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Medical image diagnosis of liver cancer by feedback GMDH-type neural network using knowledge base

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Abstract: A revised Group Method of Data Handling (GMDH)-type neural network algorithm using knowledge base for medical image diagnosis is proposed and is applied to medical image diagnosis of the liver cancer. In this algorithm, the knowledge base for medical image diagnosis is used for organizing the neural network architecture for medical image diagnosis. Furthermore, 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. It is shown that the revised GMDH-type neural network is accurate and a useful method for the medical image diagnosis of the liver cancer.
Keywords: Neural networks, GMDH, Medical image diagnosis, Artificial intelligence.

1. 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 using knowledge base is proposed and is applied to the medical image diagnosis of liver cancer. In this revised GMDH-type neural network, the knowledge base for medical image diagnosis is used for organizing the neural network architecture. In the knowledge base system, the various kinds of the knowledge such as the medical knowledge, the image processing knowledge and others, are memorized and these knowledge are used to organize the neural network architecture. Furthermore, 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. The neural network architecture is selected from three types of neural network architectures such as the sigmoid function type neural network, the radial basis function (RBF) type neural network and the polynomial type neural network using the knowledge base system. Furthermore, the structural parameters such as the number of feedback loops, the number of neurons in the hidden layers and the relevant input variables are automatically selected using heuristic self-organization method [3],[4], which is a kind of evolutional computation, so as to minimize the prediction error criterion defined as Akaike's information criterion (AIC) or Prediction Sum of Squares (PSS)[5].

2. FEEDBACK GMDH-TYPE NEURAL NETWORK USING KNOWLEDGE BASE

Neural network architecture is shown in Fig.1. In this algorithm, the neural network architecture is automatically organized using the knowledge base. The rules in the knowledge base are classified to the following five types.

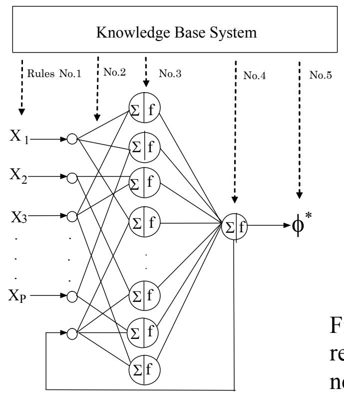


Fig.1 Architecture of revised GMDH-type neural network

2.1 Knowledge base

(1) First type rules.

These rules are concerned with the pre-processing of the original image such as the filtering, the thresh hold processing and so on and the image characteristics of the original image are extracted.

(2) Second type rules.

In the GMDH-type neural network, all combinations of the input variables are generated and the architecture of the neural network is organized using only selected combinations so as to minimize the prediction errors defined as AIC or PSS. In the revised GMDH-type neural network, the combinations of the input variables are controlled using the rules of the knowledge base.

(3) Third type rules.

In the conventional GMDH-type neural network [2], the following seven neuronal architectures are used for organizing neural network to fit the complexity of the nonlinear system. Here, u_i (i =1,2,…,p) and u_j (j =1,2,…,p) show the input variables of the neurons and p is the number of input variables. θ_1=1 and w_i (i=0,1,2,⋯) are weights between the neurons.

1) First type neuron

Σ: (Nonlinear function) $z_k= w_1u_i+w_2u_j+w_3u_iu_j+w_4u_i^2+w_5u_j^2 +w_6u_i^3+w_7u_i^2u_j+w_8u_iu_j^2+w_9u_j^3 - w_0\theta_1$ (1)

f : (Nonlinear function) $y_k= 1 / (1+\exp(-z_k))$ (2)

2) Second type neuron

Σ: (Linear function) $z_k= w_1u_1+w_2u_2+w_3u_3+\cdots+w_ru_r - w_0\theta_1$ ($r<p$) (3)

f : (Nonlinear function) $y_k= 1 / (1+\exp(-z_k))$ (4)

3) Third type neuron

Σ: (Nonlinear function) $z_k= w_1u_i+w_2u_j+w_3u_iu_j+w_4u_i^2+w_5u_j^2 +w_6u_i^3+w_7u_i^2u_j+w_8u_iu_j^2+w_9u_j^3 - w_0\theta_1$ (5)

f : (Nonlinear function) $y_k= \exp(-z_k^2)$ (6)

4) Fourth type neuron

Σ: (Linear function) $z_k= w_1u_1+w_2u_2+w_3u_3+\cdots+w_ru_r - w_0\theta_1$ ($r<p$) (7)

f : (Nonlinear function) $y_k= \exp(-z_k^2)$ (8)

5) Fifth type neuron

Σ: (Nonlinear function) $z_k= w_1u_i+w_2u_j+w_3u_iu_j+w_4u_i^2+w_5u_j^2 +w_6u_i^3+w_7u_i^2u_j+w_8u_iu_j^2+w_9u_j^3 - w_0\theta_1$ (9)

f : (Linear function) $y_k= z_k$ (10)

6) Sixth type neuron

Σ: (Linear function) $z_k= w_1u_1+w_2u_2+w_3u_3+\cdots+w_ru_r - w_0\theta_1$ ($r<p$) (11)

f : (Linear function) $y_k= z_k$ (12)

7) Seventh type neuron

Σ: (Linear function) $z_k= w_1u_1+w_2u_2+w_3u_3+\cdots+w_ru_r - w_0\theta_1$ ($r<p$) (13)

f : (Nonlinear function) $y_k= a_0+a_1z_k+a_2z_k^2+\cdots+a_mz_k^m$ (14)

In the revised GMDH-type neural network, many kinds of the functions can be used as the neuronal architecture and the desirable neuronal architecture in the hidden layer is selected using the third type rules according to the medical or the physical knowledge.

When these rules concerned with the neuronal architecture are not obtained previously, the optimum neuronal architectures fitting the complexity of the nonlinear system are selected automatically so as to minimize the prediction error defined as AIC or PSS.

(4) Fourth type rules.

The neuronal architecture in the output layer is selected using the fourth type rules. When these rules concerned with the neuronal architecture are not obtained previously, the optimum neuronal architectures is selected automatically so as to minimize AIC or PSS.

(5) Fifth type rules.

These rules are concerned with the post-processing of the output images of the neural network. The post-processing such as the closing, the opening and so on are selected using the fifth type rules.

In this paper, we apply the revised GMDH-type neural network to the medical image diagnosis of the liver cancer and the following rules are used in this application.

a) Second type rules.

We do not make the limitations in the combinations of the input variables.

b) Third type rules.

The first type neuronal architecture is used in the hidden layer.

c) Fourth type rules.

The second type neuronal architecture is used in the output layer.

The architecture of the revised GMDH-type neural network is produced concretely using these rules as follows:

2.2 First loop calculation

First, all data are set to the training data. In this study, we used PSS as the prediction error criterion.

(1)Input layer

$u_j=x_j \quad (j=1,2,\cdots,p)$ (15)

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.

(2)Hidden layer

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

Σ: (Nonlinear function) $z_k= w_1u_i+w_2u_j+w_3u_iu_j+w_4u_i^2+w_5u_j^2 +w_6u_i^3+w_7u_i^2u_j +w_8u_iu_j^2+w_9u_j^3 - w_0\theta_1$ (16)

f : (Linear function) $y_k= 1 / (1+\exp(-z_k))$ (17)

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 first 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.

This procedure is as follows:

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

$$z_k^{**} = \log_e\left(\frac{\phi'}{1-\phi'}\right) \tag{18}$$

where ϕ' is the normalized output variable whose values are between 0 and 1. Then the weights w_i (i=0,1,2,⋯,9) are estimated by using the stepwise regression analysis which selects useful input variables by using the PSS[5].

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.

$$u_i = y_i \qquad (i=1,2,\ldots,L) \tag{19}$$

(3)Output layer

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

$$z = w_0 + \sum_{i=1}^{L} w_i u_i \tag{20}$$

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.

2.3 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 (20) does not decrease, the loop calculation is terminated. The output values of the neural network (ϕ^*) are calculated from z as follows:

$$\phi^* = 1 / (1+\exp(-z)) \tag{21}$$

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

Σ: (Nonlinear function) $\quad z = w_0 + \sum_{i=1}^{L} w_i u_i \qquad (22)$

f : (Nonlinear function) $\quad \phi^* = 1 / (1+\exp(-z)) \qquad (23)$

This neuron equal to the second type neuron of the conventional GMDH-type neural network.

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

3. APPLICATION TO MEDICAL IMAGE DIAGNOSIS OF LIVER CANCER

Multi-detector row CT (MDCT) images of the liver are used in this study.

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

A liver image shown in Fig. 2 was used for organizing the revised GMDH-type neural network. By the first type rules, we used the statistics of the image densities and x and y coordinates in the neighboring regions, the $N \times N$ pixel regions, as the image features. As the results, 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 liver region, 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 5, 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 eighth 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 eighth feedback loop. 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 using the fifth type rules. 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 liver regions 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 using the fifth type rules and the liver region which contained the abnormal regions was obtained as shown in Fig.8. Figure 9 shows the extracted image of the liver. The candidate image region of the liver cancer were extracted from Fig.9 using Fig.7 and shown in Fig.10.

Fig.2 Original image

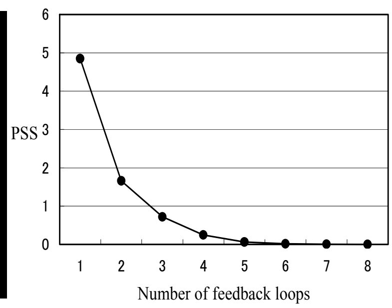


Fig.3 Variation of PSS

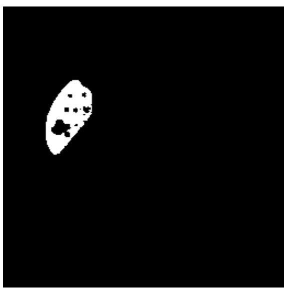


Fig.4 Output image of the neural network

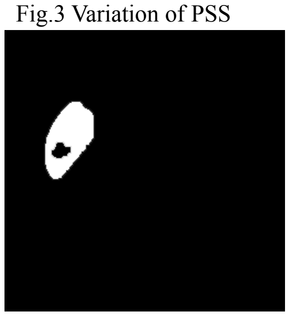


Fig.5 Output image after the first post-processing

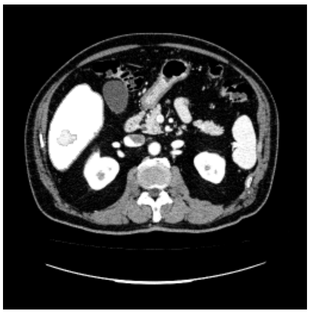


Fig.6 Overlapped image

Fig.7 Extracted image (1)

Fig.8 Output image after the second post-processing

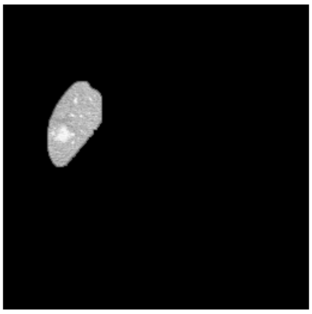


Fig.9 Extracted image (2)

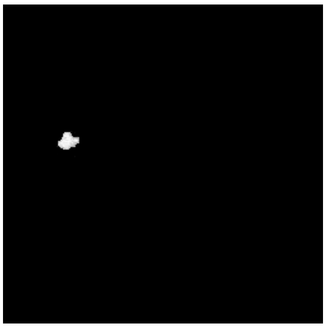
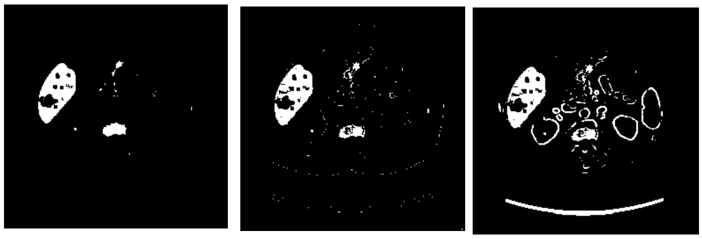


Fig.10 Candidate image region of liver cancer

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.11. These images contain more regions which are not part of the liver. 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.11 Output images of the conventional sigmoid function neural network

4. CONCLUSION

In this paper, the revised GMDH-type neural network algorithm using knowledge base for the medical image diagnosis was proposed and it was applied to the medical image diagnosis of the liver cancer and the results of revised GMDH-type neural network were compared with those of the conventional sigmoid function neural network trained using the back propagation algorithm. The revised GMDH-type neural network architecture fitting the characteristics of the medical images is organized using the knowledge base for the medical image diagnosis. It was shown that the revised GMDH-type neural network algorithm was accurate and a useful method for the medical image diagnosis of the liver cancer.

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