Feedback GMDH-Type Neural Network Self-Selecting Optimum Neural Network Architecture and Its Application to 3-Dimensional Medical Image Recognition of the Lungs

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Abstract. The feedback Group Method of Data Handling (GMDH)-type neural network algorithm is proposed and is applied to 3-dimensional medical image recognition of the lungs, the pulmonary vessels and the bronchial trees. 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. Furthermore, the structural parameters such as the number of layers, the number of neurons in the hidden layers and the relevant input variables are automatically selected so as to minimize the prediction error criterion defined as Prediction Sum of Squares (PSS). The recognition results show that the feedback GMDH-type neural network algorithm is useful for the 3-dimensional medical image recognition of the lungs, the pulmonary vessels and the bronchial trees and is ideal for such practical complex problems since the optimum neural network architecture is automatically organized.

Keywords

GMDH, Neural network, Medical image recognition

1 Introduction

In this study, the feedback GMDH-type neural network algorithm which can self-select the optimum neural network architecture is proposed. The GMDH-type neural networks [1],[2] can automatically organize the neural network architecture by using a heuristic self-organization method which is the basic premise of the GMDH algorithm [3],[4]. The heuristic self-organization method is a kind of the evolitional computations. 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. Furthermore, the structural parameters such as the number of layers, the number of neurons in the hidden layers and the relevant 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 lungs, the pulmonary vessels and the bronchial trees. The recognition results show that the feedback GMDH-type neural network algorithm is useful for the 3-dimensional medical image recognition of the lungs, the pulmonary vessels and the bronchial trees in the lungs and is ideal for such practical, complex problems since the optimum neural network architecture is automatically organized.
2 Feedback GMDH-type Neural Network

The architectures of the GMDH-type neural networks are automatically organized by using the heuristic self-organization method that is a kind of the evolitional computations.

2.1 Heuristic Self-Organization

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 \(\frac{p!}{(p-2)!2!}\). 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 2 to 5

Select \(L\) intermediate variables are set to input variables of the next layer and calculations from procedure 2 to 5 are iterated. The multilayered architecture is organized.

(6) Stopping multilayered 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.

2.2 Feedback GMDH-Type Neural Network Algorithm

The architecture of the feedback GMDH-type neural network proposed in this paper has a feedback loop as shown in Fig.1. In this algorithm, the outputs of the neurons are not combined with each other but they are combined with the input variables of the system in the next loop calculation. Therefore, the complexity of the neural network increases gradually by using feedback loop calculations and a more accurate structural identification of the nonlinear system can be carried out through the feedback loop calculations.

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. For these three types of neural network architectures, three types of neuronal architectures such as the sigmoid function, RBF and polynomial type neuronal architectures are used. Furthermore, for each type of neuronal architecture, we use two types of neurons, called the first and the second type neuron. The first type neuron has two input variables as shown in Fig.2. The second type neuron has \(r\) input variables as shown in Fig.3. In the feedback GMDH-type neural network, optimum neuron architectures fitting the characteristics of the nonlinear system are automatically selected by using PSS. The feedback GMDH-type neural network is shown as follows:

2.2.1 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 sets since PSS is used for organizing the network architectures. Then the architecture of the input layer is organized.
1) Input layer
\[ u_j = x_j \quad (j=1,2,\ldots,p) \]  
where \( x_j \quad (j=1,2,\ldots,p) \) 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 neuronal architectures, i.e. the sigmoid function type neuron, the RBF type neuron and the polynomial type neuron, are generated and \( L \) neurons which minimize PSS value are selected for each type of neuronal architecture.

Furthermore, for each combination, optimum neuronal architecture fitting the characteristics of the nonlinear system is automatically selected using PSS.

a) Sigmoid function type neuron:
  i) The first type neuron
  \[ z_k = w_1 u_1 + w_2 u_2 + w_3 u_3 + \ldots + w_r u_r - w_0 \theta \]  
  \[ f : (\text{Nonlinear function}) \]
  \[ y_k = \frac{1}{1 + e^{-(z_k)}} \]  

  ii) The second type neuron
  \[ z_k = w_1 + w_2 + w_3 + \ldots + w_r - w_0 \theta \]  
  \[ r < p \]  
  \[ f : (\text{Nonlinear function}) \]
  \[ y_k = \frac{1}{1 + e^{-z_k}} \]

b) RBF type neuron:
  i) The first type neuron
  \[ z_k = w_1 u_1 + w_2 u_2 + \ldots + w_r u_r - w_0 \theta \]  
  \[ r < p \]  
  \[ f : (\text{Nonlinear function}) \]
  \[ y_k = e^{-(z_k)} \]

  ii) The second type neuron
  \[ z_k = w_1 + w_2 + \ldots + w_r - w_0 \theta \]  
  \[ r < p \]  
  \[ f : (\text{Nonlinear function}) \]
  \[ y_k = e^{-z_k} \]

c) Polynomial type neuron:
  i) The first type neuron
  \[ z_k = w_1 u_1 + w_2 u_2 + \ldots + w_r u_r - w_0 \theta \]  
  \[ f : (\text{Linear function}) \]
  \[ y_k = z_k \]  

  ii) The second type neuron
\[
\Sigma: \text{(Linear function)}
\]

\[
z_k = w_1u_1 + w_2u_2 + w_3u_3 + ... + w_ru_r - w_0 \theta_1 \quad (r < p)
\]  

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

\[
y_k = z_k
\]  

In the first type neuron, \( \theta_1 = 1 \) and \( w_j (i=0,1,2,...,9) \) are the weights between the first and second layer. The value of \( r \), which is the number of input variables \( u \) in each neuron, is set to two for the first type neuron. The output variables \( y_k \) of the neurons are called the intermediate variables.

In the second type neuron, \( \theta_1 = 1 \) and \( w_j (i=0,1,2,...,r) \) are the weights between the first and second layer. 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 \( p \) for the second type neuron. Here \( p \) is the number of input variables \( x_i (i=1,2,...,p) \). The output variables \( y_k \) of the neurons are called the intermediate variables.

The weights \( w_i (i=0,1,2,...) \) are estimated by stepwise regression analysis using PSS. Estimation procedure of the weight \( w_i \):

First, the values of \( z_k \) are calculated for each neuronal architecture as follows:

i) Sigmoid function type neuron:

\[
z_i = \log \left( \frac{\phi_i}{1-\phi_i} \right)
\]  

ii) RBF type neuron:

\[
z_i = \sqrt{-\log \phi_i}
\]  

iii) Polynomial type neuron:

\[
z_i = \phi_i
\]

where \( \phi_i \) is the normalized output variable whose values are between zero and one and \( \phi \) is the output variable. Then weights \( w_i \) are estimated by stepwise regression analysis [7] which selects relevant input variables using PSS. Only relevant variables in Eq.(2), Eq.(4), Eq.(6), Eq.(8), Eq.(10) and Eq.(12) are selected by stepwise regression analysis using PSS and optimum neuronal architectures are organized.

In the conventional sigmoid function type neural network, PSS cannot be used to determine the optimum neural network architectures because the back propagation method is used to estimate the connection weights.

\( L \) neurons having the smallest PSS 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 neuronal 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.

\[
\phi' = a_0 + \sum_{k=1}^{L} a_k y_k
\]  

Here, \( L \) is the number of combinations of the input variables and \( y_k \) is the intermediate variable. The relevant intermediate variables \( y_k \) are selected using the stepwise regression analysis in which PSS is used as the variable selection criterion. Equation (17) 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 PSS value is selected as the GMDH-type neural network architecture from three types of neural network architectures. Then, the estimated output values \( \phi' \) 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.

2.2.2 Second and Subsequent 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 subsequent loop calculations, only one type of neuron architecture, which could be 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 \( \phi' \) is combined with the input variables and all combinations between the estimated output value \( \phi' \) 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 neuronal architecture, which is selected in the first loop
calculation, is used in the calculation. When PSS value of the linear function in (17) 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 lungs

In this study, regions containing the lungs, the pulmonary vessels and the bronchial trees are recognized automatically using the following two recognition procedures. MDCT images of the lungs are used in this study. In the first recognition procedure, the feedback GMDH-type neural network is organized to classify the lung regions and then these regions are extracted using the organized neural network. In the second recognition procedure, another new feedback GMDH-type neural network is organized to recognize the regions of the pulmonary vessels and the bronchial trees and then these regions are extracted using the new neural network. Using these recognition procedures, the lungs, the pulmonary vessels and the bronchial trees are recognized and extracted.

3.1 Recognition of the lung regions

In this study, an original MDCT image shown in Fig. 4 is used for organizing the feedback GMDH-type neural network. Then, image features are extracted and used as input variables for the neural network. Statistics of image densities in neighboring regions, $N \times N$ 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. In this case, out of these statistics, only three parameters namely, mean, standard deviation and variance were selected as relevant input variables by the proposed algorithm. Output value of the neural network is either zero or one. When $N \times N$ pixel region is contained within the regions of the lungs, neural network sets pixel value at the center of $N \times N$ pixel region to one and this pixel is shown as a white point. Neural network was organized when values of $N$ are from 2 to 15. In this case, when $N$ equaled 3, the output image was most accurate. Calculation of the feedback GMDH-type neural network was terminated at the fourth layer. Three relevant neurons were selected in each hidden layer. Figure 5 shows the variation of PSS values. PSS value at the first feedback loop calculation was considerable but decreased at subsequent feedback loop calculations and leveled off to a small value by the third feedback loop calculation. Figure 6 shows PSS values corresponding to the three types of neurons at the first feedback loop calculation. RBF type neuron had the smallest PSS value; hence RBF type neural network architecture was selected as the feedback GMDH-type neural network architecture. Fig. 7 shows the output image consisting of the lung regions, corresponding to the input image shown in Fig. 4. Then post-processing analysis of lung image was carried out, based on which contiguous regions of the lungs were extracted. During post-processing of the output image generated by the neural network, small isolated regions outside or inside of the lung regions are eliminated by image processing techniques, such as dilatation and erosion. Then, outlines of regions of the lungs were expanded outside by N/2 pixels and the outline of the lungs was extracted. Fig. 8 shows output image after this post-processing. In order to check the degree of similarity between the original image and the output image generated by the neural network, the output image was overlapped on the original image after post-processing. The overlapped image is shown in Fig. 9. From Fig. 9, we can see that the extracted regions are considerably accurate.
3.2 Generalization Ability of the Neural Network

In order to analyze the generalization ability of the feedback GMDH-type algorithm, the neural network, which was organized by the original image of the lungs (Fig.4), is applied to another original image of the lungs (Fig.10). Figure 11 shows the output image consisting of the lung regions, corresponding to the input image shown in Fig. 10. Then post-processing analysis of lung image was carried out, based on which contiguous regions of the lungs were extracted. The outline of the lung regions was expanded outside by N/2 pixels. Figure 12 shows the output image after post-processing. In order to determine the similarity between the original image and the output image of the neural network, the output image was overlapped on the original image after post-processing. Overlapped image is shown in Fig.13. From Fig.13, we can see that feedback GMDH-type neural network could extract new regions of the lungs accurately and this indicates that the feedback GMDH-type neural network has good generalization ability.

3.3 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 and the recognition results were compared with the results obtained using the feedback GMDH-type algorithm. The conventional neural network had a three layered architecture, which was constructed using the input, hidden and output layers, and the same three input variables, which were mean, standard deviation and variance, 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 4 and 7, are shown in Fig.14 and 15. These images contain more regions which are not part of the lungs and the outlines of the lungs are not extracted with required clarity compared with the output images obtained using the GMDH-type neural network algorithm, which are shown in Fig.7 and 11. 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. In case of the feedback GMDH-type neural network, the optimum neural network architecture is automatically organized so as to minimize prediction error criterion PSS using heuristic self-organization method and many iterative calculations for various structural parameters are not needed because all structural parameters are automatically determined.
3.4 Generation of 3-dimensional lung images

Three-dimensional lung images were generated using the following procedures. The lung images in Figs. 16 and 17 were subtracted from the original images in Figs. 4 and 10 using the output images after post-processing in Figs. 8 and 12. For all MDCT slice images, these image subtractions were conducted and all slice subtracted images of the lungs were generated. Then, 3-dimensional lung images were generated from these subtracted images using the rendering software. Figure 18 shows the 3-dimensional lung images generated by the GMDH-type neural network.

3.5 Recognition of the pulmonary vessel and bronchial tree regions in the lungs

The pulmonary vessel and bronchial tree regions in the lungs were recognized by the feedback GMDH-type neural network algorithm and extracted. The gray scale image of the lungs (Fig. 19) which was subtracted from the original image (Fig. 4) using the output image (Fig. 8) of the feedback GMDH-type neural network was used as a new original image to organize a new feedback GMDH-type neural network. The new feedback GMDH-type neural network was organized and was able to recognize the pulmonary vessel and bronchial tree regions in the lungs. The organization procedures of the new feedback GMDH-type neural network are the same as those for the lung regions. Neural network was organized when values of N were from 2 to 15. When N equals 2, output image was found to be most accurate. Calculation of the feedback GMDH-type neural network was terminated at the sixth layer. Three relevant neurons were selected in each hidden layer. Figure 20 shows the variation of PSS values. PSS value at the first feedback loop calculation was considerable but decreased at subsequent feedback loop calculations and leveled off to a considerably small value by the fifth feedback loop calculation. Figure 21 shows PSS values corresponding to the three types of neurons at the first feedback loop calculation. Sigmoid function type neuron had the smallest PSS value; hence sigmoid function type neural network architecture was selected as the feedback GMDH-type neural network architecture. Fig. 22 shows the output image consisting of the pulmonary vessel and bronchial tree regions, corresponding to the input image shown in Fig. 19. Feedback GMDH-type neural network was organized and the output image displayed the pulmonary vessel and bronchial tree regions. Then, gray scale images (Fig. 23) of the pulmonary vessels and the bronchial trees was subtracted from the original image (Fig. 19) using the output image (Fig. 22) of the feedback GMDH-type neural network algorithm. Such subtraction processing was carried out for all the MDCT slices. Then, 3-dimensional images of the pulmonary vessels and the bronchial trees were generated using gray scale images for all slices of MDCT by the rendering software. Figure 24 shows the 3-dimensional images.
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 types of neural network architectures, such as, sigmoid function neural type network, RBF type neural network and polynomial type 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 PSS. This algorithm was applied to 3-dimensional medical image recognition of the lungs, the pulmonary vessels and the bronchial trees and it was shown that feedback GMDH-type neural network algorithm was a valuable method for 3-dimensional medical image recognition of the lungs, the pulmonary vessels and the bronchial trees because the neural network architecture is automatically organized by the feedback GMDH-type neural network algorithm.

Fig.19. Subtraction image of the lungs (1)
Fig.20. Variation of PSS values (2)
Fig.21. PSS values of three types of neurons (2)
Fig.22. Output image
Fig.23. Subtraction image (a) Front (b) Back
Fig.24. Three-dimensional images

References