Medical Image Diagnosis of Lung Cancer by Revised GMDH-type Neural Network using Various Kinds of Neurons

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Abstract: A revised Group Method of Data Handling (GMDH)-type neural network algorithm using various kinds of neurons is applied to the medical image diagnosis of lung cancer. The optimum neural network architecture for the medical image diagnosis is automatically organized using revised GMDH-type neural network algorithm and the regions of lung cancer are recognized and extracted accurately.

Keywords: Neural network, GMDH, Medical image diagnosis

I. INTRODUCTION

The conventional GMDH-type neural networks [1]-[3] are automatically organized using the heuristic self-organization method [4],[5] and the structural parameters such as the number of layers, the number of neurons in each layer, useful input variables and optimum neuron architectures are automatically determined so as to minimize the prediction error criterion Akaike's Information Criterion (AIC) [6] or Prediction Sum of Squares (PSS) [7]. In this paper, a revised GMDH-type neural network algorithm is developed. 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 nonlinear system 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 and the output value of the neural network becomes between zero and one. The revised GMDH-type neural network is applied to the medical image diagnosis of lung cancer and it is shown that the revised GMDH-type neural network is accurate and useful method for the medical image diagnosis of lung cancer.

II. HEURISTIC SELF-ORGANIZATION

The GMDH-type neural network algorithm can automatically develop the optimum neural network architectures by the heuristic self-organization. The heuristic self-organization in the GMDH-type neural network is implemented through the following five procedures:

1) Separating the original data into training and test sets.

The original data are separated into training and test sets. The training data are used for the estimation of the weights of the neural network. The test data are used for organizing neural network architectures.

2) Generating the combinations of the input variables in each layer.

All combinations of r input variables are generated in each layer. The number of combinations is $\frac{p!}{(p-r)!\,r!}$. Here, p is the number of input variables and the number of r is usually set to two.

3) Selecting the optimum neuron architectures

For each combination, the optimum neuron architectures which describe the partial characteristics of the nonlinear system can be calculated by applying the regression analysis [8] to the training data. The output variables y_k of the optimum neurons are called intermediate variables. In the GMDH-type neural network, the optimum neurons are selected from different neuron architectures.

4) Selecting the intermediate variables.

The L intermediate variables which give the L smallest test errors calculated using the test data are selected from the generated intermediate variables y_k. Selected L intermediate variables are set to the input variables of the next layer and calculations from procedure 2 to 4 are iterated.

5) Stopping the multilayered iterative computation.

When the errors for the test data in each layer stop decreasing, the iterative computation is terminated. The complete neural network which describes the characteristics of the nonlinear system can be constructed using the optimum neurons which are generated in each layer.

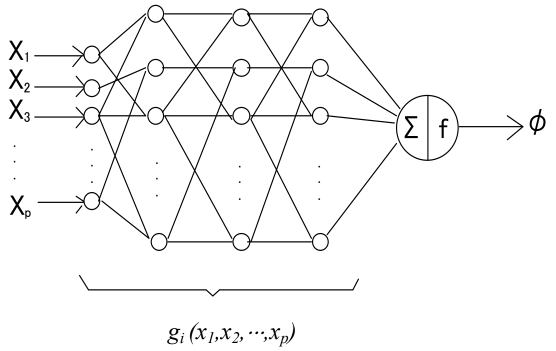
III. REVISED GMDH-TYPE NEURAL NETWORK USING VARIOUS KINDS OF NEURONS

The revised GMDH-type neural network architecture 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 polynomial neurons. The architecture of the revised GMDH-type neural network is automatically organized using the heuristic self-organization and is produced as follows:

In the revised GMDH-type neural network, the original data are not separated into training and test sets because PSS can be used as the test errors.



Σ : *(Nonlinear function)*

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

f : (Nonlinear function)

$\phi = exp\,(\,-\,z_k^2)$

Fig.1 Architecture of revised GMDH-type neural network

1. The first layer

$u_j = x_j \qquad (j=1,2,\cdots,p)$ (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 first layer, input variables are set to the output variables.

2. The second layer

Many 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)

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

f : (Linear function)

$y_k = z_k$ (4)

where θ_1=1 and w_i ($i=0,1,2,\cdots,9$) are weights between the first and second layer. The weights w_i ($i=0,1,2,\cdots,9$) are estimated by using the multiple regression analysis. This procedure is as follows:

First, the values of z_k are calculated using the following equation:

$z_k = (-log_e\, \phi')^{1/2}$ (5)

where ϕ' is the normalized output variable. Then the weights w_i ($i=0,1,2,\cdots,9$) are estimated by using the stepwise regression analysis which selects useful input variables using the PSS. Therefore, only useful variables in (3) are selected and neuron architecture can be organized by these selected useful variables.

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

3. The third and succeeding layers

In the third and succeeding layers, the same computation of the second layer is continued until PSS values of L neurons are not decreased. When the iterative computation is terminated, the following calculation of the output layer is carried out.

4. The output layer

In the output layer, the output values of the neural network are calculated from z_k as follows:

$y_k = exp\,(\,-\,z_k^2)$ (6)

So, in the output layer, the neuron architecture becomes as follows:

Σ: (Nonlinear function)

$z_k = \sum w_i\, g_i\,(x_1,x_2,\cdots,x_p)$ (7)

f : (Nonlinear function)

$\phi = exp\,(\,-\,z_k^2)$ (8)

At last, the complete neural network architecture is produced by selected neurons in each layer.

Figure 2 shows the flowchart of the revised GMDH-type neural network.

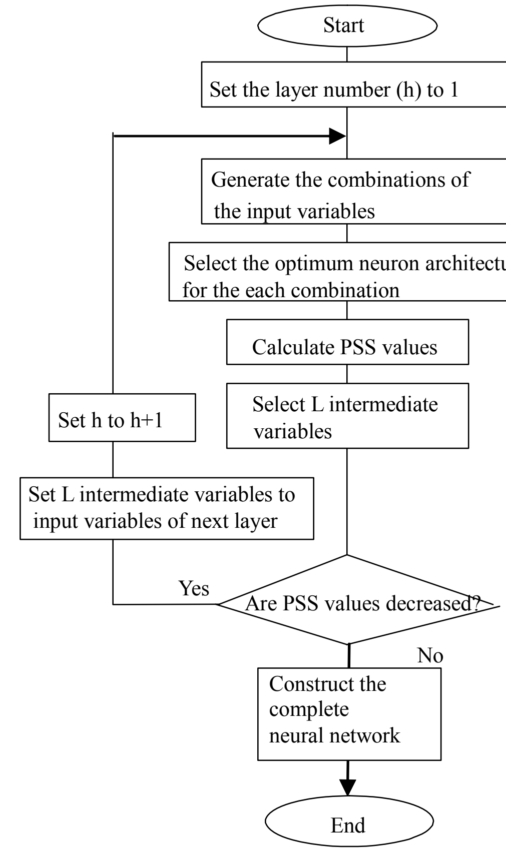


Fig. 2 Flowchart of the revised GMDH-type neural network

IV. APPLICATION TO THE 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 the lungs are used in this study. In the recognition procedure, the revised GMDH-type neural network is organized to recognize the lung regions and then the regions of lung cancer are extracted.

1. Extraction of the candidate image regions of lung cancer

A lung image shown in Fig. 3 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 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 15. 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 4 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 value in the second layer was not small but the PSS value was decreased gradually through the layers and the small PSS vale was obtained in the sixth 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, image processing such as closing, opening and so on were carried out and the small isolated regions were eliminated and the outlines of the lung regions were expanded outside by N/2 pixels. Figure 6 shows the output image after the first post-processing and the lung regions that contains the abnormal regions were extracted. The output image after the first post-processing was overlapped to the original image (Fig.3) in order to check the accuracy of the image recognition as shown in Fig.7. The recognized lung regions are accurate. The lung regions were extracted from the original image using the output image. Figure 8 shows the extracted image of the lungs. The second post-processing such as closing, opening and so on was carried out and the lung regions which did not contain the abnormal regions was obtained as shown in Fig.9. Figure 10 shows the extracted image of the lungs. The candidate image region of lung cancer were extracted from Fig.8 using Fig.10 and shown in Fig.11. The recognition results were compared with those of the conventional sigmoid function neural network trained using the back propagation method.

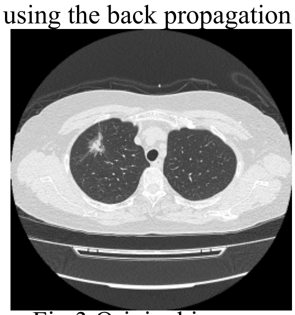


Fig.3 Original image

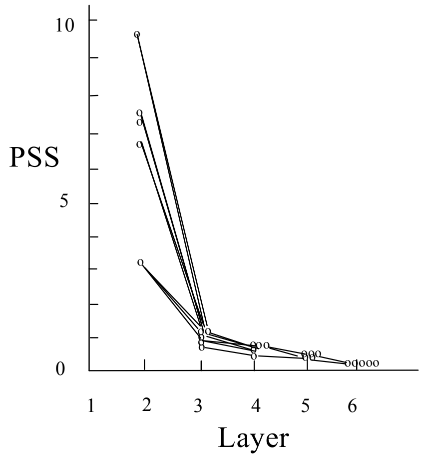


Fig.4 Variation of PSS in the revised GMDH-type neural network

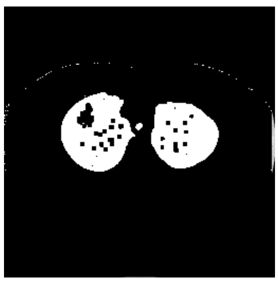


Fig.5 Output image of the neural network

Fig.6 Output image after the first post-processing

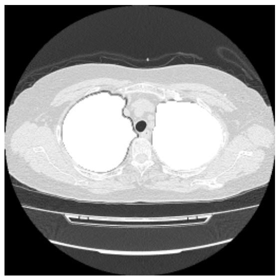


Fig.7 Overlapped image

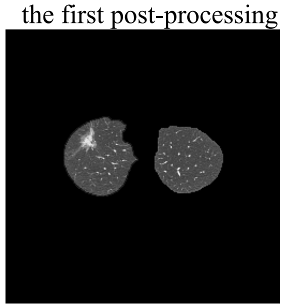


Fig.8 Extracted image (1)

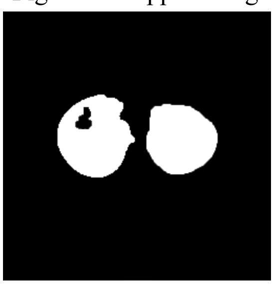


Fig.9 Output image after the second post-processing

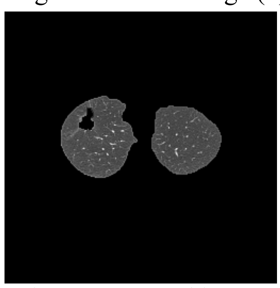


Fig.10 Extracted image (2)

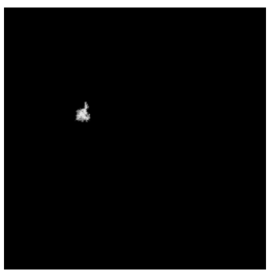


Fig.11 The candidate image region of lung cancer

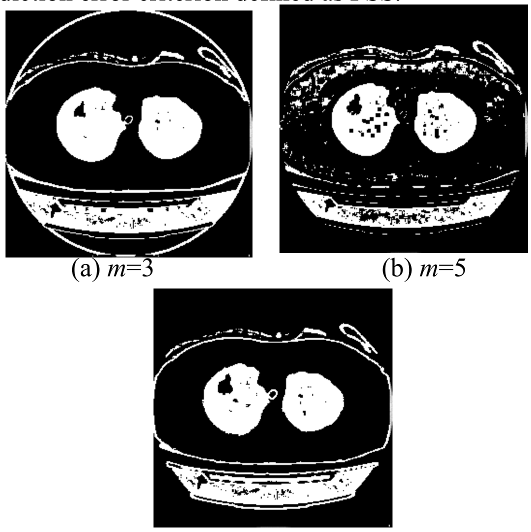
2. Recognition results of the conventional neural network trained using the back propagation algorithm

A conventional neural network trained using the back propagation algorithm was applied to the same diagnosis problem and the 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.12. These images contain more regions which are not part of the lungs 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.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. 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 diagnosis 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. 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 the medical image diagnosis of lung cancer and it was shown that the revised GMDH-type neural network algorithm was a useful method for the medical image diagnosis of lung cancer 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.12 Output images of the conventional sigmoid function neural network

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