Computer-Aided Diagnosis in Abdominal and Cardiac Radiology Using Neural Networks

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Abstract

In recent years, considerable and serious efforts have been made toward the development of computer aided diagnosis (CAD) systems in diagnostic radiology. The CAD in radiology is a diagnosis made by a clinician (radiologist) who uses the output from a computerized analysis of medical images as a second opinion. In this paper, we describe two CAD systems using artificial neural networks (ANNs). The first system is an application to the segmentation of liver region in computed tomographic images for 3D visualization. The second system is an application to classification of cardiac disease. Results show that the presented systems using the ANNs give considerably satisfactory detection and classification performance.

1. Introduction

Technological advances and challenges of providing health care to a greater number of people more efficiently than ever before are driving revolutionary change. Medical imaging, pattern recognition and soft computing technologies are the major tools for realizing this task. Recently, considerable and serious efforts have been made toward the development of computer aided diagnosis (CAD) systems in diagnostic radiology. The CAD in radiology is a diagnosis made by a clinician (radiologist) who uses the output from a computerized analysis of medical images as a second opinion [1]. The goal of the development of these systems is to assist radiologists in interpreting radiographic images and findings. The basic concept of CAD is applicable to all imaging modalities in radiology, such as conventional radiography, digital radiography, fluoroscopy, digital subtraction angiography, fluoroscopy, digital subtraction angiography, ultrasound imaging, magnetic resonance imaging, and nuclear medicine. For the development of a practical CAD scheme to be implemented clinically, it is necessary to apply new computer-analysis technologies and image-processing methods. Various computer-analysis approaches, for example, artificial neural networks (ANNs), genetic algorithms (GAs) and artificial intelligence, have been used in medical systems.

ANNs have been developed for a wide variety of computational problems in cognition, pattern recognition, and decision making. So far, ANNs have been used for diagnosis, classification and prediction tasks. In this paper, we describe two CAD systems using ANNs. The first system is an application to the segmentation of liver region in computed tomographic (CT) images for 3D visualization [2]. The segmentation method employs a three-layered ANN. Before the ANN segmentation, preprocessing is implemented to locally enhance the contrast of the region of interest. Postprocessing is also automatically applied after ANN segmentation in order to remove the unwanted spots and to smooth the detected contours. The second system is an application to classification of cardiac disease [3]. In this application, weighting coefficients of the ANNs were determined through back-propagation (BP)- and GA-learning. Comparison of the two training methods is made in terms of classification rate, learning algorithm, and reliability.

2. Segmentation of Liver Contours from CT Images

Accurate segmentation of liver structure from an abdominal image is one of the most important steps in 3D visualization for liver volume measurement, liver transplant, and treatment planning. The main goal of this work is to propose an alternative segmentation method for liver structure extraction from abdominal CT images. The proposed method is considered useful, when an "*expected liver donor*" is the subject of investigation. This ANN-based approach is to classify each pixel on an image into one of three categories: "*boundary*", "*liver region*", and "*non-liver region*". The BP algorithm is used for learning, and the learning data sets are selected from any one of a given set of images by creating gray-level histograms for the three categories. The histograms are considered as the respective feature values. For postprocessing, anatomic knowledge about liver location and area in the abdomen cross section are used.

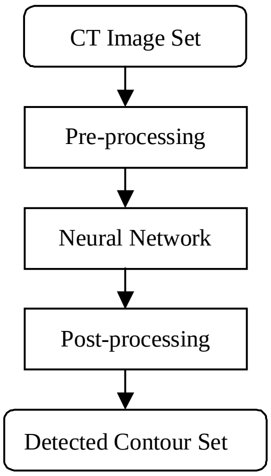

Fig. 1 Flowchart of the proposed method.

Figure 1 shows the flowchart of the proposed method. Before ANN segmentation, preprocessing was employed to locally enhance the contrast of the region of interest. Square-of-logarithm filtering was used for preprocessing to enhance the image contrast of low-gray-level spots. Subsequently, an image was randomly selected from the given set of CT images by a user (a radiological expert). A total of 40, 75, and 85 training data representing *liver region*, *boundary*, and *non-liver region*, respectively, were collected from this selected image. The use of different amounts of learning data sets was due to the different degrees of difficulty for convergence during learning process. The ANN was trained by adjusting the weights within the network according to the back propagation rule. The adjustments were made in response to repeated presentation of the training data. In this work the ANN was trained with 5,000 learning iterations. After ANN segmentation, postprocessing was employed. Postprocessing includes the following steps: (1) removal of unwanted spots, (2) removal of isolated regions, (3) Laplacian filtering, (4) dilation and erosion filtering, and (5) boundary smoothing using B-spline function. In the first two steps, anatomic knowledge about the location and area of the liver was used. Namely, the location of the liver is on the left side of the abdominal CT image, and the area of the liver in any slice image is less than 200 pixels. The processing was automatically conducted. The Laplacian filtering was applied to obtain the liver boundary. The remaining steps were used to smooth the detected liver boundary.

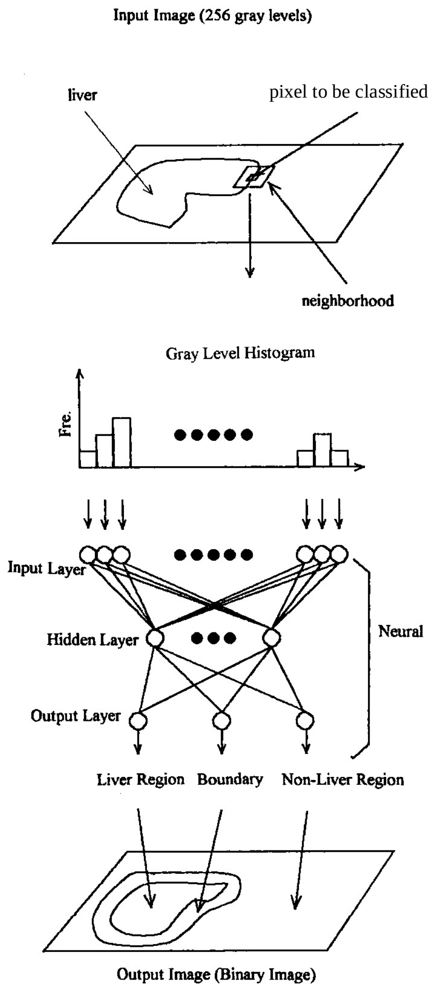

Fig. 2 Schematic diagram of our boundary detection method using a neural network.

Figure 2 illustrates the schematic diagram of the classification scheme. A gray-level histogram of 7x7 pixels was constructed and regarded as the feature values of the pixel centering at the region. The gray level of the histogram was divided into 16 units corresponding to the 16 gray levels of the histogram, while the number of output units are 3 corresponding to *boundary*, *liver region*, and *non-liver region* categories. The number of units in the hidden layer was 10, which was the optimal number in our experiments. Based on the described method, the input data set was classified into one of the three categories. The pixel value is assigned "1" (white) if ANN output is boundary or liver region, otherwise "0" (black). As a result, a binary image of the liver was obtained.

3. Classification of Myocardial Heart Disease

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 comparable 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 a computerized method, which can provide a second opinion for the diagnostician, is developed, then this subjectivity can be reduced and in turn the accuracy in diagnosis is expected to increase. In this work, we describe an ANN scheme for discrimination of three sets of echocardiographic images, namely, normal heart, dilated cardiomyopathy (DCM), and hypertrophic cardiomyopathy (HCM).

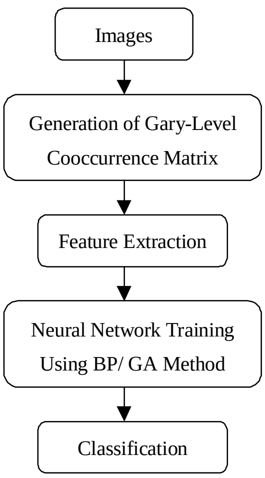

Fig. 3 Block diagram of classification scheme.

The ANN employed in this study was a 4-4-3 three-layer network. Weighting coefficients of the ANN used in this study were determined through BP- and GA-training. Figure 3 shows the procedure to classify echocardiogram. The echocardiograms used in this study were captured from a Toshiba SSH-160A device with a 2.5MHz (central frequency) transducer. The frame rate and scanned mode were 30-frames/sec and sector phased array, respectively. A logarithmic amplifier for video circuit was also used. The data set included 90 echocardiograms obtained from 45 subjects (2 sample images per subject: an end-systole image and an end-diastole image), with a mixture of normal hearts (23 cases), DCM (12 cases), and HCM (10 cases). The images were diagnosed in advance by an experienced physician. Each image was digitized by an image scanner at the resolution of 256×256 pixels. Since the original echocardiograms have 64 gray levels, the scanned images were quantized to the same gray levels.

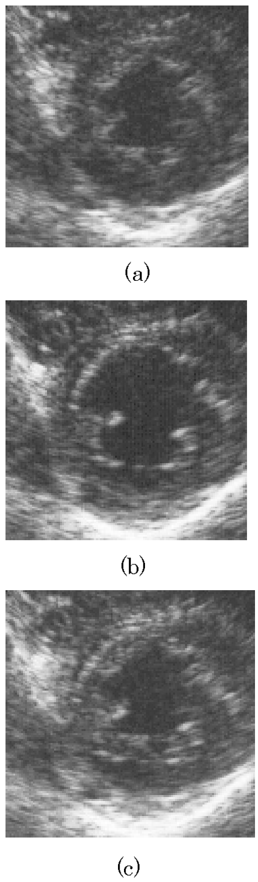

Fig.4 Image data. (a) end-systole, (b) end-diastole and (c) composite images.

In our previous study [4] 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. Therefore, in this study we used composite images $C(x,y)$ that are obtained as follows:

$$C(x,y)=max[f(x,y),g(x,y)] \quad (1)$$

where f(x,y) and g(x,y) refer to end-systole and end-diastole images, respectively. Figure 4 shows an example of image data used in the present study. We generated a gray-level co-occurrence matrix from each of the composite images. The gray-level co-occurrence 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. From the generated gray-level co-occurrence matrix, 4 features, namely, the angular second moment, contrast, correlation and entropy, were computed. It is still not very clear for the time being that these features concretely describe what kinds of physical properties of the image. However in the sense that different tissues and different quality of images provide different feature values, these statistical values can be used to present texture features of echocardiograms.

4. Results and Discussion

In Fig. 5, an example is given to illustrate how the segmentation scheme works. Figure 5(a) shows an original abdominal image. Figure 5(b) shows the preprocessed image. Figure 5(c) shows the binary image obtained by the ANN. In Fig. 5(d) and (e) the unwanted spots and the isolated regions are removed, respectively. Figure 5(f) shows the liver boundary obtained by applying Laplacian filtering. Figures 5(g) and (h) were obtained in sequence by applying dilation and erosion filtering and B-spline function, respectively. All of the post-processing steps can be executed automatically using “batch file” processing.

Figure 6 illustrates a CT image with superimposed liver contour after smoothing. The computer-determined boundary well corresponds with the visually determined edges of the liver. An image obtained by a conventionally used gray-level thresholding method is shown in Fig. 7 for comparison purpose. It is apparent from Figs. 6 and 7 that our method is superior to the gray-level thresholding operation. The computer-determined liver boundaries were also compared in terms of area with those drawn by two highly trained surgeons. The results show that the proposed method provides acceptable accuracy and is clinically applicable.

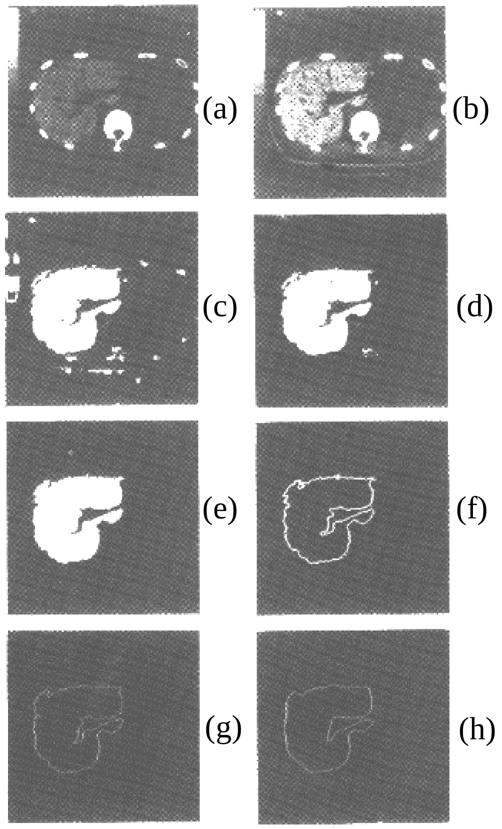

Fig. 5 (a) An original CT image. (b) The preprocessed image. (c) The binary image obtained by the neural network. (d) The image after removing the unwanted part. (e) The image after removing the isolated regions. (f) The liver boundary after applying Laplacian filter. (g) The boundary after application of a dilation and erosion filter. (h) The boundary after subsequent smoothing with a B-spline function.

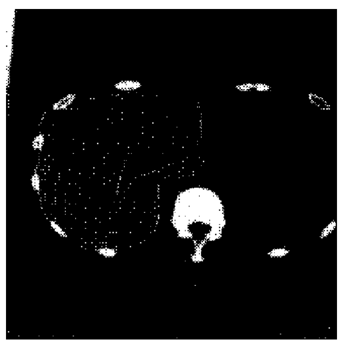

Fig.6 A CT image with superimposed liver contour after smoothing. The contour is shown in white.

Fig.7 Binary image obtained with the gray-level thresholding method.

In the case of classification of myocardial heart diseases, The ANNs were trained by BP- and GA-method. After training, the following two cases were classified by the ANNs.

Case 1: Consider the DCM and the HCM as an abnormal group, therefore two categories, *i.e.*, normal and abnormal categories are classified (in this study we call it 2-value output).

Case 2: Three categories, *i.e.*, normal, DCM, and HCM are classified (in this study we call it 3-value output).

The classification results for various angles of gray-level co-occurrence for the 2 cases using the BP- and GA-based methods are presented in Table 1. It is noted from the table that the two methods are comparable for case 1, but GA-based method is superior to the BP-based method in terms of classification rate for case 2.

Table 1 Classification rates for BP- and GA-based ANNs.

angle		0°	45°	90°	135°
BP-based	Case 1	97.8	97.8	97.8	97.8
[%]	Case 2	82.3	86.7	84.4	80
GA-based	Case 1	97.8	97.8	100	97.8
[%]	Case 2	84.4	88.9	86.7	84.4

The merits of the GA-based training method are as follows.

(1) The determination of weighting coefficients using the BP needs complicated operation. On the contrast, the GA technique only needs to compute the fitness.

(2) The convergence of the GA-based training is more stable and faster than that of the BP- based training.

In conclusion, we have presented two CAD systems using the ANN. The first system is an application to the segmentation of liver region in CT images for 3D visualization. Our results show that the proposed method has potential utility in automatic segmentation of liver structure and other organs in the human body. The second system is an application to classification of cardiac disease. The preliminary results show the superiority of GA in ANN training in terms of classification rate and learning algorithms.

References

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