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Multidimensional Neo-Fuzzy-Neuron for Solving Medical Diagnostics Tasks in Online-Mode

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Abstract. *In this paper neuro-fuzzy approach for medical data processing is considered. Special capacities for methods and systems of Computational Intelligence were introduced for Medical Data Mining tasks, like transparency and interpretability of obtained results, ability to classify nonconvex and overlapped classes that correspond to various diagnoses, necessity to process data in online mode and so on. Architecture based on the multidimensional neo-fuzzy-neuron was designed for situation of many diagnoses. For multidimensional neo-fuzzy-neuron adaptive learning algorithms that are a modification of Widrow-Hoff algorithm were introduced. This system was*

approbate on nervous system diseases data set from University of California Irvine (UCI) Repository and show high level of classification results.
Keywords: *Multidimensional neo-fuzzy-neuron, Medical Data Mining, Computational Intelligence, Parkinson disease, learning algorithm, fuzzyfication.*

1. Introduction

Medical Data Mining area solves a problem of human organism condition diagnostics, using plurality of features that were measured in certain scales. Nowadays, there are many methods of Computational Intelligence that can be used for Medical Data Mining tasks [1, 2, 3]. All this methods must have any special capacities, like:
- learning possibility using classified and unclassified data sets (that mean classification/clusterization tasks);
- transparency and interpretability of obtained results [3];
- ability to classify nonconvex and overlapped classes that correspond to various diagnoses;
- ability to process "noise" (with outliers) and nonstationary input data sets that can be extra-small or extra-large in comparison with dimensionality of input vector;
- necessity of processing input data in online-mode.

So these methods can be used in conditions of high uncertainty and overlapping of classes-diagnoses. In medical practice there are any area which correspond described conditions, such as nervous system diseases.

Parkinson's disease is a long term disorder of the central nervous system that mainly affects the motor system [4] The symptoms generally come on slowly over time. Early in the disease, the most obvious are shaking, rigidity, slowness of movement, and difficulty with walking [4]. Thinking and behavioral problems may also occur. Dementia becomes common in the advanced stages of the disease. Other symptoms include sensory, sleep, and emotional problems [4, 5].

The cause of Parkinson's disease is generally unknown, but believed to involve both genetic and environmental factors. The motor symptoms of the disease result from the death of cells in the substantia nigra, a region of the midbrain. This results in not enough dopamine in these areas [4]. The reason for this cell death is poorly understood but involves the build-up of proteins into Lewy bodies in the neurons

[6]. Diagnosis of typical cases is mainly based on symptoms, with tests such as neuroimaging being used to rule out other diseases [4].

In 2013 Parkinson's disease was present in 53 million people and resulted in about 103,000 deaths globally [7, 8]. Parkinson's disease typically occurs in people over the age of 60, of which about one percent are affected [4, 9]. Males are more often affected than females [6].

For Parkinson's disease diagnostic a physician often uses a neurological examination [10] and the medical history of patient. There is no lab test that will clearly identify this disease. That's why a problem of Parkinson's disease diagnostic became important and demanded in Medical Data Mining Tasks.

2. Multidimensional neo-fuzzy-neuron in diagnostic tasks

First systems of binary online diagnostics was Adaptive Linear Element (ADALINE) proposed by B. Widrow [11, 12] and its multidimensional modification MADALINE [13, 11, 12]. But diagnostics using ADALINE and MADALINE is possible only in the case of linearly separable classes-diagnoses. Since in real tasks classes has random form and can be overlapped – that's why neuro-fuzzy technologies in diagnostics tasks became more popular [14]. One of these nonlinear systems is the neo-fuzzy-neuron [15, 16, 17], that is close to ADALINE by its architecture, but it has high approximating properties for nonlinear functions of random forms. Neo-fuzzy-neuron can be used in situation when only one system output can solve a task of two diagnoses. In all other situations, we need a system with more than one output. In multidimensional diagnostics tasks it's possible to connect in parallel neo-fuzzy-neurons, but this system would be too unwieldy and tedious. That's why we can use modification of multidimensional neo-fuzzy-neuron [17, 18] with architecture, presented on fig.1.

In input of multidimensional neo-fuzzy-neuron became vector signal $x(k) = (x_1(k), x_2(k), \ldots, x_n(k))^T \in R^n$. Easy to see that membership function $\mu_{lj}(x_i)$ has common for all systems outputs $u_j(k), y_j(k)$, $j = 1, \ldots, m$. As a membership functions multidimensional neo-fuzzy-neuron uses triangular functions (although it's possible to use other kernel functions, such as B-splines), which value is determined by distance between value of input signal x_i and centers of these functions c_{lj}:

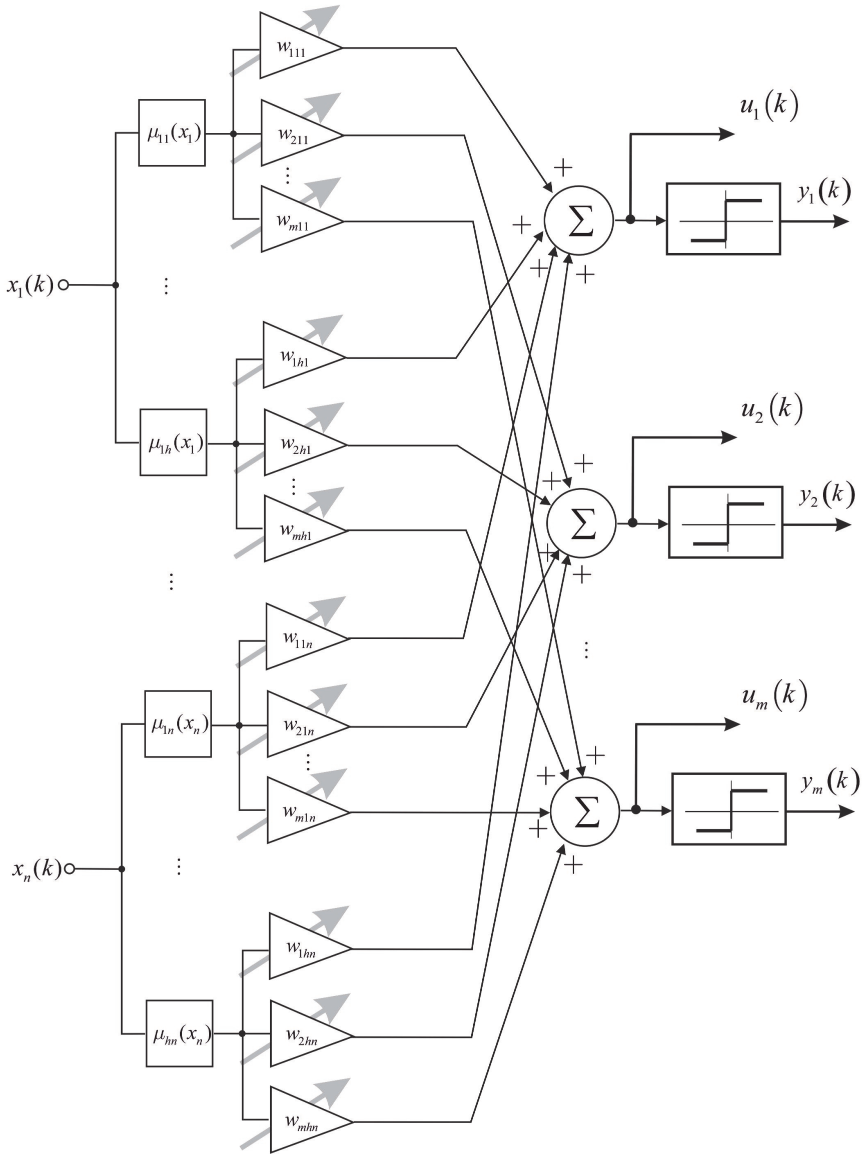

Figure 1: Multidimensional neo-fuzzy-neuron in diagnostics tasks

$$\mu_{li}(x_i) = \begin{cases} \frac{x_i - c_{l-1,i}}{c_{li} - c_{l-1,i}}, & x \in [c_{l-1,i}, c_{li}] \\ \frac{c_{l+1,i} - x_i}{c_{l+1,i} - c_{li}}, & x \in [c_{li}, c_{l+1,i}] \\ 0, & \text{otherwise} \end{cases}$$

$$\begin{cases} \mu_{1i}(x_i) = \frac{c_{1i}-x_i}{c_{2i}}, \\ \mu_{hi}(x_i) = \frac{x_i-c_{h-1,i}}{1-c_{h-1,i}}, \end{cases}$$

$c_{li} = 0, c_{2i} = \frac{1}{h-1}, \ldots, c_{li} = \frac{l-1}{h-1}, \ldots, c_{hi} = 1$, naturally it assumed that all the input data are encoded in the interval $x \in [-1, 1]$.

It's important to note that such structure of membership function automatically provides unity partition $\sum_{i=1}^{n} \mu_{li}(x_i) = 1$ that's means that neo-fuzzy-neuron does not require defuzzification of its results.

Introducing $(nh \times 1)$ vectors of current membership degree values $\mu(k) = (\mu_{11}(x_1(k)), \mu_{21}(x_1(k)), \ldots, \mu_{h1}(x_1(k)), \ldots, \mu_{li}(x_i(k)), \ldots, \mu_{hn}(x_n(k)))^T$ and $(m \times nh)$-matrix of synaptic weights values

$$W(k) = \begin{pmatrix} w_{111}(k) & \ldots & w_{1h1}(k) & \ldots & w_{1li}(k) & \ldots & w_{1hn}(k) \\ w_{211}(k) & \ldots & w_{2h1}(k) & \ldots & w_{2li}(k) & \ldots & w_{2hn}(k) \\ \vdots & \ldots & \ldots & \ldots & \ldots & \ldots & \vdots \\ w_{m11}(k) & \ldots & w_{mh1}(k) & \ldots & w_{mli}(k) & \ldots & w_{mhn}(k) \end{pmatrix}$$

we can write value of analog signal in multidimensional neo-fuzzy neuron output:

$$u_j(k) = \sum_{l=1}^{h} \sum_{i=1}^{n} w_{jli}(k) \mu_{li}(k), \tag{1}$$

and on its binary output:

$$y_j(k) = \text{sign } u_j(k). \tag{2}$$

For system training we can use modification of Widrow-Hoff algorithm [19, 17] and its multidimensional analog in the form [17, 20, 21]:

$$\begin{cases} W(k+1) = W(k) + r^{-1}(k)(d(k) - \text{sign } W(k)\mu(k))\mu^T(k), \\ r(k) = \alpha\, r(k-1) + \|\mu(k)\|^2, \quad 0 \le \alpha \le 1 \end{cases} \tag{3}$$

where $d(k)$ – reference signal, α – forgetting factor.

Using multidimensional neo-fuzzy-neuron modification, presented on fig.1 and its adaptive training algorithm we can solve wide class of online-diagnostics tasks.

3. Experiment

So we going to use multidimensional neo-fuzzy-neuron for solving diagnostic task of nervous system diseases (Parkinson Disease). Input information for our research is data set Oxford Parkinson's Disease Detection Dataset [22] from UCI Machine Learning Repository. The dataset was created by Max Little of the University of Oxford, in collaboration with the National Centre for Voice and Speech, Denver, Colorado, who recorded the speech signals. The original study published the feature extraction methods for general voice disorders.

This dataset is composed of a range of biomedical voice measurements from 31 people, 23 with Parkinson's disease. Each column in the table is a particular voice measure, and each row corresponds one of 195 voice recording from these individuals ("name" column). The main aim of the data is to discriminate healthy people from those with Parkinson's Disease, according to "status" column which is set to 0 for healthy and 1 for Parkinson's Disease.

Attribute information presented in table 1.

Therefore the data set is presented by the table "Object-Properties" that consists of 195 objects and 23 properties. It was divided on training sample (171 objects) and test sample (24 objects). As the criterion of clustering-classification we have used the percent of incorrect classified patterns in test sample.

At first step input information must be standardized and normalized using expression:

$$\widehat{X_i}(k) = \frac{2 \cdot X_i(k) - X_{i\max} - X_{i\min}}{X_{i\max} - X_{i\min}}$$

that's correspond to encoding all input data in the interval $x \in [-1, 1]$.

After that 17-th column which correspond to health status of the subject (1 – Parkinson's, -1 – healthy after encoding) was removed from table "Object- Properties" to vector $d(k)$ and all data set was processed by 3 methods of Computational intelligence: multidimensional neo-fuzzy-neuron, MADALINE, fuzzy C-means clustering algorithm. Table 2 shows the comparative analysis of clustering-classification results based on these three approaches.

Therefore, it is apparent that proposed approach provides best results of clustering-classification among considered.

Table 1: Attribute information

Attribute name in data folder	**Attribute characteristics**
name	ASCII subject name and recording number
MDVP:Fo(Hz)	average vocal fundamental frequency
MDVP:Fhi(Hz)	maximum vocal fundamental frequency
MDVP:Flo(Hz)	minimum vocal fundamental frequency
MDVP:Jitter(%), MDVP:Jitter(Abs), MDVP:RAP, MDVP:PPQ, Jitter:DDP	several measures of variation in fundamental frequency
MDVP:Shimmer, MDVP:Shimmer(dB), Shimmer:APQ3, Shimmer:APQ5, MDVP:APQ, Shimmer:DDA	several measures of variation in amplitude
NHR, HNR	two measures of ratio of noise to tonal components in the voice
Status	health status of the subject: (one) - Parkinson's, (zero) - healthy
RPDE, D2	two nonlinear dynamical complexity measures
DFA	signal fractal scaling exponent
spread1, spread2, PPE	three nonlinear measures of fundamental frequency variation

4. Conclusion

Diagnostic multidimensional neo-fuzzy system and group of it's training adaptive algorithms, assigned for medical diagnostics tasks was proposed. This system is simple by its computational realization and high speed of tuning parameters due to using of optimized training algorithms. Proposed approach was used to processing in conditions of high uncertainty and overlapping of classes-diagnoses for medical data set of nervous system diseases (Parkinson diseases) and show high percent of correct classification.

Table 2: The comparative analysis of clustering-classification results

Neural network	**Error of clustering-classification, train set**	**Error of clustering-classification, check set**
Multidimensional neo-fuzzy-neuron	5,26 %	8,33 %
MADALINE	2,92 %	20,83 %
fuzzy C-means clustering algorithm	33,91 %	25 %

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