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Feature-Based Image Analysis for Classification of Echocardiographic Images

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SUMMARY In this letter the classification of echocardiographic images is studied by making use of some texture features, including the angular second moment, the contrast, the correlation, and the entropy which are obtained from a gray-level cooccurrence matrix. Features of these types are used to classify two sets of echocardiographic images–normal and abnormal (cardiomyopathy) hearts. A minimum distance classifier and evaluation indexes are employed to evaluate the performance of these features. Implementation of our algorithm is performed on a PC-386 personal computer and produces about 87% correct classification for the two sets of echocardiographic images. Our preliminary results suggest that this method of feature-based image analysis has potential use for computer-aided diagnosis of heart diseases.

key words: *medical image processing, pattern matching, computer-aided diagnosis, echocardiographic images*

1. Introduction

The use of 2-dimensional echocardiographic images of the heart has been an important non-invasive means in clinical cardiology [1]. The diagnosis of heart functions using echocardiography is comparably common among various diagnostic methods. However, since the discrimination 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 quantitative computerized methods which provide a "second-opinion" for the diagnostician can be developed, then this subjectivity can be reduced and the accuracy in diagnosis is expected to increase.

Investigators have attempted to develop automated means for computer-aided diagnosis in a variety of diseases [2] - [6]. However, little work has dealed with heart diseases in echocardiography.

The main goal of this work is to develop a computer-aided diagnosis in echocardiography based on a feature-based classification approach. This approach consists of classifying echocardiographic images (images at end systole and end diastole) into normal or abnormal case on the basis of calculated image feature values. The features used in this work include the angular second moment and the contrast. A minimum distance classifier and the values of statistical measures are employed to evaluate the performance of our proposed technique.

2. Methods

The algorithm of our proposed method is shown in Fig. 1. Each step of the algorithm is discussed below.

2.1 Image Acquisition

A total of 62 samples of echocardiographic images from 31 subjects (2 samples per subject: an end-systole image and an end-diastole image) was collected at the Hospital of Gifu University School of Medicine. Of the 31 subjects 18 were diagnosed as normal hearts and the remaining 13 as abnormal hearts (typical case of cardiomyopathy) by an experienced physician.

The images were scanned into a PC-386 personal computer using an image digitizer (GT-6000, Epson). Since echocardiographic images have 64 gray levels, the scanned images were quantized to 64 gray levels.

2.2 Preprocessing

Because of the noisy nature of ultrasonic images, image pre-

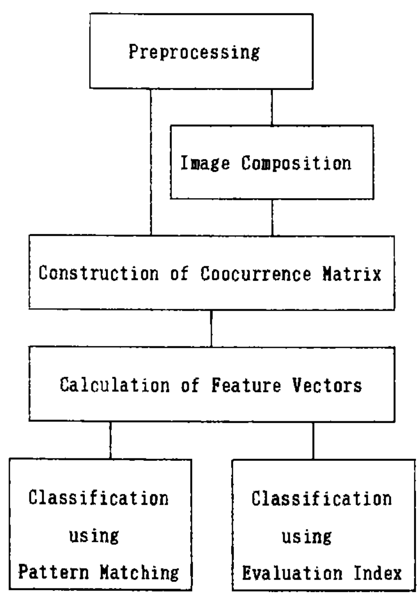

Fig. 1 Block diagram of our method.

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processing was employed to enhance the contrast of images against the background. In the present study several methods, such as histogram equalization and logarithm function, for enhancing the image contrast were compared. Our experimental result shows that the histogram equalization technique is the most effective. Thus we applied the technique to all of the samples immediately after image scanning.

2.3 Image Composition

In this study, we composed subtraction images for all of the subjects by subtracting the end-systole image from the end-diastole image obtained from the same subject, and composed summation images by adding the end-systole image to the end-diastole image. By doing so, it is expected to extract more powerful features from the composite images as compared to that from an individual image. Because the composite images contain the information about regional ventricular function, while the individual images do not possess.

2.4 Gray-Level Cooccurrence Matrix

We generated a gray-level cooccurrence matrix for every end-systole image, end-diastole image, subtraction image, and summation image, respectively. The gray-level cooccurrence matrix is a matrix used to express the correlation of spatial location and gray-level distribution of an image. From the matrix, 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. The concept of gray-level cooccurrence matrix is described as follows [7].

Assume that the gray-level values of the two pixels (pair of pixels) at (x, y) and $(x+m, y+n)$ are f_1 and f_2 (see Fig. 2 (a)). If the image is quantized by L gray levels, the possible range of the gray levels for each pixel is from 0 to $L-1$, i.e., $0 \leqq f_1 \leqq L-1$; $0 \leqq f_2 \leqq L-1$. In this case, for example, when the values of m and n are constant 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 as shown in Fig. 2 (b). In this way, a $(L-1) \times (L-1)$ cooccurrence matrix can be generated.

In the present study, we used the following conditions to generate the gray-level cooccurrence matrix.
(a) Number of gray levels: A cooccurrence matrix of 256×256 size can be obtained from a 256 gray-level image. In order to save computation time, we decompress the gray levels to 15 in our study. Experimental results showed that the size of the matrix is adequate.
(b) Direction (θ): Ideally, it is better to generate gray-level cooccurrence matrices from all directions. However, it is considerably time consuming. Therefore the directions need to be confined. Since the shape of echocardiographic images used in the present study is *"fan-like"*, we chose the direction of 90° with respect to the horizontal direction for computation. Namely, $m=0$ for the pixel at $(x+m, y+n)$ shown in Fig. 2 (a).
(c) Distance (δ): As described in (b) that the value of m is 0, therefore the distance between the mentioned two pixels is equal to n. In the present study $n=5$ was used, since we empirically found that this value was optimal.

2.5 Feature Generation

Four statistical measures of the gray-level cooccurrence matrix, namely, the angular second moment (Q_1), the contrast (Q_2), the correlation (Q_3), and the entropy (Q_4) were calculated. These measures were considered as texture features and used for the classification scheme.

2.6 Minimum Distance Classifier and Evaluation Indexes

We used a minimum distance classifier [8] which is a kind of pattern-matching method to classify normal and abnormal cases. The Euclidean distance was employed in the classifier.

In this study the earlier described four texture features from each end-systole, end-diastole, subtraction, and summation images were calculated and their respective average values were defined as "evaluation indexes". The indexes were used to quantitatively express the extent of normality and abnormality of an image.

3. Results and Discussion

Figure 3 is an example to illustrate the effect of preproc-

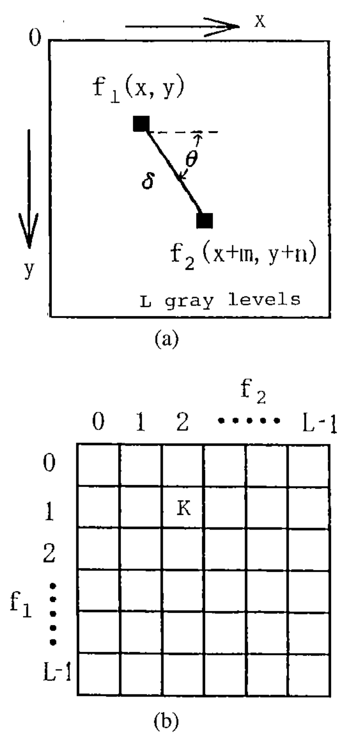
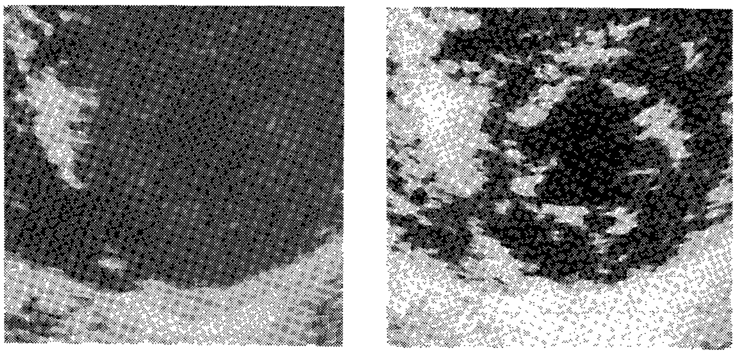


Fig. 2 (a) Explanation of how to construct a gray-level cooccurrence matrix; (b) Layout of a gray-level cooccurrence matrix.

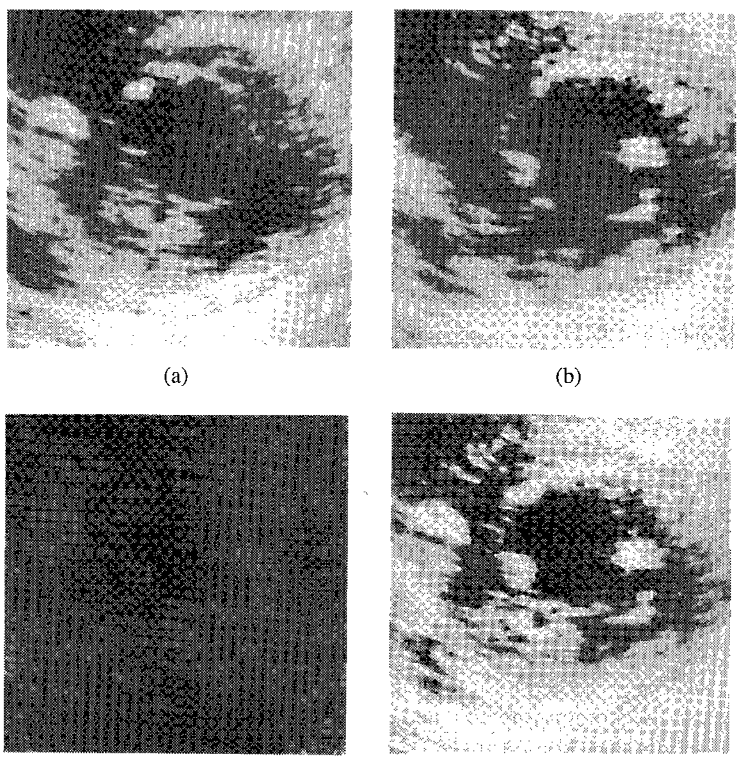
essing. Figure 3(a) is an original, echocardiographic image and Fig. 3(b) is the preprocessed image using the histogram equalization. It is obvious from the figure that the contrast of the image is much improved.

Figure 4 shows a typical, abnormal case of cardiomyopathy. The images at end-systole and end-diastole of the case are shown in Figs. 4 (a) and 4 (b), and the subtraction and summation images are shown in Figs. 4 (c) and 4 (d), respectively. The calculated "evaluation indexes" are listed in Table 1. It is apparent from the table that the most effective feature for discrimination of normal and abnormal cases is Q_2 (contrast) among the four (Q_1-Q_4) statistical measures, followed by Q_1 (angular second moment). However, in the case of subtraction images, the difference of feature values between normal and abnormal cases are insignificant. On the contrary, it is noted that the feature values Q_1 and Q_2 of summation images are approximately the same as to that of the end-diastole image and to that of the end-systole image, respectively. Therefore, we may say that the effective feature contained in the end-systole and that in the end-diastole images are both present in the summation images. We also noted that the features Q_3 and Q_4 are not



(a) (b)

Fig. 3 Effect of preprocessing. (a) Original image; (b) Preprocessed image using the histogram equalization technique.



(a) (b)

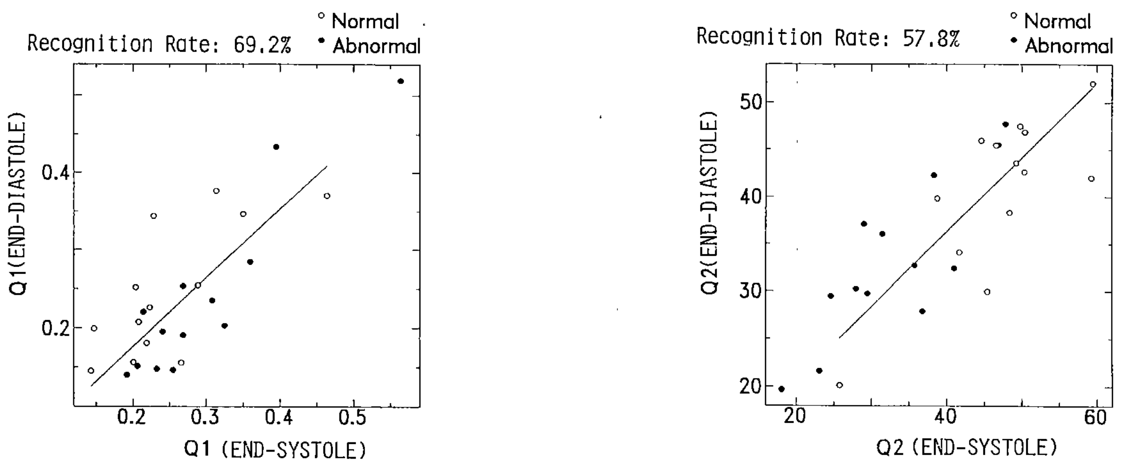
(c) (d)

Fig. 4 An example of abnormal case (cardiomyopathy). (a) and (b) are images at end-systole and end-diastole, respectively. (c) and (d) are subtraction image and summation image, respectively.

Table 1 Evaluation indexes of the normal and abnormal hearts (cardiomyopathy).

	end diastole				end systole			
	Q_1	Q_2	Q_3	Q_4	Q_1	Q_2	Q_3	Q_4
normal	0.21	29.26	-0.50	9.54	0.18	38.39	-0.51	9.84
abnormal	0.29	19.24	-0.52	8.74	0.23	19.58	-0.52	8.64

	subtraction image				summation image			
	Q_1	Q_2	Q_3	Q_4	Q_1	Q_2	Q_3	Q_4
normal	0.08	73.83	-0.51	11.02	0.21	34.88	-0.51	9.64
abnormal	0.08	64.16	-0.50	11.13	0.29	13.89	-0.51	8.67

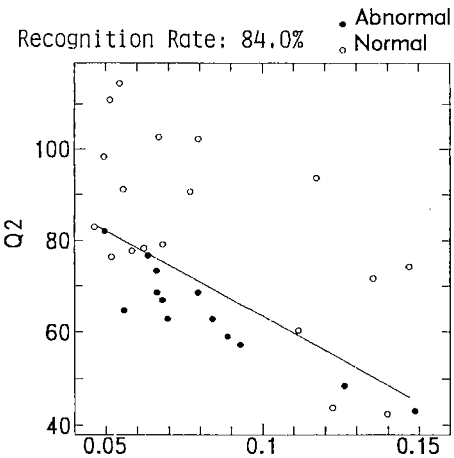


(a) (b)

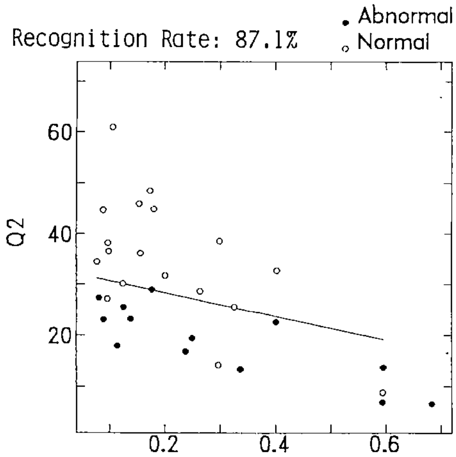
Fig. 5 Classification results using the minimum distance classifier. (a) In the case that the feature of the angular second moment is used. The recognition rate is 69.2%. (b) In the case that the feature of contrast is used. The recognition rate is 57.8%.

effective on classifying normal and abnormal cases for cardiomyopathy.

Figure 5 shows the classification results using the minimum distance classifier. In this figure the feature of angular second moment (see Fig. 5 (a)) and the feature of contrast (see Fig. 5 (b)), obtained from the images at end diastole and end systole, were used. If we use the straight line obtained from the classifier as decision boundary for normal and abnormal cases, the recognition rates for both cases are less than 70%. Figures 6 (a) and 6 (b) show the classification results for subtraction images and summation images, respectively. In the figures, the features of angular second moment and contrast are used. The respective recognition rates are 84.0% and 87.1%. Comparing to the use of individual feature extracted from the images at end diastole and end systole (see Figs. 5 (a) and 5 (b)), the use of combined features extracted from the composite images can provide higher recognition rates. Especially, summation images gives the highest recognition rate in the present study. The recognition rate of 87% determined by the proposed method is comparable to that by several-year experienced physicians. Therefore, we consider that the recognition rate obtained by using our method is satisfactory, although further improvement is required.



(a)



(b)

Fig. 6 Classification results using the minimum distance classifier. Two features of the angular second moment and the contrast are used for classification. (a) and (b) show the results of the subtraction image and the summation image. The recognition rates are 84.0% and 87.1%, respectively.

4. Conclusion

In this paper, we have proposed a method using texture features to classify echocardiographic images: normal and abnormal (cardiomyopathy) hearts. Our preliminary results suggest that the proposed method has potential use for computer-aided diagnosis of heart diseases. Future work will include (1) examining the optimal condition for constructing a gray-level cooccurrence matrix, (2) employing an artificial neural network for classification, and (3) increasing sample sets.

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