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STRUCTURAL SYNTHESIS OF HYBRID NEURAL NETWORKS ENSEMBLES

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***Abstract*—*It is considered the structural synthesis of hybrid neural networks ensembles. It is chosen the ensemble topology as parallel structure with united layer. It is developed a hybrid algorithm for the problem solution which includes some algorithms preliminary choice of classifiers(modules of neural networks-hybrid neural networks, which consist of Kohonen, basic neural networks and bi-directional associative memory), creation the bootstrap training samples for every classifier, training these classifiers, optimal choice of necessity ones, determination of layer union weight coefficients, ensemble pruning. For the solution of optimal choice classifiers it is used two criteria: accuracy and variety.*

Index Terms—Hybrid neural networks ensembles; classifier; bootstrap training sample.

I. INTRODUCTION

For today artificial neural networks (ANN) are widely used in science and industry for the solution of different problems. But for increasing of their efficiency it is necessary to design powerful ANNs, which have a high accuracy and simple algorithms of training. For this purpose it is created the methodology which includes the creation: modules of ANNs and ensembles of modules [1]–[6].

II. OVERVIEW OF METHODS FOR CONSTRUCTING ARTIFICIAL NEURAL NETWORK ASSEMBLIES

An ensemble of neural networks is a group of topologies, united into a single structure, which may differ in architecture, learning algorithms, training criteria, and types of generating neurons. In another variant, the term ensemble means "united model", the output of which is a functional combination of outputs of individual modules.

Input data can be broken down into certain groups for processing in different ANNs or applied to all networks at the same time.

Formation of the ANN ensembles requires a meaningful optimization of two criteria – the qualitative training of a separate ANNs and their optimal association. Well-known algorithms are divided into two classes: algorithms that for new classifiers change the distribution of learning examples based on the accuracy of the previous modules (boosting), and those in which new members of the ensemble learn independently from others (вagging). The main algorithms of combining the ANN in the ensemble and their disadvantages are shown in Table. I.

III. STRUCTURAL-SYNTHESIS OF HYBRID NEURAL NETWORKS ENSEMBLES ALGORITHMS

The creation of structural-synthesis of hybrid neural networks ensembles algorithms represents a very complicated problem. It is a "struggle" between accuracy and complexity. In general it must include the next algorithms:

– preliminary choice of classifiers(modules of neural networks-hybrid neural networks, which consist of Kohonen, basic neural networks and bi-directional associative memory);
– creation the bootstrap training samples for every classifier;
– training these classifiers;
– optimal choice of necessity ones;
– determination of module union coefficients;
– prunning for the solution of optimal choice classifiers, it is used two criteria: accuracy and variety.

IV. CHOICE OF ENSEMBLE STRUCTURE

Let's consider the principles of constructing ensembles of hybrid ANN of successive and parallel structures.

The structure of the organization of a consecutive ensemble consists in supplying the output data of one module to the inputs of another module. A similar structure is used to restore input data or to improve their differences (normalization) for performing the main task (approximation, classification, etc.).

The general scheme of the serial connection of the modules is shown in Fig. 1.

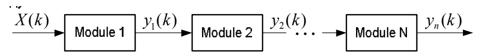

Fig. 1. Consistent connection of modules

TABLE I. CHARACTERISTICS OF THE ALGORITHMS OF THE ASSOCIATION OF EXPERT OPINIONS

Technology	Methodology for obtaining the result	Disadvantages
Static structures		
Boosting	Each new SNN is based on the results previously built.	The presence of more examples of study sample. The degeneration of the SNM ensemble into a complex inefficient neural network structure, requiring a large amount of computing resources. The latest ANN are learn on the "toughest" examples.
Stecking	Applying the concept of the meta training	The complexity of the theoretical analysis through the set of sequentially shaped models. Possible growth of metamodel levels, which can lead to a rapid depletion of computing resources.
Bagging	Formation of the ANN set on the basis of the set of subsets of the training sample and the subsequent integration of the results of the work of the ANN.	Additional computational costs associated with the need to form a large number of subsets of the learning sample. The subsets of the examples differ from each other but are not independent, since all of them are based on the same set. To operate the algorithm, a large amount of data is required for tuning and learning.
Dynamic structures		
Mixing of the results of the work of the ANN	Combining knowledge of ANNs through the use of the gateway network	An algorithm demanding computing resources in the breakdown of the output space. It becomes possible to create a large number of areas, which will lead to excessive clustering of space and will create a large group of basic ANNs with a complex mechanism of interaction through the networks of the gateway. Learning and setting up a hierarchical model represents a complex computational process. The learning process based on the stochastic gradient is based on the adjustment of the weight coefficients of the ANN, the network of the gateway of the first and second levels, which leads to a complex algorithm of complex optimization of the entire neural network machine.

An ensemble in which the input data is set simultaneously to all the modules that make up the hybrid neural network is called parallel. The main element of setting up such an association is the "layer of association", which is responsible for aggregating the results of the various components of the ensemble. The general structure of the parallel ensemble of modules of neural networks is shown in Fig. 2.

A parallel ensemble of neural network with union layer, which is the most generalizing structure, is shown in Fig. 3.

The main disadvantage of the sequential-parallel ensemble is an overly complex algorithm of training with probabilistic convergence.

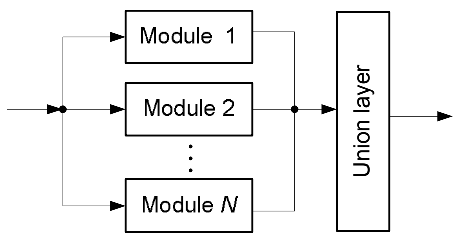

Fig. 2. Parallel connection of modules of neural networks

V. PROBLEM STATEMENT OF NECESSITY CLASSIFIERS OPTIMAL CHOICE

Let $D = \{d_1, …., d_N\}$ be the set of N data points, where $d_i = \{(x_i, y_i) \mid i \in [1, N]\}$ pair of input characters and the label representing the i-th data point, $C = \{c_1, …., c_M\}$ the set of M-modules, where c_j (x_j) gives the prediction of the ith module in the jth point of the data, $V = \{v^{(1)}, …., v^{(N)} \mid v^{(i)} = [v^{(i)}_1, …, v^{(i)}_L], i \in [1, N]\}$ is the set of vectors where $v^{(i)}_J$ is the number of predictions for the ith point of the data element of the ensemble with majority voting (by majority voting), and L is the number of output markers.

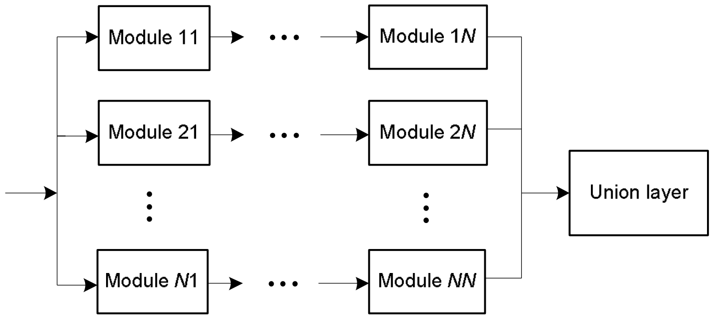

Fig. 3. Parallel structure of ensemble with union layer of neural networks

It is necessary on the basis of the accuracy and diversity of the classifiers $C = \{c_1, …., c_M\}$ to select members for the formation of the ensemble, having a test data set and considering that the networks were previously trained on bootstrap samples [1].

V. Necessity Classifiers Optimal Choice of Problem Solution

From the point of view of the criteria of accuracy, the elements of the ensemble must be hybrid neural networks (modules). Providing diversity is achieved by learning the elements of the ensemble on different sets of data that can be got through the use of the bootstrap method.

The main idea of the bootstrap is that the method of statistical tests Monte–Carlo repeatedly extract repeating samples from the empirical distribution: we take a final set of n members of the initial sample $x_1, x_2, …, x_{n-1}, x_n$, from where in each step with n sequential iterations using a random number generator that is evenly distributed in the interval $[1, n]$, "extracted" an random element x_k, which again "returns" to the output sample (that is, it can be extracted repeatedly).

Therefore, the preliminary stage of building the ensemble is the creation of the main classifiers, which should be independent [1].

1) It is had a set of learning examples $(x_1, y_1), ..., (x_m, y_m)$ with labels $y \in \{1, ..., k\}$.

2) Get t bootstrap samples D_t.

3) Independently (in parallel) to teach t classifiers h_t, each in their sample D_t.

4) Obtain the predictions of each classifier c_i for the jth data point d_j on the test sample and determine the individual contribution.

- If the forecast $c_i(x_j)$ is y_i, then c_i makes the correct predictions in c_j.

– If the forecast $c_i(x_j)$ belongs to a minority group, then the individual contribution is calculated according to the formula

$$\mathrm{IC}_i^{(j)} = 2\upsilon_{\max}^{(j)} - \upsilon_{c_i(x_j)}^{(j)}, \tag{1}$$

– If the forecast $c_i(x_j)$ belongs to the majority group, then the individual contribution is calculated by the formula

$$\mathrm{IC}_i^{(j)} = v_{\sec}^{(j)}. \tag{2}$$

- If the forecast $c_i(x_j)$ is not equal y_i, the individual contribution is calculated by the formula (2).

5) Determine the individual contribution of the classifier c_i according to the formula, where, depending on item 4, an appropriate coefficient is put into unit.

6) Add a couple $\left(c_i, \mathrm{IC}_i^{(j)}\right)$ in the list OL and sort in descending order.

7) Determine the parameter p, which is the desired percentage of classifiers C, which should be preserved at the exit of the subensemble. This parameter is determined based on existing resources such as memory and time consuming.

8) Knowing the desirable cost of resources and real, bring out the first p percent of the list as a shortened and punctured ensemble.

9) To define the weight coefficients of association of the modules in an ensemble after a formula

$$w_i = \frac{c\left(f_i(x)\right)}{\sum_{i=n}^{n} c\left(f_i(x)\right)},$$

where $c(f_i(x)) = \begin{cases} f_i(x), & \text{if } f_i(x) \geq 0.5, \\ 1 - f_i(x), & \text{other way.} \end{cases}$

10) Execute the ensemble pruning with help of Complementary Measure algoritm [5].

VI. CONCLUSION

It is created a new algorithm of structural-parametric synthesis of the ensemble of modules of hybrid neural networks, the optimal structure is defined as a parallel connection of modules of neural networks with a union layer, the choice and training are executed as a result of optimization of the criteria of accuracy and diversity by using proposed prunning algorithm and the method of dynamic averaging, which allows to improve the accuracy of the work at the minimum complexity of the ensemble.

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В. М. Синєглазов, О. І. Чумаченко, О. Р. Бедуха. Стуктурний синтез гібридних ансамблів нейронних мереж

Розглянуто структурний синтез ансамблів гібридних нейронних мереж. У якості топології ансамблю вибрана паралельна структура з шаром об'єднання. Розроблений гібридний алгоритм розв'язання задачі включає алгоритми попереднього вибору класифікаторів (модулів нейронних мереж – гібридні нейронні мережі, які складаються з нейронних мереж Кохонена, базової і двонаправленої асоціативної пам'яті), створення бутстреп навчальних вибірок для кожного класифікатора, навчання цих класифікаторів, оптимальний вибір необхідних класифікаторів, визначення вагових коефіцієнтів шару об'єднання, спрощення ансамблю. Для вирішення завдання оптимального вибору класифікаторів використовуються два критерії: точність і різноманітність.

Ключові слова: гібридні ансамблі нейронних мереж; класифікатор; бутстреп навчальної вибірки.

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В. М. Синеглазов, Е. И. Чумаченко, А. Р. Бедуха. Стуктурный синтез гибридных ансамблей нейронных сетей

Рассмотрен структурный синтез ансамблей гибридных нейронных сетей. В качестве топология ансамбля выбрана параллельная структура со слоем объединения. Разработан гибридный алгоритм решения задачи, который включает в себя некоторые алгоритмы предварительного выбора классификаторов (модулей нейронных сетей – гибридные нейронные сети, которые состоят из нейронных сетей Кохонена, базовой и двунаправленной ассоциативной памяти), создание бутстреп обучающих выборок для каждого классификатора, обучение этих классификаторов, оптимальный выбор необходимых классификаторов, определения весовых коэффициентов слоя объединения, упрощения ансамбля. Для решения задачи оптимального выбора классификаторов используются два критерия: точность и разнообразие.
Ключевые слова: гибридные ансамбли нейронных сетей; классификатор; бутстреп обучающей выборки.

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