COMPUTER-AIDED DESIGN SYSTEMS

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FEATURES OF HYBRID NEURAL NETWORKS USE WITH INPUT DATA OF DIFFERENT TYPES

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Abstract—*The modified topologies of hybrid neural networks which can work with data of different types are introduced.*

Index Terms—Fuzzy logic; hybrid neural networks.

I. INTRODUCTION

Nowadays the intelligent information systems have become widespread. The base of these is the hybrid neural networks consisting of neural networks of different topologies, for example fuzzy types (ANFIS, TSK and Wang & Mendel’s), multilayer perceptron etc. The solution of diagnostic tasks, in particular, in medicine, requires processing of data of various physical nature. This data can be divided into 4 types: crisp, linguistic, fuzzy, binary. It is necessary to choose the topology of neural networks which suits best. The known topologies of artificial neural networks do not allow to solve problems which take into account data of different types so they require modification.

To solve given problem the topologies which are based on the fuzzy perceptron, namely ANFIS, TSK and Wang & Mendel’s network were chosen. These networks allow to use fuzzy input rules for the output signal, provide high accuracy of calculations and have an acceptable performance.

II. PROBLEM STATEMENT

To solve given problem the topologies which are based on the fuzzy perceptron, namely ANFIS, TSK and Wang & Mendel’s network were chosen. These networks allow to use fuzzy input rules for the output signal, provide high accuracy of calculations and have an acceptable performance.

III. MATHEMATICAL MODELS OF THE INPUT DATA

Among the possible inputs of the hybrid neural networks four main groups of input data can be singled out:

– the crisp variables;
– the fuzzy variables;
– the linguistic variables;
– the binary variables.

Let us examine each of the groups thoroughly.

A Crisp variables

The *crisp variable* is a variable which is characterized by the ground set X range of values which can the variable possess. At the same time $X \in R$, where R is the set of real numbers.

B Fuzzy variables

The fuzzy variable can be described *with the help* of the three parameters <*a*, *X*, *A*>,
where: *a* is the name of the fuzzy variable; *X* is the ground set where the values of the variable a are set; A is the fuzzy subset of the general set *X*. For each of its elements it is determined the function μ(*x*) which sets the grade of membership of the given element to the set *A*.

Parameter *A* can be set by the table or analytical methods.

To set the parameter *A* analytically the membership functions of different types are used. The most widespread membership functions are stated below:

– the triangle function:

$$\mu(x)=\begin{cases}0, & x\le a;\\ \dfrac{x-a}{b-a}, & a<x<b;\\ \dfrac{c-x}{c-b}, & b\le x<c;\\ 0, & c\le x,\end{cases}$$

where *a*, *b*, *c* are the set numeric constants.

– the bell function:

$$\mu(x)=\frac{1}{1+\left|\dfrac{x-c}{a}\right|^{2b}},$$

where *a*, *b*, *c* are the set numeric constants.

– the Gaussian function

$$\mu(x) = e^{-\frac{(x-b)^2}{2a^2}},$$

where a, b, are the set numeric constants. [1]

C Linguistic variables

The linguistic variable is the variable which can possess the value of phrases from natural or artificial language. The phrases, the values of which the variables possess, are in turn the names of the set variables and are described by the fuzzy set, i. e. *linguistic variable* is a set of fuzzy variables.

{x, $T(x)$, X, G, M} are called the linguistic variable where:

x is a name of the variable;

$T(x)$ is a set of linguistic variable values x. Every value is a fuzzy variable in the set X;

G is a syntactical rule for the formation of the names of new values of x;

M is a semantic procedure which allows to transform a new name generated through the procedure G into the fuzzy variable (to set a form of the membership function). It associates the name with its value, notion.

$T(x)$ is also called a basic term-set, because it sets a minimal quantity of values. On the basis of these values other admissible values of the linguistic variable with the help of the rules G and M can be formed. The set $T(x)$ and new values of the linguistic variable generated with the help of G and M form an extended term-set. [2]

D Binary variables

Binary variables can possess only two values: either 0 or 1. They can signify the presence or absence of any condition, the answer (yes/no) to the question etc.

IV. SYNTHESIS OF THE TRANSFORMING BLOCK

For the following work it is necessary to transform all types of data to single type with which network will work. The proposed block converts fuzzy, binary and linguistic variables into crisp variables.

A Fuzzy variables

The conversion block is a defuzzyficator, i. e. a converter of fuzzy numbers into crisp numbers. For our system it is used the centroid method of conversion. Depending on the method of presentation of the fuzzy variable (table or analytical presentation) it exist two variants of this method realization:

– for table representation $X_i = \{X_{ij} / \alpha_j\}$, (where X_{ij} is an element of the fuzzy set; α_j is a value of membership function of the corresponding element) [3]

$$X_i^{'} = \frac{\sum_{j=1}^{k} \alpha_j X_{ij}}{\sum_{j=1}^{k} \alpha_j};$$

– for the analytical representation ($X_i = \{X_{ij} / \mu(x)\}$, where X_{ij} is the element of the fuzzy set, $\mu(x)$ is the membership function of the corresponding element). In this case the value of the output variable is defined as a center of mass for the curve $\mu(x)$, where $[a, b]$ is a domain X. [3]

$$X_i^{'} = \frac{\int_a^b x\mu(x)dx}{\int_a^b \mu(x)dx}.$$

Example

Let the fuzzy variable X be set as X = {1/0.5; 2/0.9; 3/0.4}. Then the converted value is:

$$X' = \frac{\sum_{j=1}^{k} \alpha_j X_{ij}}{\sum_{j=1}^{k} \alpha_j} = \frac{1 \cdot 0.6 + 2 \cdot 0.9 + 3 \cdot 0.5}{0.6 + 0.9 + 0.5} = \frac{3.9}{2} = 1.95.$$

B Binary data

For the binary variables processing data is normalized according to the formula:

$$X_{norm} = \frac{(x - x_{\min})(d2 - d1)}{x_{\max} - x_{\min}} + d1,$$

where x is the binary value which is subjected to normalization; $x_{\max}$ is the maximum value of the input data; $x_{\min}$ is the minimum value of the input data.

After the following procedure data is reduced to the required range [$d1$, $d2$].

Example

Let the binary variable X = 1 (i. e. "truth"), $x_{\max}$=1, $x_{\min}$.= 0. Let us reduce X to the range [25, 50]:

$$X_{norm} = \frac{(1-0)(50-25)}{1-0} + 25 = 50.$$

C Linguistic variables

The conversion block consists of two elements and has following appearance (Fig. 1).

The first block ("transformer") with help of knowledge database assigns the term of the linguistic variable with the fuzzy variable.

rule through modeling of the logical operation AND and send to the output:

$$w_i = \min\left(\mu_{i1}(X_1), ..., \mu_{in}(X_n)\right).$$

Layer 3. Neurons of this layer calculate the normalized power of the rule

$$\overline{w_i} = \frac{w_i}{\sum_{j=0}^{n} w_i}.$$

Layer 4. The value of the output variables is formed on this layer

$$y_i = \overline{w_i} f_i.$$

Layer 5. The output signal of the neural network is received and the defuzzyfication of the results is performed on this layer:

$$Y = \frac{\sum_{i=0}^{n} w_i y_i}{\sum_{i=0}^{n} w_i}$$

Then the general mathematical model of the network is a following: [3]

$$Y = \frac{\sum_{i=0}^{n} \left[\min\left(\exp\left[-\left(\frac{X_1 - c_1}{a_1} \right)^2 \right], ..., \exp\left[-\left(\frac{X_n - c_n}{a_n} \right)^2 \right] \right) \right]^2 f_i}{\left(\sum_{i=0}^{n} w_i \right)^2}.$$

The modified network TSK (Fig. 3).

Layer 0. It is analogous to the layer 0 of the modified ANFIS.

Layer 1. Every neuron of this layer is the neuron which transforms the input crisp signal with the help of the membership function (fuzzyficator). Let us use this function:

$$\mu(x) = \frac{1}{1 + \left(\frac{x_j - c_{jk}}{\sigma_{jk}} \right)^{2b_{jk}}}.$$

where c, b and σ are the constants set by the expert.

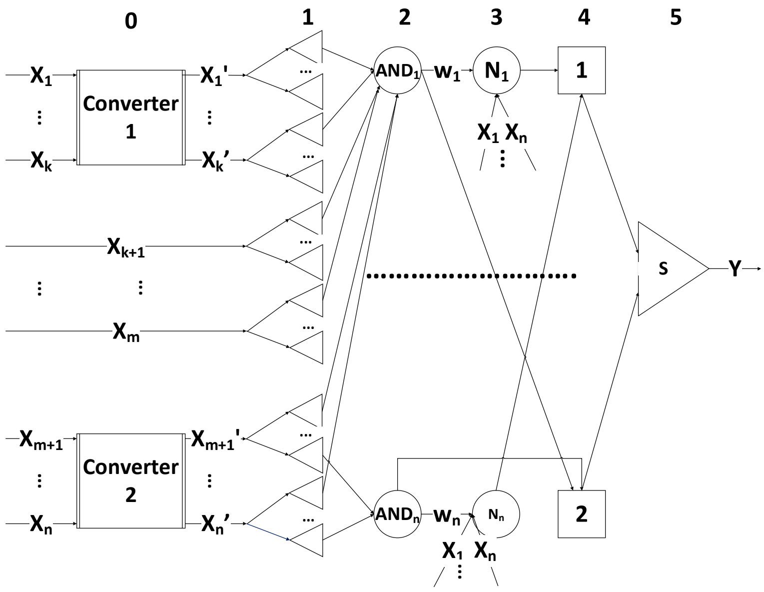

Fig. 3. Modified hybrid neural network TSK

Layer 2. Neurons of this layer perform the aggregation of truth degrees of prerequisites of each rule through modeling of the logical operation AND and send to the output:

$$t_k = \prod_{j=1}^{N} \mu_k(x_j).$$

Layer 3. Neurons of this layer generate the values of the fuzzy rules' output.

$$\overline{w_k} = t_i \left(w_0^k + \sum_{j=1}^{N} w_j^k x_j \right).$$

Layer 4. On this layer the aggregation of the m output rules and the normalizing signal takes place

$$y_1 = \sum_{k=1}^{m} w_k \overline{w_k}; \qquad y_2 = \sum_{k=1}^{m} \overline{w_k}.$$

Layer 5. The output signal of the neural network is received and the defuzzyfication of the results is performed on this layer: [1]

$$Y(x_1, x_2, ..., x_N) = \frac{y_1}{y_2}.$$

Then the general mathematical model of the network is a following:

$$Y=\frac{\sum_{k=1}^{n}\left[\prod_{j=1}^{N}\left(\frac{1}{1+\left(\frac{x_j-c_{jk}}{\sigma_{jk}}\right)^{2b_{jk}}}\right)\times\left(w_0^k+\sum_{j=1}^{N}w_j^k x_j\right)w_k\right]}{\sum_{k=1}^{n}\left[\prod_{j=1}^{N}\left(\frac{1}{1+\left(\frac{x_j-c_{jk}}{\sigma_{jk}}\right)^{2b_{jk}}}\right)\times\left(w_0^k+\sum_{j=1}^{N}w_j^k x_j\right)\right]}.$$

The modified Wang & Mendel's network (Fig. 4).

Layer 0. It is analogous to the layer 0 of the modified ANFIS

Layer 1. Every neuron of this layer is the neuron which transforms the input crisp signal with the help of the membership function (fuzzyficator). Let us use the function:

$$\mu(x)=\frac{1}{1+\left(\frac{x_j-c_{jk}}{\sigma_{jk}}\right)^{2b_{jk}}},$$

where c, b and σ are the constants set by the expert.

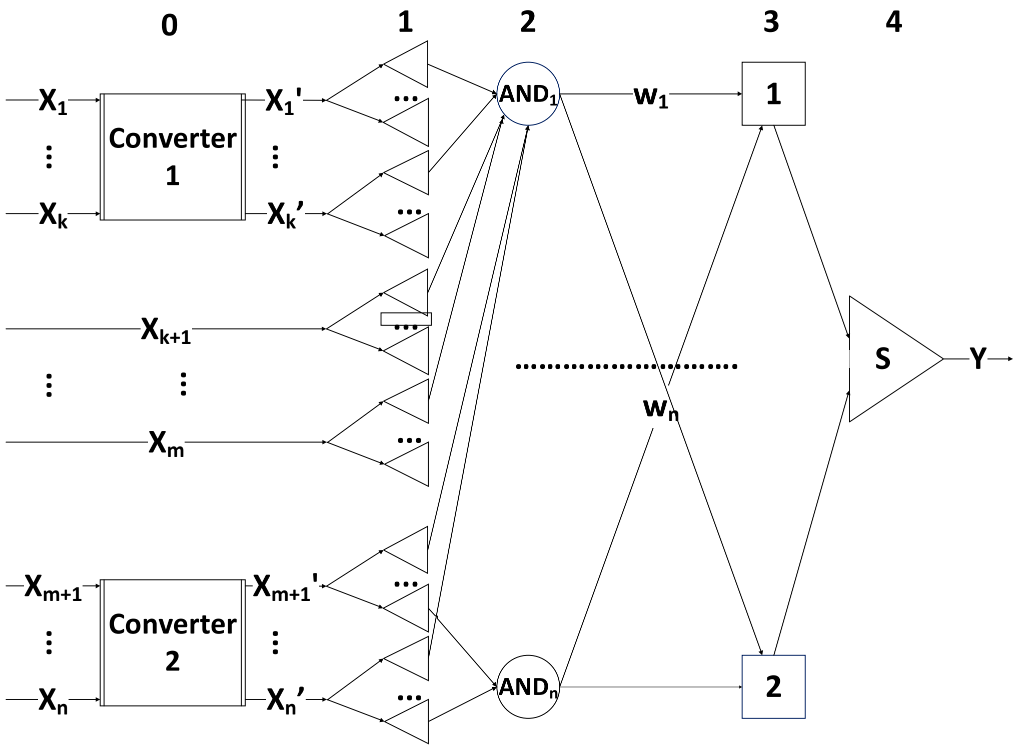

Fig. 4. Modified hybrid neural Wang & Mendel's network

Layer 2. Neurons of this layer perform the aggregation of truth degrees of prerequisites of each rule through modeling of the logical operation AND and send to the output:

$$t_k=\prod_{j=1}^{N}\mu_k(x_j).$$

Layer 3. On this layer the aggregation of the m output rules and the normalizing signal takes place

$$y_1=\sum_{k=1}^{m}w_k t_k; \qquad y_2=\sum_{k=1}^{m}t_k.$$

Layer 4. The output signal of the neural network is received and the defuzzyfication of the results is performed on this layer: [1]

$$Y(x_1,x_2,...,x_N)=\frac{y_1}{y_2}.$$

Then the general mathematical model of the network is a following:

$$Y=\frac{\sum_{k=1}^{n}\left[\prod_{j=1}^{N}\left(\frac{1}{1+\left(\frac{x_j-c_{jk}}{\sigma_{jk}}\right)^{2b_{jk}}}\right)w_k\right]}{\sum_{k=1}^{n}\left[\prod_{j=1}^{N}\left(\frac{1}{1+\left(\frac{x_j-c_{jk}}{\sigma_{jk}}\right)^{2b_{jk}}}\right)\right]}.$$

CONCLUSIONS

In The proposed approach allows to expand the functionality of hybrid neural networks to process data of the following types: crisp, fuzzy, linguistic and binary.

This allows to use these artificial neural networks as an intelligent element in diagnostic systems.

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О. І. Чумаченко, Д. Ю. Коваль, Г. О. Сіпаков, Д. Д. Шевчук. Особливості використання гібридних нейронних мереж з вхідними даними різних типів

Запропоновано модифіковані топології нейронних мереж, які можуть працювати із даними різних типів.

Ключові слова: нечітка логіка; гібридні нейронній мережі.

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Е. И. Чумаченко, Д. Ю.Коваль, Г. А. Сипаков, Д. Д. Шевчук. Особенности использования гибридных нейронных сетей с входными данными разных типов

Предложены модифицированные топологии нейронных сетей, которые могут работать с данными разных типов.
Ключевые слова: нечеткая логика; гибридные нейронные сети.

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