

Medical Image Recognition of Heart Regions by Deep Multi-Layered GMDH-Type Neural Network Using Principal Component-Regression Analysis

Tadashi Kondo

*Graduate School of Health Sciences, Tokushima University
3-18-15 Kuramoto-cho Tokushima 770-8509 Japan
Email: kondomedsci@gmail.com*

Junji Ueno

*Graduate School of Health Sciences, Tokushima University
3-18-15 Kuramoto-cho Tokushima 770-8509 Japan*

Shoichiro Takao

*Graduate School of Health Sciences, Tokushima University
3-18-15 Kuramoto-cho Tokushima 770-8509 Japan*

Abstract

In this study, a deep Group Method of Data Handling (GMDH)-type neural network using principal component-regression is applied to the medical image recognition of the heart regions. The deep GMDH-type neural network algorithm can organize the neural network architecture with many hidden layers fitting the complexity of the nonlinear systems so as to minimize the prediction error criterion defined as AIC (Akaike's Information Criterion) or PSS (Prediction Sum of Squares). This algorithm is applied to the medical image recognition of the heart regions and it is shown that this algorithm is useful for the medical image recognition of the heart regions because deep neural network architecture is automatically organized using the principal component-regression analysis from the medical images of the heart regions.

Keywords: Deep neural networks, GMDH, Medical image recognition, Evolutionary computation

1. Introduction

The deep Group Method of Data Handling (GMDH)-type neural networks and their applications have been proposed in our early works¹⁻⁴. Deep GMDH-type neural networks can automatically organize neural network architecture by heuristic self-organization method^{5,6}, which is a type of evolutionary computation. In our early works^{3,4}, we applied the conventional GMDH-type neural network algorithms to the medical image recognition of the heart regions, and these GMDH-type neural network algorithms use the stepwise regression analysis as the learning algorithm

of the neural network and the multi-colinearity of the weights which is occurred in heuristic self-organization method of the GMDH algorithms, cannot be eliminated completely. The prediction values of the neural network become unstable and these values are not accurate when the multi-colinearity occurs in the learning calculation of the neural networks. Furthermore, these conventional GMDH-type neural network algorithms cannot select automatically optimum neural network architectures from three types of neural network architectures such as sigmoid function neural network, radial basis function (RBF) neural network and polynomial neural network.

In this study, a deep GMDH-type neural network algorithm using the principal component-regression analysis is developed and applied to the medical image recognition of the heart regions. In this algorithm, the principal component-regression analysis is used as the learning algorithm of the neural network and the stable and accurate prediction values are obtained. Furthermore, optimum neural network architecture is automatically selected from three types of neural network architectures such as sigmoid function neural network, radial basis function (RBF) neural network and polynomial neural network so as to minimize the prediction error criterion defined as AIC (Akaike's Information Criterion)⁷ or PSS (Prediction Sum of Squares)⁸. This algorithm is applied to the medical image recognition of the heart regions and results show that the deep GMDH-type neural network algorithm is useful for the medical image recognition of the heart regions.

2. Heuristic self-organization^{5,6}

The architectures of the GMDH-type neural networks are automatically organized using the heuristic self-organization method. The heuristic self-organization method is constructed by the following five procedures.

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

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

(2) Generating the combinations of the 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 the partial descriptions.

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

(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. The selected L intermediate variables are set to the input variables of the next layer. The same procedures from procedure (2) to (4) are iterated and the multi-layered architecture is organized.

(5) Stopping the multi-layered iterative computation.

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

Heuristic self-organization method is a type of evolutionary computation.

3. Deep multi-layered GMDH-type neural network

Fig.1 shows the architecture of the deep multi-layered GMDH-type neural network. This neural network is organized by heuristic self-organization method. Procedures for determining architecture of deep GMDH-type neural network conform to the following:

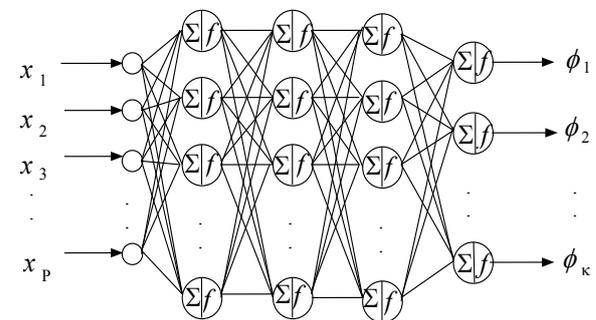


Fig.1 Architecture of the deep GMDH-type neural network

3.1 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.

3.2 The second layer

All combinations of r input variables are generated, and r is the number of input variables in each combination. For each combination, optimum neuron architectures are automatically selected from the first and second type neuron architectures. Furthermore, deep GMDH-type neural network algorithm can select optimum neuron architecture from three types of 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.

(1) Sigmoid function neural network

1) The first type neuron

Σ : (Nonlinear function)

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

f : (Nonlinear function)

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

2) The second type neuron

Σ : (Linear function)

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

f : (Nonlinear function)

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

(2) Radial basis function neural network

1) The first type neuron

Σ : (Nonlinear function)

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

f : (Nonlinear function)

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

2) The second type neuron

Σ : (Linear function)

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

f : (Nonlinear function)

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

(3) Polynomial neural network

1) The first type neuron

Σ : (Nonlinear function)

$$z_k = w_1 u_i + w_2 u_j + w_3 u_i u_j + w_4 u_i^2 + w_5 u_j^2 - w_0 \theta_l \quad (10)$$

f : (Linear function)

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

2) The second type neuron

Σ : (Linear function)

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

f : (Linear function)

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

Here, $\theta_l = 1$ and $w_i (i=0,1,2,\dots)$ are weights between the first and second layer. Value of r , which is the number of input variables (u) in each combination, 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 $x_i (i=1,2,\dots,p)$.

3.2.1 Learning procedures 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. Then the weights $w_i (i=0,1,2,\dots)$ are estimated using the principal component-regression analysis using the input variable (u) and output variable (z^{**}) in each layer.

3.2.2 Principal component-regression analysis⁹

In the GMDH-type neural network, the multicollinearity is generated in the function Σ of the neurons. In this study, the function Σ is calculated using the principal component-regression analysis⁹.

In the case of Eq.(2), the estimation procedures of z_k are shown as follows. Here, z_k is the estimated value using Eq. (2) for the z^{**} calculated in 3.2.1.

First, orthogonal vector \underline{v} is calculated.

$$\underline{v} = C \cdot \underline{u} \quad (17)$$

Here, $\mathbf{v}=(v_1, v_2, \dots, v_5)$, $\mathbf{u}=(u_i, u_j, u_i u_j, u_i^2, u_j^2)$
 \mathbf{v} is orthonormal vectors and C is orthonormal matrix. C
 is calculated using the following eigenvalue equation.

$$R \cdot C = C \cdot A \quad (18)$$

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

$$z_k = \mathbf{w}^T \cdot \mathbf{v} \\ = w_1 v_1 + w_2 v_2 + \dots + w_5 v_5 \quad (19)$$

Using the principal component-regression analysis,
 variable z_k in the function Σ is calculated without multi-
 colinearity. In Eq.(19), useful principal components are
 selected so as to minimize AIC or PSS, and the
 intermediate variables z_k are constructed using selected
 principal components.

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 deep 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 deep 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 deep GMDH-type
 neural network using the principal component-
 regression analysis is organized. Deep 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 recognition of heart regions

In this study, the heart regions were automatically
 recognized using the deep GMDH-type neural network
 and these regions were extracted. The multi-detector
 row CT (MDCT) images of the heart regions were used
 in this study.

4.1 Results of the medical image recognition by the deep GMDH-type neural network

The MDCT image shown in Fig.2 was used for
 organizing the neural network. x and y coordinates and
 the statistics of the image densities in the neighboring
 regions of the $N \times N$ pixels at the positions of the learning
 points, are used as the input variables of the neural
 network. Only five input variables which are the mean,
 the standard deviation, the variance and x and y
 coordinates were automatically selected as useful input
 variables. The output value of the neural network is zero
 or one. When $N \times N$ pixel region is contained in the heart
 regions, the neural network set the pixel value at the
 center of the $N \times N$ pixel region to one and this pixel is
 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.
 Fig.3 shows errors of the three types of neurons in the
 second layer. The sigmoid function neural network
 architecture was selected by the deep GMDH-type
 neural network algorithm. Fig.4 shows the variation of
 PSS values. PSS values decreased gradually and very

small PSS values were obtained at the tenth layer. The heart region was recognized using the organized neural network and was extracted automatically. Fig.5 shows the output image of the deep GMDH-type neural network. This output image was processed by the post-processing analysis. In the post-processing, the small isolated regions were eliminated and the outlines of the heart regions were expanded outside by $N/2$ pixels. Fig.6 shows the output image after this processing. In order to check the matching between the original image and the output image of the neural network, the output image was overlapped on the original image of Fig.2. The overlapped image is shown in Fig.7. From Fig.7, we can see that the output image was very accurate. Fig.8 shows the extracted heart image.

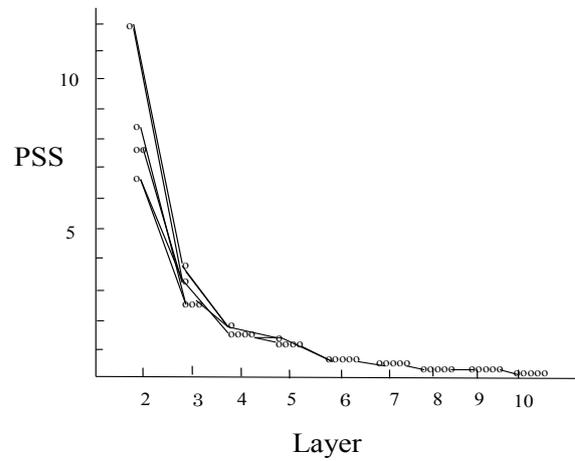


Fig. 4 Variation of PSS in each layer

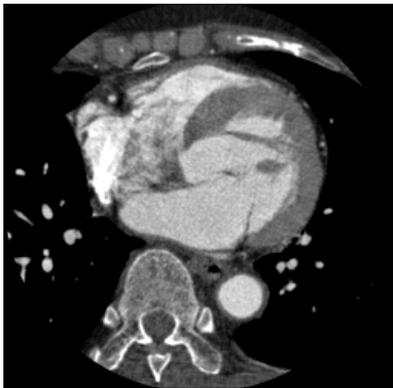


Fig. 2 Original image

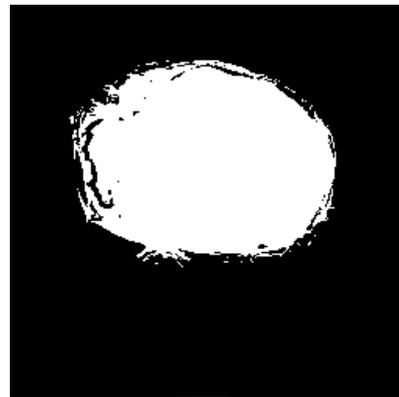


Fig. 5 Output image

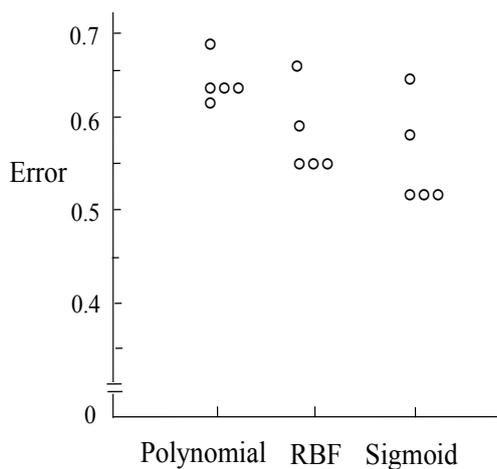


Fig. 3 Errors of three types of neurons

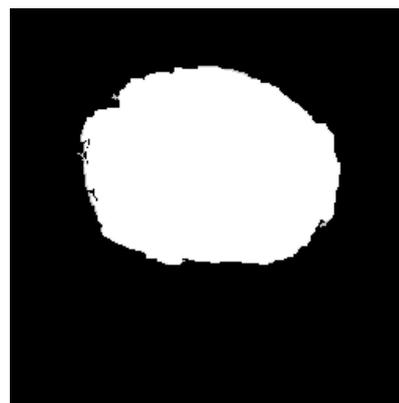


Fig.6 Output image after the post processing

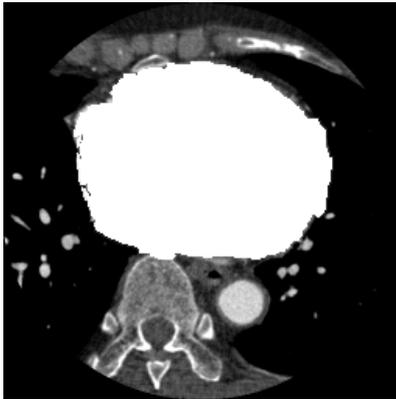


Fig. 7 Overlapped image

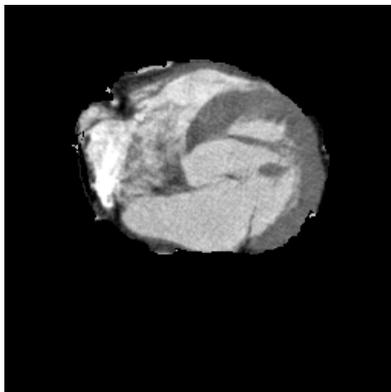


Fig. 8 Extracted image



(a) $m=5$



(b) $m=7$



(c) $m=9$

4.2 Extraction by the conventional neural network using sigmoid function.

A conventional neural network trained using the back propagation algorithm was applied to the same recognition problem. 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.9. These images contain more regions which are not part of the heart and the outlines of the heart are not extracted with required clarity compared with the output images obtained using the deep GMDH-type neural network algorithm, which are shown in Fig.5.

Fig. 9 Output images of the conventional sigmoid function neural network

5. Conclusions

In this paper, the deep multi-layered GMDH-type neural network algorithm was applied to the medical image recognition of heart regions and the results were compared with those of the conventional sigmoid function neural network trained using the back propagation algorithm. In this algorithm, the multicollinearity is completely eliminated and the stable and accurate prediction values are obtained. Furthermore, the optimum neural network architectures are automatically selected from three types of neural network architectures. In this study, the deep neural network architecture which had eight hidden layers, was automatically organized and the sigmoid function type neural network architecture was automatically selected so as to minimize PSS criterion. The medical image recognition results were very accurate. It was shown that the deep multi-layered GMDH-type neural network algorithm was a useful method for the medical image recognition of heart regions and this algorithm was easy to be applied to the practical complex problems in which very complex neural network architectures with many hidden layers were needed.

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