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Learning algorithm of the revised RBF network and its application to the media art system

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Abstract: In this study, a revised radial basis function (RBF) network is proposed and applied to the identification problems of the nonlinear system and the media art system. In the revised RBF network, the structural parameters such as means and variances of the radial basis functions in the neurons are determined automatically and so revised RBF network can be easily applied to the practical complex problems such as the media art system. The media art system outputs the art expressions such as the sound and graphics using the artificial sensibility surfaces that are identified using the revised RBF network.

Keywords: neural network, radial basis function, media art system, nonlinear system identification

I. INTRODUCTION

In this study, a revised radial basis function (RBF) network is proposed and applied to the identification problems of the nonlinear system and the media art system. In the conventional RBF network [1]-[3], the structural parameters such as means and variances of the radial basis functions in the neurons are not determined automatically and so it is needed to repeat the RBF network calculations many times changing these structural parameter values. In this study, a revised RBF network algorithm in which these structural parameters are automatically determined so as to fit the characteristics of the training data, is proposed and it is shown that the revised RBF network is accurate and easy to apply to practical complex problem because the structural parameters are automatically determined.

II. RBF NETWORK AND ITS LEARNING ALGORITHM

In this study, a revised RBF network is proposed and applied to the nonlinear system and the media art system. The revised RBF network had a 3-layered architecture with the input, hidden and output layers. Architecture of the revised RBF neural network is shown in Fig.1. In this figure, x shows the input variable and ϕ shows the output variable and h shows the radial basis function. In the revised RBF neural network, the structural parameters, which are means and variances of the radial basis functions in the neurons, are calculated automatically using the training data. The revised RBF neural network is organized as follows:

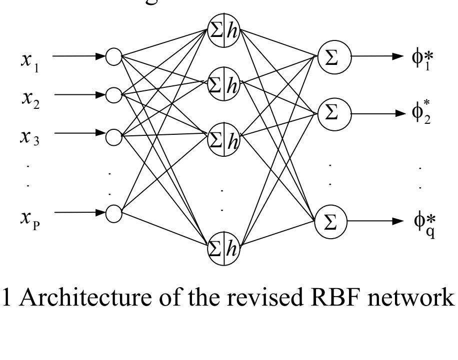


Fig.1 Architecture of the revised RBF network (1)

(1)Input layer

$$u_i = x_i \quad (i = 1,2,\ldots,p) \tag{1}$$

Here, x_i is input variable and p is the number of input variables and u_i is the output variable of the input layer.

(2)Hidden layer

In the hidden layer, the output (h_j) of the RBF neuron is calculated by the following equation:

$$h_j = \exp(-z_j^2) \quad (j = 1,2,\ldots,g) \tag{2}$$

z_j is estimated using the regression analysis [4] for the training data by the following equations.

$$z_j = a_0 + a_1 d_j \tag{3}$$

$$d_j = \|u - c\| \tag{4}$$

Here, a_j (j=0,1) are the regression coefficients and estimated using stepwise regression analysis for the training data, and d_j are the distance between the training data points (u) and the center (c) of the neuron which is the mean of the radial basis function.

In the conventional RBF network, the value z_j is described as follows,

$$z_j = \frac{d_j}{v_j} \tag{5}$$

Here, v_j is a variance of the j-th radial basis function. Equation (3) is described as follows,

$$z_j = \frac{d_j + \dfrac{a_0}{a_1}}{\dfrac{1}{a_1}} \tag{6}$$

Comparing Eq.(5) and (6), we see that v equals $1/a_1$, and a_0/a_1 is a correct value for d_j. In this algorithm, The variance v and the mean c of the radial basis function are determined so as to fit characteristics of the training data in the revised RBF network.

(3)Output layer

$$\phi_i^*(x) = \sum_{j=1}^{g} w_{i,j} h_j(u) \quad (i=1,2,\ldots,q) \tag{7}$$

Here, $w_{i,j}$ (i=1,2,…,q; j=1,2,…,g) are the weights of the neural network and q is the number of neurons in the output layer and $\phi_i^*(x)$ (i=1,2,…,q) are the outputs of the neural network.

Weights $w_{i,j}$ (i=1,2,…,q; j=1,2,…,g) are estimated using multiple regression analysis [4] as follows:

$$\underline{w}_i(n) = (H^T(n)H(n)+\Lambda)^{-1}H^T(n)\underline{\phi}_i(n)$$
$$= P(n)H^T(n)\underline{\phi}_i(n) \qquad (i=1,2,\ldots,q) \qquad (8)$$

Here,

$$\underline{w}_i(n)^T = (w_{i,1}, w_{i,2}, \ldots, w_{i,g}) \quad (i=1,2,\ldots,q) \qquad (9)$$
$$H^T=[\underline{h}(1), \underline{h}(2), \ldots, \underline{h}(n)] \qquad (10)$$
$$\underline{h}^T(k)=(h_1(k), h_2(k), \ldots, h_g(k)) \quad (k=1,2,\ldots,n) \qquad (11)$$
$$\underline{\phi}_i^T(n) = (\phi_i(1), \phi_i(2), \ldots, \phi_i(n)) \quad (i=1,2,\ldots,q) \qquad (12)$$

n is the number of training data. Λ is a diagonal matrix.

In the revised RBF network, the structural parameters such as means and variances of the radial basis functions in the neurons are automatically determined from the training data using the following procedures. The number of neurons in the hidden layer was set to the number of the training data and the centers (means) of the radial basis functions are located at the training data points. Means are determined at the training data points. Variances are estimated using the regression analysis [4] of the training data to fit the characteristics of the training data. Using these procedures, the structural parameters such as means and variances of the radial basis functions, are automatically determined from the training data.

When the (n+1)-th additional new training data ($\phi_i(n+1)$, $\underline{x}^T(n+1)$) are obtained, we can update the values of the weights using the following equations.

$$\underline{w}_i(n+1) = \underline{w}_i(n) + P(n+1)\underline{h}(n+1)e_{n+1} \qquad (13)$$
$$e_{n+1} = \phi_i(n+1) - \underline{h}^T(n+1)\underline{w}(n) \qquad (14)$$
$$P(n+1) = P(n) - \frac{P(n)\underline{h}(n+1)\underline{h}^T(n+1)P(n)}{1+\underline{h}^T(n+1)P(n)\underline{h}(n+1)} \qquad (15)$$
$$\underline{x}^T(k) = (x_1(k), x_2(k), \ldots, x_p(k)) \quad (k=1,2,\ldots,n+1) \qquad (16)$$

III. APPLICATION TO THE NONLINEAR SYSTEM IDENTIFICATION

Nonlinear system is assumed to be described by the following equations:

$$\phi_1 = (1.0+2.0x_1^2+3.0x_1x_2+4.0x_2^2+5.0exp(x_1x_2x_3))^3 \qquad (17)$$
$$\phi_2 = (1.0+2.0x_1+3.0x_1^2x_2+4.0x_2^2+5.0exp(x_1x_2x_3))^3 \qquad (18)$$
$$\phi_3 = (1.0+2.0x_1^2+3.0x_1x_2^2+4.0x_2+5.0exp(x_1x_2x_3))^3 \qquad (19)$$

Here, ϕ_i is the i-th output variable and $x_1 \sim x_3$ are input variables. Neural network is organized by ten training data. Ten other data are used to check prediction and generalization ability. Identification results of revised RBF network are compared with those of the conventional RBF network and the conventional sigmoid function neural network.

1. Identification results of the revised RBF network.

Identification results of the revised RBF network are shown as follows:

The neural network was developed as a three layered architecture. Three input variables were used in input layer and ten neurons were used in hidden layer and these neurons were located at the training data points. Weights of neural network, the values of variances and means of the radial basis functions were estimated by regression analysis.

Estimation accuracy was evaluated by the following equation:

$$J_1 = \frac{1}{10}\sum_{k=1}^{10}\left|\phi_i(k) - \phi_i^*(k)\right| \qquad (20)$$

where $\phi_i(k)$ (i=1,2,3; k=1,2,···,10) are actual values and $\phi_i^*(k)$ (i=1,2,3; k=1,2,···,10) are estimated values by the revised RBF network. $\phi_i(k)$ (i=1,2,3; k=1,2,···,10) were used to organize revised RBF network. Value of J_1 is shown in Table1.

Prediction accuracy was evaluated by using the following equation:

$$J_2 = \frac{1}{10}\sum_{k=11}^{20}\left|\phi_i(k) - \phi_i^*(k)\right| \qquad (21)$$

where $\phi_i(k)$ (i=1,2,3; k=11,12,···,20) are actual values and $\phi_i^*(k)$ (i=1,2,3; k=11,12,···,20) are predicted values by revised RBF network. $\phi_i(k)$ (i=1,2,3; k=11,12,···,20) were not used to organize revised RBF network and were used to check generalization ability. Value of J_2 is shown in Table1. Estimated and predicted values of $\phi_1(k)$ by the revised RBF network are shown in Fig.2.

Table 1 Estimation and prediction accuracy

	J1	J2
ϕ1	0.013697	0.043621
ϕ2	0.013731	0.040899
ϕ3	0.012484	0.037977

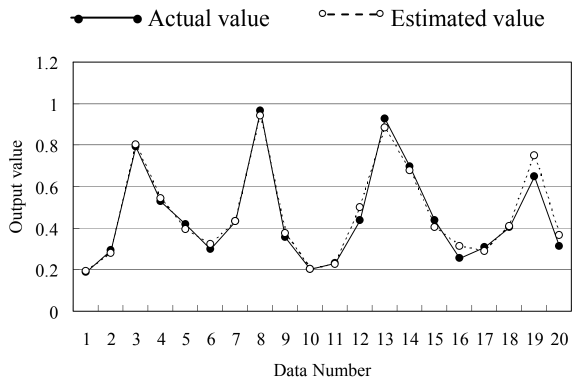


Fig.2 Estimated and predicted values ϕ_1

2. Identification results of the conventional RBF network.

Identification results of the conventional RBF network are shown as follows:

The neural network was also developed as a three layered architecture. Three input variables were used in input layer and ten neurons were used in hidden layer and these neurons were located at the training data points. Weights of neural network were estimated by regression analysis. The values of variances of the radial basis functions were set to 1.0. Estimation accuracy was evaluated by Eq. (20) and value of J_1 is shown in Table2. Prediction accuracy was evaluated by Eq.(21) and value of J_2 is shown in Table2.

Table 2 Estimation and prediction accuracy of the conventional RBF network

	J1	J2
ϕ1	0.066868	0.072537
ϕ2	0.063003	0.068088
ϕ3	0.049768	0.055042

3. Identification results of the conventional sigmoid function neural network trained using back propagation algorithm

Identification results obtained by the conventional neural network trained using back propagation algorithm are shown as follows:

In conventional multilayered neural network, the neural network was developed as a three layered architecture. Three input variables were used in input layer and four neurons were used in hidden layer. Weights of neural network were estimated by back propagation algorithm. Initial values of the weights were set to random values. The learning calculations of the weights were iterated at 100,000 times. Estimation accuracy was evaluated by Eq.(20) and value of J_1 is shown in Table3. Prediction accuracy was evaluated by Eq.(21) and value of J_2 is shown in Table3.

Table 3 Estimation and prediction accuracy of the conventional sigmoid function neural network

	J1	J2
ϕ1	0.069191	0.064316
ϕ2	0.060103	0.060559
ϕ3	0.050405	0.047165

4. Comparison of the identified results.

Identification results of revised RBF network were compared with those of the conventional RBF network and the conventional sigmoid function neural network trained using the back propagation algorithm. From these identification results, both estimation and prediction errors (J_1 and J_2) of revised RBF network are smaller than those of the conventional RBF network and the conventional sigmoid function neural network. Estimated and predicted values of ϕ by revised RBF network are accurate and the estimation and prediction errors of the revised RBF network are decreased remarkably. From these results, we can see that revised RBF network algorithm is an accurate identification method for the nonlinear system.

VI. APPLICATION TO THE MRDIA ART SYSTEM

The revised RBF network is applied to the media art system and generates the artificial sensibility in the media art system. The artificial sensibility simulates the human sensibility in the computer and outputs the art expressions using the sound and graphics.

1. Architecture of the media art system.

The architecture of the media art system is shown in Fig.3. Input signals are inputted from the sensors and these input signals from sensors are transmitted to the computer using Gainer, which is an I/O module to control actuators such as LED and motors. Input signals can be also inputted from display using a mouse. In the computer, first, the signals, which have been transmitted from Gainer or the display, are received with the processing [5], which is programming software for the production of computer art that specializes in visual expression and interaction. The revised RBF network is programmed by processing software and generates the artificial sensibility. The artificial sensibility selects the output signals according to the input signals and generates output patterns to express the art using sound and graphics.

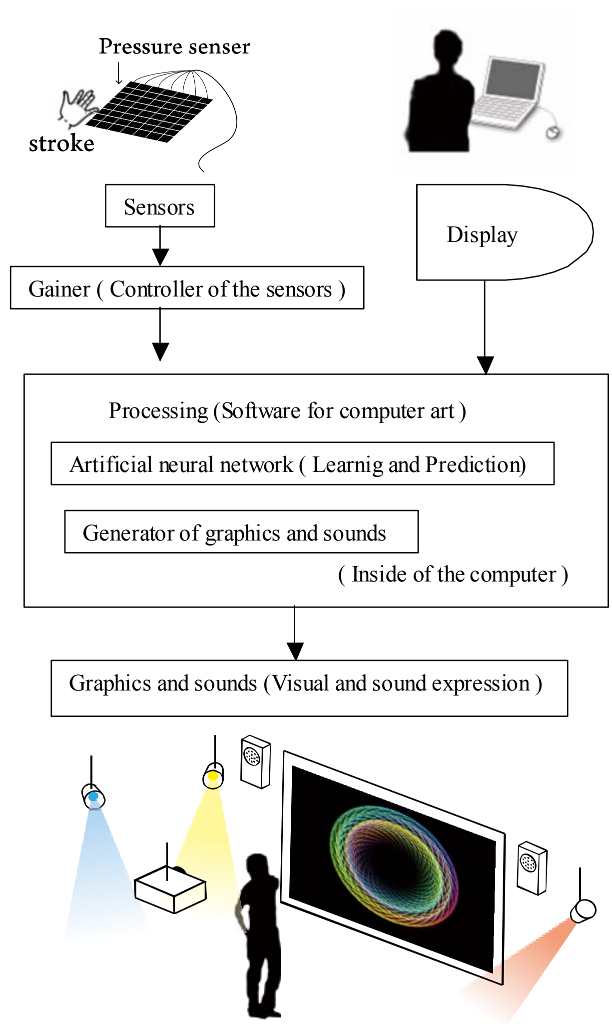


Fig. 3 Architecture of the media art system

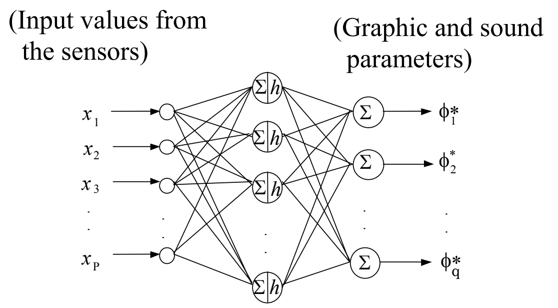


Fig.4 Architecture of the revised RBF network (2)

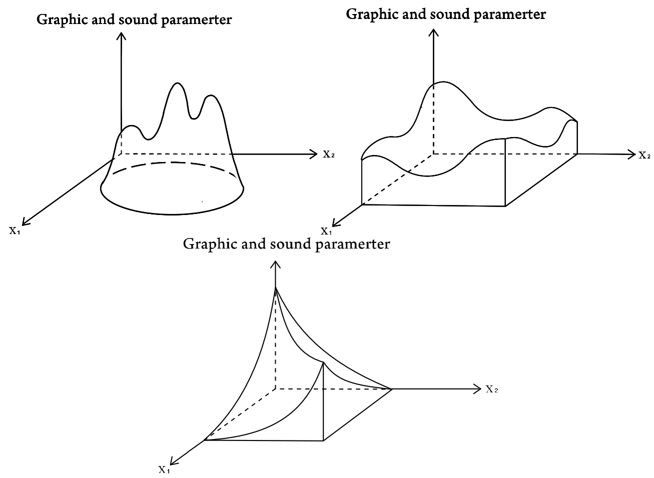


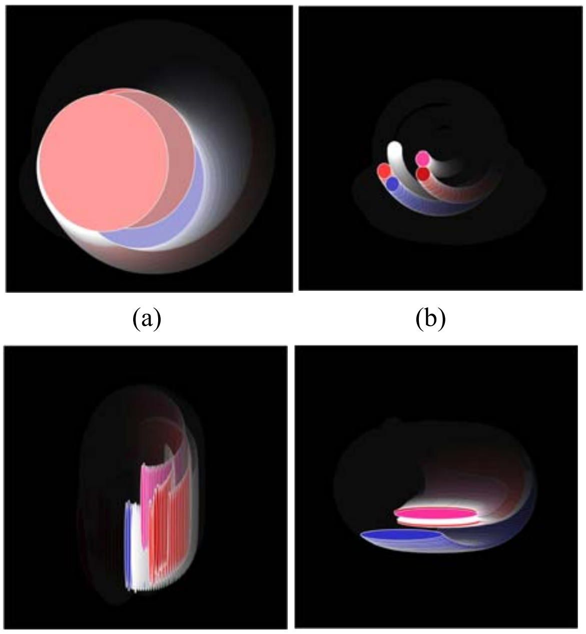
Fig.5 Identification of artificial sensibility surface using the revised RBF network

2. Identification of artificial sensibility surfaces using the revised RBF network.

The revised RBF network generates the artificial sensibility in the computer. In this study, the input signals are inputted from the sensors and the display. Figure 4 shows the architecture of the RBF network with *p* input variables obtained from the sensors and the display. Output variables of the neural network are the graphic and sound parameters such as colors of Red, Green and Blue, speed of the graphic drawing, positions of the graphics, kinds of the sound and so on. The revised RBF network identifies the artificial sensibility surfaces using the learning procedures of the neural network. In Fig.5, the examples of the artificial sensibility surfaces identified using the revised RBF network are shown. The learning data (teacher signals) for each graphical parameter are obtained through the interaction between man and the computer using the man-computer communications and the revised RBF network identifies the artificial sensibility surface using the obtained learning data. The revised RBF network can identify various kinds of the artificial sensibility surfaces accurately using the data which are obtained through the interaction between man and the computer using the man-computer communications.

3. Generation of graphics using the identified artificial sensibility surface and modification of the graphics using the man-computer communications.

The computer generated the graphics using identified artificial sensibility surface of each graphical parameter. Here, we input signals from the display and person moved the mouse and the computer read the mouse pointer positions. The revised RBF network output the graphical parameters and the new graphics were generated using the graphical parameters that were output from the revised RBF network. These processes were repeated until the processing software system was stopped. If the desirable graphics for the person are not obtained, the artificial sensibility surfaces can be modified by the additional learning procedures of the revised RBF network using Eq.(13), (14) and (15). The additional learning data were obtained through the interaction between man and the computer using the men-computer communications. We show the examples of the graphics in Fig.6 which were generated and output from the media art system. These generated graphics are changed according to the mouse pointer positions on the display.



(a) (b) (c) (d)

Fig.6 Output images from the media art system

V. CONCLUSION

In this paper, a revised RBF network algorithm was proposed. In this algorithm, the structural parameters such as means and variances of the radial basis functions in the neurons are automatically determined so as to fit the characteristics of the training data and so we can easily apply this algorithm to practical complex problems. This algorithm was applied to the identification problems of the nonlinear system and the media art system and it was shown that revised RBF network algorithm was a useful method for the nonlinear system identification and media art system.

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