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HYBRID NEURON NETWORKS BASED ON RADIAL BASIS NETWORK WITH DIFFERENT RADIAL BASIS FUNCTION

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Abstract—*It is considered the problem of structural-parametric synthesis of a hybrid neural networks based on the use of radial basis network. Hybridization is achieved through the use of various radial basis functions: Gaussian, multivariate, inverse quadratic, inverse multivariate, thin plate spline, linear, cubic, wavelet functions. The problem of structural-parametric synthesis of hybrid neural network consists in the optimal choice of the number of layers, the number of neurons in the layers, the order of alternation of layers with different neurons. The problem of optimal choice of the number of network cascades and the type of radial basis function in each cascade of the number of layers is solved. Examples of a hybrid neural network synthesis using this methodology for classification and prediction tasks solution are given.*

IndexTerms—Hybrid neural network; structural-parametric synthesis; optimization problem.

I. INTRODUCTION

In present time, many problems are solved with the help of artificial intelligence, or rather artificial neural networks. Many researchers and developers are paying attention to this new technology. This is due to many successful applications of neural networks, and in particular in the context of structural and parametric uncertainty, which is not solved by conventional approaches and algorithms. This success is due to the ability of the neural networks to learn, that is, after the training data is displayed, the algorithm studies certain properties and patterns and universal approximating properties. When learning neural networks, one of the most difficult steps is the selection of hyperparameters of the network, i.e. the type of activation function, the number of layers and neurons in them, the network topology, etc.

There are many tasks that can be solved by neural networks, but some of the most practical and demanding tasks are classification and forecasting. Each of them requires its own architecture and set of network parameters. As a rule, any architecture has its own disadvantages and advantages. Hybridization of networks is one way to solve the disadvantages of a particular architecture. This means splitting one neural network (NN) into several, where each network will be responsible for part of the solution of the problem, and collectively all parts will create a common solution. But as NN architectures and their topologies reach many, the choice of a hybrid neural network (HNN) becomes infinite. Therefore, it is necessary to solve the problem of parametric synthesis of HNN.

II. PROBLEM STATEMENT

The problem of parametric synthesis has two approaches to solving: the first is the determination of the topologies of NNs that are included in HNN, and the second is the selection of neurons and their parameters that are included in one HNN. This paper uses a second approach. As a basic topology, we use a cascade topology, where in each cascade there will be a radial-basis network with different radial-basis functions.

Consider a radial basis network. It is a neural network that has an intermediate layer of radial basis neurons. Such a neuron converts the distance from the input vector to the center by a nonlinear law. Traditionally, this is a single-layer network, which is presented in Fig. 1.

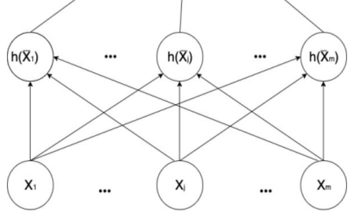

Fig. 1. Radial basis network

$$f(\bar{x}) = \sum_{i=1}^{m} w_j h_j(\bar{x}),$$

where h_j means the function of a neuron, and w_j is the weighting for a neuron j.

Thus the output of the RBF network is a linear combination of some set of basic functions:

Different radially basic functions can be considered as a neuron. In this paper, studies were conducted with the following:

- Gaussian function $h(\bar{x}) = \exp\left(-\frac{r^2}{2s^2}\right)$;
- multiquadric $h(\bar{x}) = \exp\sqrt{1+\left(\frac{r^2}{2s^2}\right)}$;
- inverse quadratic $h(\bar{x}) = \frac{1}{1+\left(\frac{r^2}{2s^2}\right)}$;
- inverse multiquadratic $h(\bar{x}) = \frac{1}{\sqrt{1+\left(\frac{r^2}{2s^2}\right)}}$;
- thin plate spline $h(\bar{x}) = r^2 \ln(r)$;
- linear $h(\bar{x}) = r$;
- cubic $h(\bar{x}) = r^3$,

where $r = \|x-c\|^2$, x is the vector input signal; c is the center vector, it is given at the beginning of training; s is the function width values.

A wavelet function from [1] can also be used as a radially basis function:

$$\varphi_i(x_i) = (1-\alpha_i t_i^2)\exp\left(-\frac{t_i^2}{2}\right),$$

where $t_i = (x_i - c_i)\sigma_i^{-1}$; c_i is the center parameter; σ_i is the width parameter and α_i shape parameter.

Cascade topology was used as the topology. Its principle is that initially the weights of a single layer, when its weights are adjusted, this layer freezes. The following layer is added. It accepts the input vector as well as the outputs of the previous layer. After adjusting the weights of the second layer, the following layer is similarly joined, etc. The topology of the cascade network is presented in Fig. 2.

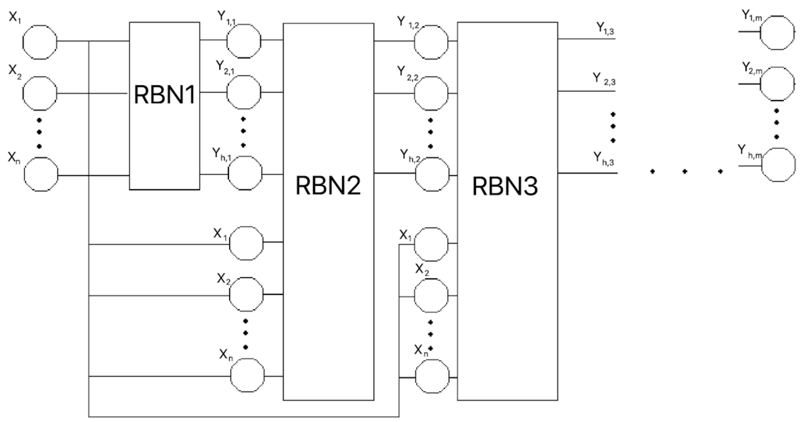

Fig. 2. Cascade topology

The problem of structural-parametric synthesis of HNN is posed, which consists in the optimal choice of the number of layers, the number of neurons in the layers, the order of alternation of layers with different neurons.

Generalized error is selected as the optimization criterion:

$$E(n) = \frac{1}{2}\sum_{j \in C} e^2(n),$$

where $e_j(n)$ is the error signal of the original j neuron at the n iteration and is determined by the ratio $e_j(n) = d_j(n) - y_j(n)$.

III. Overview of Methods

This article was considered with the problem of structural-parametric synthesis of a hybrid neural network based on the use of multilayer perceptron. Hybridization is achieved through the use of artificial neurons of different types, namely Q-neuron, W-neuron, and classic perceptron [2].

It is proposed ([3], [5]) the modification of the architecture of a multilayer hybrid GMDH-neural network by introducing hybrid Q-neurons and W-neurons into the node structure, which allowed to increase the approximate properties of the GMDH-neural networks, increase the number of inputs to the network node, optimize the structure of the hybrid network in the learning process.

A cascade GMDH-wavelet-neuro-fuzzy network was proposed [4]. As nodes of such a network are distinguished R-neurons with the function of Epanechnikov activation and block adaptive fuzzy wavelets with adaptive wavelet function of membership. Was proposed the training algorithms, which have tracking and filtering properties, allow to adjust not only synaptic scales but also the parameters of the activation-belonging function in online mode.

Thus, the problem statement is new.

IV. Problem Solution

To solve this problem, we use a genetic algorithm, namely SPEA2 [6]. The structure of the chromosome consists of the following parameter: number of network cascades, type of radial basis function in each cascade.

The algorithm for solving the problem of structural-parametric synthesis of HNN based on the use of genetic algorithm has the following form:

Set the initial iteration number $i=1$.

1) Form i-cascade network and solve the problem of optimizing the optimal choice of the radial basis function and determining the appropriate weights.

2) If the generalized error for the NN found on the test data satisfies the set threshold then the learning process ends otherwise we proceed to point 4.

3) Form $(i+1)$-cascade network and optimally using GA choice radial basis function and the corresponding weights of the $(i+1)$-cascade (the weights for the previous stages are unchanged).

4) Repeat steps 3 and 4 until the optimal topology is found.

V. Results

The results of the solution of the problem of structural-parametric synthesis of HNN are considered in the example of the problem of classification and forecasting.

A sampling of handwritten numbers from [7] was used for the classification task.

The results of the operation of the optimal HNN according to the criterion of generalized error in solving the classification problem are presented in Table I.

The sample with the lowest temperatures was used for the forecasting task [8]. This sample has a minimum temperature for each day for a specified period. Sampling takes 64 consecutive days to enter the neural network and the next 65 days to exit the neural network.

Table I. Results of Solving the Classification Problem

Number of cascade	**Type of radial basis network**			**Generalized error**
	1st cascade	***2nd cascade***	***3nd cascade***	
3	Radial basis network with inverse multiquadratic function	Radial basis network with inverse multiquadratic function	Radial basis network with wavelet function	0.2246878
2	Radial basis network with inverse multiquadratic function	Radial basis network with wavelet function		0.2255450
3	Radial basis network with cubic function	Radial basis network with gaussian function	Radial basis network with wavelet function	0.235816
2	Radial basis network with gaussian function	Radial basis network with wavelet function		0.2427712

The results of the experiments on the forecasting problem are presented in Table II.

Table II. Results of Solving the Forecasting Problem

Number of cascade	**Type of radial basis network**			**Generalized error**
	1st cascade	***2nd cascade***	***3nd cascade***	
2	Radial basis network with gaussian function	Radial basis network with wavelet function		0.008361
3	Radial basis network	Radial basis network	Radial basis network	0.008849

	with cubic function	with wavelet function	with gaussian function	
3	Radial basis network with gaussian function	Radial basis network with wavelet function	Radial basis network with gaussian function	0.008924
2	Radial basis network with wavelet function	Radial basis network with gaussian function		0.009833

VI. Conclusion

The results of HNN synthesis showed that for the optimal solution of different types of problems it is necessary to use networks with different radial-basis functions and also different alternation of cascades. For the forecasting, the best option is two stages: a Gaussian network and a wavelet function network. And for classification there are three cascades: two in a row of a network with a return multivariate function and a network with a wavelet function.

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О. І. Чумаченко, С. Т. Дичко, А. Р. Рижий. Гібридна нейронна мережа на основі радіально-базисної мережі з різними радіально-базисними функціями

Розглянуто проблему структурно-параметричного синтезу гібридних нейронних мереж на основі використання радіальних базисних мереж. Гібридизація досягається за рахунок використання різних радіальних базисних

функцій: гауссових, багатовимірних, зворотних квадратичних, зворотних багатовимірних, сплайна тонких пластин, лінійних, кубічних, вейвлет-функцій. Завдання структурно-параметричного синтезу гібридної нейронної мережі полягає в оптимальному виборі кількості шарів, кількості нейронів в шарах, порядку чергування шарів з різними нейронами. Розв'язано задачу оптимального вибору кількості мережевих каскадів і типу радіальної базисної функції в кожному каскаді з числа шарів. Наведено приклади синтезу гібридної нейронної мережі з використанням цієї методології для вирішення завдань класифікації та прогнозування.
Ключові слова: гібридна нейронна мережа; структурно-параметричний синтез; проблема оптимізації.

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Е. И. Чумаченко, С. Т. Дычко, А. Р. Рыжий. Гибридная нейронная сеть на основе радиально-базисной сети с различными радиально-базисными функциями

Рассмотрена проблема структурно-параметрического синтеза гибридных нейронных сетей на основе использования радиальных базисных сетей. Гибридизация достигается за счет использования различных радиальных базисных функций: гауссовых, многомерных, обратных квадратичных, обратных многомерных, сплайна тонких пластин, линейных, кубических, вейвлет-функций. Задача структурно-параметрического синтеза гибридной нейронной сети состоит в оптимальном выборе количества слоев, количества нейронов в слоях, порядка чередования слоев с разными нейронами. Решена задача оптимального выбора количества сетевых каскадов и типа радиальной базисной функции в каждом каскаде из числа слоев. Приведены примеры синтеза гибридной нейронной сети с использованием этой методологии для решения задач классификации и прогнозирования.
Ключевые слова: гибридная нейронная сеть; структурно-параметрический синтез; задача оптимизации.

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