Optimization for the Initial Designed Structure by Localization Using Genetic Algorithm

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Abstract: In this paper, we propose the initial optimized structure of the Radial Basis Function Networks that is simple in the part of the structure and fast converges more than neural networks with the analysis method using Time-Frequency Localization. We construct the hidden node with the Radial Basis Functions their localization are similar with approximation target function in the plane of the Time and Frequency. We finally make a good decision of the initial structure for function approximation using genetic algorithm.

1. Introduction

The neural network is famous structure in various parts because it doesn't need any mathematical modeling for complex system plant but it can control the system properly by learning process. Also, neural network operate parallel processing.

In spite of these characteristics, the neural network has a problem such that the number of weights that must be updated becomes large and that the convergence time becomes long, when the dimension of the system goes to high. To improve this problem, Radial Basis Function Network (RBF network) that is oriented from the structure of neural network was proposed by [1][2].

RBF network sets the constant of the weight between input layer and hidden layer and updates the weight between hidden layer and output layer. Therefore, RBF network is simple and the convergence time is short.

To construct the RBF network, activation function of the hidden layer must be composed by radial basis functions and then the center and radius of the each function must be set properly.

RBF network has problem such that there may be too many functions because radial basis functions are not orthogonal in each other.

In this paper, to overcome this problem we compose the hidden layer of the RBF network by choosing the radial basis function that can represent the characteristic of the target function with time-frequency localization analysis.

With RBFs made by this method, we can design the good structure proper to the target problem because we can decide the number of hidden nodes at initialization. Moreover, in this paper, we adapt the selected RBFs to optimize the size of the structure. We compose the bit string with parameters, center and radius as the chromosome of the population. After genetic process, we can cancel some similar strings with others. Finally the selected strings can be composed as the node functions of the networks and the structure with that parameters will be optimal initialized structure.

2. Radial Basis Function Networks ; RBF networks

Radial-basis functions were first introduces in the solution of the real multivariate interpolation problem. The construction of a RBF network, in its most basic form, involves three layers with entirely different roles. The input layer is made up of source nodes (sensory units) that connect the network to its environment. The second layer, the only hidden layer in the network, applies a nonlinear transformation from the input space to the hidden space; in most applications the hidden space is of high dimensionality. The output layer is linear, supplying the response of the network to the activation pattern (signal) applied to the input layer. A pattern-classification problem cast in a high-dimensional space is more likely to be linearly separable than in a low-dimensional space, hence the reason for frequently making the dimension of the hidden space in an RBF network high [7].

2.1 Radial Basis Functions (RBF)

RBF has response as increase or decrease from center. There are center, radius, main-type etc. as the variables of RBF network, but if the model is linear the variables are static. Representative RBF model is gaussian RBF, and the function is follows.

$$R_i(x) = \exp\left(\frac{(x-c_i)^2}{r_i^2}\right) \tag{1}$$

where c_i is the center point of the i th radial basis function, r_i is the radius of the i th radial basis function.

2.2 Radial Basis Function Networks

The radial basis function networks can be constructed using the RBF in the hidden node of the RBF network. There is no weight value between input layer and hidden layer. So, RBF network has the property of fast processing in the point of calculation.

In comparison with neural network process, RBF network has no weight value in the input-hidden layer connection point but the neural network has weight value in the same point. Generally, RBF network is more efficient than regular neural networks but the RBF in the hidden node of the network is strictly selected.

In summary, the RBF network is good at convergence time being compared with neural network but could be too big in the size of the network. That can be overcome by setting the variables properly. Namely, if we choose the center point and radius efficiently we can decide the radial basis function properly, and the function becomes a node of the hidden layer respectively. This provides a basis that can decide the initial structure of the RBF network.

In this paper, we decide these parameters, center and radius using time-frequency localization method. To overcome the duplication problem, we analyze the target function in the time-frequency plane and compare the localization of the target function and RBF. After that, we can decide the parameters and necessary RBF. Composing these selected RBFs in the hidden nodes of the RBF network, we can construct the initial RBF network structure properly.

In the next section we explain the method, that is, setting the variables of the RBF network using time-frequency analysis.

3. Localization and Genetic Algorithm

3.1 Time-Frequency Localization

In the time plane, to analyze the pattern of the frequency locally, we present the signal as the time-frequency localized function and analyze the signal by considering the time and frequency simultaneously. This analysis is one of the time-frequency analysis methods, is based on the uncertainty theorem by Heisenberg[4].

In the figure 1, the center and width of the time bound is represented as (2) and (3), the center and width of the frequency bound are represented as (4) and (5).

$$t_c(f) = \frac{1}{\|f\|^2}\int_{-\infty}^{\infty} t|f(t)|^2 dt, \qquad (2)$$

$$\sigma_t^2 = \frac{1}{\|f\|^2}\int_{-\infty}^{\infty} (t - t_c(f))^2 |f(t)|^2 dt, \qquad (3)$$

$$\omega_c(\hat{f}) = \frac{1}{\|\hat{f}\|^2}\int_0^{\infty} \omega|\hat{f}(\omega)|^2 d\omega \qquad (4)$$

$$\sigma_\omega^2 = \frac{1}{\|\hat{f}\|^2}\int_0^{\infty} (\omega - \omega_c(\hat{f}))^2 |\hat{f}(\omega)|^2 d\omega \qquad (5)$$

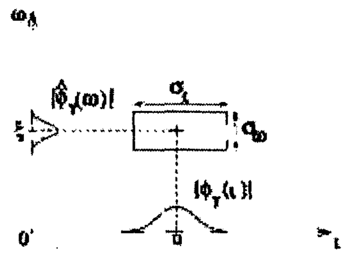

Figure 1. Time-Frequency Atom

When the center and width are decided then, we can compose the time-frequency atom as like the figure 1. This is the analysis method of the characteristic of the function. The figure 2 shows the time-frequency localization result of various RBFs. In this paper, after we analyze the target function in the point of time-frequency plane, we compose the variables of the radial basis function to cover the target function area at the same plane. At this time, radial basis function becomes the hidden node and the number of hidden node could be decided.

The figure 3 represents the result of the analysis of the target function and basis function at the same plane.

The target function is

$$f(t) = t\sin(t)\cos(5t)\sin(10t)\cos(30t)\sin(50t) \qquad (6)$$

and the function is considered in the range of $0 \le t \le 1$.

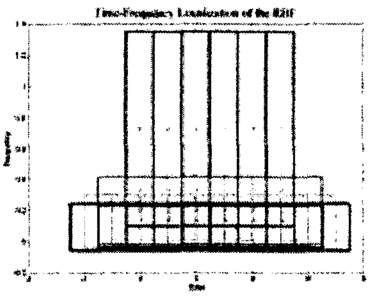

Figure 2. Time-Frequency Localization of RBFs

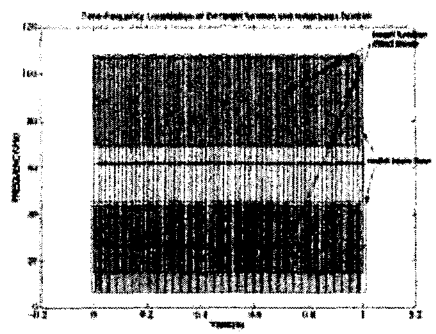

Figure 3. Result of the Time-Frequency Localization

The basis function can be decided by centers and radiuses and the total number of the pairs is 111 in this case. The

number means that the total number of the nodes in the hidden layer is 111.
By this manner, the basis functions that compose the hidden layer are decided and the number of the basis functions is decided as 111 in this case. Namely, we can decide the good structure of RBF network for approximation of the target function. We approximate the target function by learning the weight of this RBF network.

3.2 Genetic Algorithm

The genetic algorithm has been known as a global search algorithm for optimal solution. There are parameters such as string number, string bit size, crossover rate, mutation rate, etc. The genetic algorithm generated from the evolution model in the natural world.
Essentially, the technique has the follows[8].

(1) incorporated a population of individuals encoded as "chromosomes," mainly in a binary representation (i.e., 1s and 0s),
(2) propagated copies of these individuals based on external fitness criteria, and
(3) generated new individuals for each next generation by mutating bits and recombining elements from different members of the population.

The following steps are for construction of the proposed structure.
[step 1] Determine the RBF coefficients (in this paper 111 RBFs determined).

[step 2] Initialize bit string with determined 111 RBF parameters, centers and radiuses.

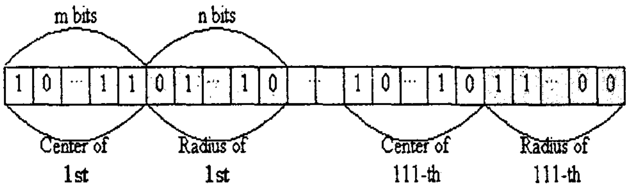

Figure 4. Initialization of Each Chromosomes

[step 3] Set the network and evaluate of the fitness

$$fitness = \frac{1}{\sqrt{\sum_{i=1}^{n}(f(x_i) - g(x_i))^2 / n + 1}} \tag{8}$$

[step 4] Determine a new generation

[step 5] Goto [step 3] until obtaining determined fitness value

[step 6] Construct the network with the selected string.

In the step 4, we use simple crossover and multi-point mutation method. The follow shows the simple crossover operation.

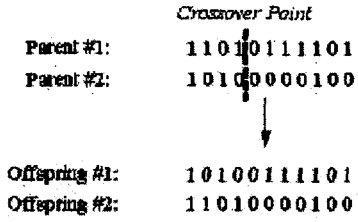

Figure 5. The One-point Crossover Operation

After step 6, we set the RBF network with the obtained center and radius value and learn the weight between hidden layer and output layer using back propagation algorithm.
In the next section, we introduce the approximation problem using the RBF network which is decided by analysis of the time-frequency and generated by genetic algorithm.

4. Simulation

The simulation is the problem of the approximation using RBF network and processes by the following steps. The target function is (6).

[step 1] Target function analysis in the time-frequency plane

[step 2] Deciding the structure of the whole RBF network by deciding number of the basis functions and variables (in this paper the number of decided RBF is 111).

[step 3] Generate the decided RBF using genetic algorithm and get last generation (in this paper the number of generated RBF is 92 and 80).

[step 4] Construct the RBFN with RBF decided after step 3 (in this paper, we select two type in exactly and similar respectively).

[step 5] Weight initialization randomly and learning weight with back-propagation algorithm

[step 6] If the result satisfies the given condition we stop the process and calculate error and result.
The output of the RBF network is like as

$$Y(x) = \sum_{i=1}^{N} \omega_i R_i(x) \tag{9}$$

where ω_i is i th weight between hidden and output layer, N is the number of the hidden node. We use the gaussian function as the basis function composing the hidden node of the RBF network.

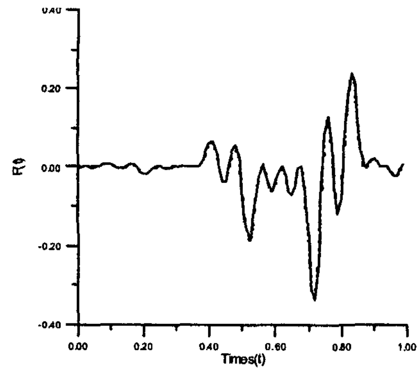

Figure 6. Result of an Approximation Not Using Genetic Algorithm (using 111 RBFs)

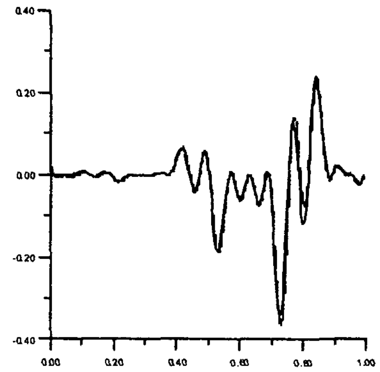

Figure 7. Result of an Approximation after Using Genetic Algorithm (using 92 RBFs)

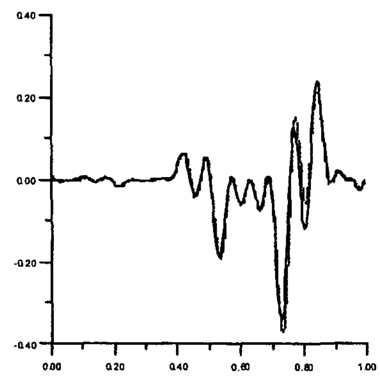

Figure 8. Result of an Approximation after Using Genetic Algorithm (using 80 RBFs)

The iteration of the back-propagation learning is 2500 times and the learning rate is 0.025. In the result, the approximation of the target function by the RBF network is like the figure 7 and figure 8. The figure 7 shows the result of approximation of target funct ion with RBFN constructed with 92 RBFs. These RBFs selected from genetic algorithm by eliminating exactly same ones. On the other hand, the figure 8 shows the result of same simulation with another RBFN constructed with 80 RBFs. These RBFs selected from genetic algorithm by eliminating similar ones. From these results, we confirm the efficiency of the RBFN determined by time-frequency localization and selected using genetic algorithm in the case of function approximation.

5. Simulation

In this paper, we propose the initial structure of the RBF network by time-frequency analysis with the method such that we compare the target function and basis function of the hidden layer of the RBF network simultaneously and decide the basis functions.

This method can overcome the RBF network' s handicap that the size of the network becomes too big. By deciding the initial number of the hidden node and variables of the basis function, we can decide the structure of the RBF network at first. After decision of the necessary RBFs, we process genetic algorithm for finding global solution. We finally decide the RBFs for RBFN from the result of genetic process. Consequently, we can eliminate the exactly same RBFs among the whole RBFs selected from pre-step, time-freqeuncy analysis. The RBF network suggested in this paper shows good performance and has small size at first step. From this result, we can design efficiently initial RBFN structure with time-frequency localization and genetic algorithm.

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References

[1] Simon Harkin, *Neural Networks : A comprehensive foundation*, Prentice Hall, 1999.

[2] Mark J. L. Orr, *Introduction to Radial Basis Function Networks*, Center for Cognitive Science, Scotland, 1996.

[3] James A, Freeman, David M. Skapura, *Neural Networks : Algorighms, Applications, and Programming Techniques*, Addison Wesley, 1991.

[4] Yagyensh C. Pati, "Wavelets and Time-Frequency Methods in Linear Systems and Neural Networks," *Thesis Report for ph.D.*, 1992.

[5] Mark J. L. Orr, *Recent Advances in Radial Basis Function Networks*, Scotland, 1999.

[6] Srinivasa V. Chakravarthy and Joydeep Ghosh, "Scale-Based Clustering Using the Radial Basis Function Network," *IEEE Trans. On Neural Networks*, Vol. 7., No. 5., 1996.

[7] Cover T.M., "Geometrical and statistical properties of systems of linear inequalities with applications in pattern recognition," *IEEE Transactions on Electronic Computers*, Vol. EC-14, pp. 326-334, 1965.

[8] David B. Fogel, *Evolutionary Computation : Toward a New Philosophy of Machine Intelligence*, IEEE Press, 2000.

[9] J. Moody and C. J. Darken, "Fast learning in networks of locally-tuned processing units," *Neural Computation*, No.1, pp.281-294, 1984.