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Medical image diagnosis of lung cancer by multi-layered GMDH-type neural network self-selecting functions

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Abstract: In this study, a revised Group Method of Data Handling (GMDH)-type neural network self-selecting optimum neuron architectures is applied to the computer aided image diagnosis (CAD) of lung cancer. 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 has 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 lung cancer and is very easy to apply practical complex problem because optimum neural network architecture is automatically organized.
Keywords: Neural networks, GMDH, Medical image diagnosis.

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], which is a kind of evolutional computation, and they can also determine automatically such structural parameters as the number of layers, the number of neurons in hidden layers and useful input variables.

In this study, a revised GMDH-type neural network algorithm self-selecting optimum neural network architecture is applied to the computer aided image diagnosis (CAD) of lung cancer. 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 so as to minimize prediction error criterion defined as Akaike's information criterion (AIC) [5] or Prediction Sum of Squares (PSS) [6]. The GMDH-type neural network algorithm is applied to CAD of lung cancer and results show that the revised GMDH-type neural network algorithm is useful for CAD of lung cancer and is very easy to apply practical complex problem because optimum neural network architecture is automatically organized.

2. MULTI-LAYERED GMDH-TYPE NEURAL NETWORK SELF-SELECTING FUNCTION

Revised GMDH-type neural network has a common feedforward multilayered architecture. Figure 1 shows architecture of revised GMDH-type neural network.

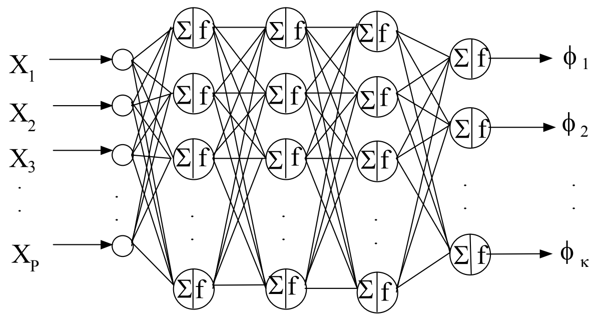


Fig.1 Architecture of revised GMDH-type neural network

2.1 The first layer

$$u_j = x_j \qquad (j=1,2,\ldots,p) \tag{1}$$

where x_j (j=1,2,…,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.

2.2 The second layer

All combinations of r input variables are generated. For each combination, optimum neuron architectures are automatically selected so as to minimize AIC or PSS.

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 in each neural network architecture are shown as follows. Neurons are constructed using the first and the second type neuron architectures.

(1) ***Sigmoid function neural network***

1) The first type neuron

Σ: (Nonlinear function)

$$z_k=w_1u_i+w_2u_j+w_3u_iu_j+w_4u_i^2+w_5u_j^2+w_6u_i^3+w_7u_i^2u_j+w_8u_iu_j^2+w_9u_j^3-w_0\theta_1 \quad (2)$$

f : (Nonlinear function)

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

2) The second type neuron

Σ: (Linear function)

$$z_k= w_1u_1+w_2u_2+w_3u_3+\cdots+w_ru_r - w_0\theta_1 \quad (r<p) \quad (4)$$

f : (Nonlinear function)

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

(2) ***Radial basis function neural network***

1) The first type neuron

Σ: (Nonlinear function)

$$z_k=w_1u_i+w_2u_j+w_3u_iu_j+w_4u_i^2+w_5u_j^2+w_6u_i^3+w_7u_i^2u_j+w_8u_iu_j^2+w_9u_j^3-w_0\theta_1 \quad (6)$$

f : (Nonlinear function)

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

2) The second type neuron

Σ: (Linear function)

$$z_k= w_1u_1+w_2u_2+w_3u_3+\cdots+w_ru_r - w_0\theta_1 \quad (r<p) \quad (8)$$

f : (Nonlinear function)

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

(3) ***Polynomial neural network***

1) The first type neuron

Σ: (Nonlinear function)

$$z_k=w_1u_i+w_2u_j+w_3u_iu_j+w_4u_i^2+w_5u_j^2+w_6u_i^3+w_7u_i^2u_j+w_8u_iu_j^2+w_9u_j^3-w_0\theta_1 \quad (10)$$

f : (Linear function)

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

2) The second type neuron

Σ: (Linear function)

$$z_k= w_1u_1+w_2u_2+w_3u_3+\cdots+w_ru_r - w_0\theta_1 \quad (r<p) \quad (12)$$

f : (Linear function)

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

Here, $\theta_1=1$ and w_i (i=0,1,2,…,9) and w_i (i=0,1,2,…,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 two for the first type neuron and set to be greater than two and smaller than p for the second type neuron. p is the number of input variables x_i (i=1,2,…,p). Weights w_i (i=0,1,2,…) in each neural network architecture are estimated by stepwise regression analysis [7] using PSS.

[Estimation procedure of weight w_i]

First, values of z_k^{**} are calculated for each neural network architecture as follows.

a)Sigmoid function neural network

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

b)RBF neural network

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

c)Polynomial neural network

$$z_k^{**}=\phi \quad (16)$$

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

Then weights w_i are estimated by stepwise regression analysis [7] which selects useful input variables using AIC or 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 AIC or PSS and optimum neuron architectures are organized by selected useful variables.

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

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.

2.3 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 AIC or 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, the revised GMDH-type neural network self-selecting functions is organized.

3. APPLICATION TO MEDICAL IMAGE DIAGNOSIS OF LUNG CANCER

In this study, the regions of lung cancer were recognized and extracted automatically by using the revised GMDH-type neural network. Multi-detector row CT (MDCT) images of lungs are used in this study. In this application, PSS was used as the prediction error criterion.

3.1 Extraction of candidate image regions of lung cancer.

A lung 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 lung regions, 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 10. It was determined that when N was equal to 4, the neural network architecture had the smallest recognition error. Five useful neurons were selected in each hidden layer. Figure 3 shows the estimation errors of three kinds of neurons in the second layer. The estimation error of the RBF neural network was smallest in three kinds of neurons. The RBF neural network architecture was selected by the revised GMDH-type neural network algorithm. Figure 4 shows the variation of PSS values in the layers. The calculation of the revised GMDH-type neural network was terminated in the eighth layer. The revised GMDH-type neural network outputs the lung image (Fig.5) and the first post-processing analysis of the lung image was carried out. In the first post-processing of the output image, the opening was carried out and small isolated regions were eliminated and the outlines of the lung regions were expanded outside by N/2 pixels. Then, the closing was carried out and the lung regions that did not contain abnormal regions were output. Figure 6 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 of the lungs as shown in Fig.7. The recognized lung regions are accurate. The lung regions was extracted from the original image using the output image. Figure 8 shows the extracted lung image. The second post-processing such as the opening, closing and so on was carried out in Fig.5 and the lung regions which contained the abnormal regions were obtained as shown in Fig.9. Figure 10 shows the extracted lung image. The candidate image regions of the lung cancer were extracted from Fig.10 using Fig.8 and shown in Fig.11.

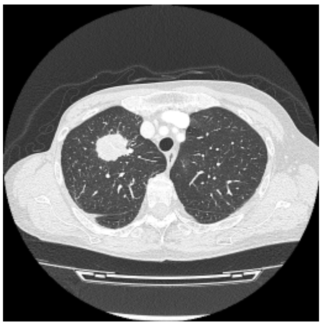


Fig. 2 Original image

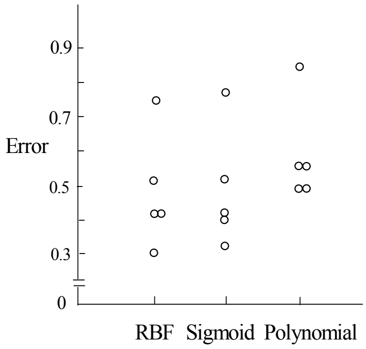


Fig.3 Estimation errors of three kinds of neurons

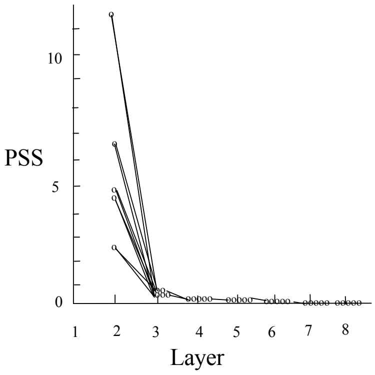


Fig.4 Variation of PSS values

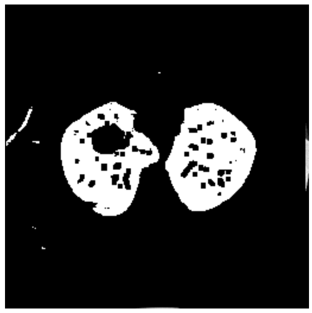


Fig.5 Output image of revised GMDH-type neural network

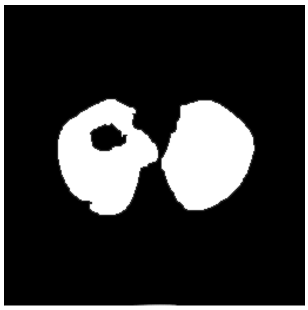


Fig.6 Output image after the first post-processing

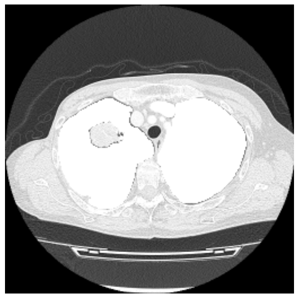


Fig. 7 Overlapped image

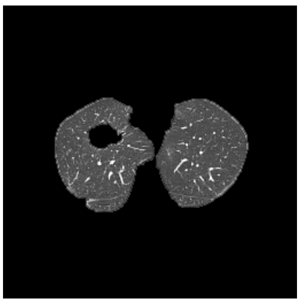


Fig.8 Extracted image of lung regions (1)

Fig. 9 Output image after second post-processing

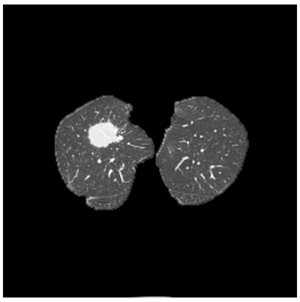


Fig. 10 Extracted image of lung regions (2)

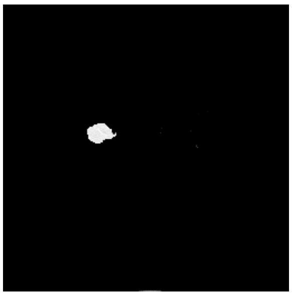
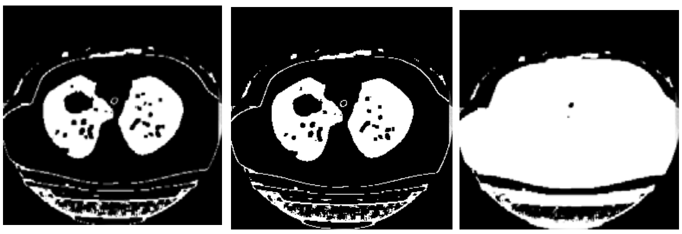


Fig. 11 The candidate image region of lung cancer

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 and the same five input variables were used in the input layer. 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 5, 7 and 9, are shown in Fig.12. These images contain more regions which are not part of the lung and the outlines of the lungs are not extracted with required clarity compared with the output image obtained using the GMDH-type neural network algorithm, which is shown in Fig.5. 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.



(a) m=5 (b) m=7 (c) m=9

Fig.12 Output images of conventional sigmoid function neural network

4. CONCLUSION

In this paper, the revised GMDH-type neural network algorithm self-selecting functions was applied to the CAD of lung cancer 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 AIC or 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. It was shown that the revised GMDH-type neural network algorithm was a useful method for CAD of lung cancer because the neural network architecture is automatically organized so as to minimize the prediction error criterion defined as AIC or PSS.

ACKNOWLEDGEMENT

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