Medical Image Recognition of Heart Regions by Deep Multi-layered GMDH-type Neural Network Using Principal Component-regression Analysis

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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 with many hidden layers is automatically organized using the principal component-regression analysis, so as to minimize AIC or PSS criterion.

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

1. Introduction

The deep Group Method of Data Handling (GMDH)-type neural networks and their applications have been proposed in our early works[1,2]. Deep GMDH-type neural networks can automatically organize neural network architecture by heuristic self-organization method[3], which is a type of evolutional computation. In this study, a deep GMDH-type neural network algorithm using the principal component-regression analysis is applied to the medical image recognition of the heart regions. In this algorithm, optimum neural network architecture is automatically selected from three 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[4] or PSS[5]. 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 and is easy to apply practical complex problem because the deep neural network architecture with many hidden layers is automatically organized so as to minimize AIC or PSS criterion.

2. Deep multi-layered GMDH-type neural network

Fig.1 shows the architecture of the deep multi-layered GMDH-type neural network.

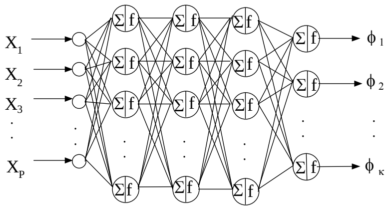

Fig.1 Architecture of the deep GMDH-type neural network

2.1 *The first layer*

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

where x_j $(j=1,2,\ldots,p)$ are input variables of the nonlinear system, and p is the number of input 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. Deep 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.

(1) Sigmoid function neural network

1) The first type neuron

Σ: (Nonlinear function)

$$z_k = w_1u_i + w_2u_j + w_3u_iu_j + w_4u_i^2 + w_5u_j^2 - w_0\theta_1 \tag{2}$$

f : (Nonlinear function)

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

2) The second type neuron

Σ: (Linear function)

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

f : (Nonlinear function)

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

(2) Radial basis function neural network

1) The first type neuron

Σ: (Nonlinear function)

$$z_k = w_1u_i + w_2u_j + w_3u_iu_j + w_4u_i^2 + w_5u_j^2 - w_0\theta_1 \tag{6}$$

f : (Nonlinear function)

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

2) The second type neuron

Σ: (Linear function)

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

f : (Nonlinear function)

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

(3) Polynomial neural network

1) The first type neuron

Σ: (Nonlinear function)

$$z_k = w_1u_i + w_2u_j + w_3u_iu_j + w_4u_i^2 + w_5u_j^2 - w_0\theta_1 \tag{10}$$

f : (Linear function)

$$y_k = z_k \tag{11}$$

2) The second type neuron

Σ: (Linear function)

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

f : (Linear function)

$$y_k = z_k \tag{13}$$

Here, $\theta_1 = 1$ and w_i $(i=0,1,2,\ldots,9)$. Value of r is the number of input variables u in each neuron. p is the number of input variables x_i $(i=1,2,\ldots,p)$.

2.2.1 *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

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

b)RBF neural network

$$z_k^{**} = \sqrt{-\log_e \phi'} \tag{15}$$

c)Polynomial neural network

$$z_k^{**} = \phi \tag{16}$$

where ϕ' is the normalized output variable. Then the weights w_i $(i=0,1,2,\cdots,5)$ are estimated by using the principal component-regression analysis.

2.2.2 *Principal component-regression analysis*

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

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

$$\underline{\boldsymbol{v}} = C \cdot \underline{\boldsymbol{u}} \tag{17}$$

Here, $\underline{\boldsymbol{v}} = (v_1, v_2, \ldots, v_5)$, $\underline{\boldsymbol{u}} = (u_i\, u_j,\, u_iu_j,\, u_i^2,\, u_j^2)$

$\underline{\boldsymbol{v}}$ is orthonormal vectors and C is orthonormal matrix. C is calculated using the following eigenvalue equation.

$$R \cdot C = C \cdot \Lambda \tag{18}$$

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

$$\begin{aligned} z_k &= \underline{\boldsymbol{w}}^{\mathrm{T}} \cdot \underline{\boldsymbol{v}} \\ &= w_1v_1 + w_2v_2 + \ldots + w_5v_5 \end{aligned} \tag{19}$$

Using the principal component-regression analysis, variable z_k in the function Σ is calculated without multi-colinearity. In (19), useful orthogonal variables v_i (i=1,2,…,5) are selected using AIC[4] or PSS[5].

From these generated neurons, L neurons which minimize AIC or 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.

2.3 *The third and successive layers*

In the second layer, optimum neural network architecture is selected from three neural network architectures which is sigmoid function neural network or RBF neural network or polynomial network. 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.

3. 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. Multi-detector row CT (MDCT) images of the heart were used in this study.

3.1 *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×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×N pixel region is contained in the heart regions, the neural network set the pixel value at the center of the N×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 the PSS values 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 by 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.

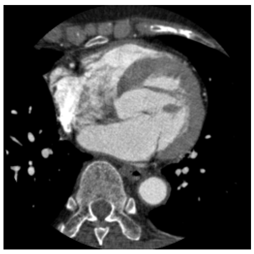

Fig. 2 Original image

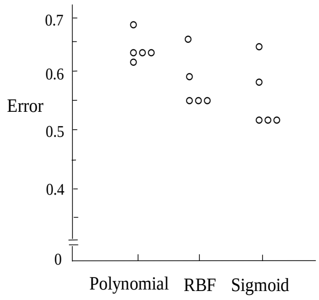

Fig. 3 PSS values of three types of neurons

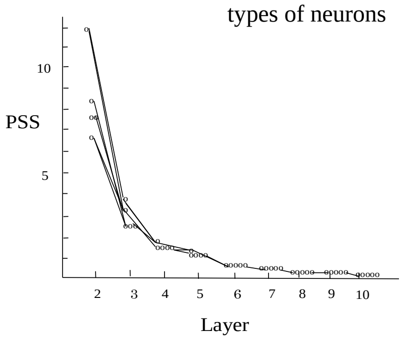

Fig. 4 Variation of PSS in each layer

Fig. 5 Output image

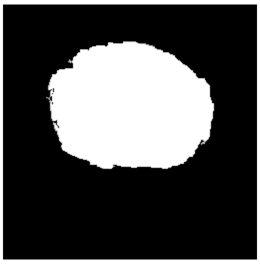

Fig.6 Output image after the post processing

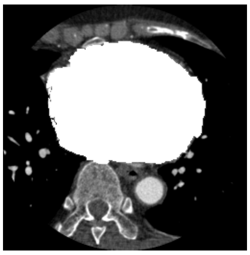

Fig. 7 Overlapped image

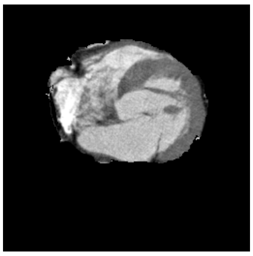

Fig. 8 Extracted image

3.2 *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.

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

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

4. 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. 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 because the deep neural network architecture with many hidden layers is automatically organized so as to minimize the prediction error criterion defined as AIC or PSS.

Acknowledgment

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