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Three-dimensional medical image recognition of cancer of the liver by the revised radial basis function (RBF) neural network algorithm

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Abstract: In this study, we propose a revised radial basis function (RBF) neural network algorithm and apply this algorithm to the computer-aided diagnosis (CAD) of the liver. First, the revised RBF neural network algorithm is applied to the recognition of the liver regions and the recognition results are compared with those obtained using the conventional RBF neural network and the conventional multi-layered neural network trained using the back propagation algorithm. It is shown that the revised RBF neural network is accurate and a useful method because the parameters are automatically determined. Then, the revised RBF neural network is applied to CAD of the liver cancer which is called Hepate-Cellular Carcinoma (HCC).
Key words **:**Medical image recognition, Neural network, Radial basis function

I. INTRODUCTION

In the conventional RBF neural network [1], the architectures of the neurons are described using the redial basis function and the neural network has the three layered architecture that is constructed with the input, hidden and output layers. The conventional RBF neural network has the structural parameters such as the mean and the variance of the radial basis function and it is difficult to determine the optimum values of these parameters automatically. So, we must iterate neural network calculations many times changing these parameters so as to find the optimum values of these parameters.

In this paper, we propose the revised RBF neural network algorithm, in which the structural parameters are automatically determined so as to fit the characteristics of the nonlinear system. The means are determined at the training data points and the variances of the radial basis functions are estimated by the regression analysis [2] of the training data and so we do not need to iterate the neural network calculation many times. The revised RBF neural network algorithm is applied the recognition of the liver regions and the recognition results are compared with those obtained using the conventional RBF neural network and the conventional multi-layered neural network trained using the back propagation algorithm. It is shown that the revised RBF neural network is accurate and a useful method because the parameters are automatically determined. Then, we apply the revised RBF neural network algorithm to the computer-aided diagnosis (CAD) of the liver cancer.

Recently, the number of slices scanned by the multi detector raw computed tomography (MDCT) is increasing according to the development of medical imaging technology, and the number of images for the diagnosis becomes large and the doctor's burden is increasing. The CAD for the medical images is expected to reduce the doctor's diagnosis works and to improve diagnosis speed and accuracy. In this study, we applied the revised RBF neural network to the CAD of the liver cancer which is called HCC.

In this application, MDCT images are used. Ten input variables, which are four statistical image features, such as mean, variance, standard variation and range, and four texture features and the two coordinates (x and y) of the neighboring regions are used. The neural network is applied to extract the liver regions and the candidate region images of the HCC are extracted. Then, the density difference image between the early phase and late phase image of MDCT is extracted. The regions of HCC are identified using the density difference images and candidate region images of HCC. These image processing are carried out for all slices of MDCT and 3-dimentionl images of HCC is clearly displayed with the volume rendering software.

II. REVISED RADIAL BASIS FUNCTION NEURAL NETWORK ALGORITHM

In this paper, the regions of the liver and the liver cancer were recognized and extracted using the revised RBF neural network. In this application, the image recognition accuracy of the neural network is very important. The revised RBF neural network had a 3-layered architecture with the input, hidden and output layers. Architecture of the revised RBF neural network is shown in Fig.1. In this figure, x shows the input variable and ϕ shows the output variable and h shows the radial basis function.

In the revised RBF neural network, the structural parameters, which are mean (the center of the neuron) and variance of the radial basis function, are calculated automatically using the training data. The revised RBF neural network is calculated as follows:

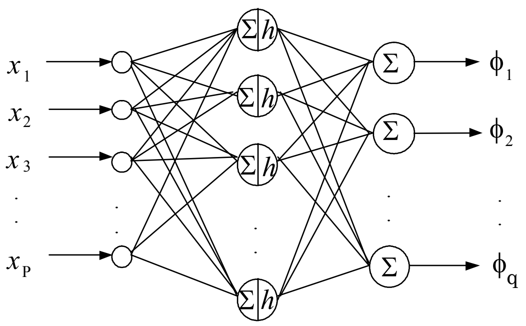


Fig.1 Architecture of the revised RBF neural network

(1)Input layer

$$u_i=x_i \quad (i = 1,2,\ldots,p) \tag{1}$$

Here, x_i is input variable and p is the number of input variables and u_i is the output variable of the input layer.

(2)Hidden layer

In the hidden layer, the output (h_j) of the RBF neuron is calculated by the following equation:

$$h_j = \exp(-z_j^2) \quad (j = 1,2,\ldots,g) \tag{2}$$

Here, z_j is estimated using the regression analysis [2] for the training data.

$$z_j=a_0+a_1d_j \tag{3}$$

$$d_j = \|u-c\| \tag{4}$$

Here, a_j ($j=0,1$) are the regression coefficients and d_j are the distance between the training data (u) and the center (c) of the neuron.

(3)Output layer

$$\phi_i(x) = \sum_{j=1}^{g} w_j h_j(u) \quad (i=1,2,\ldots,q) \tag{5}$$

Here, w_j $(j=1,2,\ldots,g)$ are the weights of the neural network and q is the number of neurons in the output layer and $\phi_i(x)(i=1,2,\ldots,q)$are the output variables.

Weights w_j $(j=1,2,\ldots,g)$ are estimated using multiple regression analysis as follows:

$$\underline{w} = (H^T H + \Lambda)^{-1} H^T \underline{\phi}_i \tag{6}$$

Here,

$$H = \begin{bmatrix} h_1(u_1) & h_2(u_1) & \cdots & \cdots & h_g(u_1) \\ h_1(u_2) & h_2(u_2) & \cdots & \cdots & h_g(u_2) \\ \vdots & \cdots & \ddots & \cdots & \vdots \\ \vdots & \cdots & \cdots & \ddots & \vdots \\ h_1(u_n) & h_2(u_n) & \cdots & \cdots & h_g(u_n) \end{bmatrix} \tag{7}$$

$$\Lambda = \begin{bmatrix} \lambda_1 & 0 & \cdots & \cdots & \cdots & 0 \\ 0 & \lambda_2 & 0 & \cdots & \cdots & 0 \\ 0 & 0 & \ddots & 0 & \cdots & 0 \\ 0 & \cdots & 0 & \ddots & 0 & 0 \\ 0 & \cdots & \cdots & 0 & \ddots & 0 \\ 0 & \cdots & \cdots & \cdots & 0 & \lambda_g \end{bmatrix} \tag{8}$$

$$\underline{\phi_i}^T = (\underline{\phi_i}(u_1), \underline{\phi_i}(u_2), \ldots, \underline{\phi_i}(u_n)) \tag{9}$$

$$\underline{w}^T = (w_1, w_2, \ldots, w_g) \tag{10}$$

Here, n is the number of training data.

In the revised RBF-neural network, the structural parameters such as means and variances of the radial basis functions, are automatically determined from the training data as follows. The number of neurons in the hidden layer was set to the number of the training data and the centers (means) of the radial basis functions are located at the training data points. Means are determined at the training data points. Variances are estimated using the regression analysis [2] of the training data to fit the characteristics of the nonlinear system. Using these procedures, the structural parameters such as means and variances of the radial basis functions, are automatically determined from the training data.

III. INPUT VARIABLES OF THE NEURAL NETWORK

In the neural network, ten input variables, which are four statistical image features, such as mean, variance, standard variation and range, and four texture features [3] and two coordinates (x and y) of the neighboring region were used. The four texture features were calculated with a co-occurrence matrix. Co-occurrence matrix is constructed with probability $P_\delta(i,j)$ $(i,j=0,1,\ldots,n-1)$ in the $n \times n$ neighboring region using a parameter $\delta = (r,\theta)$. Here, r is a distance between gray level i and gray level j and θ is an angle. Four texture features are calculated using the co-occurrence matrix as follows;

Angular second moment:

$$ASM = \sum_{i=0}^{n-1}\sum_{j=0}^{n-1}\{P_\delta(i,j)\}^2 \tag{11}$$

Contrast:

$$CON = \sum_{k=0}^{n-1} k^2 \cdot p_{x-y}(k), \quad P_{x-y}(k) = \sum_{i=0}^{n-1}\sum_{\substack{j=0 \\ |i-j|=k}}^{n-1} P_\delta(i,j) \quad k = 0,1,\ldots,n-1 \tag{12}$$

Entropy:

$$ENT = -\sum_{i=0}^{n-1}\sum_{j=0}^{n-1} P_\delta(i,j) \cdot \log\{P_\delta(i,j)\} \tag{13}$$

Inverse difference moment:

$$IDM = \sum_{i=0}^{n-1}\sum_{j=0}^{n-1}\frac{1}{1+(i-j)^2}P_\delta(i,j) \tag{14}$$

VI. MEDICAL IMASGE RECOGNITION OF THE LIVER BY THE REVISED RBF NEURAL NETWORK

In this study, The revised RBF neural network algorithm was applied to the medical image recognition of the liver regions and the recognition results were compared with those obtained using the conventional RBF neural network and the conventional multi-layered neural network trained using the back propagation algorithm. MDCT images of the abdomen were used. An original image shown in Fig.2 was used for organizing the artificial neural networks. Ten input variables, which are four statistical image features and four texture features and the two coordinates (x and y) of the N×N regions were used. The output value of the neural network was zero or one. When N×N pixel region was contained in the region of the liver, the neural network set the pixel value at the center of the N×N pixel region to one and this pixel was shown as the white point. In this study, we set the value of N to 3. Fig.3 shows the output images of neural network. Then we calculated the concordance rate of the liver and outside area of the liver and compared them. Table.1 show the concordance rate of the liver and outside area of the liver. It is shown that the revised RBF neural network is most accurate in three neural networks.

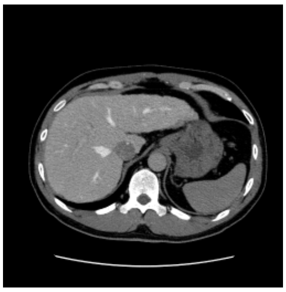
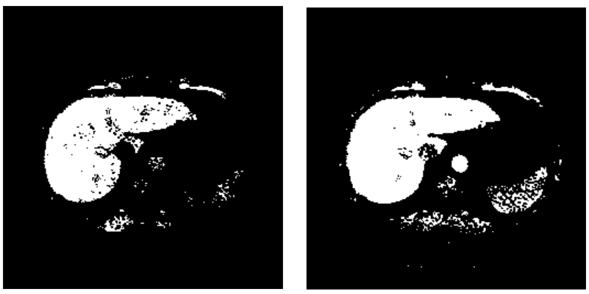


Fig.2 Original image

(a)Revised RBF-NN



(b)Conventional RBF-NN (c)Sigmoid function-NN

Fig.3 The output images of the neural networks

Table.1 The concordance rate of the liver and outside area of the liver

	Revised RBF-NN	Conventional RBF-NN	Sigmoid function-NN
Concordance rate of the liver	0.984	0.905	0.968
Outside area of the liver (pixels)	379	568	1611

V. MEDICAL IMAGE RECOGNITION OF THE LIVER CANCER (HCC)

The revised RBF neural network algorithm was applied to the medical image recognition of HCC. MDCT images of the liver, which are obtained in the early phase and the late phase, were used in this study.

1. Extraction of the liver region

An original image shown in Fig.4 was used for organizing the artificial neural network. This image is an early phase image of MDCT. Ten input variables, which are four statistical image features and four texture features and the two coordinates (x and y) of the N×N regions were used. The output value of the neural network was zero or one. When N×N pixel region was contained in the region of the liver, the neural network set the pixel value at the center of the N×N pixel region to one and this pixel was show as the white point. In this study, we set the value of N to 3. Fig.5 shows the output image after the post processing such as the dilatation and erosion.

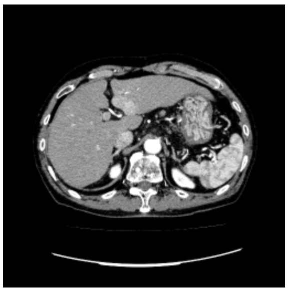


Fig.4 Original image obtained in early phase

Fig.5 Output image of the neural network after the post processing (1)

2. Extraction of HCC regions

The post-processing such as the dilatation and erosion was carried out so as to eliminate the isolate regions in the liver. Fig.6 shows the output image of the liver region including the abnormal regions and the blood vessels regions in the liver. Then the candidate regions of the HCC, which contained the abnormal regions and the blood vessels regions in the liver, were subtracted from the liver regions using the output image of the revised RBF neural network after the post-processing. Figure 7 shows the candidate regions of HCC.

Figure 8 shows the late phase image of MDCT. In the late phase image of MDCT, the densities of HCC regions are lower than those of liver regions. In the early phase image (Fig.4) of MDCT, the densities of HCC regions are higher than those of liver regions. Therefore, the density difference image between the early and late phase image contains the HCC regions. The density difference image between the early and late phase image of MDCT was subtracted and the threshold processing was carried out to obtain the binary image. Fig.9 shows the density difference image after the threshold processing.

Fig.6 The liver region after the post-processing(2)

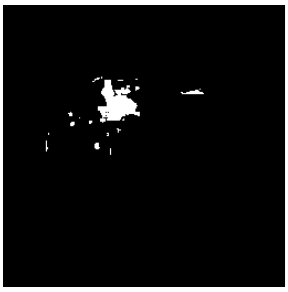


Fig.7 The candidate regions of HCC

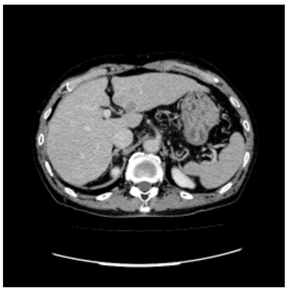


Fig.8 Original image obtained in late phase

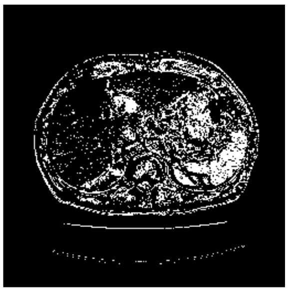


Fig.9 The density difference image

HCC regions were contained in both images in Fig.7 and 9 and so HCC regions can be detected using Fig.7 and Fig.9. The common area between Fig.7 and 9 were subtracted and the post processing analysis was carried out so as to eliminate the small isolated regions such as the blood vessels in the liver and the other regions outside the liver. In the post processing, the image processing such as the circumference length processing and the dilatation and the erosion were carried out to eliminate the small isolate regions. Fig.10 shows the HCC regions after these post processing.

These image processing were carried out for all slices of MDCT images and 3-dimentional images of HCC were displayed clearly with volume rendering software as shown in Fig.11.

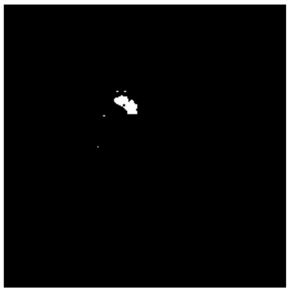


Fig.10 HCC regions after the post processing (3)

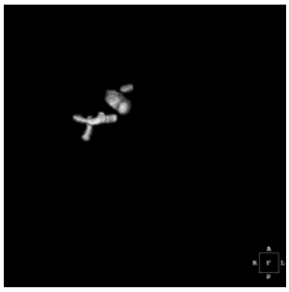


Fig.11 Three-dimensional image of HCC

VI. CONCLUSION

In this paper, we proposed the revised RBF neural network algorithm and applied this algorithm to recognition of the liver regions and extraction of the liver cancer (HCC). In the revised RBF neural network, the structural parameters such as means and variances of the radial basis functions, are automatically determined to fit the characteristics of the nonlinear system. So it is not needed to iterate the neural network calculations many times so as to find the optimum values of the structural parameters. We applied this algorithm to the medical image recognition of the liver and obtained 3-dimensional image of HCC.

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