Three dimensional medical image recognition of the brain by feedback GMDH-type neural network self-selecting optimum neural network architecture

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Abstract

The feedback Group Method of Data Handling (GMDH)-type neural network algorithm proposed in this paper is applied to 3-dimensional medical image recognition of the blood vessels in the brain. The neural network architecture fitting the complexity of the medical images is automatically organized by the feedback GMDH-type neural network algorithm so as to minimize the prediction error criterion defined as Akaike's Information Criterion (AIC). In this feedback GMDH-type neural network algorithm, the optimum neural network architecture is automatically 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. The recognition results show that the feedback GMDH-type neural network algorithm is useful for the 3-dimensional medical image recognition of the blood vessels in the brain and is very easy to apply the practical complex problem because the optimum neural network architecture is automatically organized.

Keywords: GMDH, Neural network, Medical image recognition

1 Introduction

The Group Method of Data Handling (GMDH)-type neural networks and their applications have been proposed in our early works [1],[2]. The GMDH-type neural networks can automatically organize the neural network architecture by using the heuristic self-organization method [3],[4]. In this study, a feedback GMDH-type neural network algorithm self-selecting the optimum neural network architecture is proposed. In the feedback GMDH-type neural network algorithm, the optimum neural network architecture is automatically 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. Furthermore, the structural parameters such as the number of layers, the number of neurons in the hidden layers and the useful input variables are automatically selected so as to minimize the prediction error criterion defined as Akaike's Information Criterion (AIC) [5] or Prediction Sum of Squares (PSS) [6]. The feedback GMDH-type neural network has a feedback loop and the complexity of the neural network increases gradually using feedback loop calculations so as to fit the complexity of the nonlinear system.

The feedback GMDH-type neural network algorithm proposed in this paper is applied to 3-dimensional medical image recognition of the blood vessels in the brain. The neural network architecture fitting the complexity of the medical images is automatically organized by the feedback GMDH-type neural network algorithm so as to minimize the prediction error criterion defined as AIC.

2 Feedback GMDH-type neural network

The architecture of the feedback GMDH-type neural network proposed in this paper has a feedback loop as shown in Fig.1. The feedback GMDH-type neural network algorithm can select the optimum neural network architecture from three types of neural network architectures such as the sigmoid function type neural network, the RBF type neural network and the polynomial type neural network. The feedback GMDH-type neural network algorithm uses three types of neuron architectures which are the sigmoid function type neuron, the RBF type neuron and the polynomial type neuron. In the feedback GMDH-type neural network, optimum neuron architectures fitting the characteristics of the nonlinear system are automatically selected by using AIC.

The feedback GMDH-type neural network is shown as follows.

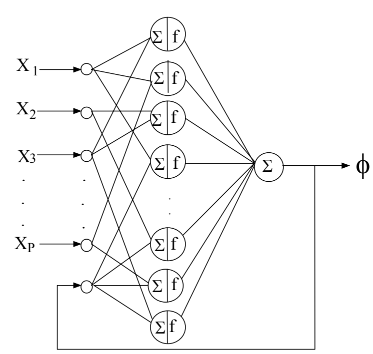


Fig.1 Architecture of the feedback GMDH-type neural network

2.1 First loop calculation

First, all data are set to the training data. In this algorithm, it is not necessary to separate the original data into the training and test data because AIC can be used for organizing the network architectures. Then the architecture of the input layer is organized.

1) Input layer

$$u_j=x_j \quad (j=1,2,...,p) \tag{1}$$

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) Hidden layer

All combinations of the r input variables are generated. For each combination, three types of neuron architectures which are the sigmoid function type neuron, the RBF type neuron and the polynomial type neuron, are generated and L neurons which minimize AIC value are selected for each type of neuron architectures.

Furthermore, for each combination, optimum neuron architectures fitting the characteristics of the nonlinear system are automatically selected by using AIC.

a) Sigmoid function type neuron:

i) The first type neuron

Σ: (Nonlinear function)

$$z_k= w_1u_i+w_2u_j+w_3u_iu_j+w_4u_i^2+w_5u_j^2+w_6u_i^3+w_7u_i^2u_j +w_8u_iu_j^2 +w_9u_j^3 - w_0\theta_l \tag{2}$$

f : (Nonlinear function)

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

ii) The second type neuron

Σ: (Linear function)

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

f : (Nonlinear function)

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

b) RBF type neuron:

i) The first type neuron

Σ: (Nonlinear function)

$$z_k= w_1u_i+w_2u_j+w_3u_iu_j+w_4u_i^2+w_5u_j^2+w_6u_i^3+w_7u_i^2u_j+w_8u_iu_j^2 +w_9u_j^3 - w_0\theta_l \tag{6}$$

f : (Nonlinear function)

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

ii) The second type neuron

Σ: (Linear function)

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

f : (Nonlinear function)

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

c) Polynomial type neuron:

i) The first type neuron

Σ: (Nonlinear function)

$$z_k= w_1u_i+w_2u_j+w_3u_iu_j+w_4u_i^2+w_5u_j^2+w_6u_i^3+w_7u_i^2u_j+w_8u_iu_j^2 +w_9u_j^3 - w_0\theta_l \tag{10}$$

f : (Linear function)

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

ii) The second type neuron

Σ: (Linear function)

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

f : (Linear function)

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

Here, $\theta_l =1$ and w_i $(i=0,1,2,\ldots)$ are the weights between the first and second layer and estimated by applying the stepwise regression analysis [7] to the training data. Only useful input variables u_i $(i=1,2, ...)$ are selected by using AIC. In the first type neuron, the value of r, which is the number of input variables u in each neuron, is set to two. In the second type neuron, the value of r, which is the number of input variables u in each neuron, is set to be greater than two and smaller than p. p is the number of input variables x_i $(i=1,2,\ldots,p)$. The output variables y_k of the neurons are called as the intermediate variables.

L neurons having the smallest AIC values are selected for three types of neuron architectures which are the sigmoid function type neuron, the RBF type neuron and the polynomial type neuron. The output variables y_k of L selected neurons for three types of neuron architectures are set to the input variables of the neurons in the output layer.

3) Output layer

For three types of neural network, the outputs y_k of the neurons in the hidden layer are combined by the following linear function.

$$\phi^* = a_0 + \sum_{k=1}^{L} a_k y_k \tag{14}$$

Here, L is the number of combinations of the input variables and y_k is the intermediate variables. The useful intermediate variables y_k are selected by using the stepwise regression analysis in which AIC is used as the variable selection criterion.

Equation (14) is calculated for three types of neural network architectures which are the sigmoid function type neural network, the RBF type neural network and the polynomial type neural network. Then, the neural network architecture which has smallest AIC value is selected as the GMDH-type neural network architecture from three types of neural network architectures

Then, the estimated output values ϕ^* which is selected in the output layer is used as the feedback value and it is combined with the input variables in the next loop calculation.

2.2 Second and successive loop calculations

The optimum neural network architecture is selected from three types of neural network architectures in the output layer. Therefore, in the second and successive loop calculations, only one type of neuron architecture, which is the sigmoid function type neuron or the RBF type neuron or the polynomial type neuron, is used for the calculation.

First, the estimated output value ϕ^* is combined with the input variables and all combinations between the estimated output value ϕ^* and the input variables are generated. The same calculation as the first feedback loop is carried out for each combination. Here, only one type of neuron architecture, which is selected in the first loop calculation, is used in the calculation. When AIC value of the linear function in (14) is increased, the loop calculation is terminated and the complete neural network architecture is organized by the L selected neurons in each feedback loop.

3 Application to 3-dimensional medical image recognition of the blood vessels in the brain

In this study, regions of the blood vessels in the brain is recognized automatically using the following two recognition procedures. Multidetector row computed tomography (MDCT) images of the brain are used in this study. In the first recognition procedure, the feedback GMDH-type neural network is organized to recognize the brain regions and then these regions are extracted using organized neural network. In the second recognition procedure, another new feedback GMDH-type neural network is organized to recognize the blood vessel regions and then these regions are extracted using organized new neural network. Using these recognition procedures, the blood vessel regions are recognized and extracted.

3.1 Recognition of brain regions

In this study, an original MDCT image shown in Fig. 2 is used for organizing the feedback GMDH-type neural network. Then, image features are extracted and used as input variables of neural network. Statistics of image densities in neighboring regions, N×N pixel regions, are used as image features. The following statistics are used as input variables. 1) mean, 2) standard deviation, 3) variance, 4) median, 5) minimum, 6) maximum, 7) range. Out of these statistics, only three parameters namely, mean, standard deviation and variance are selected as useful input variables. Output value of neural network is zero or one. When N×N pixel region is contained in regions of the brain, neural network sets pixel value at the center of N×N pixel region to one and this pixel is shown as white point. Neural network was organized when values of N are 5, 10 and 15. When N equals 5, output image is most accurate. Calculation of the feedback GMDH-type neural network was terminated at the fourth layer. Three useful neurons were selected in each hidden layer. RBF neural network architecture was selected as the feedback GMDH-type neural network in the first feedback loop calculation. Feedback GMDH-type neural network output brain image and post-processing analysis of brain image was carried out, based on which regions of the brain were extracted. In post-processing of output image of the neural network, small isolated regions outside or inside of the brain regions are eliminated by the image processing such as the dilatation and the erosion. Then, outlines of regions of the brain were expanded outside by N/2 pixels and outline of the brain were extracted. Fig.3 shows output image after this processing. In order to check matching between original image and output image of the neural network, the output image was overlapped on original image after post-processing. Overlapped image is shown in Fig.4. From Fig.4, we can see that extracted regions are very accurate.

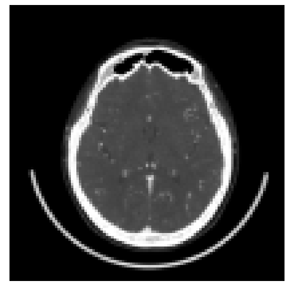


Fig.2 Original image(1)

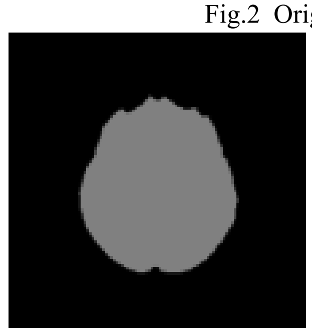


Fig.3 Output image after post-processing (1)

Fig.4 Overlapped image (1)

3.2 Recognition of blood vessel regions in the brain

The blood vessel regions are recognized by the feedback GMDH-type neural network and extracted. First, gray scale image of the brain (Fig.5) was subtracted from the original image (Fig.2) by using the output image of the feedback GMDH-type neural network (Fig.3). This gray scale image is used as a new original image to organize new feedback GMDH-type neural network. The new feedback GMDH-type neural network was organized and recognized the blood vessel regions. The organization procedures of the new feedback GMDH-type neural network are the same as those of the brain regions. Image features are extracted and used as input variables of neural network. Statistics of image densities in neighboring regions, N×N pixel regions, are used as image features. Only three parameters namely, mean, standard deviation and variance are selected as useful input variables. Neural network was organized when values of N are 5, 10 and 15. When N equals 5, output image is most accurate. RBF neural network architecture was selected as the feedback GMDH-type neural network architecture in the first feedback loop calculation. Feedback GMDH-type neural network output blood vessel image and post-processing analysis was carried out, based on which regions of the blood vessels were extracted. Fig.6 shows output image after the post-processing. Then, gray scale image of the blood vessel was subtracted from the original image by using the output image of the feedback GMDH-type neural network (Fig.6). Figure 7 shows overlapped image of blood vessel regions. These subtraction processing were carried out for the all slices of MDCT. Then, 3-dimensional images of the blood vessels were generated using gray scale images for all slices of MDCT by the rendering software. Figure 8 are 3-dimensional blood vessel images.

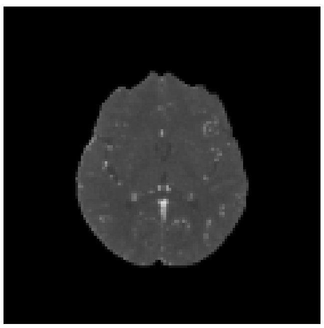


Fig.5 Subtraction image of the brain (1)

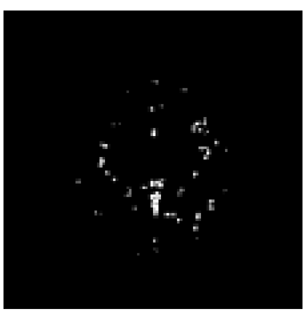


Fig.6 Output image of blood Vessel regions (1)

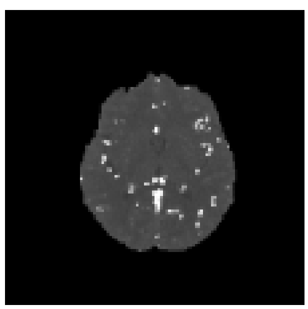
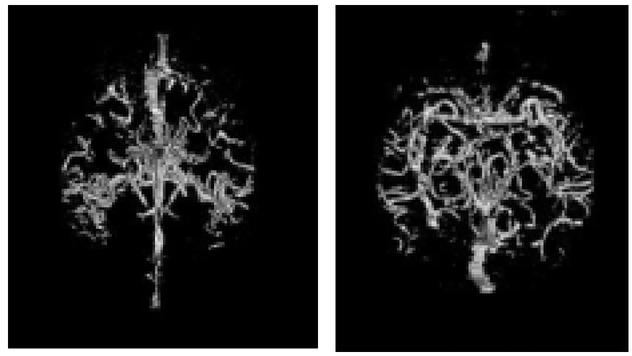


Fig.7 Overlapped image of blood vessel regions (1)

4 Conclusion

In this paper, the feedback GMDH-type neural network algorithm self-selecting optimum neural network architecture was proposed. In this algorithm, optimum neural network architecture is automatically selected from three neural network architectures such as sigmoid function neural network, RBF neural network and polynomial neural network. 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.

In this paper, this algorithm was applied to 3-dimensional medical image recognition of the blood vessels in the brain and it was shown that feedback GMDH-type neural network algorithm was a useful method for 3-dimensional medical image recognition of the blood vessels in the brain because the neural network architecture is automatically organized by the feedback GMDH-type neural network algorithm.



(a) (b)

Fig.8 3-dinensional images of the blood vessels

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