Comparison of Different Neuro-Fuzzy Classification Systems for the Detection of Prostate Cancer in Ultrasonic Images

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Abstract - We selected five trainable Neuro-Fuzzy classification algorithms in order to investigate their ability to differentiate areas of malign tissue in ultrasonic prostate images. The algorithms were compared with results from two commonly used classifiers, the K-nearest neighbor (KNN) classifier and the Bayes classifier. The best Neuro-Fuzzy classification system, which is based on a mountain clustering algorithm published by Yager *et al* and refined by Chiu reached recognition rates above 86 % in comparison to the Bayes classifier (79 %) and the KNN classifier (78 %). Our results suggest that Neuro-Fuzzy classification algorithms have the potential to significantly improve common classification methods for the use in ultrasonic tissue characterization.

INTRODUCTION

The aim of our work was to investigate the performance of different Neuro-Fuzzy classification methods for the distinction of benign and malign tissue in ultrasound prostate diagnosis. The motivation to use Neuro-Fuzzy systems is based on different observations: (1) In most of the cases biological data exhibit a priori unknown statistical properties. Therefore, trainable classification algorithms based on some kind of learning procedure promise better performance than non-adaptive classifiers such as the Bayes classifier or the KNN classifier. (2) Neuro-Fuzzy systems use a learning procedure to determine an appropriate set of Fuzzy membership functions (msf). This set of membership functions can be expressed in linguistical terms and hence provides an understanding about the properties of the classification problem. (3) Fuzzy systems allow to incorporate a priori knowledge into the classification process which enables to include some of the experience of the physician into the classifier.

METHODS

The five selected Neuro-Fuzzy systems are able to deal with multiple parameter input and multiple class output problems. In the following we will give a short overview over the implemented algorithms:

(1) '*trainable Fuzzy system'* [5][13]: This method is based on the division of the pattern input space by equally spaced membership functions. This approach leads to a Fuzzy set with a high number of rules. For each rule a 'grade of certainty' is computed which is adjusted during the learning procedure. The output of each rule is weighted by the grade of certainty during the classification process.

(2) '*histogram based Fuzzy System*' [1]: During the learning phase this system builds up histogram based look-up tables (LUT) with a varying number of partitions for all parameters and each class. The distance between the histograms of each pair of classes is determined by the Mahalanobis distance [8] which is used during the classification process to obtain a 'vote' for the most possible class for a given pattern. Even though this approach can not be considered to be strictly a Neuro-Fuzzy system in the sense of producing a Fuzzy system as output, we selected this algorithm because of its ability to determine the most significant parameters during the learning procedure and the very small time necessary for training in comparison to other methods (see Table 2).

(3) 'mountain clustering/*ANFIS*': This algorithm is based on a mountain clustering algorithm introduced by Yager *et al* [16] and refined by Chiu [2].

The determined cluster centers are used to initialize a Neuro-Fuzzy system that is trained by ANFIS, an ‘Adaptive-Network-Based Fuzzy Interference System’, proposed by Jang [6]. Both algorithms are provided by the MATLAB Fuzzy Toolbox.

(4) ‘*NEFCLASS*’: The NEFCLASS algorithm was introduced by Nauck and his coworkers in 1994 [9][12]. The algorithm is based on a common multilayer perceptron structure whose weights are modeled by Fuzzy sets and the activation, the output and the propagation functions are adapted accordingly. This approach preserves the common neural network structure, but allows the interpretation of the resulting system by the associated Fuzzy system. During the learning procedure the shape and position of the triangular membership functions are adapted iteratively. The algorithm is available in the Internet.

(5) ‘*Fuzzy-Kohonen Net*’: This algorithm was developed by Mitra *et al* [11] and is based on a modified Kohonen classifier [8], where the input is modified to accept linguistic representations of crisp input values, and the output provides Fuzzy decisions in the form of membership values. The learning procedure is similar to the learning procedure of a Kohonen map [8].

The Neuro-Fuzzy classifiers were tested on the well-known set of Iris data introduced by Fisher [4] which consists of a three class problem based on four parameters of the Iris plant, i.e. the petal length and width and the sepal length and width. One type of the plant can be separated linearly from the two other types whereas the other two types of the plant cannot be separated linearly from each other.

Our in vivo data of the prostate consist of 200 RF-images with histologically characterized pathology. The data were acquired with a Kretz Combison 330 scanner and a 7.5 MHz transrectal probe from patients who were undergoing radical prostatectomy. The data were corrected for diffraction and global attenuation as described in [14]. We selected 4 out of 17 tissue parameters which were already employed successfully in prior studies [15]. The selected parameters are well documented in the literature [3][7][14]: the local attenuation at center frequency (α_m), the backscatter coefficient at center frequency (b_m), the normalized deviation (S^2_{rel}) of the frequency dependent backscatter coefficient from the linear fit, and the co-occurrence parameter correlation (COR). The extracted parameters correspond to segments in the ultrasonic image of the approximate size of 3 x 3 mm. Our training data set contained pattern vectors of approximately 3000 segments from 33 patients with class information which was determined from a histology report after the prostatectomy.

We used a Jack-knife test of 50 % for the Iris data and the leave-one-out method for the prostate data in order to obtain an estimate for the classifier performance. Therefore, the results indicated in Table 1 and Table 2 present a pessimistic estimate of the real classifier performance.

In order to compare the quality of the implemented systems we determined the overall classification rate (accuracy), its sensitivity and specificity, and the standard deviations of the classification results over all patients leaving each patient out of the training set. From the medical point of view we preferred classification results which showed a balanced relationship between sensitivity and specificity which is in contrast to non-medical applications, where a high number of correctly classified patterns can be more desirable.

algorithm	best system parameters	accuracy
trainable Fuzzy system (Nozaki, *et al*)	6 membership func., 100 epochs	96.00
histogram based Fuzzy system (Blackmore)	number of partitions: $P = 3$	**97.33**
mountain clustering/ANFIS (Yager, *et al*/Chiu/Jang)	cluster radius: $R = 0.8, 0.9, 1.0$	**97.33**
NEFCLASS (Nauck, *et al*)	hidden neurons $N = 10$	96.67
Fuzzy Kohonen Net (Mitra, *et al*)	net size 10x10, 100 epochs	91.33
KNN	no. of neighbors $K = 4, 6, 8$	96.67
Bayes	assumption of normal distribution	**97.33**

Table 1: Performance of the implemented Neuro-Fuzzy classification systems on the Iris data set introduced by Fisher [4]. ‘*accuracy*’ refers to total number of correctly classified input patterns.

algorithm	best parameters	approximate time of learning	accuracy (std. dev.) in %	specificity (std. dev.) in %	sensitivity (std. dev.) in %
trainable Fuzzy system (Ishibuchi, Nozaki, *et al*)	50 epochs, 16 rules, 2 Gaussian shaped membership functions	ca. 30 min	82.6 (3.4)	81.0 (9.7)	84.7 (7.8)
histogram based Fuzzy system (Blackmore)	Mahalanobis-distance partitioning: P = [4 6 4 6]	ca. 1-2 min	83.3 (3.8)	81.4 (6.4)	85.0 (4.7)
mountain clustering/ANFIS (Yager, *et al*/Chiu/Jang)	Cluster radius: R = 0.5 0 epochs, Euklid-distance 3 membership functions, 3 rules	ca. 23 min	**86.1 (3.6)**	**84.6 (5.1)**	**87.2 (4.3)**
NEFCLASS (Nauck, *et al*)	500 epochs, ∅ 25 rules 4 triangular membership functions, hidden layer with 20 neurons	ca. 10 min	84.3 (3.8)	78.5 (6.3)	87.9 (5.6)
Fuzzy Kohonen Net (Mitra, *et al*)	1 epoch, Euklid distance, 10 neurons, 2 membership functions	ca. 60 min for 10 epochs	78.8 (5.4)	78.2 (19.4)	78.0 (15.0)
KNN	K = 1, Mahalanobis distance	ca. 15 min	78.4 (16.3)	79.7 (25.8)	77.7 (23.0)
Bayes	assumption of Gaussian distribution	ca. 15 min	79.0 (18.7)	71.4 (25.8)	79.6 (32.0)

Table 2: Performance of the implemented Neuro-Fuzzy classification systems on the prostate data with four parameters and two classes 'malign' and 'benign'. The learning time refers to the time per patient during the leave-one-out test with a training data set of 3000 samples and a 200 MHz Pentium PC. '*std. dev.*' indicates the standard deviation computed over all 33 patients during the leave-one-out test

RESULTS

In Table 1 we present the results which were obtained with the classification of the Iris data. The classifiers with the best performance are highlighted in bold. We find that the classification results of the KNN and the Bayes classifier are comparable to the performance of the Neuro-Fuzzy classifiers.

The results obtained with the human prostate data are presented in Table 2. Due to its memory demand, which was caused by the high number of rules, we were restricted to use a maximum of three membership functions for the trainable Fuzzy system. However, this algorithm was very robust and held a balanced relationship between specificity and sensitivity.

For the histogram based Fuzzy system we varied the number of bins of the histograms and achieved our best results with a partitioning of P = [4 6 4 6].

The mountain clustering algorithm showed best results with a cluster radius of R = 0.5. The learning procedure with ANFIS led to an increasing gap between sensitivity and specificity. Even though the absolute recognition rate was steadily increasing between 0 to 400 epochs from 86.1 % to 86.5 %, the difference between specificity and sensitivity was increasing from 4 % to 15 % with a significant decrease in specificity from 84.6 % to 77.0 %.

Similarly, the NEFCLASS algorithm reached high recognition rates on the expense of a balanced relationship between specificity and sensitivity.

In general the Fuzzy Kohonen Net performed least satisfying in comparison to the other algorithms. Even though we trained the net with 10 epochs and more, the best results were obtained with one epoch only. Due to the high time necessary for training (60 min per patient) we did not investigate this system in closer detail.

The KNN classifier yielded best results with K = 1. As can be seen in Table 2, both, the Bayes classifier and the KNN classifier had very low recognition rates in comparison to the Neuro-Fuzzy systems.

DISCUSSION

In general the Bayes classifier and the KNN classifier could not handle the prostate data as good as the Neuro-Fuzzy classification systems. This supports our earlier findings using artificial neural networks [15]. This effect was not observed with the Iris data which can be contributed to the different statistical properties of the two data sets. With the Iris data every system had problems to identify the same four outliers which limited the achievable recognition rate to 97.33 %. The algorithm which was the most effective on both data sets was the mountain clustering algorithm with no ANFIS applied. This preserved a good relationship between sensitivity and specificity and yielded high recognition rates.

This study was done on segments with confirmed histology in small regions of interest within the prostate area. We are currently continuing to collect RF data in order to obtain a data base of classified prostate images with histologically confirmed two-dimensional class information. With these data we plan to extend our approach to more than two tissue types.

CONCLUSIONS

With this work we investigated five different trainable Neuro-Fuzzy classification algorithms which were based on different approaches to organize and classify biological data sets by the construction of a Fuzzy interference system. The best classifier based on a mountain clustering algorithm reached recognition rates above 86 % in comparison to the Bayes classifier (79 %) and the KNN classifier (78 %). These results suggest that Neuro-Fuzzy algorithms have the potential to significantly improve common classification methods for the use in ultrasonic tissue characterization.

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