The Fifteenth International Symposium on Artificial Life and Robotics 2010 (AROB 15th '10),
B-Con Plaza, Beppu,Oita, Japan, February 4-6, 2010

Feedback GMDH-type neural network algorithm and its application to medical image analysis of cancer of the liver.

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Abstract: A revised Group Method of Data Handling (GMDH)-type neural network algorithm for medical image recognition is proposed and is applied to the medical image analysis of cancer of the liver. The revised GMDH-type neural network algorithm has a feedback loop and can identify the characteristics of the medical images accurately using feedback loop calculations. In this algorithm, the polynomial type and the radial basis function (RBF) type neurons are used for organizing the neural network architecture. The optimum neural network architecture fitting the complexity of the medical images is automatically organized so as to minimize the prediction error criterion defined as Prediction Sum of Squares (PSS).

Keywords: Neural network, GMDH, Medical image recognition.

I. INTRODUCTION

The conventional GMDH-type neural network algorithms were proposed in our early works [1],[2]. In this paper, a revised GMDH-type neural network algorithm for medical image recognition is proposed and is applied to the medical image analysis of cancer of the liver. The revised GMDH-type neural network algorithm has a feedback loop and can identify the characteristics of the medical images accurately using feedback loop calculations. In this algorithm, the polynomial type and the radial basis function (RBF) type neurons are used for organizing the neural network architecture. A lot of complex nonlinear combinations of the input variables fitting the complexity of the medical images are generated using the polynomial type neurons and only useful combinations of the input variables are selected for organizing the neural network architecture. In the output layer, the RBF type neuron is used for organizing the neural network.

The revised GMDH-type neural network algorithm proposed in this study is applied to medical image analysis of cancer of the liver. The neural network architecture that fits the complexity of the medical images is automatically organized by the revised GMDH-type neural network algorithm so as to minimize the prediction error criterion defined as PSS [3] using the heuristic self-organization method [4],[5]. Heuristic self-organization method is a kind of the evolutional computation and can organize the optimum neural network architecture so as to minimize the prediction errors. The outlines of the liver are recognized using the neural network organized by the revised GMDH-type neural network algorithm and the regions of cancer of the liver are extracted. The results are compared with those obtained using the conventional neural network trained using the back propagation method. It is shown that the revised GMDH-type neural network algorithm is useful for the medical image analysis of cancer of the liver and it is very easy to apply the practical complex problem because the optimum neural network architecture is automatically organized so as to minimize the prediction error criterion PSS.

II. REVISED GMDH-TYPE NEURAL NETWORK ALGORITHM

In the conventional GMDH-type neural network [2], many kinds of neuron architectures such as the sigmoid function type, the RBF type and polynomial type neuron architectures are used for organizing neural network to fit the complexity of the nonlinear system. The optimum neuron architectures fitting the complexity of the nonlinear system are automatically selected by using the PSS [3]. Therefore, many kinds of nonlinear systems can be automatically identified by using the conventional GMDH-type neural network.

In the revised GMDH-type neural network, many kinds of nonlinear combinations of the input variables are generated by using the polynomial type neurons and only useful nonlinear combinations of the input variables are selected. Optimum neural network architectures are organized by using selected useful combinations of the input variables.

The revised GMDH-type neural network is shown in Fig.1. Here, nonlinear function g_i is described by the following Kolmogorov-Gabor polynomial:

$$g_i(x_1,x_2,\cdots,x_p) = a_0 + \sum_i a_i x_i + \sum_i \sum_j a_{ij} x_i x_j + \cdots \qquad (1)$$

This nonlinear function is automatically organized by using the second type neuron of the conventional GMDH-type neural network which is a polynomial type neuron.

The architecture of the revised GMDH-type neural network is produced as follows:

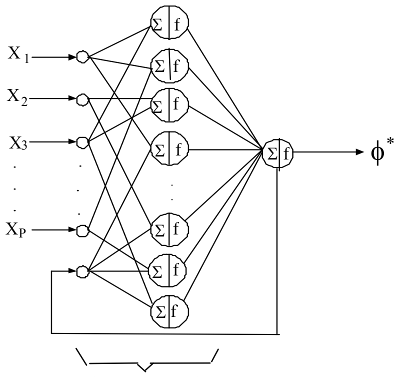
1. First loop calculation

First, all data are set to the training data. In this algorithm, it is not necessary to separate the original data into the training and test sets because PSS can be used for organizing the neural network architectures.

(1) Input layer

$$u_j=x_j \quad (j=1,2,\cdots,p) \tag{2}$$

where x_j (j=1,2,···,p) are the input variables of the system, and p is the number of input variables. In the input layer, input variables are set to the output variables.



$g_i\,(x_1,x_2,\cdots,x_p)$

Output layer:

Σ*: (Nonlinear function)*

$z = \sum w_i\, g_i\,(x_1,x_2,\cdots,x_p)$

f : (Nonlinear function)

$\phi^* = \exp(-z^2)$

Fig.1 Architecture of revised GMDH-type neural network

(2) Hidden layer

All combinations of two variables (u_i,u_j) are generated. For each combination, the neuron architecture is described by the following equations:

Σ: (Nonlinear function)

$$z_k= w_1u_i+w_2u_j+w_3u_iu_j+w_4u_i^2+w_5u_j^2+w_6u_i^3+w_7u_i^2u_j +w_8u_iu_j^2+w_9u_j^3 - w_0\theta_1 \tag{3}$$

f : (Linear function)

$$y_k= z_k \tag{4}$$

where θ_1 =1 and w_i (i=0,1,2,···,9) are weights between the input and hidden layer. This neuron is equal to the second type neuron of the conventional GMDH-type neural network. The weights w_i (i=0,1,2,···,9) are estimated by using the multiple regression analysis [6]. This procedure is as follows:

First, the values of z^{**} are calculated by using the following equation:

$$z^{**}=(-\log_e(\phi'))^{1/2} \tag{5}$$

where ϕ' is the normalized output variable whose values are between 0 and 1. ϕ' is calculated using following equation.

$$\phi'=\frac{\phi-\phi_{\min}}{|\phi_{\max}-\phi_{\min}|} \tag{6}$$

Here, ϕ_{max} is the maximum value of the output variable (ϕ), and ϕ_{min} is the minimum value of ϕ. Then the weights w_i (i=0,1,2,···,9) are estimated by using the stepwise regression analysis [6] which selects useful input variables by using the PSS[3]. Therefore, only useful variables in Eq.(3) are selected and neuron architecture are organized by these selected useful variables.

PSS is described by the following equation:

$$PSS=\sum_{\alpha=1}^{n}\left\{\frac{z_\alpha^{**}-z_{k\alpha}}{1-\underline{u}_\alpha^T(U^TU)^{-1}\underline{u}_\alpha}\right\}^2 \tag{7}$$

where

$$z_{k\alpha}=w_1u_{i\alpha}+w_2u_{j\alpha}+w_3u_{i\alpha}u_{j\alpha}+w_4u_{i\alpha}^2+w_5u_{j\alpha}^2+w_6u_{i\alpha}^3 +w_7u_{i\alpha}^2u_{j\alpha}+w_8u_{i\alpha}u_{j\alpha}^2+w_9u_{j\alpha}^3 - w_0\theta_1, \quad \alpha=1,2,\ldots,n \tag{8}$$

$$\underline{u}_\alpha^T=[1,\ u_{i\alpha},\ u_{j\alpha},\ u_{i\alpha}u_{j\alpha},\ u_{i\alpha}^2,\ u_{j\alpha}^2], \quad \alpha=1,2,\ldots,n \tag{9}$$

$$U^T=[\ \underline{u}_1\ ,\ \underline{u}_2\ ,\ \ldots,\ \underline{u}_n\ ] \tag{10}$$

$z_{k\alpha}$ is the α-th estimated value obtained by the multiple regression analysis of all the data. PSS criterion does not contain the statistical assumption in the regression model.

From these generated neurons, L neurons which minimize the PSS are selected. The output values (y_i) of L selected neurons are set to the input values (u_i) of the neuron in the output layer.

$$u_i=y_i \quad (i=1,2,\ldots,L) \tag{11}$$

(3) Output layer

The inputs (u_i) of the neuron in the output layer are combined by the following linear function.

$$z = w_0 + \sum_{i=1}^{L} w_i u_i \tag{12}$$

The useful intermediate variables (u_i) are selected by using the stepwise regression analysis in which PSS is used as the variable selection criterion. Then, the estimated output values (z) is used as the feedback value and it is combined with the input variables in the next loop calculation.

2. Second and subsequent loop calculations

First, the estimated output value (z) is combined with the input variables and all combinations between the estimated output value (z) and the input variables are generated. The same calculation as the first feedback loop is carried out for each combination. When PSS value of the linear function in (12) does not decrease, the loop calculation is terminated. The output values of the neural network (ϕ^*) are calculated from z as follows:

$$\phi^* = \exp(-z^2) \tag{13}$$

So, in the last feedback loop, the neuron architecture becomes as follows:

Σ: (Nonlinear function)

$$z = w_0 + \sum_{i=1}^{L} w_i u_i \tag{14}$$

f : (Nonlinear function)

$$\phi^* = \exp(-z^2) \tag{15}$$

By using these procedures, the revised GMDH-type neural network can be organized.

III. APPLICATION TO THE MEDICAL IMAGE ANALYSIS OF CANCER OF THE LIVER

In this study, the regions of cancer of the liver were recognized and extracted automatically by using the revised GMDH-type neural network. Multi-detector row CT (MDCT) images of the liver are used in this study. In the recognition procedure, the revised GMDH-type neural network is organized to recognize the liver regions and then the regions of cancer of the liver are extracted.

1. Extraction of the candidate image regions of the cancer of the liver.

A liver image shown in Fig. 2 was used for organizing the revised GMDH-type neural network. The statistics of the image densities and x and y coordinates in the neighboring regions, the N×N pixel regions, were used as the image features. Only five parameters namely, mean, standard deviation, variance and x and y coordinates were selected as the useful input variables. 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. The neural networks were organized when the values of N were from 3 to 15. It was determined that when N was equal to 7, the neural network architecture had the smallest recognition error. Five useful neurons were selected in each hidden layer. Figure 3 shows the variation of PSS values in the layers. The calculation of the revised GMDH-type neural network was terminated in the sixth feedback loop. The PSS value in the first feedback loop was not small but the PSS value was decreased gradually through the feedback loops and the small PSS vale was obtained in the sixth layer. The revised GMDH-type neural network outputs the liver image (Fig.4) and the first post-processing analysis of the liver image was carried out. In the first post-processing of the output image, the small isolated regions were eliminated and the outlines of the liver regions were expanded outside by N/2 pixels. Figure 5 shows the output image after the first post-processing. The output image after the first post-processing was overlapped to the original image (Fig.2) in order to check the accuracy of the image recognition as shown in Fig.6. The recognized liver regions are accurate. The regions of the liver were extracted from the original image using the output image. Figure 7 shows the extracted image of the liver. The second post-processing such as the closing was carried out and the region of the liver which contained the abnormal regions was obtained as shown in Fig.8. Figure 9 shows the extracted image of the liver. The candidate image regions of cancer of the liver were extracted from Fig.9 using Fig.7 and shown in Fig.10. The recognition results were compared with those of the conventional sigmoid function neural network trained using the back propagation method.

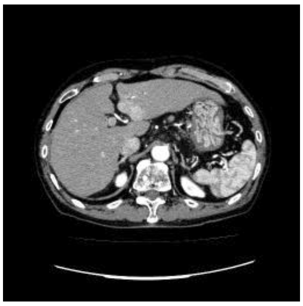


Fig.2 Original image

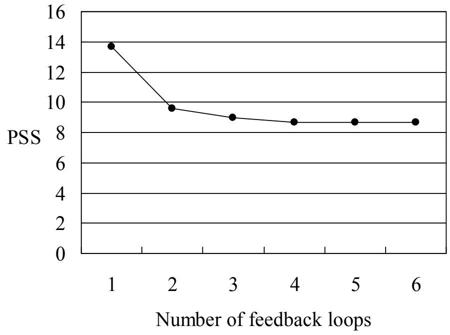


Fig.3 Variation of PSS in the revised GMDH-type neural network

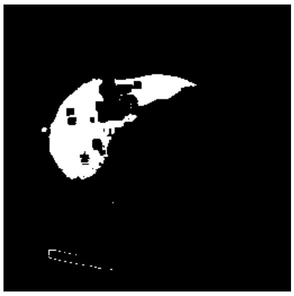


Fig.4 Output image of the neural network

Fig.5 Output image after the first post-processing

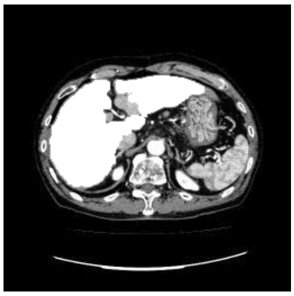


Fig.6 Overlapped image

Fig.7 Extracted image (1)

Fig.8 Output image after the second post-processing

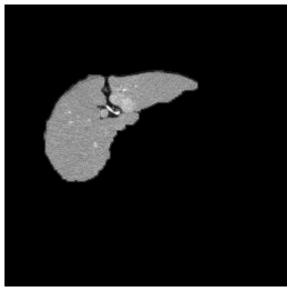


Fig.9 Extracted image (2)

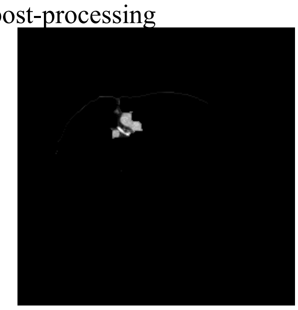


Fig.10 The candidate image regions of cancer of the liver

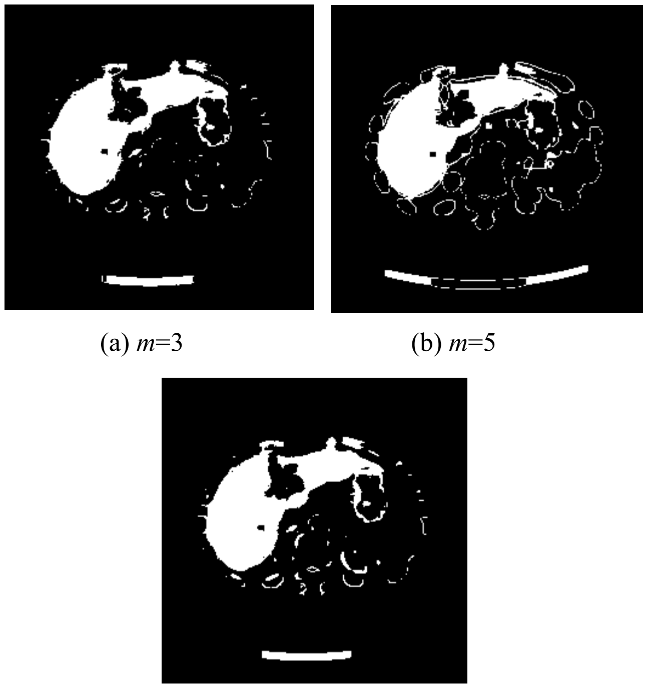
2. Recognition results of the conventional neural network trained using the back propagation algorithm

A conventional neural network trained using the back propagation algorithm was applied to the same recognition problem and the recognition results were compared with the results obtained using the revised GMDH-type algorithm. The conventional neural network had a three layered architecture, which was constructed using the input, hidden and output layers, and the same five input variables, which were mean, standard deviation, variance, x and y cordinates, were used in the input layer. Weights of the neural network were estimated using the back propagation algorithm and initial values of the weights were set to random values. The learning calculations of the weights were iterated changing structural parameters such as the number of neurons in the hidden layer and the initial values of the weights. The output images, when the numbers of neurons in the hidden layer (m) are 3, 5 and 7, are shown in Fig.11. These images contain more regions which are not part of the liver and the outlines of the liver are not extracted with required clarity compared with the output images obtained using the GMDH-type neural network algorithm, which is shown in Fig.4. Note that, in case of the conventional neural network, we obtain many different output images for various structural parameters of the neural network and many iterative calculations of the back propagation are needed for various structural parameters in order to find more accurate neural network architecture. In case of the revised GMDH-type neural network, the optimum neural network architecture is automatically organized so as to minimize prediction error criterion PSS using heuristic self-organization method [4],[5] and many iterative calculations for various structural parameters are not needed because all structural parameters are automatically determined.

V. CONCLUSION

In this paper, the revised GMDH-type neural network algorithm was applied to the medical image analysis of cancer of the liver and the results of the revised GMDH-type neural network were compared with those of the conventional sigmoid function neural network trained using the back propagation algorithm. Structural parameters such as the number of feedback loops, the number of neurons in hidden layers and useful input variables are automatically selected to minimize prediction error criterion defined as PSS. In the case of the conventional neural network, we obtain many different output images for various structural parameters of the neural network and many iterative calculations of the back propagation are needed for various structural parameters in order to find more accurate neural network architecture.

In this paper, the revised GMDH-type neural network algorithm was applied to the medical image analysis of cancer of the liver and it was shown that the revised GMDH-type neural network algorithm was a useful method for the medical image analysis of cancer of the liver because the neural network architecture is automatically organized so as to minimize the prediction error criterion defined as PSS.



(a) m=3 (b) m=5 (c) m=7

Fig.11 Output images of the conventional sigmoid function neural network

Acknowledgment This work was supported by (JSPS) KAKENHI 21560428.

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