

Measurements of Texture Features of Medical Images and Its Application to Computer-Aided Diagnosis in Cardiomyopathy

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ABSTRACT

In this paper we use four texture features of ultrasonic images for the classification of heart disease. The texture features are measured from a gray-level cooccurrence matrix generated from the heart images and are used as inputs to our classification system incorporated with soft computing technologies, which include fuzzy logic-based systems, neural-network-based systems and genetic algorithms. We evaluate the performance of our proposed method in terms of sensitivity, specificity and overall accuracy. Experimental results show that the proposed method has potential utility for computer-aided diagnosis of myocardial heart disease.

Keywords: feature measurement, soft computing, medical imaging, classification

1. INTRODUCTION

The diagnosis of heart functions using echocardiography is comparably common among a variety of diagnostic methods. Cardiomyopathy is one of the most common heart diseases. It is a serious disease in which the heart muscle becomes inflamed and does not work as well as it should. Cardiomyopathy can be classified into three principal types: dilated, hypertrophic and restrictive. Echocardiography is one of the best tools for diagnosing cardiomyopathy. However, since the clinical interpretation process and the results largely depend on physician's subjective point of view and his/her experience, the criteria of diagnosis are somewhat indeterminate. If a computer-aided technique, which provides a second opinion for the physician, can be developed, then this subjectivity may be reduced and in turn the accuracy in diagnosis is expected to increase.

In a previous study [1], we presented an artificial neural network (NN) for classification of two sets of echocardiographic images, namely, normal heart and abnormal (myopathic) heart. In the training phase, weighting coefficients of the NN used in this study were determined through backpropagation (BP). The preliminary results showed that the NN technique had the

potential for computer-aided-diagnosis (CAD) of the heart disease. More recently, we also reported a different training method using a genetic algorithm (GA) instead of the BP method for the NN [2]. The experimental results showed that the performance of the GA-based NN was superior to that of the BP-based NN in terms of classification rate. However, there is still much room for improvement in meeting the requirements for practical CAD.

This paper describes a fuzzy classification technique to attempt further improving the CAD performance for diagnosis of cardiomyopathy. This fuzzy classification approach is to exploit the GA-based training for optimization of membership functions. Recent attempts to use GA to optimize fuzzy reasoning have been made [3],[4],[5]. Ishibuchi *et al.* [3] proposed a GA-based method for selecting a small number of significant fuzzy if-then rules to construct a compact fuzzy classification system. Perneel *et al.* [4] reported an optimization method that used a GA to tune the parameters of the decision-making system. The method was subsequently tested on a vehicle recognition system. The shapes of the pre-set membership functions used were triangular and trapezoidal. Ohki *et al.* [5] proposed an optimization method of fuzzy reasoning by use of GA with variable bit-selection probability. The method was tested on a crossroad travelling of an autonomic robot. However, so far none of the literatures known to the authors regarding the use of GA for optimization of fuzzy membership functions has been reported

In our proposed method, unlike the conventional types of membership functions, Gaussian-distributed membership functions (GDMFs) are employed. The GDMFs are initially generated using various texture-based features computed from gray-level co-occurrence matrices. The gray-level cooccurrence matrix is a matrix used to express the correlation of spatial location and gray-level distribution of an image. From it, the local variation of gray levels on an image can be statistically investigated and in turn, enable us to know the manner of change in gray level as a whole. Subsequently, the shapes of the GDMFs are optimized using genetic-algorithm learning process. After optimization, the classifier is used to discriminate two sets of echocardiographic images,

namely, normal and abnormal cases. All of the imaged used for the study were diagnosed in advance by a highly trained physician. We experimentally evaluate the performance of the proposed method against various methods been reported in terms of accuracy, sensitivity, specificity, and total accuracy.

2. MATERIALS AND METHODS

2.1 Data Set

In this work, a total of 90 samples of echocardiographic images from 45 subjects (2 sample images per subject: an end-diastole image and an end-systole image) were collected at the Hospital of Gifu University School of Medicine. The images were captured from a Toshiba SSH-160A device with a 2.5 MHz (central frequency) transducer. The frame rate and scanned mode used were 30frames/sec and sector phased array, respectively.

Of the 45 subjects, 23 subjects were diagnosed as normal and the remaining 22 as abnormal (dilated cardiomyopathy or hypertrophic cardiomyopathy). Each image was digitized at the resolution of 256x256 pixels. Since the original echocardiographic images have 64 gray levels, the scanned images were quantized to the same level.

In our previous study [1] we noted that the use of composite images could provide higher recognition rate as compared to that of individual images at end systole and end diastole. The reason might be that the information about the contours and shapes of the two extreme states can be obtained together by using a composite image. Therefore, in the present study we used composite images $h(x,y)$, which are obtained as follows:

$$h(x,y)=\max[m(x,y), n(x,y)], \quad (1)$$

where $m(x,y)$ and $n(x,y)$ refer to the images at end-systole and end-diastole states, respectively. Figure 1 shows an example of the normal case. The images at end-systole and end-diastole states are shown in Fig. 1(a) and 1(b), and the composite image is shown in Fig. 1(c).

2.2 Measurements of Texture Features

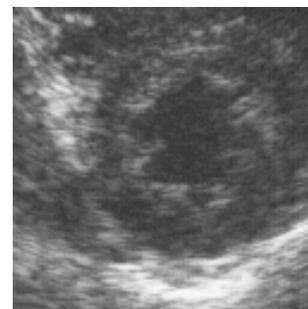
Assume that the gray-level values of the two pixels (pair of pixels) at (x,y) and $(x+p, y+q)$ are f_1 and f_2 . If an image is quantized by L gray levels, the possible range of the gray levels for each pixel is from 0 to $L-1$. In this case, for example, when the values of p and q are constants and when the occurrence frequency of $f_1=1$ and $f_2=2$ is K , then the number K is filled into the corresponding element of the matrix. In this way, a $(L-1) \times (L-1)$ occurrence matrix can be generated. The details of the cooccurrence are given in the literature [6].

In the current application, we used the following conditions to generate gray-level cooccurrence matrices. (a) Number of gray levels: A cooccurrence matrix of 64x64 size can be obtained from a 64 gray-level image. In order to save computation time, we compress the gray

level to 16 gray-levels in this study, since our experiments showed that the matrix size of 16x16 was adequate.

(b) Direction: In general the gray-level cooccurrence matrices from 0° , 45° , 90° , and 135° directions are used. Since the difference of the results from the 4 directions are insignificant in our preliminary investigation, only the direction of 0° was used in the study.

(c) Distance: The length of 5-pixel was used. It is considered that if the distance between two pixels is extremely short or long, accurate representation of image features becomes difficult. We investigated the performance of various distances ranging from 2 to 7 pixels in terms of classification rate at training phase. Our experimental results showed that the length of 5-pixel was the best among the various lengths used.



(a)



(b)



(c)

Fig. 1. Sample images from the data set. (a) end-systole, (b) end-diastole and (c) composite images.

From the generated gray-level cooccurrence matrices, a total of 14 statistical features of each image can be calculated, namely, angular second moment, contrast, correlation, variance, inverse different moment, sum average, sum variance, sum entropy, entropy, difference variance, difference entropy, information measure of correlation A, information measure of correlation B, and maximal correlation coefficient. We experimentally evaluated all of these features on their ability to discriminate between normal and abnormal cases. Our evaluation method was that we first investigated the classification performance of all the possible combinations of the features and then ranked them. Of the 14 features, we found that the following four features have the most powerful discrimination ability as texture features of the composite images:

- Angular Second Moment (ASM; Q_1) :

$$Q_1 = \sum_{f_1} \sum_{f_2} P(f_1, f_2)^2, \quad (2)$$

where, $P(f_1, f_2)$ is the probability obtained by dividing the number of (f_1, f_2) element in the matrix by the total number of occurrence in the matrix.

- Contrast (CON; Q_2) :

$$Q_2 = \sum_{f_1} \sum_{f_2} (f_1 - f_2)^2 P(f_1, f_2) \quad (3)$$

- Correlation (COR; Q_3) :

$$Q_3 = \frac{\sum_{f_1} \sum_{f_2} f_1 f_2 P(f_1, f_2) - f_1 \hat{\mu}_1 \hat{\mu}_2}{f_1 \hat{\sigma}_1 \hat{\sigma}_2}, \quad (4)$$

where,

$$\mu_1 = \sum_{f_1} f_1 \sum_{f_2} P(f_1, f_2)$$

$$\mu_2 = \sum_{f_2} f_2 \sum_{f_1} P(f_1, f_2)$$

$$\sigma_1^2 = \sum_{f_1} (f_1 - \mu_1)^2 \sum_{f_2} P(f_1, f_2)$$

$$\sigma_2^2 = \sum_{f_2} (f_2 - \mu_2)^2 \sum_{f_1} P(f_1, f_2)$$

- Entropy (ENT; Q_4) :

$$Q_4 = - \sum_{f_1} \sum_{f_2} P(f_1, f_2) \ln \{P(f_1, f_2)\} \quad (5)$$

The feature Q_1 represents the uniformity of textures. The more the number of specific gray-level pairs appears, the higher the value of Q_1 . The feature Q_2 represents the mean of the gray-level differences of various gray-level pairs (f_1-f_2) . The value of Q_2 increases with the increase of image contrast. The feature Q_3 represents pattern periodicity of specific directions. The feature Q_4 represents the contrary property of Q_1 . It is still not very clear that these features completely describe what kinds of physical properties of the tissue, respectively. However, in the sense that different tissue or different quality of image provides different feature values, these statistic values can be used to represent texture features of echocardiographic images.

2.3 Fuzzy Membership Functions

The major components of the fuzzy-logic decision-making system are fuzzy sets, fuzzy membership

function, and fuzzy rules. Each fuzzy set has a corresponding fuzzy membership function. The value of the membership function ranges from zero to one and can be considered a degree of truth [7]. While almost any type of fuzzy membership functions such as trapezoid, triangle, S curve and singleton can be used, the GDMFs were employed in this study. The main reason for using the GDMFs is that a specific texture-based feature for a certain category, normal or abnormal, is statistically Gaussian distributed.

Consider a specific feature value x that can be measured from an image. Let the mean value of x from a set of images belonging to the same category be μ and the standard deviation of the feature values be σ . Define a fuzzy set with a GDMF having the maximum value of unity (normalized). The normalized membership function can be expressed as follows:

$$f(x) = \exp \left\{ -\frac{1}{2} \left(\frac{x - \hat{\mu}_2}{\hat{\sigma}_2} \right)^2 \right\} \quad (6)$$

The parameters of μ and σ can be used to completely define a single membership function. If the number of sample images is limited, the value of σ may not accurately reflect the characteristic of all images of the same category. Therefore in this study we propose a method to use GA at a training phase for determining the optimal membership function by varying the value of σ with a coefficient c as shown below.

$$f(x) = \exp \left\{ -\frac{1}{2} \left(\frac{x - \hat{\mu}_2}{c \hat{\sigma}_2} \right)^2 \right\}, \quad (7)$$

In the current study, simplified fuzzy rules as shown in (8) are used:

$$\text{Rule } i : \text{ If } x_1 \text{ is } c_{i1} \text{ and, } \dots, \text{ and } x_M \text{ is } c_{iM} \text{ then } y \text{ is } w_i, \quad (8)$$

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

The following two fuzzy rules are used in our application.

Rule 1) If (the value of ASM is the mean of the ASM of the normal cases) and (the value of CON is the mean of the CON of the normal cases) and (the value of COR is the mean of COR of the normal cases) and (the value of ENT is the mean of ENT of the normal cases), then the case is classified as normal with 100% confidence.

Rule 2) If (the value of ASM is the mean of the ASM of the abnormal cases) and (the value of CON is the mean of the CON of the abnormal cases) and (the value of COR is the mean of COR of the abnormal cases) and (the value of ENT is the mean of ENT of the abnormal cases), then the case is classified as abnormal with 100% confidence.

2.4 Encoding and GA Operators

Encoding is a way of representing the decision variables of the optimization problem in a string of binary digits called chromosomes. Each chromosome is a possible solution to the optimization problem [8]. It is assumed that an individual (chromosome) comprises 2 fuzzy rules. Each fuzzy consists of four GDMFs with various coefficients c_{ij} and standard deviations σ_{ij} ($i=1,2$, and $j=1,2,3,4$). The $c_{ij}\sigma_{ij}$ is optimized by the GA. Since the values of σ_{11} , σ_{12} , σ_{13} , σ_{14} , σ_{21} , σ_{22} , σ_{23} , and σ_{24} are constant once the data set is determined, in practice only the coefficients are used in the phase of optimization.

A simple GA that has given good results in a variety of engineering problems is composed of three operators: (1) selection (reproduction), (2) crossover, and (3) mutation. These operators are implemented by performing the basic tasks of copying strings, exchanging portions of strings, and generating random numbers [8], [9]. The GA begins by randomly generating a population of individuals (strings). Each individual is a possible solution to the optimization problem. In general, the population is initialized at random to a bit string of 0's and 1's. For details of GA operation, reference should be made to Goldberg [10].

2.5 GA-Based Fuzzy Classification

In this application, we randomly selected 12 normal and 12 abnormal echocardiograms from the 45 subjects and called them "set A", and called the remaining (11 normal and 10 abnormal) hearts "set B". We used set B as learning data for training to obtain optimal membership functions, and used set A as test data for classification, and vice versa. The classification results were then averaged.

It is clear that a "leave-one-out" (jackknife) approach would be preferred over dividing the training and testing sets in two groups, if data set is small. In fact, we also had a try to utilize this jackknife approach at training phase. Both of the two approaches could reach to 100% of classification performance, though the jackknife approach was faster in term of learning iterations.

The first step for optimizing the membership functions is to generate membership functions. We used Eq. (7) to generate GDMFs, where the coefficients c is temporarily set at 1, and the mean μ and the standard deviation σ are calculated using the values of the texture features (Q_1 - Q_4) obtained from the gray-level cooccurrence matrix. In this way a total of eight GDMFs as shown in Fig.2 for the antecedent parts of two fuzzy rules (rule 1: normal case, rule 2: abnormal case) can be initially generated. The eight coefficients are subsequently used for optimizing the respective GDMFs.

The second step for optimizing the membership functions is to encode the variables of the string. In this study each variable is encoded as an 8-digit binary number, and the population used is 200.

The third step for optimization is to compute the fitness value of each string through training phase. As shown in Fig.2, the texture features (Q_1 - Q_4) obtained from each composite image used for training are input to the fuzzy

system. The shape of the consequent-part membership functions employed in the study is a right isosceles triangle with the maximum value of unity (normalized). While many kinds of defuzzification approaches could be used, the MIN-MAX compositional rule of fuzzy inference is employed in this study. A modified "height method" rather than center-of-gravity method is employed for defuzzification. The MIN-MAX compositional height method is described as follows.

First, assuming that $\mu_{nor}(Q_1)$, $\mu_{nor}(Q_2)$, $\mu_{nor}(Q_3)$ and $\mu_{nor}(Q_4)$ are the respective GDMF values for the normal case, and $\mu_{ab}(Q_1)$, $\mu_{ab}(Q_2)$, $\mu_{ab}(Q_3)$, and $\mu_{ab}(Q_4)$ are the respective GDMF values for the abnormal case. Then, the minimum value of $\mu_{nor}(Q_1)$, $\mu_{nor}(Q_2)$, $\mu_{nor}(Q_3)$ and $\mu_{nor}(Q_4)$, and that of $\mu_{ab}(Q_1)$, $\mu_{ab}(Q_2)$, $\mu_{ab}(Q_3)$ and $\mu_{ab}(Q_4)$ are given by

$$\mu_{nor} = \min[\mu_{nor}(Q_1), \mu_{nor}(Q_2), \mu_{nor}(Q_3), \mu_{nor}(Q_4)] \quad (9)$$

and

$$\mu_{ab} = \min[\mu_{ab}(Q_1), \mu_{ab}(Q_2), \mu_{ab}(Q_3), \mu_{ab}(Q_4)] \quad (10)$$

This is usually called MIN (minimum) operation. Finally, the larger value is taken from the two. It is called MAX (maximum) operation and is given by

$$\mu_{nor \text{ Uab}} = \max[\mu_{nor}, \mu_{ab}] \quad (11)$$

The classification scheme in our application is:

$$\text{If } \mu_{nor \text{ Uab}} = \mu_{nor} \rightarrow \text{normal case} \quad (12)$$

$$\text{If } \mu_{nor \text{ Uab}} = \mu_{ab} \rightarrow \text{abnormal case.} \quad (13)$$

In the case of $\mu_{nor} = \mu_{ab}$, it is a "cannot decide" case. In this study the "cannot decide" cases were considered a failure and were regarded as misclassification. The detailed description regarding the MIN-MAX operation is provided in the literature [11].

As shown in Fig. 2, supposing that the minimum values for rules 1 and 2 are 0.4 and 0.2 (absolute value), respectively. Since 0.4 (fuzzy rule 1 for normal case) is greater than 0.2 (fuzzy rule 2 for abnormal case), the output of the fuzzy inference is "it is a normal heart (normal case)". The result is subsequently compared to the teacher signal. If the result is identical to the diagnostic result made by the physician, then the case is correctly classified.

A two-step fitness functions in the selection operation were employed to attempt increasing the accuracy of classification. Fitness values are computed by the fitness functions shown as follows.

$$f_1 = \frac{n - m}{n} \quad (14)$$

and

$$f_2 = \sum_{i=1}^n (d_{1i} - d_{2i})^2 \quad (15)$$

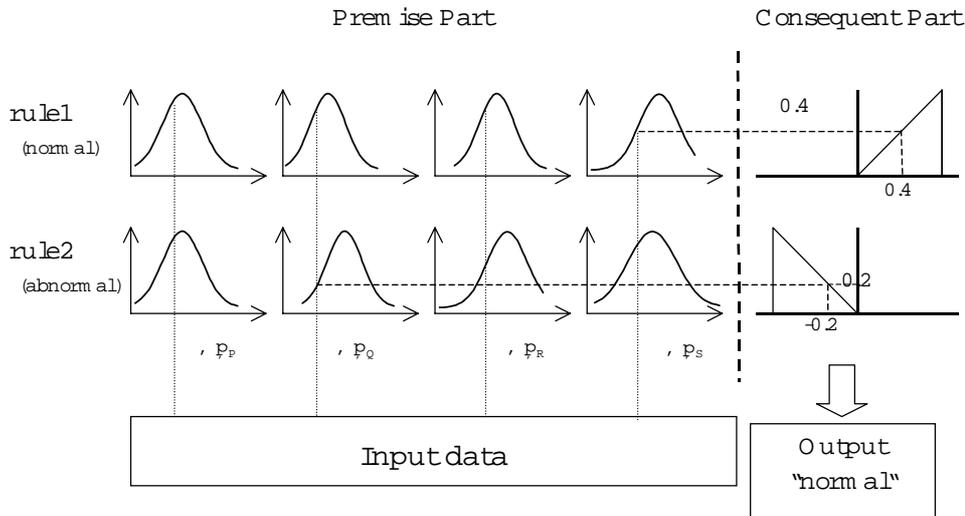


Fig. 2 Fuzzy reasoning using 8 Gaussian-distributed membership functions.

where n and m refer to the numbers of learning data and misclassification. The d_{1i} and d_{2i} represent the minimum values obtained from fuzzy rule 1 and rule 2, respectively. When $m=n$, i.e., all of learning data are misclassified, then $f_1=0$. On the contrary, when $m=0$, namely, all learning data are correctly classified during the training phase, then $f_1=1$. Moreover, when the difference between d_{1i} and d_{2i} increases, then the value of f_2 becomes greater. The fitness values obtained from Eqs. (14) and (15) are used for ranking the strings. The ranking process is as follows.

- (1) First, the strings are ranked according to the fitness value of f_1 .
- (2) Second, those strings having the same value of f_1 are further ranked according to the value of f_2

In this study we use elite selection for reproduction. Of the 200 randomly generated initial strings, the first 160 parent strings in terms of fitness value are selected for crossover and mutation operations in order to produce the same number of children strings. And then the first 40 higher ranked parent strings together with the 160 offsprings are treated as the strings of the next generation. The single-point crossover is used in this study. Emphasis should be made here that the crossover is performed for each variable having 8-digit binary number, namely, the crossover are simultaneously performed at 8 positions. A probability of 0.05 is used for mutation. The number of generation employed is 50. On the completion of 50 iterations (generations), the individual having the highest ranking is finally selected, and the 8 variables of this individual corresponding to the 8 coefficients of GDMFs are considered as optimal, and the training process finishes, followed by classification phase.

3. RESULTS AND DISCUSSION

We evaluate the performance of the proposed method in terms of sensitivity, specificity and overall accuracy.

Sensitivity (true positive fraction) is the probability that a diagnostic test is positive, given that the person has the disease. Specificity (true negative fraction) is the probability that a diagnostic test is negative, given that the person does not have the disease. Overall accuracy is the probability that a diagnostic test is correctly performed. The three indices are defined as follows

$$\text{Sensitivity} = \frac{TP}{TP + FN} \quad (16)$$

$$\text{Specificity} = \frac{TN}{TN + FP} \quad (17)$$

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \quad (18)$$

where TP, FP, TN and FN refer to true positive, false positive, true negative and false negative, respectively.

Table I shows the classification rates for performing the GA-based fuzzy method. We also provide the results of BP-based NN method, GA-based NN method, and fuzzy method (without GA operation) for comparison. The sensitivity rates for BP-NN/ GA-NN/ Fuzzy/ Fuzzy-GA methods were 83.0%/91.7%/91.7%/ 91.7%, respectively. Except the BP- NN method, the sensitivity rates for the other three methods are comparable. The reason why the BP-NN method has lower sensitivity is because the number of FN cases. Specificity rates for BP-NN/ GA-NN/ Fuzzy/ Fuzzy-GA methods were 80.8%/86.4%/91.3%/100%, respectively. The Fuzzy-GA method provided the highest specificity, followed by Fuzzy, GA-NN, and BP-NN methods. We noticed from the table that none of the FP cases was misclassified. The

TABLE I
CLASSIFICATION RATES FOR THE VARIOUS METHODS.

Method	Data set	TP	TN	FP	FN	Sensitivity (%)	Specificity (%)	Accuracy (%)
BP-NN	A	9	11	1	3	83.0	80.8	82.1
	B	10	7	3	1			
GA-NN	A	10	12	0	2	91.7	86.4	88.7
	B	10	8	3	0			
Fuzzy	A	10	11	1	2	91.7	91.3	91.4
	B	10	10	1	0			
GA-Fuzzy	A	10	12	0	2	91.7	100	95.9
	B	10	11	0	0			

results indicated that the Fuzzy-GA method was effective. The overall accuracy for BP-NN/ GA-NN/ Fuzzy/ Fuzzy-GA methods were 82.1%/ 88.7% / 91.4%/ 95.9%, respectively. The results showed the superiority of the GA-based Fuzzy method.

For the two fuzzy-logic-based methods (Fuzzy and Fuzzy-GA methods), noticed that the employment of GA for optimization of GDMFs could achieve better classification rates, a 4.5% increase in accuracy. The results suggest that our proposed Fuzzy-GA method for determining the GDMFs is useful, especially in the case of small number of training data available.

4. CONCLUSION

In this paper we have described a fuzzy classification technique for further improving the CAD performance for diagnosis of cardiomyopathy. The fuzzy classification approach was to exploit the GA-based training for optimization of membership functions. Unlike the conventional types of membership functions, Gaussian-distributed membership functions (GDMFs) were employed. The proposed method enabled the classification to achieve an average of 96%. This result suggests that our method has the potential to become clinically useful for computer-aided diagnosis of cardiomyopathy. Future work increasing sample sets for further feasibility test on the proposed method is needed. In addition, investigation in the issue of "how will the presence of other heart diseases influence the classification performance" is on going.

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