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FEEDBACK GMDH-TYPE NEURAL NETWORK AND ITS APPLICATION TO MEDICAL IMAGE ANALYSIS OF LIVER CANCER

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Abstract. *A feedback Group Method of Data Handling (GMDH)-type neural network algorithm is proposed, and is applied to nonlinear system identification and medical image analysis of liver cancer. 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 sigmoid function neural network, radial basis function (RBF) neural network, and polynomial neural network. Furthermore, the structural parameters, such as the number of feedback loops, 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) or Prediction Sum of Squares (PSS). 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 results of the feedback GMDH-type neural network are compared to those obtained by GMDH and conventional neural network trained using the back propagation algorithm. It is shown that the feedback GMDH-type neural network algorithm is accurate and a useful method for the nonlinear system identification and the medical image analysis of liver cancer, and is ideal for practical complex problems since the optimum neural network architecture is automatically organized.*

Keywords: GMDH, Neural network, Medical image analysis, CAD, Liver cancer

1. **Introduction.** Conventional Group Method of Data Handling (GMDH)-type neural network algorithms were proposed in our early works [1-6], and can automatically organize the neural network architecture by using a heuristic self-organization method, which is the basic premise of the GMDH algorithm [7,8]. The heuristic self-organization method is a type of evolutionary computation. In this study, a feedback GMDH-type neural network algorithm which can self-select the optimum neural network architecture, is proposed. In this new feedback GMDH-type neural network algorithm, the 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. Furthermore, structural parameters, such as the number of feedback loops, 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) [9] or Prediction Sum of Squares (PSS) [10]. 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. In conventional feedback GMDH-type neural networks [3,4], the

type of neural network architecture cannot be 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, and therefore, we have to determine the type of the GMDH-type neural network architecture in advance from three types of neural network architectures, and it is difficult to determine the type of neural network architecture because we do not have information about the neural network architecture in advance. On the other hand, in case of the conventional neural network trained using back propagation algorithm, the optimum neural network architecture cannot be organized automatically, and we have to organize the neural network architecture before the calculation of back propagation. We obtain many different learning results for various structural parameters of the neural network, such as the initial values of weights, the number of the hidden layers, and the number of neurons in the hidden layers. Many iterative calculations of the back propagation are needed for various structural parameters in order to find a more accurate neural network architecture. In the feedback GMDH-type neural network, the neural network architecture is automatically organized so as to minimize the prediction error criterion AIC or PSS using the heuristic self-organization method [7,8]. Many iterative calculations for various structural parameters are not needed because all structural parameters are automatically determined in the GMDH-type neural network.

The feedback GMDH-type neural network algorithm proposed in this paper was applied to the nonlinear system identification and the medical image analysis of liver cancer. In the nonlinear system identification problem, generally speaking, it is very difficult to identify the architecture of the model fitting the complexity of the nonlinear system because the architectures of the nonlinear systems are complex and we cannot obtain sufficient information about the nonlinear systems. In the medical image analysis, digital image processing in the various kinds of medical images, such as magnetic resonance imaging (MRI) image, X-ray computed tomography (CR) image, digital mammography, and others, is widely used in the clinical diagnosis, and 3-dimentinal medical images, such as MRI image, and X-ray CT image, are used for computed-aided diagnosis (CAD) system. These medical image characteristics are very complex and different each other. The information which is contained in 3-dimensional medical images, such as MRI, and X-ray CT images, is very huge and therefore, CAD systems using these digital medical images, are needed for many organs [11-15]. When we apply the neural network to CAD systems, we have to organize the neural network architectures fitting the characteristics of many kinds of medical images for many organs, but we cannot obtain sufficient information about the neural network architectures from these medical images, and so it is very difficult to determine the neural network architectures fitting the characteristics of the medical images. When we apply the feedback GMDH-type neural network algorithm to the nonlinear system identification problem and the medical image analysis of liver cancer, optimal neural network architectures fitting the complexity of the nonlinear system and the medical images, are automatically organized from the input and output data of the nonlinear systems and the medical images, using the heuristic self-organization method. The feedback GMDH-type neural network is automatically organized so as to minimize the prediction error criterion defined as PSS and AIC, and therefore, we can organize neural network architecture even if we cannot obtain the information in advance about the architecture of the neural networks from the nonlinear system and the medical images. The identification results show that the feedback GMDH-type neural network algorithm is accurate and a useful method for the nonlinear system identification and the medical image analysis of liver cancer, and is ideal for practical complex problems since the optimum neural network architecture is automatically organized from the input and output data of the nonlinear system and the medical images.

2. **Heuristic Self-organization.** Architectures of the GMDH-type neural networks are automatically organized using the heuristic self-organization method [7,8]. First, we show the procedures of the heuristic self-organization method because it plays very important roles in the organization of the GMDH-type neural networks.

The heuristic self-organization method is constructed using the following five procedures.

(1) Separating the original data into the training and test sets. The original data are separated into the training and test sets. The training data are used in estimating the parameters of the partial descriptions, which describe the partial relationships of the nonlinear system. The test data are used in 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 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. Procedures (2) to (4) are iterated, and the multi-layered architecture is organized.

(5) Stopping the multi-layered iterative computation. When 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 using the partial descriptions generated in each layer.

The heuristic self-organization method is a type of the evolutional computation.

3. **Feedback GMDH-Type Neural Network.** Architecture of the feedback GMDH-type neural network developed in this paper, has a feedback loop as shown in Figure 1. In this algorithm, the outputs of neurons are not combined with each other but they are combined with input variables of the system in the next loop calculation. Therefore, the complexity of the neural network increases gradually 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 sigmoid function neural network, RBF neural network and polynomial neural network. The feedback GMDH-type neural network algorithm uses three types of neuron architectures, which are sigmoid function neuron, RBF neuron, and polynomial neuron. For each type of neuron architecture, we use two types of neurons called the first and second type neuron. The first type neuron has two input variables, as shown in Figure 2(a). The second type neuron has r input variables, as shown in Figure 2(b). In the feedback GMDH-type neural network, optimum neuron architectures fitting characteristics of the nonlinear system are automatically selected using AIC or PSS.

Feedback GMDH-type neural network is shown as follows.

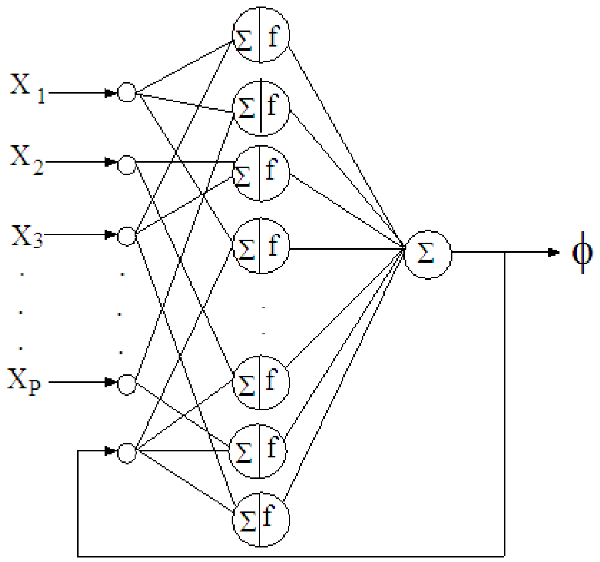
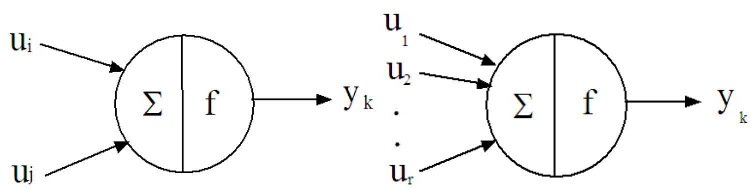


FIGURE 1. Architecture of the feedback GMDH-type neural network



(a) The first type neuron (b) The second type neuron

FIGURE 2. Architectures of the neurons

3.1. **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 because AIC or PSS can be used to organize the network architectures. In this study, we use PSS as the prediction error criterion. Then the architecture of the input layer is organized.

(1) Input layer.

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

where x_j $(j = 1, 2, \ldots, p)$ 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 neuron architectures which are sigmoid function neuron, RBF neuron, and polynomial neuron, are generated, and L neurons which minimize PSS 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 using PSS.

a) Sigmoid function neuron:

i) The first type neuron

Σ: (Nonlinear function)

$$z_k = w_1 u_i + w_2 u_j + w_3 u_i u_j + w_4 u_i^2 + w_5 u_j^2 + w_6 u_i^3 + w_7 u_i^2 u_j + w_8 u_i u_j^2 + w_9 u_j^3 - w_0 \theta_l \tag{2}$$

f: (Nonlinear function)

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

ii) The second type neuron

Σ: (Linear function)

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

f: (Nonlinear function)

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

b) RBF 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)

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

f: (Nonlinear function)

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

c) Polynomial 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)

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

f: (Linear function)

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

In the first type neuron, $\theta_1 = 1$ and w_i $(i = 0, 1, 2, \ldots, 9)$ are weights between the first and second layer and estimated by applying the stepwise regression analysis [16] to the training data. Only useful input variables u_i $(i = 1, 2, \ldots)$ are selected using PSS. 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 intermediate variables.

In the second type neuron, $\theta_1 = 1$ and w_i $(i = 0, 1, 2, \ldots, r)$ are weights between the first and second layer and estimated by applying the stepwise regression analysis [16] to the training data. Only useful input variables u_i $(i = 1, 2, \ldots)$ are selected using PSS. 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 $(i = 1, 2, \ldots, p)$. The output variables y_k of the neurons are called intermediate variables.

Weights w_i $(i = 0, 1, 2, \ldots)$ in each neuron are estimated by the stepwise regression analysis using PSS.

Estimation procedure of weight $\boldsymbol{w_i}$: First, values of z_k are calculated for each neuron architecture as follows.

i) Sigmoid function neuron:

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

ii) RBF neuron:

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

iii) Polynomial neuron:

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

where ϕ' is the normalized output variable whose values are between zero and one, and ϕ is the output variable.

Weights w_i are estimated by the stepwise regression analysis [16] which selects useful input variables using PSS. Only useful variables in Equation (2), Equation (4), Equation (6), Equation (8), Equation (10), and Equation (12), are selected by the stepwise regression analysis using PSS and optimum neuron architectures are organized by selected useful variables.

L neurons with the smallest PSS values, are selected from three types of neuron architectures, which are sigmoid function neuron, RBF neuron, and polynomial neuron. 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, outputs y_k of the neurons in the hidden layer are combined by the following linear function.

$$\phi^* = a_0 + \sum_{k=1}^{L} a_k y_k \tag{17}$$

here, L is the number of combinations of the input variables, and y_k is the intermediate variables. Useful 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 sigmoid function neural network, RBF neural network, and polynomial neural network.

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

3.2. **Second and subsequent loop calculations.** 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.

In the second feedback loop calculations, the neural network architecture with smallest mean PSS value, which is a mean PSS value of the first and second feedback loop calculations, is selected as the GMDH-type neural network architecture from three types of neural network architectures. The optimum neural network architecture is selected from three types of neural network architectures. Therefore, in the third and subsequent loop calculations, 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 first feedback loop is iterated.

When PSS value of the linear function in (17) is increased, the loop calculation is terminated and the complete neural network architecture is organized using the L selected neurons in each feedback loop.

By using these procedures, the feedback GMDH-type neural network self-selecting optimum neural network architecture can be organized. Figure 3 shows the flowchart of the feedback GMDH-type neural network. The feedback GMDH-type neural network proposed in this paper, have an ability of self-selecting the optimum neural network architecture, and the neural network architecture is automatically selected from three types of neural network architectures. Furthermore, structural parameters, such as the number of feedback loops, 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 PSS.

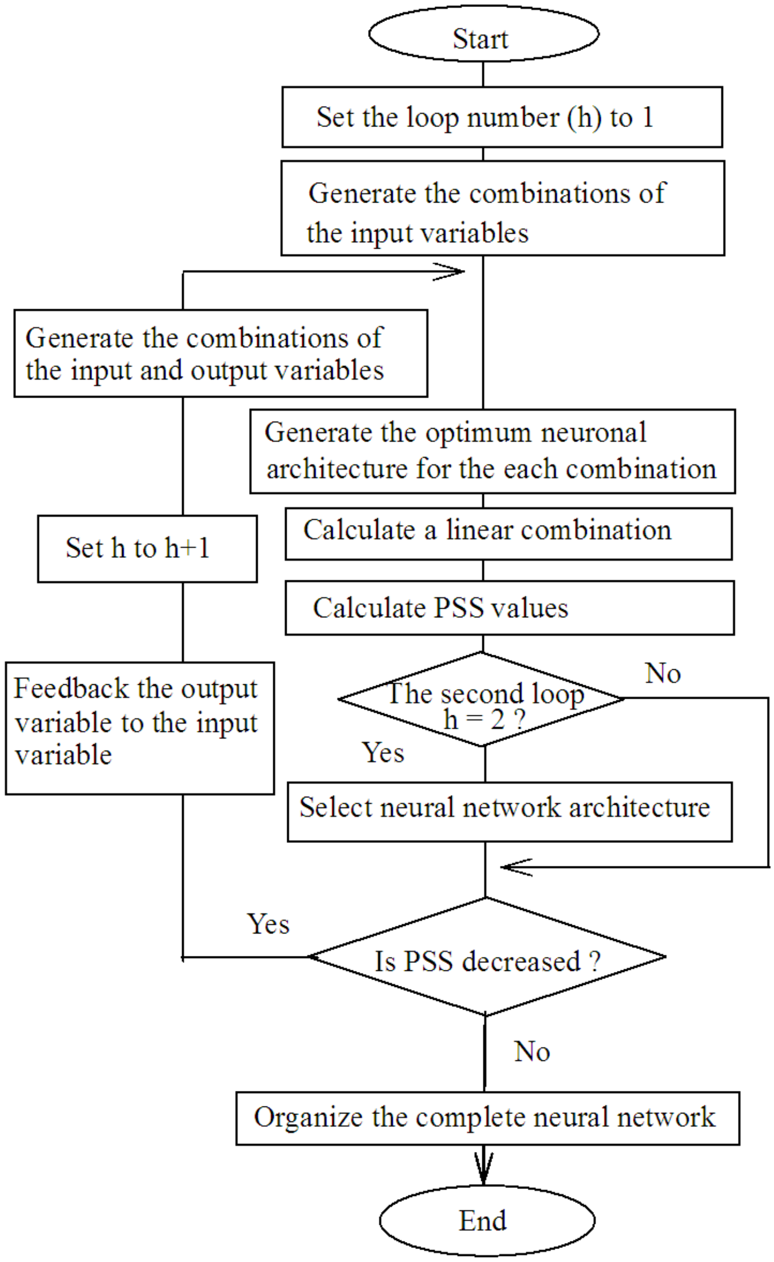


FIGURE 3. Flowchart of the feedback GMDH-type neural network

4. **Application to Nonlinear System Identification.** Feedback GMDH-type neural network was applied to the nonlinear system identification problem and identification results were compared to those obtained by conventional GMDH algorithm and conventional multilayered neural network trained using back propagation.

4.1. **Nonlinear system identification problem.** The nonlinear system was assumed described by the following equations:

$$\phi_1 = (1.0 + 1.1x_1 + 1.2x_2 + 1.3x_3)^4 + \varepsilon_1 \tag{18}$$
$$\phi_2 = (1.0 + 1.4x_1 + 1.5x_2 + 1.6x_3)^4 + \varepsilon_2 \tag{19}$$
$$\phi_3 = (1.0 + 1.7x_1 + 1.8x_2 + 1.9x_3)^4 + \varepsilon_3 \tag{20}$$
$$\phi_4 = (1.0 + 2.0x_1 + 2.1x_2 + 2.2x_3)^4 + \varepsilon_4 \tag{21}$$

here, $\phi_1 \sim \phi_4$ are output variables, $x_1 \sim x_3$ are input variables, and $\varepsilon_1 \sim \varepsilon_4$ are noises. An additional input (x_4) was added as the input variable of the neural network to check that the feedback GMDH-type neural network can eliminate useless input variables. The neural network was organized using 20 training data points, and 20 other data points were used to check prediction and generalization ability. Identification results of the feedback GMDH-type neural network were compared to those of GMDH algorithm and conventional neural network trained using back propagation algorithm.

4.2. **Identification results obtained by the feedback GMDH-type neural network.**

(1) Input variables. Four input variables were used and the useless input variables (x_4) was automatically eliminated.

(2) Selection of the neurons in the hidden layer. Four neurons were selected in the hidden layer.

(3) Selection of the neural network architecture. Figure 4 shows mean PSS values of three kinds of neurons in the first and second feedback loop calculations. Polynomial neuron had the smallest PSS value and polynomial neural network architecture was selected as the feedback GMDH-type neural network architecture.

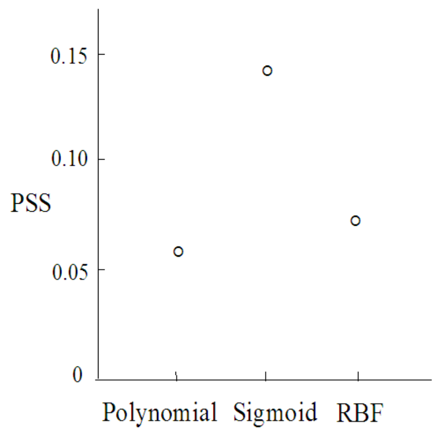


FIGURE 4. Mean PSS values of three kinds of neurons

(4) Structure of the neural network. The calculation of the GMDH-type neural network was terminated at the fifth feedback loop calculation.

(5) Estimation accuracy J_1. Estimation accuracy J_1 for the training data was evaluated using the following equation:

$$J_{1i} = \frac{\sum_{j=1}^{20} \left|\phi_{ij} - \phi_{ij}^*\right|}{\sum_{j=1}^{20} |\phi_{ij}|} \tag{22}$$

where ϕ_{ij} $(i = 1, 2, \cdots, 4;\ j = 1, 2, \cdots, 20)$ are the actual values, and ϕ_{ij}^* $(i = 1, 2, \cdots, 4;$ $j = 1, 2, \cdots, 20)$ are estimated values for the training data by the feedback GMDH-type neural network. The values of J_{1i} $(i = 1, 2, \ldots, 4)$ for four output variables, are shown in Table 1, where GMDH-NN shows the feedback GMDH-type neural network, GMDH shows conventional GMDH, and NN shows conventional neural network trained using back propagation.

Table 1. Estimation accuracy

Models	J	ϕ_1	ϕ_2	ϕ_3	ϕ_4
GMDH-NN	J_1	0.029	0.029	0.013	0.013
	J_2	0.038	0.037	0.017	0.017
GMDH	J_1	0.056	0.058	0.038	0.039
	J_2	0.055	0.058	0.044	0.044
NN	J_1	0.119	0.133	0.108	0.11
	J_2	0.114	0.133	0.102	0.109

(6) The estimation accuracy J_2. Estimation accuracy J_2 for the test data was evaluated using the following equation

$$J_{2i} = \frac{\sum_{j=21}^{40} \left|\phi_{ij} - \phi_{ij}^*\right|}{\sum_{j=21}^{40} |\phi_{ij}|} \tag{23}$$

where ϕ_{ij} $(i = 1, 2, \cdots, 4;\ j = 21, 22, \cdots, 40)$ are the actual values, and ϕ_{ij}^* $(i = 1, 2, \cdots, 4;\ j = 21, 22, \cdots, 40)$ are the estimated values for the test data by the feedback GMDH-type neural network. The values of J_{2i} $(i = 1, 2, \ldots, 4)$ for four output variables, are shown in Table 1.

(7) Variation of PSS and estimated values. The variation of PSS of the output variables (ϕ_1), is shown in Figure 5. It decreased gradually by the feedback loop calculations, and converged at the fifth feedback loop calculation. The estimated values of ϕ_1 by the feedback GMDH-type neural network is shown in Figure 6. Note that the estimated values are very accurate.

4.3. **Comparison of the feedback GMDH-type neural network and other models.** Identification results were compared to those obtained by conventional GMDH algorithm and conventional multilayered neural network trained using back propagation algorithm.

(1) GMDH algorithm. Identification results were referred from [17]. Four input variables were used and the useless input variable (x_4) was automatically eliminated. Four intermediate variables were selected. The calculation was terminated at the fourth layer. Values of J_1 and J_2, are shown in Table 1.

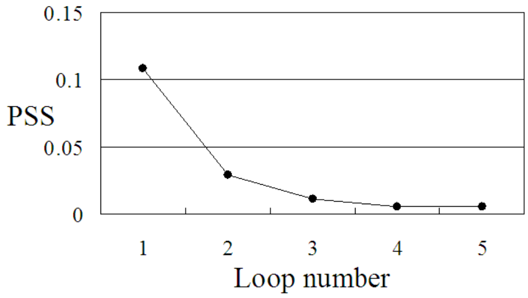


FIGURE 5. Variation of PSS

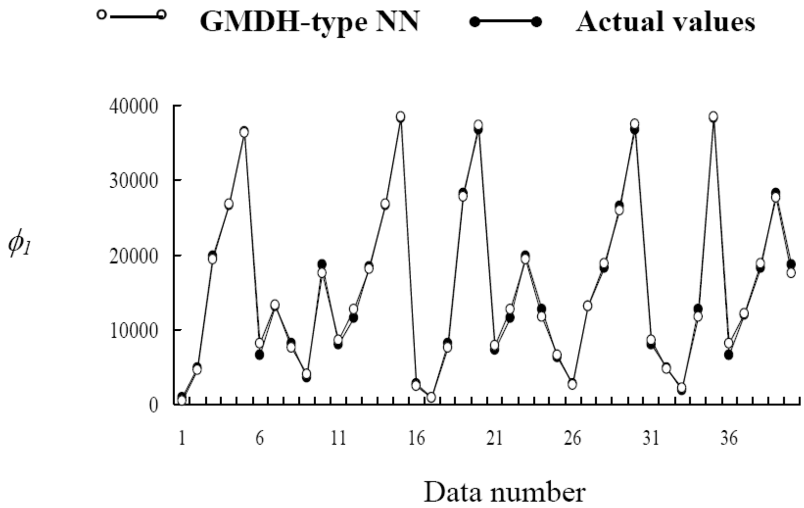


FIGURE 6. Estimated values of ϕ_1 by feedback GMDH-type neural network

(2) Conventional multilayered neural network. The neural network had three layered structures. Four input variables were used in the input layer and eight neurons were used in the hidden layer. Estimated values of ϕ_1 by the conventional neural network are shown in Figure 7. Values of J_1 and J_2, are shown in Table 1.

4.4. **Discussions.** From the identification results, we can see the following:

(1) Both estimation accuracy J_1 and J_2 of the feedback GMDH-type neural network, were smallest in the three identified models. We can see that the feedback GMDH-type neural network was a very accurate identification method for the nonlinear system.

(2) In the feedback GMDH-type neural network, PSS value at the first loop calculation was not small but it was gradually decreased by the feedback loop calculations. So we can see that the feedback loop calculation plays a very important role in the feedback GMDH-type neural network.

(3) In the conventional neural network, effects of high order terms of the input variables are not considered. Furthermore, it does not have the ability of self-selecting useful input variables. So the accuracy of the neural network was not good.

The feedback GMDH-type neural network can organize the conventional neural network architecture (sigmoid function type architecture) and the GMDH architecture (polynomial type architecture). This algorithm contains both characteristics of the conventional neural network and the GMDH algorithm, and it is a very flexible method for the identification problem of the complex nonlinear system.

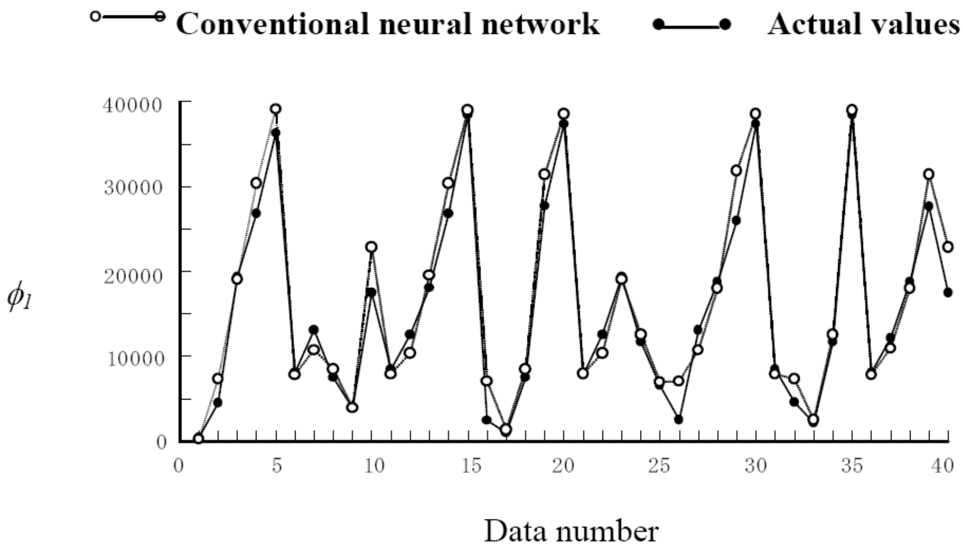


FIGURE 7. Estimated values of ϕ_1 by conventional neural network

5. **Application to the Medical Image Analysis 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 were used in this study. In the recognition procedure, the revised GMDH-type neural network was organized to recognize the liver regions and then the regions of liver cancer were extracted.

5.1. **Extraction of candidate image regions of liver cancer.** A liver image shown in Figure 8 was used in 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, i.e., mean, standard deviation, variance and x and y coordinates, were selected as useful input variables. The output value of the neural network was zero or one. When $N \times N$ pixel region was within the 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 15. 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 9 shows the mean PSS values in the first and second feedback loops. The mean PSS value of the sigmoid function neuron was smallest in three kinds of neurons. The sigmoid function neural network architecture was selected by the feedback GMDH-type neural network. Figure 10 shows the variation of PSS values in the feedback loops. The calculation of the feedback GMDH-type neural network was terminated in the tenth feedback loop. The PSS value in the first feedback loop was not small but the PSS value was decreased gradually through the feedback loops and the small PSS vale was obtained in the tenth layer. The revised GMDH-type neural network outputs the liver image (Figure 11), and the first post-processing analysis of the liver image was carried out. In the first post-processing of the output image, the small isolated regions were eliminated and the outlines of the liver regions were expanded outside by $N/2$ pixels. Figure 12 shows the output image after the first post-processing. The output image after the first post-processing and the original image (Figure 8), were overlapped in order to check the accuracy of the image recognition, as shown in Figure 13. The recognized liver regions were accurate. The liver regions were extracted from the original image using the output image. Figure 14 shows the extracted image of the liver. The second post-processing, such as the closing was carried out, and the liver region which contained the abnormal regions was obtained, as shown in Figure 15. Figure 16 shows the extracted image of the liver. The candidate image regions of liver cancer were extracted from Figure 16 using Figure 14, and shown in Figure 17. The recognition results were compared with those obtained by the conventional sigmoid function neural network trained using the back propagation algorithm.

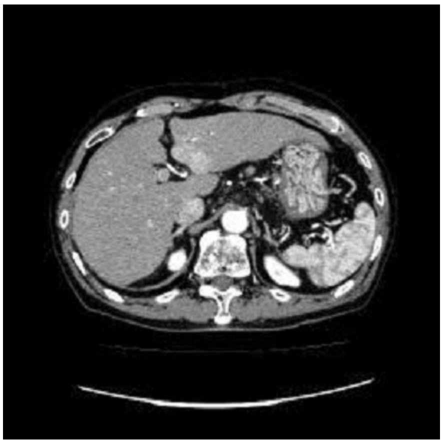


Figure 8. Original image

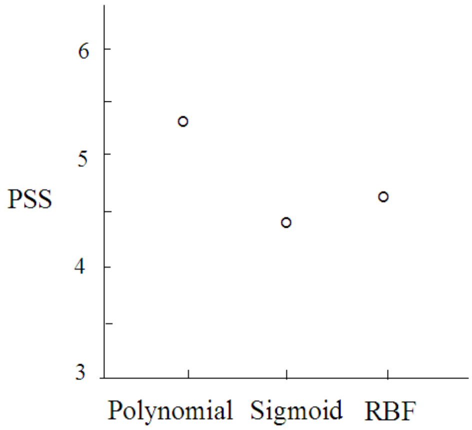


Figure 9. Mean PSS values of three kinds of neurons

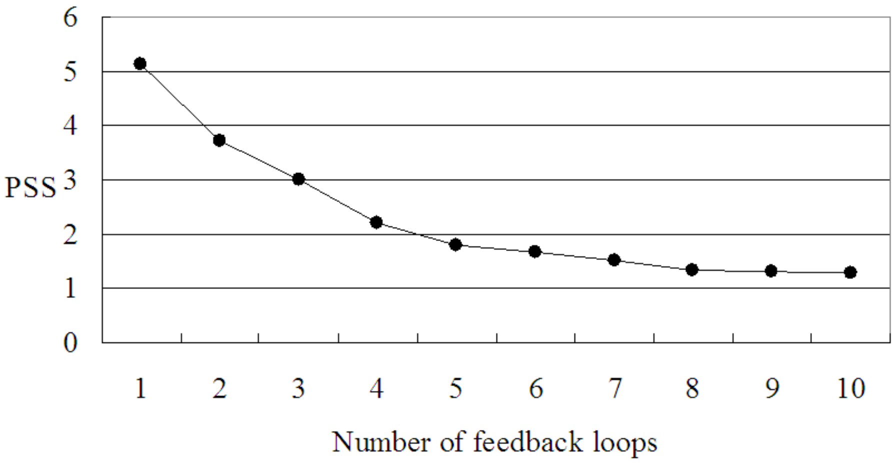


Figure 10. Variation of PSS in the revised GMDH-type neural network

5.2. **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 revised 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 five input variables, which were mean, standard deviation, variance, x and y coordinates, were used in the input layer.

Figure 11. Output image of the neural network

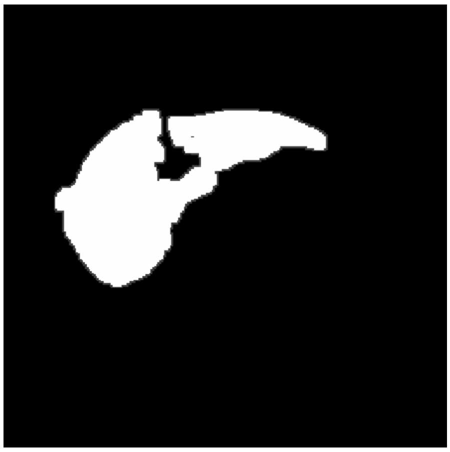


Figure 12. Output image after the first post-processing

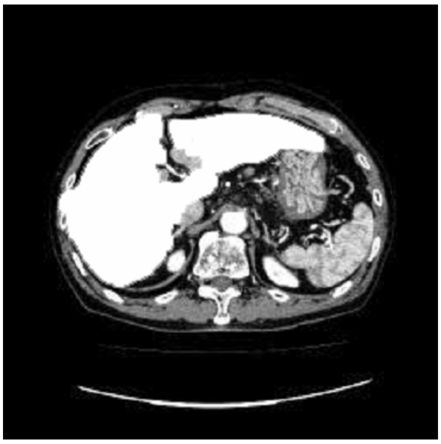


Figure 13. Overlapped image

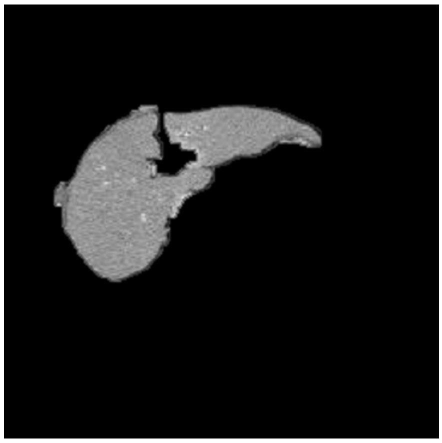


Figure 14. Extracted image (1)

Figure 15. Output image after the second post-processing

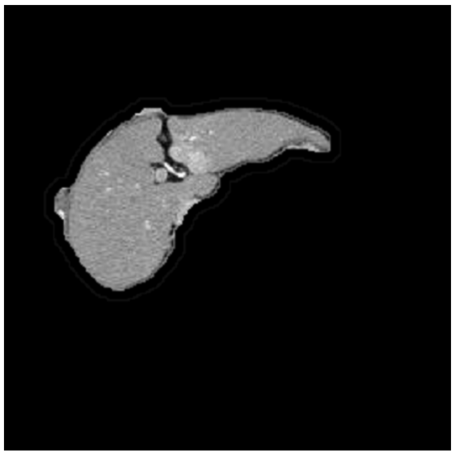
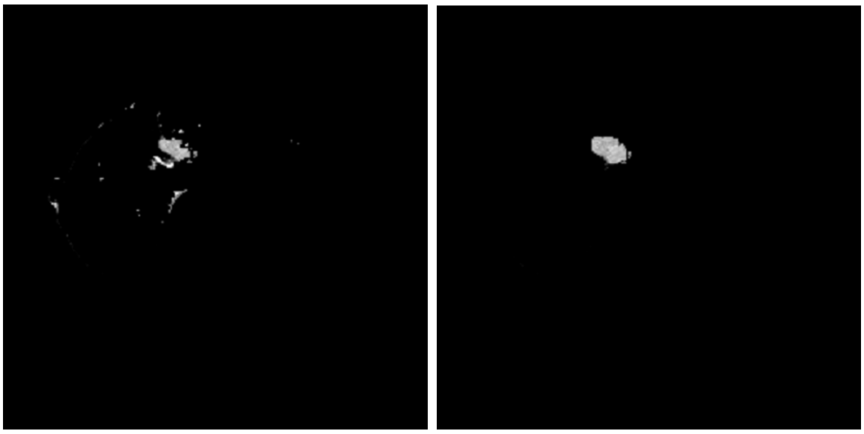
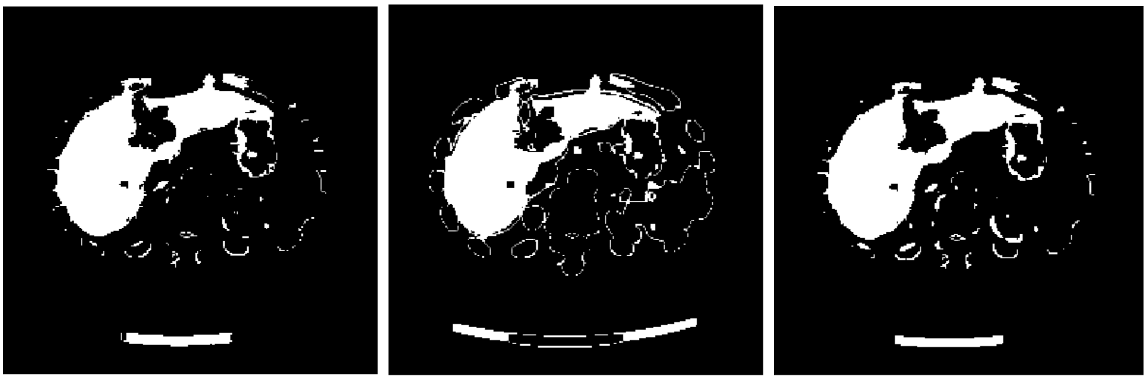


Figure 16. Extracted image (2)



(a) Extracted image (b) After the post-processing

FIGURE 17. Candidate image regions of liver cancer



(a) $m = 3$ (b) $m = 5$ (c) $m = 7$

FIGURE 18. Output images of the conventional neural network

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 3, 5 and 7, are shown in Figure 18. These images contain more regions that are not part of the liver, and the outlines of the liver are not extracted with required clarity, compared with the output images (Figure 11) obtained using the feedback GMDH-type neural network algorithm. 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 the feedback GMDH-type neural network, the neural network architecture is automatically organized so as to minimize the prediction error criterion PSS using heuristic self-organization method [7,8]. Many iterative calculations for various structural parameters are not needed because all structural parameters are automatically determined in the feedback GMDH-type neural network.

6. **Conclusions.** In this paper, the feedback GMDH-type neural network algorithm was proposed, and was applied to the nonlinear system identification and the medical image analysis of liver cancer, and the results of the feedback GMDH-type neural network were compared to those obtained by GMDH and conventional neural network trained using the back propagation algorithm. 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 sigmoid function neural network, RBF neural network, and polynomial neural network. The feedback GMDH-type neural network can organize the conventional neural network architecture, which is sigmoid function neural network architecture, and conventional GMDH architecture, which is polynomial network architecture. The feedback GMDH-type neural network contains both characteristics of the conventional neural network and conventional GMDH, and therefore, the feedback GMDH-type neural network is a flexible method for the nonlinear system identification and the medical image analysis of liver cancer. Furthermore, 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. Structural parameters, such as the number of feedback loops, the number of neurons in hidden layers, and useful input variables, are automatically selected to minimize the prediction error criterion defined as AIC or PSS. In the conventional neural network, we obtain many different output images for various structural parameters of the neural network in the medical image analysis of liver cancer, and many iterative calculations of the back propagation were needed for various structural parameters in order to find a more accurate neural network architecture. It was shown that the feedback GMDH-type neural network algorithm was accurate and a useful method for the nonlinear system identification and the medical image analysis of liver cancer, and is ideal for practical complex problems since the optimum neural network architecture is automatically organized so as to minimize the prediction error criterion defined as AIC or PSS.

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