Hybrid Multi-layered GMDH-type Neural Network Using Principal Component Regression Analysis and Its Application to Medical Image Diagnosis of Liver Cancer

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Abstract

In this study, a hybrid multi-layered Group Method of Data Handling (GMDH)-type neural network algorithm using principal component-regression analysis is proposed and applied to the computer aided image diagnosis (CAD) of liver cancer. In the GMDH-type neural network, a heuristic self-organization method that is a type of evolutionary computation, is used to organize the neural network architecture. In this revised GMDH-type neural network, the optimum neural network architecture is automatically organized from three types of neural network architectures, such as the sigmoid function neural network, the radial basis function (RBF) network and the polynomial neural network architecture, by the heuristic self-organization method. Furthermore, the structural parameters such as the number of layers, the number of neurons in hidden layers and useful input variables, are automatically determined using the heuristic self-organization method. In the revised GMDH-type neural network proposed in this paper, the principal component-regression analysis is used to protect multi-collinearity which has occurred in the learning calculations of neurons, and accurate and stable prediction values are obtained. This new algorithm is applied to the medical image diagnosis of liver cancer. In this application, two types of neural network architectures fitting the complexity of the multi-detector row CT (MDCT) medical images, are automatically organized using the revised GMDH-type neural network algorithm. The first neural network recognizes and extracts the liver regions from the MDCT images of the liver, and the second neural network recognizes and extracts the liver cancer regions. These results are compared with the conventional sigmoid function neural network trained using the back propagation method, and this GMDH-type neural network algorithm is shown to be useful for CAD of liver cancer.

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1. Introduction

The Group Method of Data Handling (GMDH)-type neural networks and their applications have been proposed in our early works [1]-[4]. GMDH-type neural networks can automatically organize neural network architecture by heuristic self-organization method [5],[6] and they can also determine such structural parameters such as the number of layers, the number of neurons in hidden layers and useful input variables. But, in the conventional GMDH-type neural network algorithms [3],[4], multi-collinearity occurs in the learning calculations of the neurons and the prediction values become unstable. In this study, a revised GMDH-type neural network algorithm using principal component-regression analysis is proposed. In this algorithm, multi-collinearity does not occur and the accurate and stable prediction values are obtained. This new algorithm is applied to the computer aided image diagnosis (CAD) of liver cancer. In the previous study [1], the GMDH-type neural network was applied to the medical image recognition of liver and blood vessel regions in the liver, and these regions were extracted and displayed automatically using the revised GMDH-type neural network. In this paper, the liver cancer regions are recognized and extracted automatically using new revised GMDH-type neural network algorithm. In this algorithm, the structural parameters such as the number of layers, the number of neurons in hidden layers and useful input variables can be automatically selected so as to minimize prediction error criterion defined as Akaike’s information criterion (AIC) [7] or Prediction Sum of Squares (PSS) [8]. The recognition results show that the revised GMDH-type neural network algorithm is useful for CAD of liver cancer and is easy to apply practical complex problem because optimum neural network architecture is automatically organized.


Heuristic self-organization method is a basic theory of the conventional GMDH algorithm [5],[6] and was applied to the GMDH-type neural network algorithm [4]. Architectures of GMDH-type neural network are automatically organized using heuristic self-organization method. First, the procedures of heuristic self-organization method are shown because it plays very important roles for organization of GMDH-type neural network. Heuristic self-organization method is a kind of the evolutionary computation.

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 \(p!/(p-2)!2!\). 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 4)**
   Select \(L\) intermediate variables are set to input variables of the next layer and calculations from procedure 2) to 4) are iterated. The multi-layered architecture is organized.
6) **Stopping multi-layered 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.

In this paper, heuristic self-organization method is applied to the hybrid multi-layered GMDH-type neural network algorithm which is proposed concretely as follows.

### 3. Hybrid Multi-layered GMDH-type Neural Network Algorithm

Hybrid multi-layered GMDH-type neural network has a common feedforward multilayered architecture. Figure 1 shows architecture of the hybrid multi-layered GMDH-type neural network. This neural network is organized using heuristic self-organization method.

![Fig. 1. Architecture of revised GMDH-type neural network](image)

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

#### 3.1. **The first layer**

\[ u_j = x_j \quad (j=1,2,\ldots,p) \quad (1) \]

where \( x_j \) \( (j=1,2,\ldots,p) \) 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.

#### 3.2. **The second layer**

All combinations of \( r \) input variables are generated. Optimum neuron architecture for each combination is selected from the first and second type neuron architectures. Revised GMDH-type neural network algorithm can select optimum neuron architecture from three neuron architectures such as sigmoid function neuron, RBF neuron and polynomial neuron.

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

#### 3.2.1. **Sigmoid function neuron**

1) **The first type neuron**

\[ \Sigma: \text{(Nonlinear function)} \]

\[ z_k = w_1 u_1 + w_2 u_2 + w_3 u_3 + w_4 u_4^2 + w_5 u_5^2 - w_6 \theta \quad (2) \]

\[ f': \text{(Nonlinear function)} \]
The second type neuron

\[ z_k = w_1 u_1 + w_2 u_2 + w_3 u_3 + \cdots + w_r u_r - w_0 \theta_1 \quad (r < p) \]  

\[ f : (\text{Nonlinear function}) \]

\[ y_k = \frac{1}{1 + e^{(-z_k)}} \]  

3.2.2. Radial basis function neuron

1) The first type neuron

\[ z_k = w_1 u_1 + w_2 u_2 + w_3 u_3 + w_4 u_1^2 + w_5 u_2^2 - w_0 \theta_1 \]  

\[ f : (\text{Nonlinear function}) \]

\[ y_k = e^{(-z_k)} \]  

2) The second type neuron

\[ z_k = w_1 u_1 + w_2 u_2 + w_3 u_3 + \cdots + w_r u_r - w_0 \theta_1 \quad (r < p) \]  

\[ f : (\text{Nonlinear function}) \]

\[ y_k = e^{(-z_k)} \]  

3.2.3. Polynomial neuron

1) The first type neuron

\[ z_k = w_1 u_1 + w_2 u_2 + w_3 u_3 + w_4 u_1^2 + w_5 u_2^2 - w_0 \theta_1 \]  

\[ f : (\text{Linear function}) \]

\[ y_k = z_k \]  

2) The second type neuron

\[ z_k = w_1 u_1 + w_2 u_2 + w_3 u_3 + \cdots + w_r u_r - w_0 \theta_1 \quad (r < p) \]  

\[ f : (\text{Linear function}) \]

\[ y_k = z_k \]  

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

3.2.4. Estimation procedure of weight \( w_i \)

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

1) Sigmoid function neural network

\[ z_k^{**} = \log_e\left(\frac{\phi^i}{1 - \phi^i}\right) \]
2) \textit{RBF neural network}

\[ z_k^* = \sqrt{-\log_e \phi} \]  

(15)

3) \textit{Polynomial neural network}

\[ z_k^* = \phi \]  

(16)

where \( \phi \) is an output variable and \( \phi' \) is the normalized output variable whose values are between 0 and 1. \( \phi' \) is calculated using following equation.

\[ \phi' = \frac{\phi - \phi_{\text{min}}}{\phi_{\text{max}} - \phi_{\text{min}}} \]  

(17)

Here, \( \phi_{\text{max}} \) is the maximum value of the output variable (\( \phi \)), and \( \phi_{\text{min}} \) is the minimum value of \( \phi \).

Weights \( w_i (i=0,1,2,\ldots) \) in each neural network architecture are estimated by the principal component-regression analysis.

3.2.5. \textit{Principal component-regression analysis.}

Multicolinearity is generated in the function \( \Sigma \) of the neurons because heuristic self-organization method is used. In this study, the function \( \Sigma \) is calculated using the principal component-regression analysis.

In the case of Eq.(2), orthogonal vector \( \mathbf{v} \) is calculated.

\[ \mathbf{v} = C \cdot \mathbf{u} \]  

(18)

Here,

\[ \mathbf{v} = (v_1,v_2,\ldots,v_5) \]

\[ \mathbf{u} = (u_i u_j, u_i u_j, u_i^2, u_j^2) \]

\( \mathbf{v} \) is orthonormal vectors and \( C \) is orthonormal matrix. \( C \) is calculated using the following eigenvalue problem.

\[ R \cdot C = C \cdot \Lambda \]  

(19)

Here, \( R \) is a correlation matrix. Then, variable \( z_k \) is calculated using orthogonal regression analysis.

\[ z_k = \mathbf{w}^T \cdot \mathbf{v} \]

\[ = w_1 v_1 + w_2 v_2 + \ldots + w_5 v_5 \]  

(20)

Using the principal component-regression analysis, variable \( z_k \) in the function \( \Sigma \) is calculated without multicolinearity. In (20), useful orthogonal variables \( v_i (i=1,2,\ldots,5) \) are selected using AIC [7] or PSS [8] criterion.
For each combination, three neuron architectures which are sigmoid function neuron, RBF neuron and polynomial neuron, are generated and \( L \) neurons which minimize AIC or 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 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.

3.3. 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 using the principal component-regression analysis 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 AIC or PSS.

4. Application to the Medical Image Diagnosis of Liver Cancer

In this study, the regions of liver cancer were recognized and extracted automatically using the revised GMDH-type neural network. Multi-detector row CT (MDCT) images of the liver are used in this study. First, the GMDH-type neural network is organized using the MDCT image of the liver and the liver regions are recognized and extracted using the organized revised GMDH-type neural network. Then, new another revised GMDH-type neural network is organized using the extracted image of the liver. The candidate regions of liver cancer is recognized and extracted using this new revised GMDH-type neural network. In this application, we used PSS as the prediction error criterion.

4.1. Extraction of image regions of 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 \( N \times N \) 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 liver regions, 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 3 shows the PSS values in the second layer. PSS value of RBF neuron was smallest in three kinds of neurons. The RBF neural network architecture was selected by the revised GMDH-type neural network. Figure 4 shows the variation of PSS values in the layers. The calculation of the revised GMDH-type neural network was terminated in the eleventh 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 values were obtained in the eleventh layer. Figure 5 shows the output images of the revised GMDH-type neural network in each layer. It is shown the output liver regions became clear and more accurate gradually through the layers. At the eleventh layer, the revised GMDH-type neural network outputs the liver image (Fig.6) and the first post-processing analysis of the liver image was carried out.

In the first post-processing analysis of the output liver image, the isolate regions outside the liver were eliminated and the outlines of the liver were expanded outside by \( \frac{N}{2} \) pixels and the isolate regions inside the liver were eliminated using the circumference image processing, the closing and opening image processing and so on.

Fig. 2 Original image

Fig. 3 PSS values of three kinds of neurons (1)

Fig. 4 Variation of PSS in each layer (1)

Fig. 5 Output images of the revised GMDH-type neural network in each layer

(a)Second  (b) Sixth  (c) Eighth  (d) Tenth

Fig. 6 Output image in the eleventh layer (1)

Fig. 7 Output image after the first post processing

Fig. 8 Overlapped image

Fig. 9 Extracted image (1)
Figure 7 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.8. The recognized liver regions are accurate. The liver regions were extracted from the original image using the output image (Fig.7). Figure 9 shows the extracted gray scale image of the liver.

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

A liver image shown in Fig.9 was used for organizing new another 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 used as the useful input variables. The neural networks were organized when the values of $N$ were from 2 to 10. It was determined that when $N$ was equal to 3, the neural network architecture had the smallest recognition error. Five useful neurons were selected in each hidden layer. Figure 10 shows the PSS values in the second layer. PSS value of sigmoid neuron was smallest in three kinds of neurons. The sigmoid neural network architecture was selected by the revised GMDH-type neural network. Figure 11 shows the variation of PSS values in each layer. The calculation of the revised GMDH-type neural network was terminated in the fifth 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 value was obtained in the fifth layer. Figure 12 shows output images of the revised GMDH-type neural network in each layer. It is shown that regions of the liver cancer became clear gradually through the layers. At the fifth layer, the revised GMDH-type neural network outputs the liver cancer image and the second post-processing analysis of the output image such as the circumference image processing, the closing and opening image processing and so on, was carried out. Figure 14 shows the output image after the second post-processing. Figure 15 shows the overlapped image. The candidate image regions of liver cancer were extracted from Fig.9 using Fig.14 and shown in Fig.16.
4.3. 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. The conventional neural network had a three layered architecture, and the same five input variables 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 5, 7 and 9, are shown in Fig.17. 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.6. 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.
5. Conclusions

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

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References