of all classes.

The essential issue of the learning algorithm is to construct the RBF network-based function approximators. Let us address how to estimate the value of the probability density function at a training sample. Assume that the sampling density is sufficiently high [24]. Then, by the law of large numbers in statistics, we can estimate the value of the probability density function $f_t(.)$ at a class-t sample c_j as follows:

$$f_t(c_j) \approxeq \frac{(k_1+1)}{|S_\mu|}\left[\frac{R(c_j)^m \pi^{\frac{m}{2}}}{\Gamma\left(\frac{m}{2}+1\right)}\right]^{-1} \quad (5)$$

where $R(c_j)$ is the maximum distance between and its nearest training samples of the same class, $\frac{R(c_j)^m \pi^{\frac{m}{2}}}{\Gamma\left(\frac{m}{2}+1\right)}$ is the volume of a hypersphere with radius $R(c_j)$ in an m-dimensional vector space; $\Gamma(.)$ is the Gamma function and k_1 is a parameter to be set either through cross validation or by the user .

A. Performance assessment

The performance of the studied methods was also tested on clinical data from Physionet. The performance was evaluated by estimating the ectopic beat reduction (EBR) [25], i.e., the beat-by-beat reduction of the ectopic-peak amplitude that the algorithm under evaluation is able to achieve. Therefore, the EBR was a vector of values defined as:

$$EBR(dB) = 10\log\left(R_{ECG}/R_{EB}\right) \quad (6)$$

where R_{ECG} is the R-peak amplitude of the original ECG, and R_{EB} is the residual ectopic peak amplitude.

The reliability of the method for recognition of ventricular ectopic beats was estimated by the two statistical indices sensitivity (Se) and specificity (Sp):

$$Se = \frac{TP}{TP+FN}, \quad Sp = \frac{TN}{TN+FP} \quad (7)$$

where TP is the number of the true positive classifications (for ectopic beats classified in Group 2 'EVBs'); TN is the number of the true negative classifications (for beats NB, PVC, LBBB, RBBB and PB classified in Group 1 'NVBs'); FP is the number of the false positive classifications for beats NB, PVC, LBBB, RBBB and PB classified in Group 2 'EVBs'); FN is the number of the false negative classifications (for ectopic beats classified in Group 1 'NVBs').

IV. Results

The rules for classification of ventricular ectopic beats were trained and tested with independent ECG databases to obtain unbiased accuracy evaluation, i.e., training and testing with different MIT database.

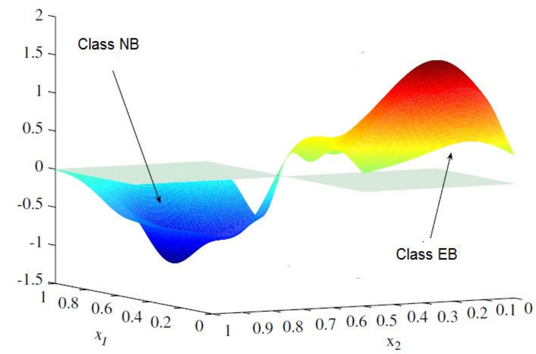

Fig. 2. Decision surface after updating the network parameters.

Table I list the results for the training and testing for the proposed method with different number of neurons and the figure 2 shows the final decision surface**.** RBFNN gives the best classification performance with 25 neurons**.** The table II contains the calculated statistical indices for the training MIT database, including the Sp values for the respective beat annotations in Group1 'NVBs' and the Se values for the beats belonging to Group 2 'EVBs'. Sp. In the previous table, the classification methods based in: Estimation of morphology and RR interval features with linear discriminants classifier [4], estimation of morphology features with neural networks classifier [3] and estimation of morphology features with Kth nearest neighbors classifier [12] have been compared.

On the other hand, the proposal method has been compared with systems based in TMS**.** The table III summarizes the obtained values of EBR for ECG recording. Note that significant statistical differences between RBFNN and TMS are reported for all the analyzed recordings.

TABLE I
COMPARISON OF Se FOR DIFFERENT STRUCTURES RBFNN

# of neurons	Training - Se(%)	Test -Se(%)
15	88.23	87.23
20	95.17	95.05
25	99.21	99.10
30	99.11	99.09

TABLE II
RESULTS PROVIDED BY THE COMPARISON BETWEEN DIFFERENT METHODS FOR CLASSIFICATION ECTOPIC BEATS

	Sp(%)	Se(%)
Chazal[2]	98.8	77.7
Christov an Bortolan[1]	99.7	98.5
Christov et al [11]	99.13	96.27
RBFNN	99.4	99.1

As a graphical summary, figure 3 shows the ectopic beat reduction corresponding to an ECG recording. As can be appreciated, the proposed method RBF obtains a more accurate cancellation template**,** and maintain the remaining

TABLE III

RESULTS PROVIDED BY THE COMPARISON BETWEEN TMS AND RBF OBTAINED FOR ECG RECORDINGS. VALUES INDICATE MEAN $\pm$ STANDARD DEVIATION FOR EBR.

	TMS	RBFNN
EBR	4.05±2.13	7.23±2.18

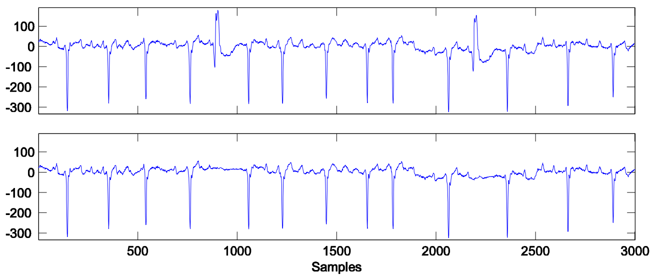

Fig. 3. Comparison between original ECG and after of ectopic beat cancellation by the proposed method.

QRS complexes. That is because of a good ectopic beats classification and corresponding reduction.

V. CONCLUSIONS

This work has presented how the proposed RBFNN has been used to ectopic beats cancellation from ECG recordings. The proposed method was evaluated using a large dataset, which can be considered very similar to the conditions met in clinical environment. The achieved high sensitivity for Group2 'EVBs' and high specificity for all annotations in Group1 'NVBs,' prove that the provided parameter set could be a reliable facility for automatic recognition. The results have shown that RBFNN is able to obtain a very accurate representation of ECG, thus providing high quality ectopic beat reduction for single-lead ECG recordings. As a way of conclusion, suffice is to say that the neural network-based approach obtains both ectopic beats reduction and low modification of QRST complex results in comparison with other methods.

ACKNOWLEDGEMENTS

This work was partly sponsored by University of Castilla-La Mancha an supported by the projects TEC2010–20633 from the Spanish Ministry of Science and Innovation, PII1C09–0036–3237 and PII2C09–0224–5983 from Junta Comunidades de Castilla la Mancha.

REFERENCES

[1] L. Sörnmo and P. Laguna, *Bioelectrical Signal Processing in Cardiac an Neurological Applications*. Elsevier Academic Press, 2005.

[2] K. Solem, P. Laguna, and L. Sörnmo, "An efficient method for handling ectopic beats using the heart timing signal," *IEEE Trans. Biomed. Eng.*, vol. 53, no. 1, pp. 13–20, 2006.

[3] I. Christov and G. Bortolan, "Ranking of pattern recognition parameters for premature ventricular contraction classification by neural networks," *Physiol. Meas*, vol. 25, pp. 1281–1290, 2006.

[4] P. de Chazal, M. OŠDwyer, and R. Reilly., "Automatic classification of heartbeats using ecg morphology and heartbeat interval features." *IEEE Trans. Biomed. Eng.*, vol. 51, pp. 1196–1206, 2004.

[5] I. Jekova, G. Bortolan, and I. Christov, "Assessment and comparison of different methods for heartbeat classification," *Med Eng Phys*, vol. 30, no. 2, pp. 248–257, 2008.

[6] K. Minami, H. Nakajima, and T. Toyoshima, "Real-time discrimination of ventricular tachyarrhythmia with fourier transform neural network." *IEEE Trans. Biomed. Eng.*, vol. 46, no. 2, pp. 179–185, 2007.

[7] O. Wieben, V. Afonso, and W. Tompkins, "Classification of premature ventricular complexes using filter bank features, induction of decision trees and a fuzzy rule-based system," *Med. Biol. Eng. Comput*, vol. 37, pp. 560–565, 1999.

[8] G. Gómez-Herrero, I. Jekova, V. Krasteva, I. Christov, A. Gotchev, and K. Egiazarian., "Relative estimation of the karhunen-loève transform basis functions for detection of ventricular ectopic beats." *Comput. Cardiol*, vol. 33, pp. 569–572, 2006.

[9] M. Lemay, J. Vesin, A. van Oosterom, V. Jacquemet, and L. Kappenberger, "Cancellation of ventricular activity in the ecg: evaluation of novel and existing methods," *IEEE Trans. Biomed. Eng.*, vol. 54, no. 3, pp. 542–546, 2007.

[10] M. Lagerholm, G. Peterson, G. Braccini, L. Edenbrandt, and L. Sörnmo, "Clustering ecg complex using hermite functions and self-organizing maps," *IEEE Trans. Biomed. Eng.*, vol. 47, no. 7, pp. 838–848, 2000.

[11] J. Mateo and P. Laguna, "Analysis of heart rate variability in the presence of ectopic beats using the heart timing signal," *IEEE Trans. Biomed. Eng.*, vol. 50, no. 3, pp. 334–343, 2003.

[12] I. Christov, G. Gómez-Herrero, V. Krasteva, I. Jekova, A. Gotchev, and K. Egiazarian, "Comparative study of morphological and time-frequency ecg descriptors for heartbeat classification," *Med Eng Phys*, vol. 28, no. 9, pp. 876–887, 2006.

[13] T. Last, C. Nugent, and F. Owens, "Multi-component based cross correlation beat detection in electrocardiogram analysis," *Biomed Eng Online*, vol. 3, no. 26, p. 14, 2004.

[14] V. Krasteva and I. Jekova, "Qrs template matching for recognition of ventricular ectopic beats," *Annals of Biomedical Engineering*, vol. 35, no. 12, pp. 2065–2076, 2007.

[15] R. Acharya, P. Bhat, S. Iyengar, A. Roo, and S. Dua, "Classification of heart rate data using artificial neural network and fuzzy equivalence relation," *Pattern Recognition*, vol. 36, no. 1, pp. 61–68, 2003.

[16] Y. Ozbay, R. Ceylan, and B. Karlik, "A fuzzy clustering neural network architecture for classification of ecg arrhythmias," *Comput in Biol and Med*, vol. 36, pp. 376–388, 2006.

[17] S. Foo, G. Stuar, B. Harvey, and A. Meyer-Baese, "Neural network-based ecg pattern recognition," *Eng. Appl. Artif. Intell.*, vol. 15, no. 1, pp. 253–260, 2002.

[18] A. L. Goldberger, L. A. N. Amaral, L. Glass, J. M. Hausdorff, P. C. Ivanov, R. G. Mark, J. E. Mietus, G. B. Moody, C.-K. Peng, and H. E. Stanley, "PhysioBank, PhysioToolkit, and PhysioNet: Components of a new research resource for complex physiologic signals," *Circulation*, vol. 101, no. 23, pp. e215–e220, 2000 (June 13), circulation Electronic Pages: http://circ.ahajournals.org/ cgi/content/full/101/23/e215.

[19] A. Webb and S. Shannon, "Shape-adaptive radial basis functions," *IEEE Trans. Neural Netw.*, vol. 9, no. 6, pp. 1155–1166, 1998.

[20] C.-C. Lee, P.-C. Chung, J.-R. Tsai, and C.-I. Chang, "Robust radial basis function neural networks," *IEEE Trans. Syst. Man Cybern. B, Cybern.*, vol. 29, no. 6, pp. 674–685, 1999.

[21] L. Jianming, L. Yonggon, S. D. Sudhoff, and H. S. ß. Zak, "Self-organizing radial basis function network for real-time approximation of continuous-time dynamical systems," *IEEE Trans. Neural Netw.*, vol. 19, no. 3, pp. 460–474, 2008.

[22] J. Gonzalez, I. Rojas, J. Ortega, H. Pomares, F. J. Fernandez, and A. F. Diaz, "Multiobjective evolutionary optimization of the size, shape, and position parameters of radial basis function networks for function approximation," *IEEE Trans. Neural Netw.*, vol. 14, no. 6, pp. 1478–1495, 2007.

[23] C. Bishop, *Neural Networks for Pattern Recognition*. Oxford University Press, Oxford, UK, 1995.

[24] Y.-J. Oyang, S.-C. Hwang, Y.-Y. Ou, C.-Y. Chen, and Z.-W. Chen, "Data classification with radial basis function networks based on a novel kernel density estimation algorithm," *IEEE Trans. Neural Netw.*, vol. 16, no. 1, pp. 225–236, 2005.

[25] J. J. Rieta and F. Hornero, "Comparative study of methods for ventricular activity cancellation in atrial electrograms of atrial fibrillation," *Physiological Measurement*, vol. 28, pp. 925–936, 2007.