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COMPARISON OF THREE DIFFERENT METHODS FOR AUTOMATED DISCRIMINATION OF MYOCARDIAL HEART DISEASE

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Abstract: The aim of this paper is to compare the performance of three different methods, i.e., neural network with backpropagation learning, neural network with genetic-algorithm-based learning, and genetic-algorithm-based (GA-based) fuzzy logic approach, for automated discrimination of myocardial heart disease. In our experiments, a total of 90 samples of echocardiographic images from 45 subjects were used. Four statistical features, namely, angular second moment, contrast, correlation and entropy, were extracted from each image. These four features were subsequently used in our classification schemes. Our results showed that the GA-based fuzzy logic approach is superior to the other two methods. This method enables the classification to achieve a 95.9% of the average recognition rate. Thus the use of GA-based fuzzy logic approach has the potential to become clinically useful for the computer-aided diagnosis of the heart disease.
Keywords: medical images, computer-aided diagnosis, classification

1 INTRODUCTION

In recent years computerized classification has the potential of increasing diagnostic accuracy in medical imaging such as ultrasonography, computed tomography, magnetic resonance image, and nuclear medicine. These schemes are generally referred to as computer-aided diagnosis (CAD) schemes. A CAD scheme can provide the advantage of having a second reader when one would otherwise be absent.

The use of ultrasonic heart (echocardiographic) images has been an important non-invasive means in clinical cardiology. The diagnosis of heart functions using echocardiography is comparably common among a variety of diagnostic methods. However, since the classification of normal and abnormal cases largely depends on diagnostician's subjective point of view and his/her experience, the criteria of diagnosis are indeterminate. If a CAD can be developed, this subjectivity may be reduced and in turn the accuracy in diagnosis is expected to increase.

In a previous study we presented an artificial neural network (ANN) for classification of two sets of echocardiographic images, namely, normal heart and abnormal (myocardial) heart [1]. Weighting coefficients of the ANN used in this study were determined through backpropagation (BP) training. Recently, we reported an alternative training method using a genetic-algorithm (GA) instead of the BP method for the ANN [2]. More recently, we presented a fuzzy classification technique in order to improve the CAD performance for diagnosis of myocardial heart disease [3]. The fuzzy classification approach is to exploit the GA-based training for optimization of membership functions.

The aim of this paper is to compare the performance of these three different methods in terms of accuracy, sensitivity and specificity.

2 METHODS

Figure 1 shows the schematic diagrams of the ANNs used in this study. Figure 1(a) is the ANN trained by the BP method and Fig. 1(b) is that trained by GA method. The ANNs employed are 4-4-3 three-layer networks. Consequently there are 28 weighting coefficients. As shown in Fig. 1(a), the BP-based training occurs by adjusting the values of weighting coefficients to minimize the mean squared error between the desired value (teacher's signal) and actual value of the output units. The desired value is the output component of the input/output pairs in the training set. Figure 2 shows the block diagram illustrating the procedure of how to determine the weighting coefficients using GA.

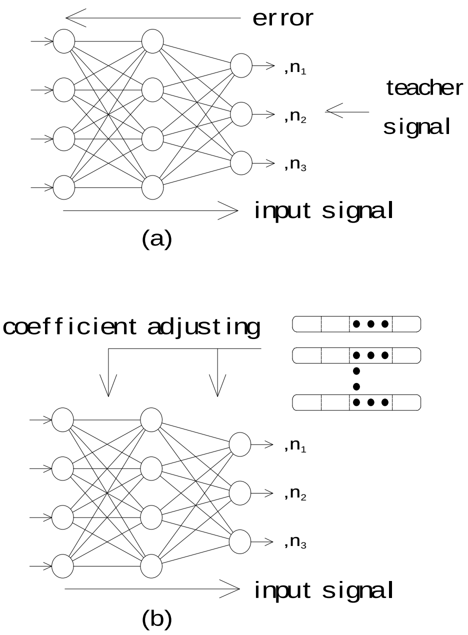


Figure 1. Schematic diagrams of NNs used (a) trained by a BP method and (b) trained by a GA

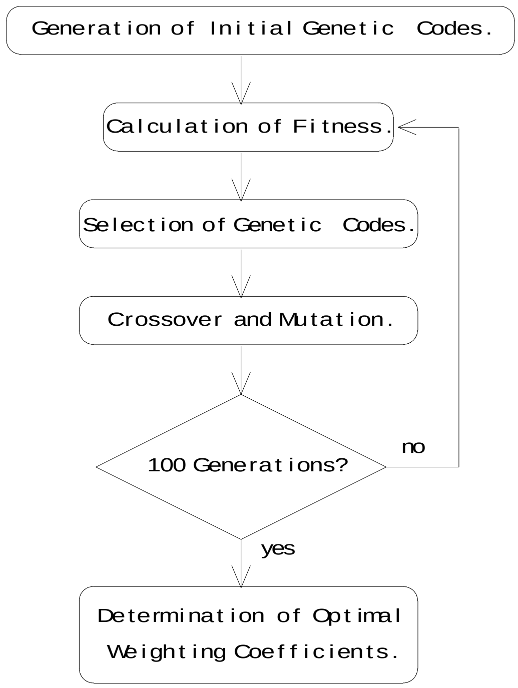


Figure 2. Procedure of how to determine the weighting coefficients using the GA method

Our GA-based fuzzy reasoning for classification scheme is to use a fuzzy set with Gaussian–distributed membership functions (MSFs) having the maximum value of unity (normalized). The normalized MSFs can be expressed as follows.

$$f(x) = \exp\{-\frac{1}{2}(\frac{x - ì}{ó})^{2}\} \tag{1}$$

where x is a feature value, ì is the mean value of x from a set of images belonging to the same category, andó is the standard deviation of the feature values. As shown in Fig. 3 (solid line), the two parameters, ì andó, can be used to completely define a single MSF. When x is gradually apart from ì, the membership value should become small. If the number of sample images are limited, the value ofó may not completely reflect the characteristic of all images of the same category. Therefore we employ a method to use GA at training phase for searching optimal MSF by varying the value of ó with an coefficient as shown below.

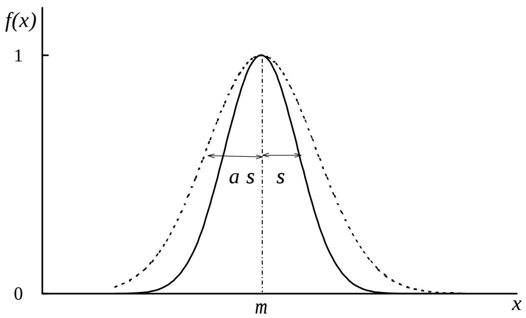


Figure 3. Gaussian-distributed membership Functions.

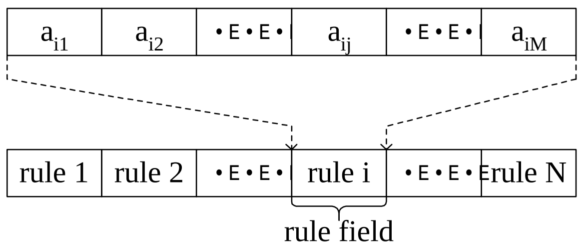


Figure 4. Configuration of an individual consisting of N fuzzy rules.

$$f(x) = \exp\{-\frac{1}{2}(\frac{x-\mu}{a\sigma})^2\} \qquad (2)$$

where a is acted as an optimal parameter through GA-based training process.
In the current simplified fuzzy rules as shown in eq.(3) are used:

Rule1: If x_1 is a_{i1} and, …, and x_M is a_{iM}, then y is w_i, (3)

where i (i=1,2,3, ……., N) are rule numbers, x_1, x_2,…..x_M are input variables to the fuzzy reasoning, y is the output, a_{i1},……,a_{iM} are fuzzy labels corresponding to the input variables, and w_i is a real number of the consequent part of the fuzzy rule.

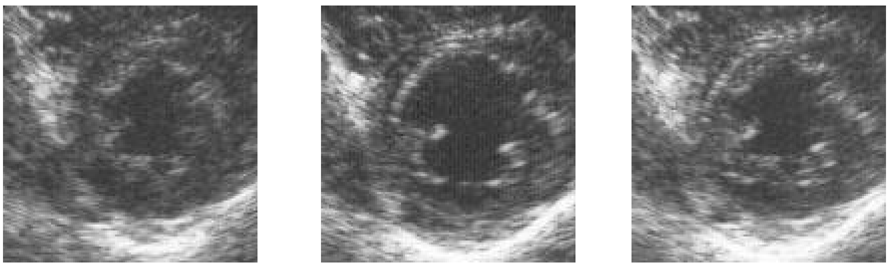
As shown in Fig. 4, an individual (a chromosome) consisting of N fuzzy rules is generated. One individual represents one rule set, namely, fuzzy reasoning, and each fuzzy rule is assigned by a rule field. The premise part (antecedent) membership functions of each fuzzy rule consisting of input variables are partitioned in a rule field. Each variable is encoded as an n-digit binary number. The variable set is then expressed by a finite-length string (an individual*).*

3 EXPERIMENTS

A total of 90 samples of echocardiographic images from 45 subjects (2 sample images per subject: an end-systole image and an end-diastole image) were used in this study. Of the 45 subjects 23 were diagnosed by a highly trained physician as normal hearts and the remaining 22 as abnormal hearts. Each image was digitized by an image scanner at the resolution of 256×256 pixels. In our investigation we found that the use of composite images could provide higher recognition rate as compared to that of individual images at end-systole and end-diastole. Therefore, in the experiments we used composite images a(x,y),,,, which were obtained as follows:

$$a(x,y)=max[f(x,y), g(x,y)], \qquad (4)$$

where f(x,y) and g(x,y) refer to the images at end-systole and end-diastole states, respectively. Figure 5 shows an example of the normal case. The images at end-systole and end-diastole states are shown in Figs. 5(a) and 5(b), and the composite image is shown in Fig. 5(c).



(a) (b) (c)

Figure 5. An examples of image data. (a) end-systole, (b) end-diastole, and (c) composite images.

We generated a gray-level cooccurrence matrix from each of composite images. From the gray-level cooccurrence matrix, 4 features, namely, angular second moment, contrast, correlation and entropy, were selected as the texture features of the composite images. These features were subsequently used in the three classification schemes.

Figure 6 illustrates the procedure of our classification schemes for the BP- and GA-based ANNs. Figure 7 shows the classification mechanism of the fuzzy reasoning using 8 Gaussian-distributed MSFs.

4 RESULTS

Table 1 shows the classification on the basis of three parameters, namely, accuracy, sensitivity and specificity for the three methods. It is noted from the table that the performance of the GA-based fuzzy logic method is superior to the other two methods. The GA-based fuzzy logic method enables the classification to achieve a 95.9% of the average recognition rate.

In conclusion, we compared the performance of the BP-and GA-based ANNs and GA-based fuzzy logic for automated classification of heart diseases from ultrasound images. Our preliminary results suggest that the GA-based fuzzy logic method has the potential to become clinically useful for the CAD of heart disease. Future work increasing sample sets for further feasibility test on the described methods is needed.

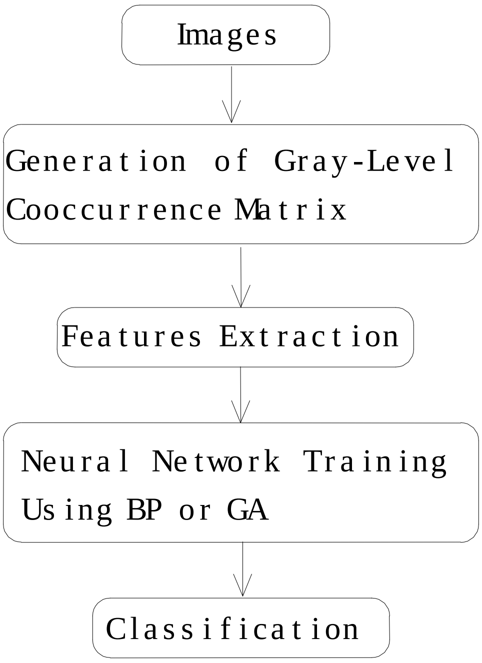


Figure 6. Block diagram of classification scheme for our ANN.

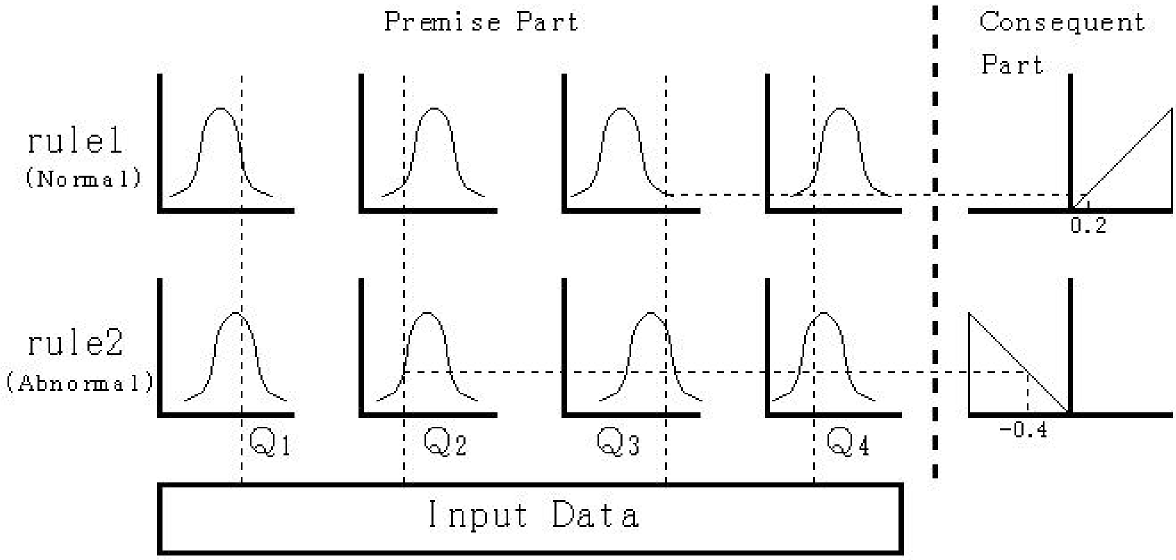


Figure 7. Fuzzy reasoning using 8 Gaussian-distributed MSFs.

Table 1. Comparison of parameters for evaluating the various methods' performance.

Method	Accuracy(%)	Sensitivity(%)	Specificity(%)
BP-NN	84.5	90.9	70.0
GA-NN	88.7	91.7	86.4
GA-Fuzzy	95.9	91.7	100

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