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Fuzzy pattern classification and the connectionist approach

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Abstract

Several hybrid architectures combining fuzzy pattern classification and the connectionist approach will be developed and tested for the particular problem of diagnostic classification in computerized electrocardiography. The first level of fuzzy description of the input parameters is performed by a layer of Radial Basis Functions, and this step can be seen as a level of data abstraction. A subsequent classical NN processes these fuzzy descriptions. Several experiments have been performed on the components of the resulting architecture in order to point out their influence on the overall performance in the diagnostic classification task. A large validated database has been used for the validation of the proposed hybrid architecture.

1. Introduction

In the last years an increasing interest in solving pattern recognition tasks with the connectionist approach has been observed. In fact, the neural network approach has gained considerable consensus in pattern recognition problems, and in particular, in all fields with large databases it expresses its better potentiality. Lately several attempts to include in an NN the possibility to cope with uncertain or imprecise information has been studied. Fuzzy set theory from its beginning has proven to be a powerful tool for the management and the propagation of uncertainty in many areas (Dubois et al., 1993), and several applications have been successfully implemented and tested. The main objective of this paper is to describe a hybrid architecture combining the fuzzy approach with the connectionist approach for the particular problem of diagnostic classification in computerized electrocardiography. The fuzzy module performs a fuzzy pre-processing obtained by a layer of Radial Basis Function units. This layer is responsible for the characterization in linguistic terms of the input feature space.

Several hybrid systems have been implemented and tested in order to verify the potentiality of the proposed approach. The components of the resulting architecture have been arranged and tuned in order to point out their influence on the overall performance. The main characteristics of the proposed method will be described and reported in detail.

2. The problem of ECG diagnostic classification

The particular problem of diagnostic classification of electrocardiographic signals has been chosen for this study. The first aspect to consider is the level at which the ECG diagnostic classification task (Fig. 1)

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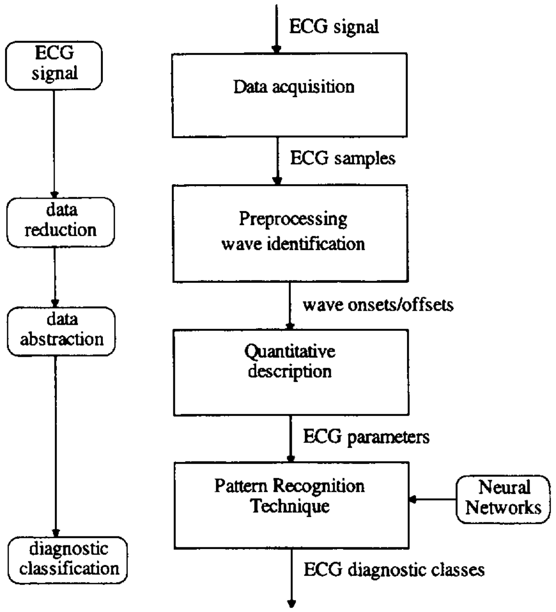

Fig. 1. The Neural Network approach in the ECG signal processing.

will be performed by the combination of the fuzzy pattern classification and the connectionist approach. An ECG signal is composed by 12 standard leads acquired at the frequency of 500 Hz for a period of 10 seconds and hence for a total of 60K sample points. The NN architecture could be applied directly to the sample points, but this approach is not very well feasible mainly because of problems in the learning phase (it would require a very large database). Consequently a first data reduction is performed with classical pattern recognition methods. A set of algorithms, from signal conditioning to pattern identification, from wave identification to the measurements of wave amplitudes, duration and area, is able to perform a quantitative description of the signal and hence parameter extraction (see Fig. 1).

Starting from the set of ECG parameters, several methodologies for the problem of ECG diagnostic classification can be used: from probabilistic approaches to heuristic models, from fuzzy pattern matching models to knowledge-based systems (Degani, 1992; Pedrycz et al., 1991; Special Issue CSE, 1990). In addition, the connectionist approach has been successfully applied and tested with satisfactory results (Bortolan et al., 1991a,b; Bortolan and Willems, 1994). The main objective of this paper it to investigate the possibility of performing a first level of data abstraction (Clancey, 1985) on the ECG parameters in order that a classical neural network may process the results of this data abstraction. This task is achieved by combining the fuzzy approach with the connectionist approach, with the objective of performing the two steps in the same framework. The first level of data abstraction is performed by applying a layer of Radial Basis Function units, and this pre-processing can be interpreted as a fuzzy representation of the input feature space in terms of linguistic descriptions.

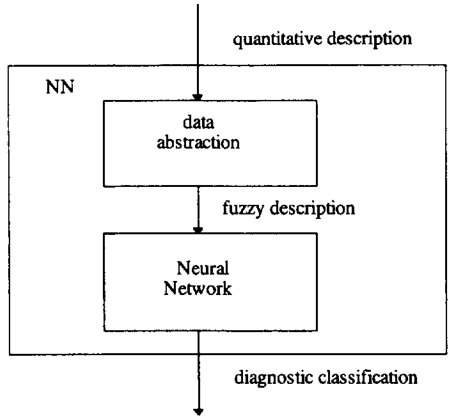

Fig. 2. Diagram of the hybrid architecture.

Consequently the NN will not process and combine the numerical values of the input parameters, but the fuzzy description based on linguistic terms and more or less imprecise concepts (Fig. 2). The resulting architecture should have the characteristic to better simulate the reasoning process of an expert.

3. The ECG database

The proposed architecture has been applied to and tested on the problem of diagnostic classification of rest ECG signals. In order to have a significant validation procedure, a large database developed at the University of Leuven and already tested with other classical classification methods has been used (Willems and Lesaffre, 1987; Willems et al., 1987).

The database consists of 3266 12-lead rest ECGs, 2140 from males and 1113 from females. It is validated by ECG independent clinical data. Seven diagnostic classes were taken into account: normal, Left Ventricular Hypertrophy (LVH), Right Ventricular Hypertrophy (RVH), Biventricular Hypertrophy (BVH), Inferior Myocardial Infarction (IMI), Anterior Myocardial Infarction (AMI) and Mixed Myocardial Infarction (MIX). A random set of 2446 patients was selected for the learning phase, and the remaining 820 cases were used for the testing. Each ECG signal is characterized by 540 primary measurements (45 for each of the 12 leads) obtained by a Computerized ECG Program (Balda et al., 1977). These features are mainly derived from QRS and T wave measurements, in particular the amplitudes and duration of the QRS and T waves, QRS axis, ST-segment elevation or depression, and the area under the QRS and T waves are included.

A first reduced dataset of 166 parameters was established as a result of a clinical selection. From this subset, a second selection of the most statistically significant parameters regarding the seven diagnostic classes was determined resulting in 39 parameters. For this study, the second subset of 39 ECG features was used taking into account the dimensions of the resulting neural networks.

The same database was used in order to establish the performance of linear discriminant analysis and logistic discriminant analysis (Willems et al., 1987). In addition several experiments were made with the same database in order to test the connectionist approach (Bortolan et al., 1991; Bortolan and Willems, 1994).

4. An hybrid architecture for fuzzy pattern classification

4.1. The RBF pre-processing layer

In order to characterize the input patterns in terms of a set of linguistic variables and to perform the data abstraction step (Fig. 2), fuzzy pre-processing was applied (Fig. 3). Each input parameter is represented by means of a set of membership functions, which are related to the different diagnostic classes under examination, and which are represented by Gaussian functions or Radial Basis Functions (RBF).

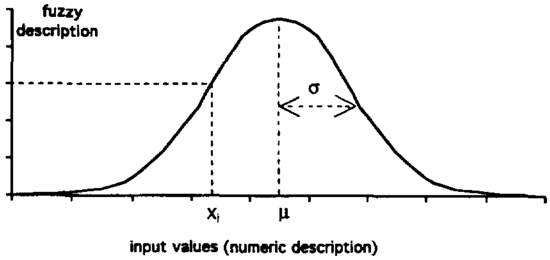

Fig. 3. Fuzzy description of the input feature space.

The shapes of these RBF can be represented as follows:

$$RBF^h(x_j) = \frac{1}{2\sigma_j^h} \exp - \frac{\left(x_j - \mu_j^h\right)^2}{\left(2\sigma_j^h\right)^2}$$

where μ_j^h and σ_j^h are the central value and the dispersion factor of the bell shaped functions. The initial values of these parameters can be derived from the statistics of the input features, and in particular the estimated mean and standard deviation of the input parameter x_j in the diagnostic class h can be utilized for this purpose. In this way, the RBF functions are used as activation functions in the input layer, which can be interpreted as a fuzzy pre-processing of the input feature space. This input layer will feed a normal feed-forward neural network completely connected, in which the activation functions are sigmoidal units (Fig. 4).

The resulting hybrid architecture can be developed in the same connectionist framework, and con-

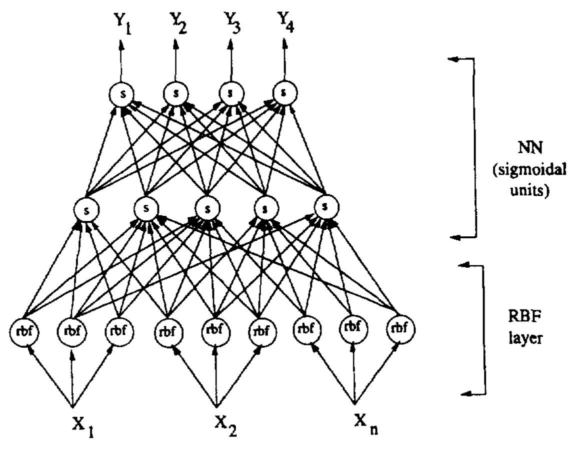

Fig. 4. The hybrid architecture: fuzzy pre-processing and the neural network.

sequently the learning process can be carried out by a modified back-propagation algorithm (Gori and Tesi, 1992; Jang, 1993; Moody and Darken, 1989).

During the training phase, the Root Mean Square (RMS) error was adopted as the error function:

$$E = \sum_{k \in T, i \in O} (d_{k,i} - y_{k,i})^2,$$

where T is the training set and O is the output space, d is the desired target and y is the output of the neural network. The update of the weights is computed following the back-propagation algorithm

$$\Delta w_{ijl} = -\eta_1 \frac{\partial E}{\partial w_{ijl}}.$$

Following the same delta rule algorithm, it is possible to update the parameters μ_j^h and σ_j^h of the RBF units in the following way:

$$\Delta \mu_j^h = -\eta_2 \frac{\partial E}{\partial \mu_j^h},$$

$$\Delta \sigma_j^h = -\eta_2 \frac{\partial E}{\partial \sigma_j^h}.$$

The two learning rates η_1 and η_2 are designed to be adaptive, in order to avoid the problem of local minima. In fact, the use of an RBF for each diagnostic class has the effect to increase the dimension of the resulting neural network, with possible oscillations due to the local minima. Initially the two factors η_1 and η_2 were set to be equal. In case the system error started to oscillate, these values were reduced by a factor of 2. First η_2 is reduced, while η_1 is reduced in case the error behaviour does not change after the reduction of η_2. This adaptive algorithm revealed to be effective in the various experiments performed in this study.

4.2. The hybrid architectures

The hybrid architecture proposed is achieved by considering a fuzzy characterization of the input parameters with respect to all the considered diagnostic classes (**Multi-RBF**) as shown in Fig. 5. Consequently each input feature is connected with m RBF nodes, where m is the number of diagnostic

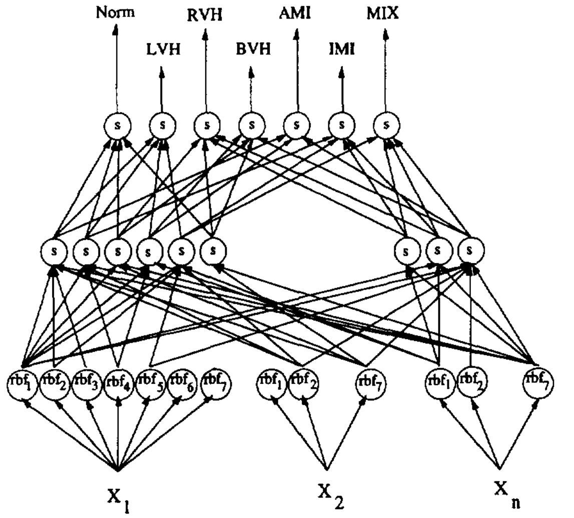

Fig. 5. The Multi-RBF architecture.

classes considered. In this case m is equal to 7. The RBF units are characterized by two parameters: the mean and the standard deviation of the bell shaped functions, and they are tuned considering the statistics of the learning set. In particular, the initial values of the parameters of the RBF nodes are obtained by the following procedure: the learning set is clustered according to the known diagnostic classification, and the mean and standard deviations of all the features are considered as possible values or initial values of the μ_j^h and σ_j^h parameters (original μ and σ). In this case 39 input parameters were selected and seven diagnostic classes were considered, for a total of 273 RBF units (Fig. 5).

In addition, a simplified version was tested, considering only one RBF unit for every input feature (**Single-RBF**). The critical point of this approach is the choice of the appropriate RBF, and in this study the statistics of the "normal" diagnostic class (from the learning set) was considered for the computation of the initial values of μ_j^h and σ_j^h.

In order to have a direct comparison with the simple neural network approach, a three-layer, feed-forward completely connected ANN with only sigmoidal activation functions and trained with the back-propagation algorithm (**Ref**) was used in the same simulation studies.

4.3. The classification strategies

Different classification strategies were adopted and implemented in order to cope with or to test different aspects of the classification task:
(a) all the output nodes with a positive outcome are considered as possible candidates to the classification;
(b) same strategy as (a) but in case all the outcomes are negative, the normal class is chosen;
(c) same strategy as (a) but in case all the outcomes are negative, the highest output is considered as the outcome of the classifier;
(d) the max rule is followed, i.e., the class with the highest output is considered as the outcome of the classifier.

The sensitivity and the specificity are the indices used for the validation and for the comparisons of the different architectures proposed and tested.

5. Results

Several hybrid systems were implemented and tested in order to verify the potentiality of the resulting NN. The components of the resulting architecture were arranged and tuned in order to point out their influence on the overall performance.

The learning rates for the sigmoidal units (η_1) and for the RBF units (η_2) are both adaptive with an initial value set to 0.001 in **Ref** and **Single-RBF** architectures and to 0.0001 in the **Multi-RBF** case. Several experiments were performed for choosing the number of nodes in the hidden layer, trying to find a good trade-off between learning speed and generalization property. Consequently 30 units were chosen in the **Single-RBF** and in the **Ref** architecture and 50 units in the **Multi-RBF** case.

The initial values of the parameters that characterize the RBF units were computed from the distribution of the ECG parameters in the learning set in the different diagnostic classes.

The role of the RBF functions derived from the statistics of the input parameters in the different diagnostic classes was investigated, studying in particular the effect of the initial shape of the RBF. In general, the initial values of σ were set equal to the standard deviation of the corresponding input parameters (original σ values). In addition increasing values of σ for the RBF nodes (σ equals to twice, three and four times the standard deviation) were adopted in order to avoid the saturation phenomenon in the RBF units, and σ values equal to twice, three and four times the standard deviation were tested.

The following four experimental conditions were tested in this study:
- the RBF unit parameters and the input weights were trained (**tr:RBF + inp.w**);
- the RBF unit parameters were set to their initial values and the input weights were trained (**tr:inp.w**);
- the RBF unit parameters were trained and the input weights were set to the unit value (**tr:RBF**);
- the RBF unit parameters were set to their initial values and the input weights were set to the unit value (**tr:--**).

In Fig. 6 the sensitivity and the specificity of the four different experimental conditions are reported for the

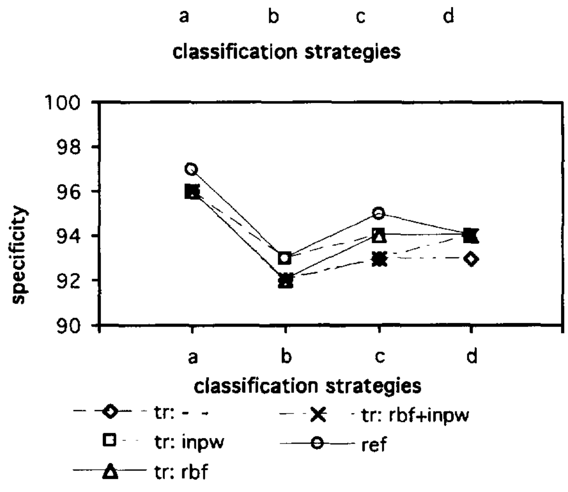

Fig. 6. Sensitivity and specificity of the Single-RBF architecture (original σ values).

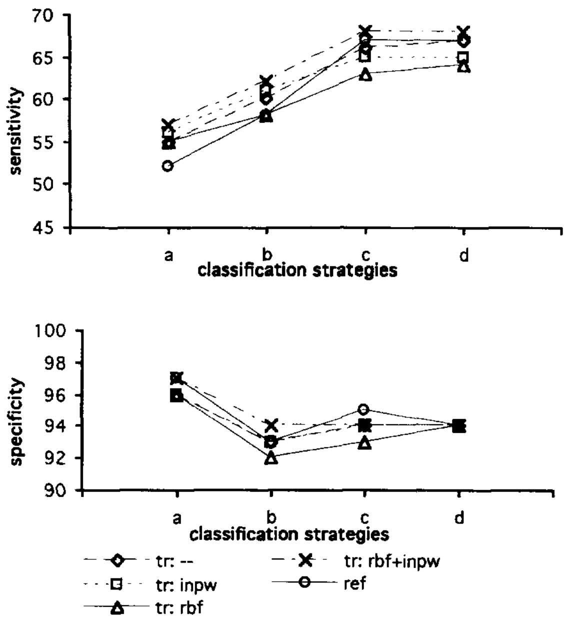

Fig. 7. Sensitivity and specificity of the Multi-RBF architecture (original σ values).

Single-RBF architecture, considering the four classification strategies (a), (b), (c), (d).

In Fig. 7 the sensitivity and the specificity of the four different experimental conditions are reported for the **Multi-RBF** architecture. In general, the classification strategies (c) and (d) realize better performances. In fact (c) and (d) yield higher sensitivity values and a satisfactory specificity in the two hybrid architectures.

5.1. The influence of the initial values of the parameters of the RBF units

The influence of the initial values of the two parameters of the RBF units was studied. Large initial values of σ_j^h in the RBF units cause a faster learning process, preventing saturation phenomena in the RBF units. On the other hand, the use of too large σ_j^h values may damage the fuzzy pre-processing, because the fuzzy sets loose their original scope, and they are no longer able to characterize the input parameters in a meaningful way. In order to visualize the convergence properties with different strategies in the choice of the initial values of the RBF units, the RMS error plots are reported.

In Fig. 8, the RMS error in the training phase is reported for the **Ref** and the **Single-RBF** architecture. On the x-axis, the epoch number is reported, while on the y-axis the corresponding RMS error

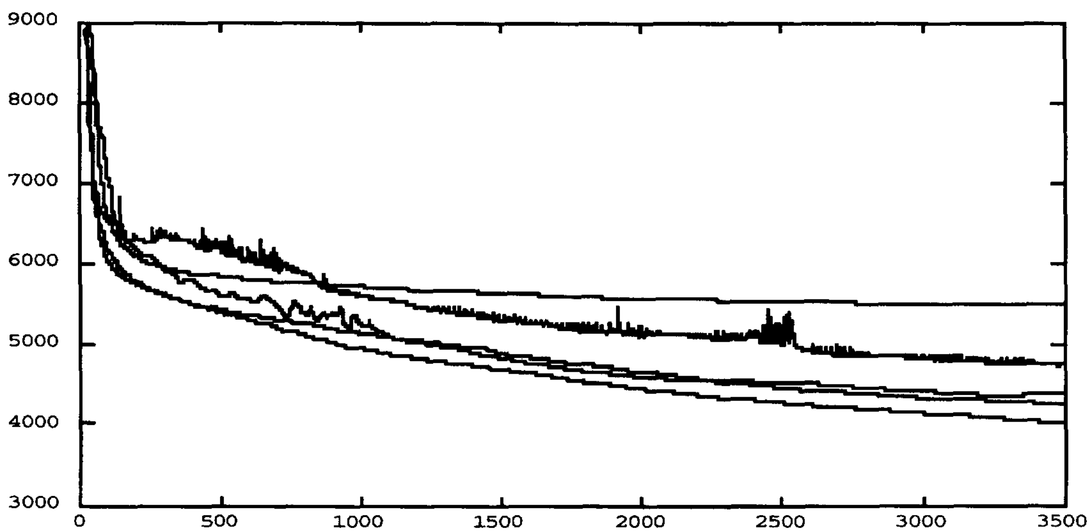

Fig. 8. Training error plots of the evaluated systems (Single-RBF, tr:RBF + inp.w) with original RBF σ values compared with the reference system error.

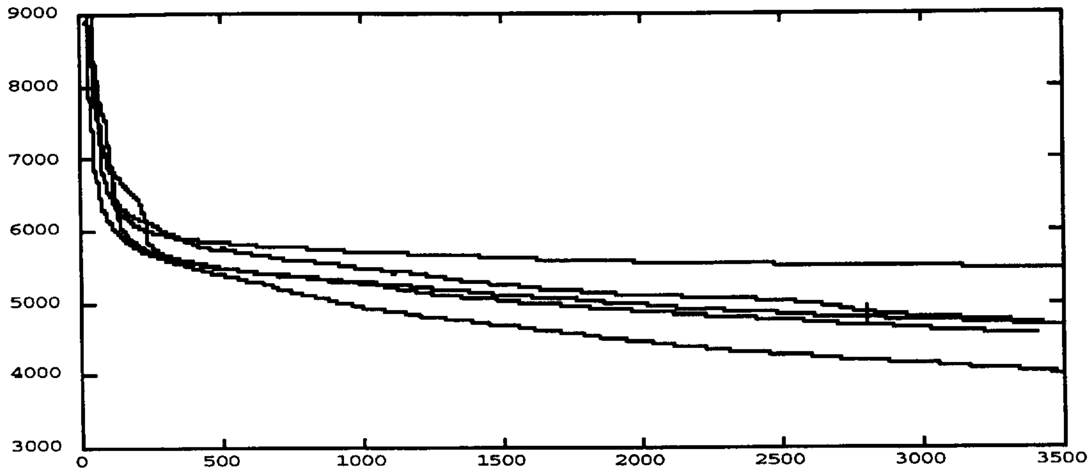

Fig. 9. Training error plots of system Single-RBF (tr:inp.w) with different σ values compared with the reference system error.

values are reported. The curves from top to bottom (at epoch number 3500) correspond to
(1) the reference system (Ref),
(2) the system with trained RBF parameters and input weights (tr:RBF + inp.w),
(3) the system with trained RBF parameters (tr:RBF),
(4) with no trained components (tr:--), and
(5) with trained input weights (tr:inp.w).

A test was performed choosing different initial values of the parameters, which were initially set to once, twice, three and four times the original standard deviation extracted from the learning set.

Fig. 9 reports the influence of the choice of different values of the standard deviation of the RBF nodes; the error plot of the **Single-RBF** architecture in the case of training the input weights (tr:inp.w) is shown. In this figure the following cases can be observed from top to bottom:
(1) the reference system,
(2) twice the original σ,
(3) three times the original σ,
(4) four times the original σ,
(5) the original σ.

In Fig. 10 is the error plot corresponding to the

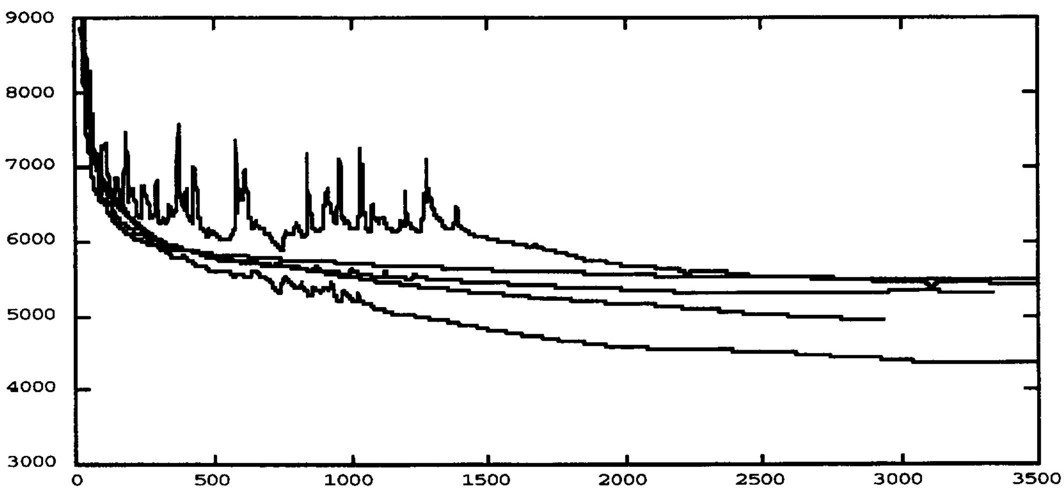

Fig. 10. Training error plots of system Single-RBF (tr:RBF), and different σ values compared with the reference system error.

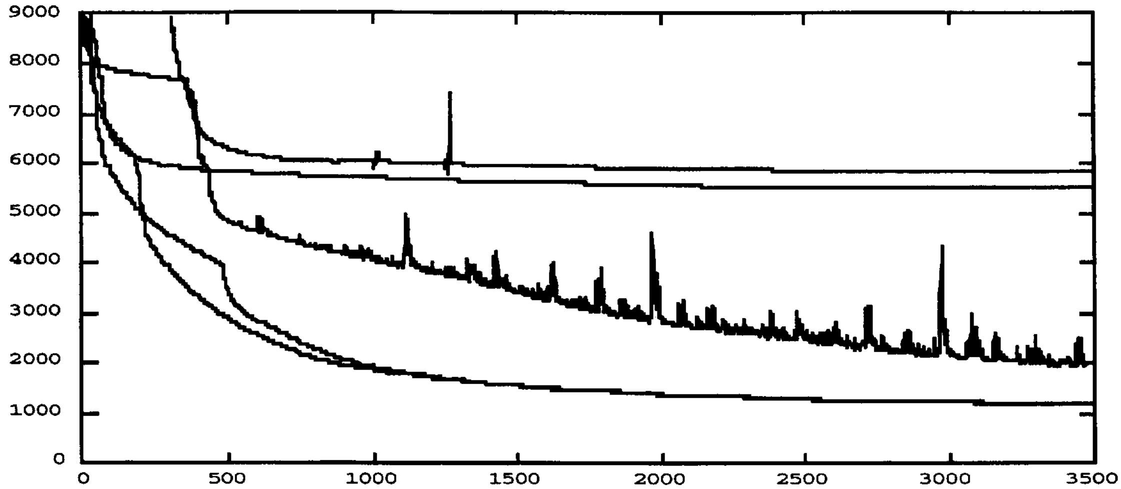

Fig. 11. Training error plots of the evaluated systems (Multi-RBF) with original RBF σ values compared with the reference system error.

Single-RBF architecture in the case of training the parameters of the RBF units (tr:RBF); from top to bottom we have the following:
(1) the reference system,
(2) twice the original σ,
(3) four times the original σ,
(4) three times the original σ,
(5) the original σ.

In Fig. 11 the error plots as obtained with the Multi-RBF architecture are shown. From top to bottom the following cases can be observed:
(1) tr:RBF + inp.w,
(2) the reference system,
(3) tr:inp.w,
(4,5) tr:--, tr:RBF.

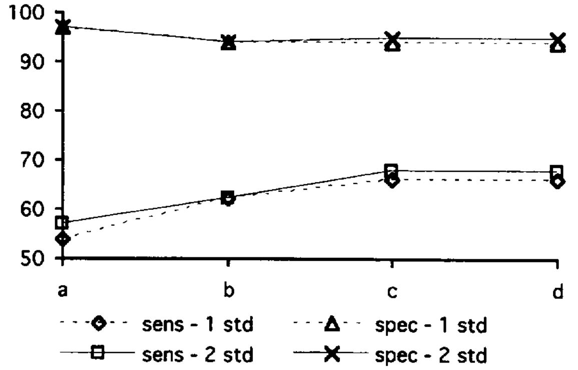

Fig. 12. Sensitivity and specificity of the Multi-RBF architecture with original (1 std) and double original standard deviation (2 std).

In Fig. 12 the sensitivity and specificity of the Multi-RBF architecture with original (1 std) and twice the original standard deviation (2 std) is reported for the various classification strategies.

We observe that the learning speed of convergence is higher in systems where training of the input weights is not performed. Moreover, those systems having original initial RBF standard deviation values learn much faster than the other ones, even if the resulting performances are quite similar. The slowest system in learning is almost always the reference system, while the evaluated hybrid structures become slower and slower in learning when larger initial RBF σ values are applied. Finally, when both RBF units and input weights are trained, the error plots show many oscillations, because there can be more local minima than with the other configuration structures. In this case, the error trends are also closer to each other than in the previous situations.

5.2. Pruning techniques

A pruning algorithm was applied in order to study the possibility to simplify the neural network and in order to decrease the dimension or the size of the network. In addition, the influence of this procedure on the performance of the classification task was

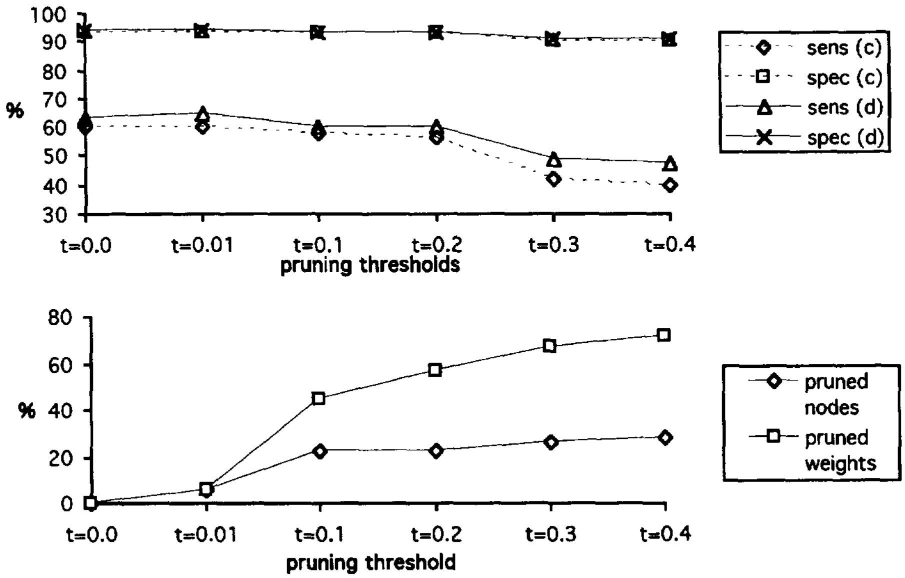

Fig. 13. Performance of the Single-RBF architecture with the pruning procedure.

studied. A penalty term was added to the cost function of the back-propagation algorithm, in order to lead the network to configurations in which the weights assume low values (Reed, 1993). In this way the pruning algorithm consists in setting to zero the weights with a value lower than a pre-defined threshold t, i.e.

IF abs(w_{ij}) $< t$

THEN set $w_{ij} = 0$.

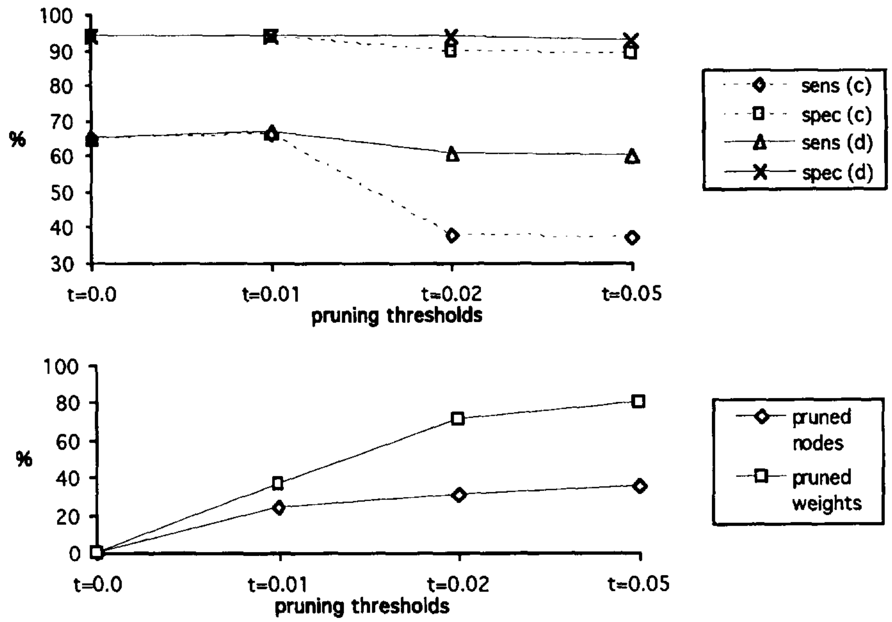

Fig. 14. Performance of the Multi-RBF architecture with pruning.

In Fig. 13 the results of pruning the Single-RBF architecture are illustrated. The sensitivity and the specificity with the classification strategies (c) and (d) are reported with different values of the pruning thresholds: $t = 0.0$, $t = 0.01$, $t = 0.1$, $t = 0.2$, $t = 0.3$, $t = 0.4$. In addition, the percentage of pruned nodes and weights in the corresponding situations are reported.

The results reported in Fig. 14 concern the Multi-RBF architecture. The sensitivity and the specificity with strategies (c) and (d) are reported with different values of the pruning thresholds: $t = 0.0$, $t = 0.01$, $t = 0.02$, $t = 0.5$. Again, in the lower figure the percentage of nodes and weights are reported.

From these results, it is evident that the specificity is not significantly influenced by the pruning algorithm at the different threshold values. On the other hand, the sensitivity shows a higher dependence on the pruning procedure. In addition, classification strategy (c) is more sensitive than strategy (d), and this is more evident in the Multi-RBF architecture.

6. Conclusions

In this paper several hybrid architectures of neural networks have been tested for the particular problem of diagnostic classification in computerized electrocardiography. The possibility to combine the fuzzy approach with the connectionist approach has been investigated. A first level of data abstraction on the feature space has been performed with a layer of RBF units which produce a fuzzy description of the input parameters. The subsequent NN will not process numerical values but the fuzzy description based on linguistic terms or concepts. Several systems have been implemented and tested and the components of the resulting architectures have been arranged and tuned in order to point out their influence on the overall performance in the diagnostic classification task.

In particular, several experiments have been analyzed implementing and testing different training strategies concerning the weights of the input layer and the parameters of the RBF units. The influence on the speed of convergence has been considered. In addition, a pruning algorithm has been applied in order to simplify the resulting architecture preserving the generalization property.

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