17th Int. Conf. on IFSs, Sofia, 1–2 November 2013
Notes on Intuitionistic Fuzzy Sets
Vol. 19, 2013, No. 3, 81–89

Intuitionistic fuzzy Multilayer Perceptron as a part of integrated systems for early forest-fire detection

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Abstract: In this paper we present intuitionistic fuzzy neural network as a part of generalized net model of multi-sensorial integrated systems for early detection of forest fires. Many information and data sources have been used, including infrared images, visual images, sensors data, and geographic data bases. One of the main purpose is using of the intelligent methods for decision when must alarm starts. Here we use intuitionistic fuzzy neural networks, as a one of the possibilities of intelligent systems.

Keywords: Intuitionistic fuzzy set, Index Matrix, Modelling, Neural network.
AMS Classification: 03E72.

1 Introduction

Forest-fire detection is a real-time problem. In fact, early fire detection should be carried out in few seconds or minutes at large [1]. The location of fire with enough resolution is also very important.

The intelligent systems are useful for detections the conditions in natural environments. The detection problem is more complex than in other industrial fields, and then, the direct application of some detection technologies fails.

Here we will use neural network to detect real fire using the intuitionistic fuzzy data, taken from the infrared images, visual images, radar images and others. Infrared images are the basic information source of some existing detection systems. The few existing application have a False Alarm Reduction system to avoid the relatively high false alarm rate of these systems increases significantly their reliability. This is the basic problem that we want to remove.

Visual image processing is also the basis of some existing detection techniques. These techniques can be applied to detect smoke plumes in appropriated lighting conditions and good contrast to segment the plume. Furthermore, it should be noted that all the infrared detection systems provide visual images to the operator.

In this paper is constructed a GN model for integrated systems for early forest-fire detection that use MLP. The mentioned above Intuitionistic Fuzzy Multilayer Perceptron (IFMLP) is a part of this system.

A flame is a mixture of reacting gases and solids emitting visible, infrared, and sometimes ultraviolet light, the frequency spectrum of which depends on the chemical composition of the burning material and intermediate reaction products. In many cases, such as the burning of organic matter, for example wood, or the incomplete combustion of gas, incandescent solid particles called soot produce the familiar red-orange glow of 'fire'. This light has a continuous spectrum.

Flame color depends on several factors, the most important typically being black-body radiation and spectral band emission, with both spectral line emission and spectral line absorption playing smaller roles. In the most common type of flame, hydrocarbon flames, the most important factor determining color is oxygen supply and the extent of fuel-oxygen pre-mixing, which determines the rate of combustion and thus the temperature and reaction paths, thereby producing different color hues.

Here we use one of the first mathematically defined color spaces is the CIE XYZ color space (also known as CIE 1931 color space, Fig. 1), created by the International Commission on Illumination in 1931 [7]. These data were measured for human observers and a 2-degree field of view. In 1964, supplemental data for a 10-degree field of view were published.

The transformation of the RGB and XYZ is shown below [1].

$$\begin{bmatrix} X \\ Y \\ Z \end{bmatrix} = \begin{bmatrix} 0.412453 & 0.357580 & 0.180423 \\ 0.212671 & 0.715160 & 0.72169 \\ 0.019334 & 0.119193 & 0.950227 \end{bmatrix} * \begin{bmatrix} R \\ G \\ B \end{bmatrix}$$

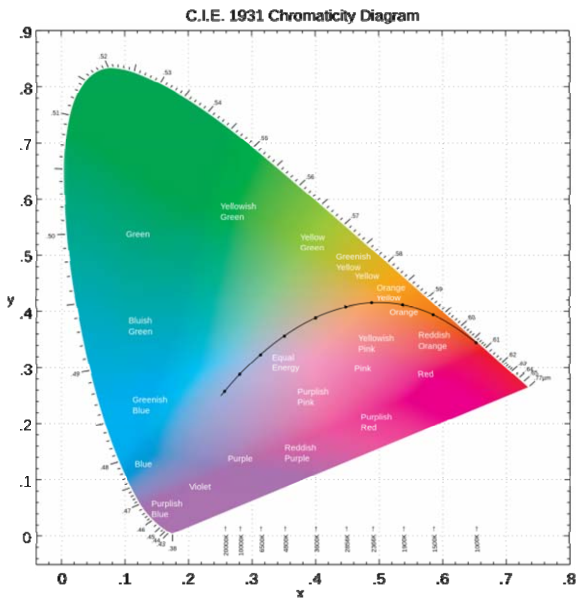

Figure 1. XYZ color space

One application with picture transformation from RGB to XYZ color space and recognition of the fire with Intuitionistic Fuzzy Multi-Layer Perceptron (IFMLP) is shown below.

The process is described below as a follow:

- On the first step we take original picture.
- Second we make transformation from RGB to XYZ color space.
- Third, the regions of fire obtained using the segmentation is utilized in training the MLP neural network. The MLP neural network is trained with the XYZ color space values of the pixels that belong to fire regions.

The IFMLP is ready for recognition. It has a structure 9:15:3 (nine inputs from aperture 3*3; 15 neurons in hidden layer; three outputs neuron in the output layer).

The purpose of verification is to protect the neural network from overfitting. In this case we use for training 90% of the input vector, 5 % for verifications and 5 % for testing.

In a series of papers, the process of functioning and the results of the work of different types of neural networks are described by Generalized Nets [2, 6, 10, 13, 15].

In [14] was proposed a Multilayer Perceptron Neural Network that uses intuitionistic fuzzy logic (IFL). The formal description of the MLP is the following

$$\Big\langle \langle p_1, p_2, \ldots, p_{n0} \rangle^T, \left\{ \langle a_1^i, a_2^i, \ldots, a_{n_i}^i \rangle^T \middle| 1 \le i \le k \right\},$$

$$\left\{ \langle W_{1,1}^j, W_{1,2}^j, \ldots, W_{1,n_0}^j; W_{2,1}^j, W_{2,2}^j, \ldots, W_{2,n_1}^j; \ldots, W_{n_{k-1},1}^j, W_{n_{k-1},2}^j, \ldots, W_{n_{k-1},n_k}^j \rangle \;\middle|\; 0 \le j \le k \right\},$$

$$\left\{ \langle b_1^i, b_2^i, \ldots, b_{n_i}^i \rangle^T \middle| 1 \le i \le k \right\}, \left\{ \langle F_1^i, F_2^i, \ldots, F_{n_i}^i \rangle^T \middle| 1 \le i \le k \right\} \Big\rangle,$$

where

- T – operation "transposition";
- k – number of layers of neurons;
- n_k – number of neurons in the layer with number k (n_0 is a number of the zero (input) layer);
- $p_1, p_2, \ldots, p_{n_0}$ – input values for nodes from layer 1;
- $a_1^i, a_2^i, \ldots, a_{n_i}^i$ – outputs for the neurons on i-th layer;
- $W_{x,y}^z$ – weight coefficient from the input node x to the neuron numbered with y on layer z;
- $b_1^i, b_2^i, \ldots, b_{n_i}^i$ – bias coefficient for the neurons on i-th layer;
- $F_1^i, F_2^i, \ldots, F_{n_i}^i$ – transfer function for the neurons on i-th layer.

Intuitionistic Fuzzy Logic [4] (IFL) are defined as extensions of ordinary fuzzy sets. All results which are valid for fuzzy sets can be transformed here too. Also, all research, for which the apparatus of fuzzy sets can be used, can be used to describe the details of IFL.

On the other hand, there have been defined over IFL not only operations similar to those of ordinary fuzzy sets, but also operators that cannot be defined in the case of ordinary fuzzy sets.

Let a set E be fixed. An IFS A in E is an object of the following form:

$$A = \{\langle x, \mu_A(x), \nu_A(x) \rangle \mid x \in E\},$$

where functions $\mu_A : E \to [0, 1]$ and $\nu_A : E \to [0, 1]$ define the degree of membership and the degree of non-membership of the element $x \in E$, respectively, and for every $x \in E$:

$$0 \le \mu_A(x) + \nu_A(x) \le 1,$$

For every $x \in E$, let

$$\pi_A(x) = 1 - \mu_A(x) - \nu_A(x).$$

Therefore, the function π determines the degree of uncertainty.

Obviously, for every ordinary fuzzy set $\pi_A(x) = 0$ for each $x \in E$, these sets have the form:

$$\{\langle x, \mu_A(x), 1 - \mu_A(x)\rangle \mid x \in E\}.$$

Let a universe E be given. One of the geometrical interpretations of the IFL uses the interpretational triangle F as shown on Figure 2.

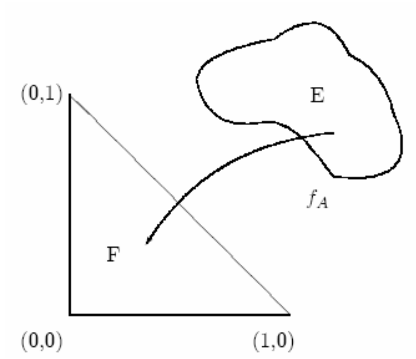

Figure 2. Geometrical interpretation of an IFS

For each input p of the IFMLP we have respective element

$$p = \langle\langle \mu_{p_1}, \nu_{p_1}\rangle, \langle \mu_{p_2}, \nu_{p_2}\rangle, \ldots, \langle \mu_{p_R}, \nu_{p_n}\rangle\rangle$$

with weight coefficient from the IF weight matrix w.

$$w = \langle\langle \mu_{w_{1,1}}, \nu_{w_{1,1}}\rangle, \langle \mu_{w_{1,2}}, \nu_{w_{1,2}}\rangle, \ldots, \langle \mu_{w_{1,R}}, \nu_{w_{1,R}}\rangle\rangle$$

On the inputs $p_1, \ldots, p_n$ of the IFMLP there are values from the XYZ color space (given below).

Outputs a_μ, a_ν and a_π obtain intuitionistic fuzzy evaluations. The first output gives the degree of the affiliations of the fire – μ; the second – degree of a non affiliations of the fire – ν, and the third – degree of uncertainty $\pi = 1 - \mu - \nu$. The estimation reflects the possibilities of fire occurrence.

Initially when still no information has been obtained, all estimations are given initial values of $\langle 0, 0\rangle$. When $k \geq 0$, the current $(k + 1)$-st estimation is calculated on the basis of the previous estimations according to the recurrence relation

$$\langle \mu_{k+1}, \nu_{k+1}\rangle = \left\langle \frac{\mu_k k + m}{k+1}, \frac{\nu_k k + n}{k+1} \right\rangle,$$

where $\langle \mu_k, \nu_k\rangle$ is the previous estimation, and $\langle \mu, \nu\rangle$ is the estimation of the latest measurement, for $m, n \in [0, 1]$ and $m + n \leq 1$.

2 GN-Model

The below constructed GN-model [3, 5] is a reduced one. It does not have temporal components, the priorities of the transitions, places and tokens are equal, the place and arc capacities are equal to infinity.

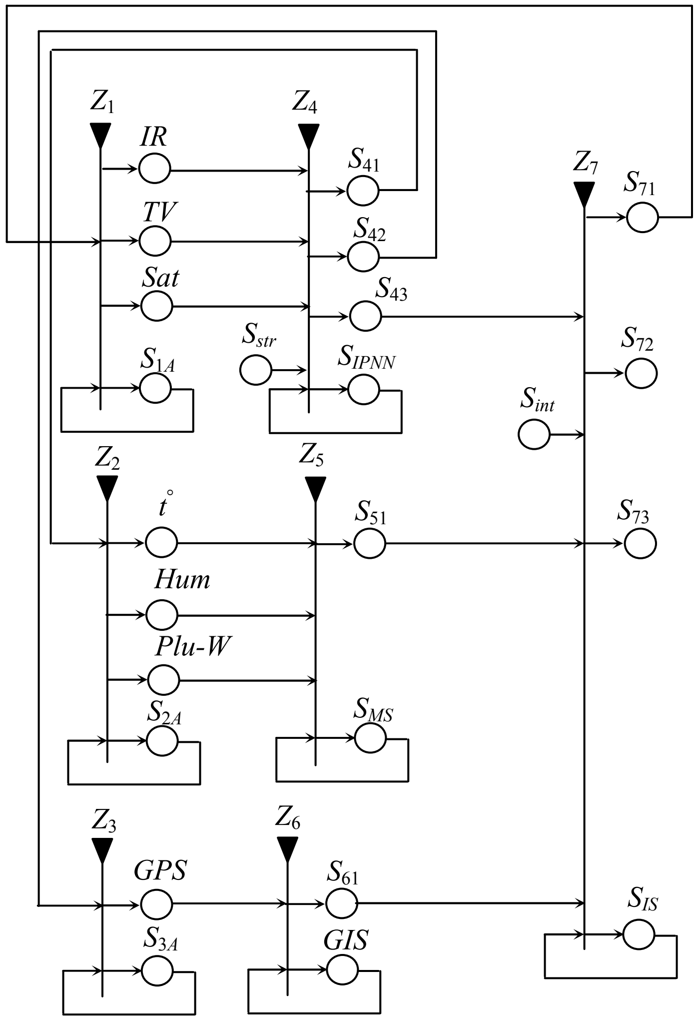

Figure 3. Generalized net model of the integrated systems for early forest-fire detection

Initially, the tokens α, β, γ, δ, ε, ξ and τ stay in places S_{1A}, S_{2A}, S_{3A}, S_{IP}, S_{MS}, S_{GIS} and S_{IS}. They will remain in their own places during the whole time during which the GN functions. All tokens that enter transitions Z_1, Z_2, Z_3, Z_4, Z_5, Z_6 and Z_7 will unite with the corresponding original token (α, β, γ, δ, ε, ξ and τ, respectively). While the α, β, γ, δ, ε, ξ and τ tokens may split into two or more tokens, the original token will remain in its own place the whole time. The original tokens have the following initial and current characteristics:

- token α in place S_{1A}: x_{cu}^{α} = "Current image devices",
- token β in place S_{2A}: x_{cu}^{β} = "Current local meteorological devices",
- token γ in place S_{3A}: x_{cu}^{γ} = "GPS system",
- token δ in place S_{IPNN}: x_{cu}^{δ} = "Systems for image processing and IFMLP",
- token ε in place S_{MS}: x_{cu}^{ε} = "Local meteorological station",
- token ξ in place S_{GIS}: x_{cu}^{ξ} = "Geo-information system",
- token τ in place S_{IS}: x_{cu}^{τ} = "Decision makers system".

The generalized net is presented by a set of transitions:

$$A = \{Z_1, Z_2, Z_3, Z_4, Z_5, Z_6, Z_7\},$$

where the transitions describe the following processes:

- Z_1 – Work of the image devices;
- Z_2 – Work of the local meteorological devices;
- Z_3 – Work of the GPS system;
- Z_4 – Image processing and work of the IFMLP;
- Z_5 – Meteorological processing;
- Z_6 – Work of the Geo Information system;
- Z_7 – Work of the decision making system.

The transitions of GN-model have the following form.

$$Z_1 = \langle \{S_{1A}, S_{71}\}, \{IR, TV, Sat, S_{1A}\}, R_1, \vee(S_{1A}, S_{71})\rangle,$$

$$R_1 = \begin{array}{c|cccc} & IR & TV & Sat & S_{1A} \\ \hline S_{1A} & W_{1A,IR} & W_{1A,TV} & W_{1A,Sat} & True \\ S_{71} & False & False & False & True \end{array},$$

where:

- $W_{1A,IR}$ = "There is an information from an infrared camera",
- $W_{1A,TV}$ = "There is an information from a TV camera",
- $W_{1A,Sat}$ = "There is an information from a satellite".

The τ_1-token that enters place S_{1A} (from place S_{71}) do not obtain new characteristic. It unites with the α-token in place S_{1A} with the above mentioned characteristic.

The α_1-, α_2- and α_3-tokens that enter places *IR*, *TV* and *Sat* obtain characteristic respectively: $x_{cu}^{\alpha_1}$ = "Information from infrared camera" in place *IR*, $x_{cu}^{\alpha_2}$ = "Information from TV camera" in place *TV*, $x_{cu}^{\alpha_3}$ = "Information from satellite" in place *Sat*.

$$Z_2 = \langle \{S_{2A}, S_{41}\}, \{t^\circ, Hum, Plu\text{-}W, S_{2A}\}, R_2, \vee(S_{2A}, S_{41})\rangle,$$

$$R_2 = \begin{array}{c|cccc} & t^\circ & Hum & Plu-W & S_{2A} \\ \hline S_{2A} & W_{2A,t} & W_{2A,Hum} & W_{2A,Plu-W} & True \\ S_{41} & False & False & False & True \end{array},$$

where

- $W_{2A,t}$ = "There is an information from a thermometer",
- $W_{2A,Hum}$ = "There is an information from a humidity sensor",
- $W_{2A,Plu\text{-}W}$ = "There is an information from a pluviometer and wind speed".

The α_4-token that enters place S_{2A} (from place S_{41}) do not obtain new characteristic. It unites with the β-token in place S_{2A} with the above mentioned characteristic.

The β_1-, β_2- and β_3-tokens that enter places t°, *Hum* and *Plu-W* obtain characteristic respectively: $x_{cu}^{\beta_1}$ = "Information from thermometer" in place t°, $x_{cu}^{\beta_2}$ = "Information from humidity sensor" in place *Hum*, $x_{cu}^{\beta_3}$ = "Information from pluviometer and wind speedometer" in place *Plu-W*.

$$Z_3 = \langle \{S_{3A}, S_{42}\}, \{GPS, S_{3A}\}, R_3, \vee(S_{3A}, S_{42})\rangle,$$

$$R_3 = \begin{array}{c|cc} & GPS & S_{3A} \\ \hline S_{3A} & W_{3A,GPS} & True \\ S_{42} & False & True \end{array},$$

where $W_{3A,GPS}$ = “There is an information from a satellite”.

The α_5-token that enters place S_{3A} (from place S_{42}) do not obtain new characteristic. It unites with the γ-token in place S_{3A} with the above mentioned characteristic.

The γ_1-token that enters place *GPS* obtain characteristic: $x_{cu}^{\gamma_1}$ = “Information from satellite” in place *GPS*.

From place S_{STR} ω-token enters the net with characteristic x_{cu}^{ω} = “Current structure of the IFMLP”.

$$Z_4 = \langle\{IR, TV, Sat, S_{IP}, S_{STR}\}, \{S_{41}, S_{42}, S_{43}, S_{IP}\}, R_4, \vee(\wedge(IR, TV, Sat), S_{IP}, S_{STR})\rangle,$$

$$R_4 = \begin{array}{c|cccc} & S_{41} & S_{42} & S_{43} & S_{IP} \\ \hline IR & False & False & False & True \\ TV & False & False & False & True \\ Sat & False & False & False & True \\ S_{IP} & W_{IP,41} & W_{IP,42} & W_{IP,43} & True \\ S_{STR} & False & False & False & True \end{array},$$

where

- $W_{IP,41}$ = “There is a query for information from local meteorological devices”,
- $W_{IP,42}$ = “There is a query for information from satellite”,
- $W_{IP,43}$ = “There is an information from image devices”.

The α_1-, α_2- and α_3-tokens that enter place S_{IP} (from places *IR*, *TV* and *Sat*) do not obtain new characteristic. They unite with the δ-token in place S_{IP} with the above mentioned characteristic.

The α_4-, α_5- and α_6-tokens that enter places S_{41}, S_{42} and S_{43} obtain characteristic respectively: $x_{cu}^{\alpha_4}$ = “Query for information from local meteorological devices” in place S_{41}, $x_{cu}^{\alpha_5}$ = “Query for information from satellite” in place S_{42}, and $x_{cu}^{\alpha_6}$ = “Information from image devices, $\langle\mu, \nu\rangle$” in place S_{43}.

$$Z_5 = \langle\{t°, Hum, Plu\text{-}W, S_{MS}\}, \{S_{51}, S_{MS}\}, R_5, \vee(\wedge(t°, Hum, Plu\text{-}W), S_{MS})\rangle,$$

$$R_5 = \begin{array}{c|cc} & S_{51} & S_{MS} \\ \hline t° & False & True \\ Hum & False & True \\ Plu-W & False & True \\ S_{MS} & W_{MS,51} & True \end{array},$$

where $W_{MS,51}$ = “There is an information from a thermometer”.

The β_1-, β_2- and β_3-tokens that enter place S_{MS} do not obtain new characteristic. They unite with the ε-token in place S_{MS} with the above mentioned characteristic.

The β_4-token that enters place S_{51} obtain characteristic: $x_{cu}^{\beta_3}$ = “Information from local meteorological devices”.

$$Z_6 = \langle\{GPS, GIS\}, \{S_{61}, GIS\}, R_6, \vee(GPS, GIS)\rangle,$$

$$R_6 = \begin{array}{c|cc} & S_{61} & GIS \\ \hline GPS & False & True \\ GIS & W_{GIS,61} & True \end{array},$$

where $W_{GIS,61}$ = "There is an information from a satellite".

The γ_1-token that enters place *GIS* (from place *GPS*) do not obtain new characteristic. It unites with the ξ-token in place *GIS* with the above mentioned characteristic.

The γ_2-token that enters place S_{61} obtain characteristic: $x_{cu}^{\gamma_2}$ = "Information from satellite".

From place S_{int} τ_0-token enters the net with characteristic: $x_{cu}^{\tau_0}$ = "New decision making system".

$$Z_7 = \langle \{S_{43}, S_{51}, S_{61}, S_{IS}\}, \{S_{71}, S_{72}, S_{73}, S_{IS}\}, R_7, \vee(\wedge(S_{43}, S_{51}, S_{61}), S_{IS})\rangle,$$

$$R_7 = \begin{array}{c|cccc} & S_{71} & S_{72} & S_{73} & S_{IS} \\ \hline S_{43} & False & False & False & True \\ S_{51} & False & False & False & True \\ S_{61} & False & False & False & True \\ S_{IS} & W_{IS,71} & W_{IS,72} & W_{IS,73} & True \end{array},$$

where

- $W_{IS,71}$ = "There is a query for setup of the image devices",
- $W_{IS,72}$ = "There is an information for external devices",
- $W_{IS,73}$ = "There is a signal for the alarm".

The α_6-, β_4- and γ_2-tokens that enter place S_{IS} (from places S_{43}, S_{51} and S_{61}) do not obtain new characteristic. They unite with the τ-token in place S_{IS} with the above mentioned characteristic.

The τ_1-, τ_2- and τ_3-tokens that enter places S_{71}, S_{72} and S_{73} obtain characteristic respectively: $x_{cu}^{\tau_1}$ = "Query for information from local meteorological devices" in place S_{41}, $x_{cu}^{\tau_2}$ = "Query for information from satellite" in place S_{42}, and $x_{cu}^{\tau_3}$ = "Information from image devices" in place S_{43}.

3 Conclusion

In this paper was presented an intuitionistic fuzzy neural network as a part of generalized net model of multi-sensorial integrated systems for early detection of forest fires. On the inputs of the IFMLP we put intuitionistic fuzzy values taken from the YXZ color space. On the outputs we obtain intuitionistic fuzzy estimations of the possibilities for the real fire. The neural network is learned with data that are in spectrum of the fire of XYZ color space. The IFMLP is a part from one integrated early forest fire detection system that use many information and data sources – infrared images, visual images, sensors data, and geographic data bases. One of the main purposes is using of the intelligent methods for decision when must a fire alarm be triggered.

Acknowledgements

This research is supported by the National Science Fund of Bulgaria (Grant DFNI-I-01-0006).

References

[1] Angayarkkani, K., N. Radhakrishnan, An Intelligent System For Effective Forest Fire Detection Using Spatial Data, *International Journal of Computer Science and Information Security*, Vol. 7, 2010, No. 1, 202–208.

[2] Antonov, A., Generalized net model for parallel training of hidden units in neural networks with radial basis functions, *Comptes rendus de l'Academie bulgare des Sciences*, Vol. 66, 2013, No. 9, 1239–1246.

[3] Atanassov, K. *Generalized Nets*, World Scientific, Singapore, 1991.

[4] Atanassov, K. *On Generalized Nets Theory*, "Prof. M. Drinov" Academic Publishing House, Sofia, 2007.

[5] Atanassov, K. *On Intuitionistic Fuzzy Sets Theory*. Studies in fuzziness and soft computing, Springer Physica-Verlag, Berlin, 2012.

[6] Atanassov, K., S. Sotirov, A. Antonov, Generalized net model for parallel optimization of feed-forward neural network, *Advanced Studies in Contemporary Mathematics*,Vol.15, No. 1, 2007, 109–119.

[7] *Commission internationale de l'Eclairage proceedings*, 1931. Cambridge: Cambridge University Press.

[8] Hagan, M., H. Demuth, M. Beale, *Neural Network Design*, PWS Publishing, Boston, MA, 1996.

[9] Haykin, S. *Neural Networks: A Comprehensive Foundation*, NY: Macmillan, 1994.

[10] Krawczak, M. *Generalized Net Models of Systems*, Bulletin of Polish Academy of Science, 2003.

[11] Rumelhart, D., G. Hinton, R. Williams. Training representation by back-propagation errors, *Nature*, Vol. 323, 1986, 533–536.

[12] Sotirov, S. A method of accelerating neural network training, *Neural Processing Letters*, Springer Science+Business Media B.V., Formerly Kluwer Academic Publishers B.V., Vol. 22, Oct 2005, Issue 2, 163–169.

[13] Sotirov, S. Modeling the algorithm Backpropagation for training of neural networks with generalized nets. Part 1, *Proceedings of the 4th International Workshop on Generalized Nets*, Sofia, 23 September 2003, 61–67.

[14] Sotirov, S., K. Atanassov, Intuitionistic Fuzzy Feed Forward Neural Network. Part 1, *Cybernetics and Information Technologies*, Vol. 2, 2009, 62–68.

[15] Sotirov, S., M. Krawczak. Modeling the algorithm Backpropagation for training of neural networks with generalized nets. Part 2, *Issues in Intuitionistic Fuzzy Sets and Generalized nets, Warsaw*, 2003, 65–70.