New Trends in Fuzzy Sets, Intuitionistic Fuzzy Sets, Generalized Nets and Related Topics
Volume II: Applications

Editors

Krassimir T. Atanassov
Władysław Homenda
Olgierd Hryniewicz
Janusz Kacprzyk
Maciej Krawczak
Zbigniew Nahorski
Eulalia Szmidt
Sławomir Zadrożny

SRI PAS **IBS PAN**

New Trends in Fuzzy Sets,
Intuitionistic Fuzzy Sets,
Generalized Nets and Related Topics
Volume II: Applications

Editors

Krassimir Atanassov
Władysław Homenda
Olgierd Hryniewicz
Janusz Kacprzyk
Maciej Krawczak
Zbigniew Nahorski
Eulalia Szmidt
Sławomir Zadrożny

IBS PAN iBS PAN **SRI PAS**

Systems Research Institute
Polish Academy of Sciences
Newelska 6, 01-447 Warsaw, Poland
www.ibspan.waw.pl

ISBN 83-894-7547-2

Modelling the brain-state-in-a-box neural network with a generalized net

Sotir Sotirov[1], Maciej Krawczak[2] and Krassimir Atanassov[1,3]
[1]Prof. Asen Zlatarov University, Bourgas, Bulgaria, ssotirov@btu.bg
[2]Systems Research Institute, Polish Academy of Sciences, Warsaw, Poland
krawczak@ibspan.waw.pl
[3]IBFME, Bulgarian Academy of Sciences, Sofia, Bulgaria
krat@bas.bg

Abstract

Here we discuss the possibilities to use the used generalized net for modeling some recurrent neural networks. The current type of neural network is one of the recurrent types with name "Brain stay in a box"

Keywords: Generalized Nets, Modelling, Recurent Neural network,

1. Introduction

The proposed generalized net model describe an associative memory by studying the *brain-state-in-a-box (BSB) model,* which was first described by Anderson et al. [1]. The BSB model is basically a *positive feedback system with amplitude limitation.* It consists of a highly interconnected set of neurons that feed back upon themselves. This model operates by using the built-in positive feedback to *amplify* an input pattern until all the neurons in the model are driven into saturation. The BSB model may thus be viewed as a categorization device in that an analog input pattern is given a digital representation defined by a stable state of the model.

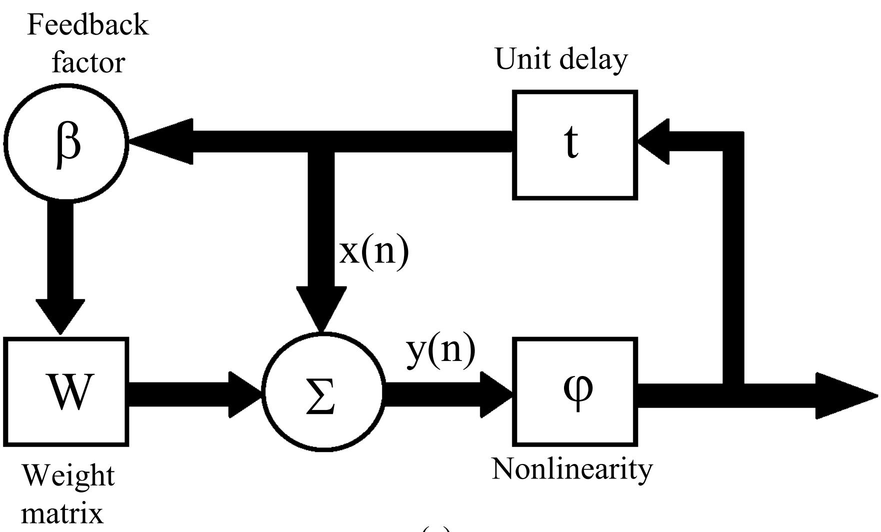
Let W denote a *symmetric weight matrix* whose largest eigenvalues have positive real components. Let x(0) denote the *initial state vector* of the model, representing an input activation pattern. Assuming that there are *N* neurons in the model, the state vector of the model has dimension *N,* and the weight matrix W is an *N-by-N* matrix. The BSB algorithm is then completely defined by the following pair of equations:

$$y(n) = x(n) + \beta W x(n)$$
$$x(n+1) = \varphi(y(n)) \qquad (1) \text{ and } (2)$$

where β is a small positive constant called *the feedback factor* and *x(n)* is the state vector of the model at discrete time *n.* Next Figure (a) shows a block diagram of the combination of Eqs. (1) and (2); the block labeled W represents a single-layer linear neural network, as depicted in Fig. b. The activation function φ is a *piecewise-linear function* that operates on *y(n),* the j-th component of the vector y*(n),* as follows:

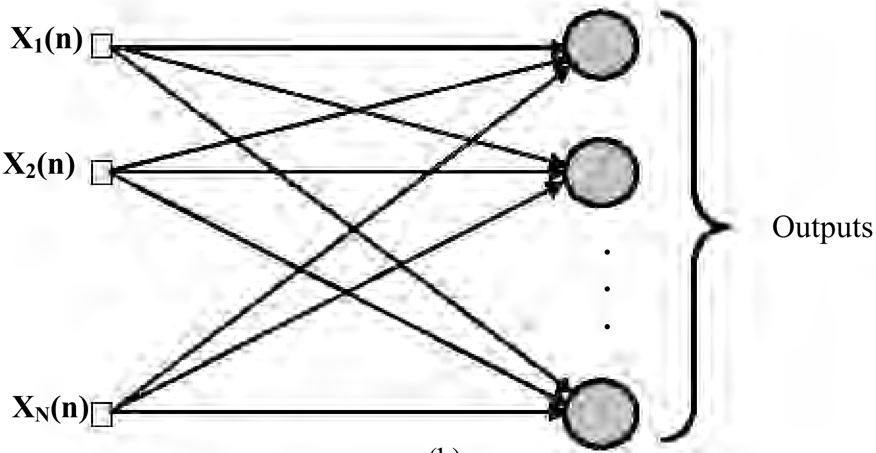
$$x_j(n+1) = \varphi(y_j(n))$$
$$= \begin{cases} +1 \text{ if } y_j(n) > +1 \\ y_j(\text{n}) \text{ if -} 1 \le y_j(n) \\ +1 \text{ if } y_j(n) > -1 \end{cases} \qquad (3)$$

The algorithm thus proceeds as follows. An activation pattern x(0) is input into the BSB model as the initial state vector, and Eq. (1) is used to compute the vector y(0). Equation (2) is then used to truncate y(0), obtaining the updated state vector x(l). Next, x(l) is cycled through Eqs. (1) and (2), thereby obtaining x(2).



(a)

This procedure is repeated until the BSB model reaches a *stable state* represented by a particular corner of the unit hypercube. Intuitively, positive feedback in the BSB model causes the initial state vector **x**(0) to increase in Euclidean length (norm) with an increasing number of iterations until it hits a wall of the box (unit hypercube), then slides along the wall and eventually ends up in a stable corner of the box, where it keeps on "pushing" but cannot get out of the box described by Kawamoto and Anderson in [6], hence the name of the model.



(b)

Figure 2. (a) Block diagram of the brain-state-in- a-box (BSB) model, (b) Signal- flow graph of the linear associator represented by the weight matrix W.

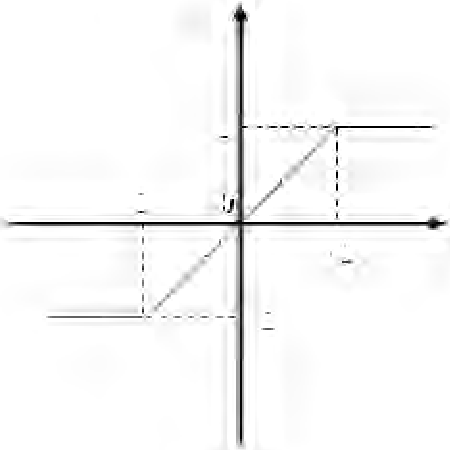


Figure 3. Piecewise- linear activation function used in the BSB model.
causes the initial state vector **x**(0) to increase in Euclidean length (norm) with an increasing number of iterations until it hits a wall of the box (unit hypercube), then slides along the wall and eventually ends up in a stable corner of the box, where it keeps on "pushing" but cannot get out of the box (Kawamoto and Anderson, 1985), hence the name of the model.

2 GN-Model

All definitions related to the concept "GN" are taken from [1, 2]. The network, describing the work of the neural network learned by "Backpropagation" algorithm [3, 4], is shown on Figure 4.
The below constructed GN-model is 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.

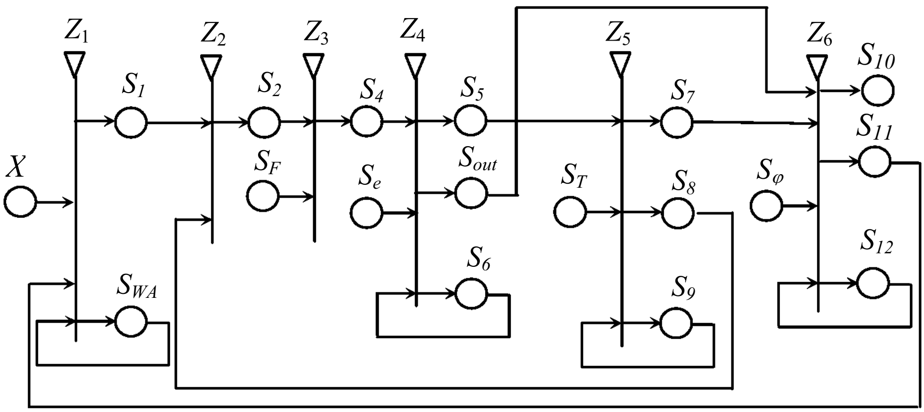


Figure 4. Modelling the brain-state-in-a-box neural network with a generalized net

Initially the following tokens enter in the generalized net:
in place X - α-token with characteristic

$x_0^{\alpha} =$ "input values that enter in neural network";
in place S_e – β-token with characteristic

$x_0^{\beta} =$ "error in neural network learning (-1;+1)";
in place S_F - one δ-token with characteristic

$x_0^{\delta} =$ "f";
in place S_T - ξ-token with a characteristics

$x_0^{\xi} =$ "time t for delay"

in place Sφ - one δ-token with characteristic

$x_0^{\delta} =$ "*feedback factor- β*";

in place SWA - one γ-token with characteristic

$x_0^{\gamma} =$ "*Initial values on the W*".

Generalized net is presented by a set of transitions:

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

where transitions describe the following processes:

Z_1 – Multiplying the input vector and weight coefficients;

Z_2 – Summing the all input influences;

Z_3 – Calculating the transfer function;

Z_4 – Checking for the end of the proceses.

Z_5 – Time delaying;

Z_6 – Calculating the feedback.

Transitions of GN-model have the following form.

$Z_1 = <\{X, S_{10}, S_{WA}\}, \{S_1, S_{WA}\}, R_1, \wedge (X \vee (S_{10}, S_{WA}))>$,

$R_1=$

	S_1	S_{WA}
X	*True*	*False*
S_{10}	*False*	*True*
S_{WA}	*True*	*True*

The token that enters in place S_{11} on the first activation of the transition Z_1 obtain characteristic

$$x_0^{\theta'} = "pr_1 x_0^{\alpha}, [1; x_0^{\xi}], pr_2 x_0^{\alpha}, x_0^{\gamma}, x_0^{\beta}".$$

Next it obtains the characteristic

$$x_{cu}^{\theta'} = "pr_1 x_0^{\alpha}, [l_{\min}; l_{\max}], pr_2 x_0^{\alpha}, x_0^{\gamma}, x_0^{\beta}",$$

where [lmin; lmax] is the current characteristics of the token that enters in place S_{13} from place S_{43}.

The token that enters place S_{12} obtains the characteristic $[l_{\min}; l_{\max}]$.

$Z_2 = <\{S_1, S_7\}, \{S_2\}, R_2, \wedge (S_1, S_7)>$,

$R_2=$

	S_2
S_1	*True*
S_7	*True*

The tokens that enter places S_{21} and S_{22} obtain the characteristics respectively:

$$x_{cu}^{\eta'} = "x_{cu}^{\varepsilon'}, x_0^{\gamma}, x_0^{\beta'}, x_0^{\sigma}, a_1, pr_1\, x_0^{\alpha}, [l_{\min}], pr_2 x_0^{\alpha}"$$

and

$$x_{cu}^{\eta''} = "x_{cu}^{\varepsilon'}, x_0^{\gamma}, x_0^{\beta''}, x_0^{\sigma}, a_2, pr_1\, x_0^{\alpha}, [l_{\max}], pr_2 x_0^{\alpha}".$$

$Z_3 = <\{S_3, S_F\}, \{S_4\}, R_3, \wedge (S_3, S_F)>$,

R_3=

	S_4
S_3	*True*
S_F	*True*

$Z_4 = <\{S_4, S_e, S_6\}, \{S_5, S_6, S_{out}\}, R_4, \wedge (S_4, S_e, S_6)>$,

R_4=

	S_5	S_6	S_{out}
S_4	*False*	*True*	*False*
S_e	*False*	*True*	*False*
S_6	$W_{6,5}$	*False*	$W_{6,out}$

and

$W_{6,5}$= "$y(n) > -1$ or $y(n) < 1$";

$W_{6,out}$= "$y(n) = -1$ or $y(n) = 1$";

The token that enters place S'_{31} obtains the characteristic "first neural network: $w(k+1)$, $b(k+1)$". The λ'_1 and λ'_2 tokens that enter place S'_{32} and S'_{33} obtain the characteristic

$$x_0^{\lambda'_1} = x_0^{\lambda'_2} = "l_{\min}".$$

$Z_5 = <\{S_5, S_T, S_9\}, \{S_7, S_8, S_9\}, R_5, \vee(\wedge(S_5, S_T), S_9)>$,

R_5=

	S_7	S_8	S_9
S_5	*False*	*False*	*True*
S_T	*False*	*False*	*True*
S_9	*True*	*True*	$W_{9,9}$

and

$W_{9,9}$= "$t_{cu} < t$".

Where t_{cu} – current time delay.

$Z_6 = <\{ S_{out}, S_7, S_\varphi, S_{12}\}, \{S_{10}, S_{11}, S_{12}\}, R_6, \vee(\wedge(S_{out}, S_7, S_{11}), S_\varphi)>,$

$R_6=$

	S_{10}	S_{11}	S_{12}
S_{out}	*False*	*False*	*True*
S_7	*False*	*False*	*True*
S_φ	*False*	*False*	*True*
S_{12}	*True*	*True*	*False*

Conclusion

The proposed GN-model introduces the work and training of NN with name "Brain stay in a box". This type neural network is different from the classical FeedForward networks. It has positive feedback and that give it different properties.

References

[1] Atanassov, K. Generalized nets, World Scientific, Singapore, New Jersey, London 1991.

[2] Atanassov, K., S. Sotirov, A. Antonov, Generalized net model for parallel optimization of feed-forward neural network, Advanced studies in contemporary Mathematics, 2007.

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

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

[5] J. A. Anderson, J. W. Silverstein, S. A. Ritz, and R. S. Jones,"Distinctive features, categorical perception, probability learning:Some applications of a neural model," in Neurocomputing;Foundations of Research, J. A. Anderson and E. Rosenfeld, Eds.Cambridge, MA: The MIT Press, 1989, ch. 22, pp. 283–325,reprint from Psychological Review 1977, vol. 84, pp. 413–451.

[6] Kawamoto A. H. and Anderson, J. A. A neural network model for multystable perceptron, Acta Psychologica 59 ,1985, 35-65

The papers presented in this Volume 2 constitute a collection of contributions, both of a foundational and applied type, by both well-known experts and young researchers in various fields of broadly perceived intelligent systems.
It may be viewed as a result of fruitful discussions held during the Eleventh International Workshop on Intuitionistic Fuzzy Sets and Generalized Nets (IWIFSGN-2012) organized in Warsaw on October 12, 2012 by the Systems Research Institute, Polish Academy of Sciences, in Warsaw, Poland, Institute of Biophysics and Biomedical Engineering, Bulgarian Academy of Sciences in Sofia, Bulgaria, and WIT - Warsaw School of Information Technology in Warsaw, Poland, and co-organized by: the Matej Bel University, Banska Bystrica, Slovakia, Universidad Publica de Navarra, Pamplona, Spain, Universidade de Tras-Os-Montes e Alto Douro, Vila Real, Portugal, Prof. Asen Zlatarov University, Burgas, Bulgaria, and the University of Westminster, Harrow, UK:

Http://www.ibspan.waw.pl/ifs2012

The Workshop has also been in part technically supported by COST Action IC0806 ``Intelligent Monitoring, Control and Security of Critical Infrastructure Systems" (INTELLICIS).

The consecutive International Workshops on Intuitionistic Fuzzy Sets and Generalized Nets (IWIFSGNs) have been meant to provide a forum for the presentation of new results and for scientific discussion on new developments in foundations and applications of intuitionistic fuzzy sets and generalized nets pioneered by Professor Krassimir T. Atanassov. Other topics related to broadly perceived representation and processing of uncertain and imprecise information and intelligent systems have also been included. The Eleventh International Workshop on Intuitionistic Fuzzy Sets and Generalized Nets (IWIFSGN-2012) is a continuation of this undertaking, and provides many new ideas and results in the areas concerned.

We hope that a collection of main contributions presented at the Workshop, completed with many papers by leading experts who have not been able to participate, will provide a source of much needed information on recent trends in the topics considered.

ISBN-13 9788389475473

9 788389 475473