Medical image recognition of cancer of the liver by GMDH-type neural network

Tadashi Kondo¹⁾, Masahiro Nakagawa, Shoichiro Takao and Junji Ueno
Graduate School of Health Sciences, The University of Tokushima,
3-18-15 Kuramoto-cho Tokushima 770-8509, Japan
¹⁾ kondo@medsci.tokushima-u.ac.jp

Abstract

In this study, the multi-layered Group Method of Data Handling (GMDH)-type neural network self-selecting optimum neural network architecture is applied to the computer aided image diagnosis (CAD) of the cancer of the liver. The GMDH-type neural network algorithm has an ability of self-selecting optimum neural network architecture from three neural network architectures such as sigmoid function neural network, radial basis function (RBF) neural network and polynomial neural network. The GMDH-type neural network also have abilities of self-selecting the number of layers, the number of neurons in hidden layers and useful input variables. This algorithm is applied to CAD and it is shown that this algorithm is useful for CAD of the cancer of the liver and is very easy to apply practical complex problem because optimum neural network architecture is automatically organized.

1 Introduction

Group Method of Data Handling (GMDH)-type neural networks and their applications have been proposed in our early works [1],[2]. GMDH-type neural networks can automatically organize neural network architecture by heuristic self-organization method [3],[4] and they can also determine such structural parameters as the number of layers, the number of neurons in hidden layers and useful input variables. But, these conventional GMDH-type neural network algorithms do not have an ability of selecting the type of neural network architectures such as sigmoid function neural network, radial basis function (RBF) neural network and polynomial neural network.

In this study, a revised GMDH-type neural network algorithm self-selecting optimum neural network architecture [5] is applied to the computer aided image diagnosis (CAD) of the cancer of the liver. In this algorithm, optimum neural network architecture is automatically selected from three neural network architectures such as sigmoid function neural network, RBF neural network and polynomial neural network. Furthermore, structural parameters such as the number of layers, the number of neurons in hidden layers and useful input variables are

automatically selected to minimize prediction error criterion defined as Prediction Sum of Squares (PSS)[6]. The GMDH-type neural network algorithm is applied to CAD of the cancer of the liver and results show that the GMDH-type neural network algorithm is useful for CAD of the cancer of the liver and is very easy to apply practical complex problem because optimum neural network architecture is automatically organized.

2 GMDH-type neural network

Architectures of GMDH-type neural network are automatically organized by heuristic self-organization method. First, we show procedures of heuristic self-organization method because it plays very important roles for organization of GMDH-type neural network.

2.1 Heuristic self-organization

Heuristic self-organization method is constructed by the following six procedures:

(1) Separating original data into training and test sets

Original data is separated into training and test sets. Training data is used for estimating parameters of partial descriptions which describe partial relationships of the nonlinear system. Test data is used for organizing complete description which describes complete relationships between input and output variables of the nonlinear system.

(2) Generating combinations of input variables in each layer

All combinations of two input variables (x_i, x_j) are generated in each layer. The number of combinations is $\frac{p!}{(p-2)!2!}$. Here, p is the number of input variables.

(3) Calculating partial descriptions

For each combination, partial descriptions of the nonlinear system can be calculated by applying regression analysis to training data. Output variables of partial descriptions are called as intermediate variables.

(4) Selecting intermediate variables

L intermediate variables which give L smallest test errors calculated using test data are selected from generated intermediate variables.

(5) Iterating calculations from procedure 2 to 5

Select L intermediate variables are set to input variables of the next layer and calculations from procedure 2 to 5 are iterated. The multi-layered architecture is organized.

(6) Stopping multilayered iterative calculation

When errors of test data in each layer stop decreasing, iterative calculation is terminated. Finally, complete description of the nonlinear system is constructed by partial descriptions generated in each layer.

2.2 Revised GMDH-type neural network algorithm [5]

Revised GMDH-type neural network has a common feedforward multilayered architecture. Figure 1 shows architecture of revised GMDH-type neural network. This neural network is organized by heuristic self-organization method.

Fig.1 Architecture of revised GMDH-type neural network

Procedures for determining architecture of revised GMDH-type neural network conform to the following:

(1) The first layer

$$u_j = x_j \quad (j=1, 2, \dots, p) \quad (1)$$

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

(2) The second layer

All combinations of r input variables are generated. For each combination, optimum neuron architectures are automatically selected from the following two neurons.

Architectures of the first and second type neurons are shown in Fig.2 and Fig.3 respectively. Optimum neuron architecture for each combination is selected from the first and second type neuron architectures.

Fig.2 Neuron architecture with two inputs (The first type neuron)

Fig.3 Neuron architecture with r inputs (The second type neuron)

Revised GMDH-type neural network algorithm can select optimum neural network architecture from three neural network architectures such as sigmoid function neural network, RBF neural network and polynomial neural network.

Neuron architectures of the first and second type neurons in each neural network architecture are shown as follows.

<Sigmoid function neural network>

i) The first type neuron

Σ : (Nonlinear function)

$$z_k = w_1 u_i + w_2 u_j + w_3 u_i u_j + w_4 u_i^2 + w_5 u_j^2 + w_6 u_i^3 + w_7 u_j^3 + w_8 u_i u_j^2 + w_9 u_i^2 u_j - w_0 \theta_l \quad (2)$$

f : (Nonlinear function)

$$y_k = \frac{1}{1 + e^{(-z_k)}} \quad (3)$$

Here, $\theta_l = 1$ and w_i ($i=0, 1, 2, \dots, 9$) are weights between the first and second layer. Value of r , which is the number of input variables u in each neuron, is set to two for the first type neuron.

ii) The second type neuron

Σ : (Linear function)

$$z_k = w_1 u_1 + w_2 u_2 + w_3 u_3 + \dots + w_r u_r - w_0 \theta_l \quad (r < p) \quad (4)$$

f : (Nonlinear function)

$$y_k = \frac{1}{1 + e^{(-z_k)}} \quad (5)$$

Here, $\theta_l = 1$ and w_i ($i=0, 1, 2, \dots, r$) are weights between the first and second layer. Value of r , which is the number of input variables u in each neuron, is set to be greater than two and smaller than p for the second type neuron. Here p is the number of input variables x_i ($i=1, 2, \dots, p$).

<Radial basis function neural network>

i) The first type neuron

Σ : (Nonlinear function)

$$z_k = w_1 u_i + w_2 u_j + w_3 u_i u_j + w_4 u_i^2 + w_5 u_j^2 + w_6 u_i^3 + w_7 u_j^3 + w_8 u_i u_j^2 + w_9 u_i^2 u_j - w_0 \theta_l \quad (6)$$

f : (Nonlinear function)

$$y_k = e^{(-z_k^2)} \quad (7)$$

Here, $\theta_l = 1$ and w_i ($i=0, 1, 2, \dots, 9$) are weights between the first and second layer. Value of r , which is the number of input variables u in each neuron, is set to two for the first type neuron.

ii) The second type neuron

Σ : (Linear function)

$$z_k = w_1 u_1 + w_2 u_2 + w_3 u_3 + \dots + w_r u_r - w_0 \theta_l \quad (r < p) \quad (8)$$

f : (Nonlinear function)

$$y_k = e^{(-z_k^2)} \quad (9)$$

Here, $\theta_l = 1$ and w_i ($i=0, 1, 2, \dots, r$) are weights between the first and second layer. Value of r , which is the number of input variables u in each neuron, is set to be greater than two and smaller than p for the second type neuron. Here p is the number of input variables x_i ($i=1, 2, \dots, p$).

<Polynomial neural network>

i) The first type neuron

Σ : (Nonlinear function)

$$z_k = w_1 u_i + w_2 u_j + w_3 u_i u_j + w_4 u_i^2 + w_5 u_j^2 + w_6 u_i^3 + w_7 u_j^3 + w_8 u_i u_j^2 + w_9 u_i^2 u_j - w_0 \theta_i \quad (10)$$

f : (Linear function)

$$y_k = z_k \quad (11)$$

Here, $\theta_i = 1$ and $w_i (i=0,1,2,\dots,9)$ are weights between the first and second layer. Value of r , which is the number of input variables u in each neuron, is set to two for the first type neuron.

ii) The second type neuron

Σ : (Linear function)

$$z_k = w_1 u_1 + w_2 u_2 + w_3 u_3 + \dots + w_r u_r - w_0 \theta_i \quad (r < p) \quad (12)$$

f : (Linear function)

$$y_k = z_k \quad (13)$$

Here, $\theta_i = 1$ and $w_i (i=0,1,2,\dots,r)$ are weights between the first and second layer. Value of r , which is the number of input variables u in each neuron, is set to be greater than two and smaller than p for the second type neuron. Here p is the number of input variables $x_i (i=1,2,\dots,p)$.

Weights $w_i (i=0,1,2,\dots)$ in each neural network architecture are estimated by stepwise regression analysis using PSS.

[Estimation procedure of weight w_i]

First, values of z_k are calculated for each neural network architecture as follows.

i) Sigmoid function neural network

$$z_k = \log_e \left(\frac{\phi'}{1 - \phi'} \right) \quad (14)$$

ii) RBF neural network

$$z_k = \sqrt{-\log_e \phi'} \quad (15)$$

iii) Polynomial neural network

$$z_k = \phi' \quad (16)$$

where ϕ' is normalized output variable whose values are between zero and one and ϕ is output variable.

Then weights w_i are estimated by stepwise regression analysis [7] which selects useful input variables using PSS. Only useful variables in Eq.(2), Eq.(4), Eq.(6), Eq.(8), Eq.(10) and Eq.(12) are selected by stepwise regression analysis using PSS and optimum neuron architectures are organized by selected useful variables.

PSS is described by the following equation:

$$PSS = \sum_{\alpha=1}^n (\phi_{\alpha}^* - y_{\alpha}^*)^2 \quad (17)$$

where

$$y_{\alpha}^* = b_0 + b_1 x_{i\alpha} + b_2 x_{j\alpha} + b_3 x_{i\alpha} x_{j\alpha} + b_4 x_{i\alpha}^2 + b_5 x_{j\alpha}^2, \quad \alpha=1,2,\dots,n \quad (18)$$

n is the number of training data, ϕ_{α} is the α -th observed value for the output variable, $x_{i\alpha}$ is the α -th observed value for the input variable x_i and y_{α}^* is the α -th estimated value

obtained by the multiple regression analysis of all the data except the α -th datum. In order to calculate PSS in (17), the multiple regression analysis must be repeated n times, and the amount of calculations increases in the number of data. But PSS in (17) can be reduced as follows,

$$PSS = \sum_{\alpha=1}^n \left\{ \frac{\phi_{\alpha} - y_{\alpha}}{1 - \underline{x}_{\alpha}^T (X^T X)^{-1} \underline{x}_{\alpha}} \right\}^2 \quad (19)$$

where

$$y_{\alpha} = b_0 + b_1 x_{i\alpha} + b_2 x_{j\alpha} + b_3 x_{i\alpha} x_{j\alpha} + b_4 x_{i\alpha}^2 + b_5 x_{j\alpha}^2, \quad (20)$$

$$\underline{x}_{\alpha}^T = [1, x_{i\alpha}, x_{j\alpha}, x_{i\alpha} x_{j\alpha}, x_{i\alpha}^2, x_{j\alpha}^2], \quad \alpha=1,2,\dots,n \quad (21)$$

$$X^T = [\underline{x}_1, \underline{x}_2, \dots, \underline{x}_n] \quad (22)$$

y_{α} is the α -th estimated value obtained by the multiple regression analysis of all the data. With this procedure, we need not repeat the regression analysis n times. PSS criterion do not contain the statistical assumption in the regression model.

For each combination, three neuron architectures which are sigmoid function neuron, RBF neuron and polynomial neuron, are generated and L neurons which minimize test error calculated using test data are selected for each neuron architecture. From these L selected neurons for each neuron architecture, mean test errors of L neurons are calculated. Then, neural network architecture which has minimum mean test error is selected as revised GMDH-type neural network architecture from three neural network architectures such as sigmoid function neural network, RBF neural network and polynomial neural network.

After the type of revised GMDH-type neural network architecture is selected, output variables y_k of L selected neurons are set to input variables of neurons in the third layer.

(3) The third and successive layers

In the second layer, optimum neural network architecture is selected from three neural network architectures. In the third and successive layers, only one neuron architecture, which is sigmoid function neuron or RBF neuron or polynomial neuron, is used for calculation and the same calculation of the second layer is iterated until PSS values of L neurons with selected neuron architecture stop decreasing. When iterative calculation is terminated, neural network architecture is produced by L selected neurons in each layer.

By using these procedures, revised GMDH-type neural network self-selecting optimum neural network architecture is organized. Revised GMDH-type neural network has an ability of self-selecting optimum neural network architecture. Therefore, neural network architecture is automatically selected from three neural network architectures. Furthermore, structural parameters such as the number of layers, the number of neurons in hidden layers and useful input variables are automatically selected to minimize prediction error criterion defined as PSS. The number of layers is equal to the number of iterative calculations of the GMDH. The number of neurons in the

hidden layers is equals to the number (L) which is set to a big number in the first layer but becomes to a small one automatically because the neurons with similar characteristics are generated through the layers.

3 Application to the medical image recognition of the cancer of the liver

In this study, the regions of the 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 the cancer of the liver are extracted.

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

A liver image shown in Fig. 4 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 $N \times N$ 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 $N \times N$ pixel region was contained in the region of the liver, the neural network set the pixel value at the center of the $N \times N$ 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 10. 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 5 shows the mean test errors of three kinds of neurons in the second layer. The mean test error of the RBF network was smallest in three kinds of neurons. RBF neural network architecture was selected by the revised GMDH-type neural network algorithm. Figure 6 shows the variation of PSS values in the layers. The calculation of the revised GMDH-type neural network was terminated in the sixth layer. The PSS values in the second layer were not small but the PSS values were decreased gradually through the layers and the small PSS values were obtained in the sixth layer. The revised GMDH-type neural network outputs the liver image (Fig.7) and the first post-processing analysis of the liver image was carried out. Figure 8 shows the output image after the first post-processing. The region of the liver was extracted from the original image using the output image. Figure 9 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 were obtained as shown in Fig.10. Figure 11 shows

the extracted image of the liver. The candidate image regions of the cancer of the liver were extracted from Fig.11 using Fig.9 and shown in Fig.12. The recognition results were compared with those of the conventional sigmoid function neural network trained using the back propagation method.

Fig.4 Original image

Fig.5 Test errors of three kinds of neurons in the second layer

Fig.6 Variation of PSS values in the layers

Fig.7 Output image of the revised GMDH-type neural network

Fig.8 Output image after the first post-processing

Fig.9 Extracted image of the liver regions

Fig.10 Output image after the second post-processing

Fig.11 Extracted image (2)

Fig.12 The candidate image regions of the cancer of the liver

3.2 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 coordinates, 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.13, 14 and 15. These images contain more regions which are not part of the liver and the outlines of the lungs are not extracted with required clarity compared with the output images obtained using the GMDH-type neural network algorithm, which is shown in Fig.7. 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 and many iterative calculations for various structural parameters are not needed because all structural parameters are automatically determined.

Fig.13 Output image of the conventional sigmoid function neural network ($m=3$)

Fig.14 Output image of the conventional sigmoid function neural network ($m=5$)

Fig.15 Output image of the conventional sigmoid function neural network ($m=7$)

4 Conclusion

In this paper, the revised GMDH-type neural network

algorithm self-selecting optimum neural network architecture was applied to the CAD of the 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. In this revised GMDH-type neural network algorithm, optimum neural network architecture is automatically selected from three neural network architectures such as sigmoid function neural network, RBF neural network and polynomial neural network. Furthermore, structural parameters such as the number of layers, 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 CAD of the cancer of the liver and it was shown that the revised GMDH-type neural network algorithm was a useful method for CAD of the cancer of the liver because the neural network architecture is automatically organized so as to minimize the prediction error criterion defined as PSS.

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