Neural Network Approach for the Computer-Aided Diagnosis of Coronary Artery Diseases in Nuclear Medicine

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ABSTRACT

We have developed a computerized scheme that can aid in the radiologist's diagnosis in the detection and classification of coronary artery diseases in ^{201}Tl myocardial SPECT (single photon emission computed tomography) bull's-eye images by use of artificial neural networks. The multi-layer feed-forward neural network used with a back-propagation algorithm has 41-256 input units (pattern : compressed images), 50 or 100 units in a single hidden layer, and eight output units (diagnosis : one normal and seven different types of abnormalities). The neural networks consisting of two major networks for "EXTENT" and "SEVERITY" images were trained using pairs of training input data (bull's-eye image) and desired output data ("correct" diagnosis). The results show that the recognition performance of our neural-network-based system is comparable to that of the experienced radiologists (two to ten years). Our study suggests that the neural network approach is useful for the computer-aided diagnosis of coronary artery diseases in myocardial SPECT bull's-eye images.

INTRODUCTION

Visual interpretation of nuclear images, even by experienced observers, is subject to substantial variability (1). Thallium-201 (^{201}Tl) myocardial SPECT (single photon emission computed tomography) imaging (2) has been reported to offer major improvements over planar imaging in the diagnosis of coronary artery disease. However, to overcome the difficulties of the interpretation of the myocardial SPECT images, a polar-map display, called a bull's-eye image, has been developed to characterize the three-dimensional images of the left ventricle in two dimensions (2). Even with this technique, many problems have been indicated. Also, the number of experienced radiologists in this field is substantially few. The development of a computer-aided diagnostic system or expert system, therefore, is considered to be helpful for the diagnosis of bull's-eye images in nuclear medicine.

The purpose of this paper is to develop a computerized system, which can aid radiologists's diagnosis in the detection and classification of coronary artery diseases in ^{201}Tl SPECT bull's-eye images, by employing artificial neural networks. One of the advantages of the neural network approach is its powerful ability to analyze the physician's complicated decision-making or pattern-recognizing process in diagnosis without any need to write a special computer program. As a pilot study, we recently investigated the applicability of the neural network technique in the computer-aided diagnosis of coronary artery diseases only when the bull's-eye "EXTENT" images were used for analysis (3). The recognition performance of the neural network was better than that of the radiology resident but worse than that of the ten-year experienced radiologists. In this paper, we present the improved results of recognition performance when EXTENT and "SEVERITY" images were used for analysis with multi neural networks.

MATERIALS AND METHODS

Thirty-six planar images of 64 × 64 matrix and 64 gray levels were obtained (30 sec/view) with a gamma camera (Shimadzu LFOV dual head) and these data were transferred to a data processing system (Shimadzu SCINTIPAC-2400) at the Department of Radiology, National Cardiovascular Center. This system produces three different types of bull's-eye images at the same time, i.e., "PIXEL CT", "EXTENT", and "SEVERITY" images, which respectively represent the original bull's-eye image, the image simply showing the extent area of disease relative to the averaged normal case, and the image showing the severity of the disease within the extent area. In the present study, we used both of EXTENT and SEVERITY images. Actually, when physicians interpret the bull's-eye images, they first look at the EXTENT image, and then look at the SEVERITY image carefully.

Coronary artery territories in the bull's-eye display are illustrated in Fig. 1, where the regions of three main coronary arteries, left anterior descending coronary artery (LAD), left circumflex coronary artery (LCX), and right coronary artery (RCA), are segmented (4). It should be noted that this figure shows approximate territories and many variations, overlaps and exceptions in each territory can exist, so if one utilizes an AI rule-based expert system it may not be easy to construct a system. The coronary artery diseases can therefore be classified into seven different types due to the existence of single-, double-, and triple-vessel diseases. We collected a total of 74 bull's-eye images (Table 1). All of them had been examined by coronary angiography, in which a coronary artery of more than 75% stenosis was diagnosed as "disease" according to the criteria of the American Heart Association (AHA). These results were employed as a gold standard or "correct diagnosis".

We employed a personal neuro-computer system (Neuro-07, NEC), which consists of a personal computer (PC-9801 VX21, NEC), a neuro-engine board (PC-98XL-02, NEC), and a neuro-software package ("Michi-Zane", NEC). This board, called "ImPP board"(5), has four original data flow pipeline processors (μ PD7281), all of which can carry out processing in parallel. The neural network software written in C language is based upon a feed-forward layered model with an input layer, one to three middle or hidden layer(s), and an output layer.

A preprocessing of the image data is required due to the limitation of memory capacity of the neuro-engine board. This is also important to save the computation time. Therefore, all of the bull's-eye images studied were compressed to produce the images of 16 × 16 matrices by averaging the neighbouring pixel values and also to produce binary-gray-level images for the

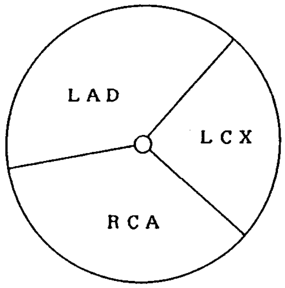

Figure 1 Coronary artery territories in the bull's-eye image
LAD: left anterior descending coronary artery
LCX: left circumflex coronary artery
RCA: right coronary artery

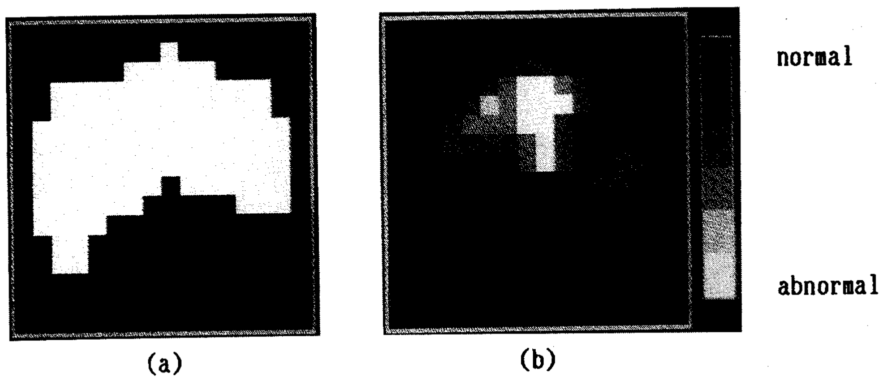

Figure 2 Preprocessed bull's-eye images in the case of LAD+LCX double vessel disease. (a) EXTENT image of a 16×16-matrix size with binary gray levels. (b) SEVERITY image of a 16×16-matrix size with 6 gray levels.

Table 1 Number of image data for eight classified coronary artery diseases including normal used in neural network analysis

	TRAINING	TESTING	TOTAL
NOR	8	2	10
LCX	8	2	10
RCA	8	2	10
LAD	8	2	10
AX	8	2	10
XR	8	2	10
AR	8	2	10
AXR	2	2	4
TOTAL	58	16	74

NOR:normal, LCX:left circumflex coronary artery, RCA:right coronary artery LAD:left anterior descending coronary artery, AX (=LAD+LCX), XR (=LCX+RCA) AR (=LAD+RCA), AXR(=LAD+LCX+RCA)

EXTENT and six-gray-level images for the SEVERITY. As an example, preprocessed images are shown in Fig. 2, which is a case of LAD+LCX double-vessel disease. These compressed images were employed as an input to the neural network. The number of neurons in the output layer was fixed to eight units corresponding to the eight different types of diagnoses including normal. The neural network was trained using pairs of training input images (compressed images) and the desired output data ("correct diagnosis" based on the gold standard).

The overall flow of our system, called a "BULLsNET", for the recognition (testing) process is shown in Fig. 3, which includes the multi neural networks. In the case that the confidence level of the "extent neuro" is lower than 0.9, the "severity neuro" is performed, in which the each part of the vessel regions based upon the territories in Fig. 1 is examined by LAD, LCX and RCA sub-neuro networks, then the output result from the severity neuro is used as diagnosis. The confidence level was determined from the weight values in the output layer of the network. On the other hand, in the case that the confidence level is equal or larger than 0.9, the output result from the extent neuro is simply used as diagnosis.

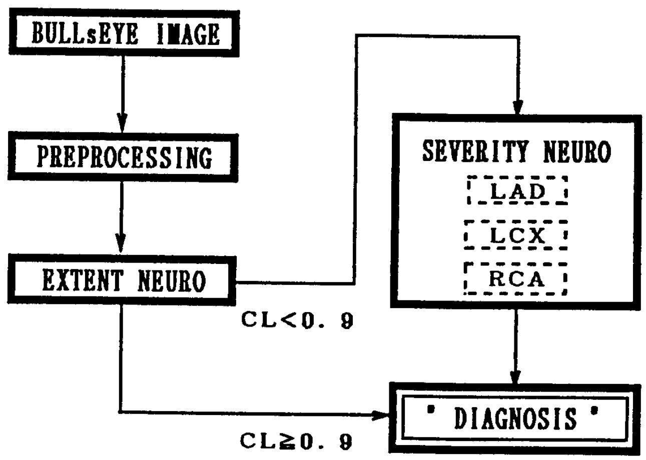

Figure 3 "BULLsNET" system for computer-aided diagnosis of bull's-eye images in nuclear cardiology

Table 2 Recognition rate for three different combinations of image data, only when the extent neuro was employed.

	Case A	Case B	Case C	Average
NN	69 %	75 %	88 %	77 %
I	56 %	81 %	69 %	69 %
II	75 %	75 %	88 %	79 %
III	75 %	88 %	88 %	83 %

NN: Neural network, I: three-month RI-experienced resident
II: two-year RI-experienced radiologist, III: ten-year RI-experienced radiologist

RESULTS AND DISCUSSION

We varied combinations of image data for the training and testing (recognition) processes in the neural network and made three different combinations, cases A, B, and C, in which all images were chosen at random from a data base of 74 images (Table 1).

In the case that only the extent neuro was performed, the following results were obtained. After the training procedure, all 58 images used for training were recognized correctly in the recognition process. The recognition rates (percentage of correct recognition) determined by the neural network (NN) for the 16 image data never used in the training process are listed in Table 2, together with those by one resident (I) and two radiologists (II and III) for comparison. This table demonstrates that the recognition rate depends on the image combinations, which can be explained from two different view points. One is that image data used for the training may be insufficient to recognize image data for testing. The other is that the inclination of image data in terms of their category in the training process and the degree of difficulty in diagnosis in the recognition process may cause variances in the recognition rate. These effects may be decreased by increasing the image data for training as well as for recognition. By comparing the averaged results, the performance of the neural network is better than that of the resident, and comparable to that of the two-year experienced radiologist, but worse than that of the ten-year experienced radiologist. All results shown above were obtained using the network that involves one hidden layer with 100 hidden units and 200 training iterations. Under these conditions the pure computation time for training was approximately 23 minutes. However, the time for training is not so important, because the user at the hospital may simply utilize the results obtained from the training process. On the other hand, the recognition of one image data in the testing process, including the preprocessing procedure, was performed in "real time".

It is worthwhile to include the SEVERITY image for analysis, as shown in Fig. 3, because they can help to differentiate lesions from artifacts. Actually, in the case of the physicians, we observed that the recognition rate with both of EXTENT and SEVERITY images results in 6-10% higher relative to that only with EXTENT images. The recognition rate determined by the neural networks using both images when the confidence level from the extent neuro is lower than 0.9 was 90%. It is considered to be comparable to that by two-to-ten-year experienced radiologist. The numbers of pixels of input image data (input units) for each region were 61 (LAD), 41 (LCX), and 47 (RCA), respectively. The number of training iterations was 150 for each region with 50 units in the hidden layer. The percentage of the case that the confidence level of the extent neuro was smaller than 0.9, that is, the severity neuro was necessary for analysis, was 35%.

Differing from AI expert systems in which complicate large programming is required for formation of rules based on capturing the knowledge of one or more experts, the neural network systems are able to form those rules by training procedure using pairs of training input data and desired output data (strength of neural networks). However, understanding how to effectively execute this "training" is the key point for the neural network system; in general, one has to collect enough patterns to train the network (weakness of neural networks). On the other hand, a rule-based expert system might be a better approach in the case of difficulty in preparing enough patterns to train it. Therefore, the process of learning or training can be an advantage of the neural network approach as well as a disadvantage. Moreover, hybrid systems, called "expert networks", that include both neural networks and rule-based expert systems, may be useful for further complicated applications (6).

CONCLUSION

The approach with artificial neural networks for a computer-aided diagnostic system of coronary artery disease in nuclear cardiology appears to show considerable promise, as shown in this study, when both of EXTENT and SEVERITY bull's-eye images are employed. The recognition performance of our improved system (BULLsNET) is comparable to that of the experienced radiologists (two to ten years). However, it is required to increase the number of image data for training and testing processes. In addition, because image information is only one portion needed for a physician's diagnosis, other clinical information, such as sex, temperature, and electrocardiogram data, has to be included in the overall analysis, as reported by others for different applications in radiology (7).

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