Proceedings of the 2009 IEEE International Conference on Systems, Man, and Cybernetics
San Antonio, TX, USA - October 2009

Testing Artificial Metaplasticity in MLP Applications

Diego Andina, Alexis Marcano-Cedeño
Group for Automation in Signals and Communications.
Technical University of Madrid (UPM).
Madrid, Spain.
d.andina, a.marcano@gc.ssr.upm.es

Joaquín Torres, Martin J Alarcón
Group for Automation in Signals and Communications.
Technical University of Madrid (UPM).
Madrid, Spain.
joaquin, martin@gc.ssr.upm.es

***Abstract*—In this work we tested and compared Artificial Metaplasticity (AMP) results for Multilayer Perceptrons (MLPs). AMP is a novel Artificial Neural Network (ANN) training algorithm inspired on the biological metaplasticity property of neurons and Shannon's information theory. During training phase, AMP training algorithm gives more relevance to less frequent patterns and subtracts relevance to the frequent ones, claiming to achieve a much more efficient training, while at least maintaining the MLP performance. AMP is specially recommended when few patterns are available to train the network. We implement an Artificial Metaplasticity MLP (AMMLP) on standard and well-used databases for Machine Learning. Experimental results show the superiority of AMMLPs when compared with recent results on the same databases.**

***Index Terms*—Neural Network, MLPs, Backpropagation Algorithm, Pattern Recognition, Metaplasticity.**

I. Introduction

Correct classification is a very important problem in real world applications of Cybernetics and Computational Intelligence (CI). Manufacturing, telecommunications, aerospace and medical industries, among many others, are examples of the wide, variate and relevant industries and interdisciplinary problems that benefit of the application of CI algorithms, like ANNs [1]-[2].

In this work we will apply a novel ANN training Algorithm, the AMMLP, and compare it with classical Backpropagation algorithm as well as the recently proposed algorithms and methods applied to standard databases (Wisconsin Breast Cancer Database, iris database and Ionosphere database). Our results prove that the AMMLP is superior or at least an interesting alternative.

The paper is organized as follows: In Section II we present an introduction to neuronal plasticity and metaplasticity, to allow an insight of this biological property of neurons. In Section III we present the ANNs computational model with embedded neuronal plasticity and metaplasticity properties. In Section IV The AMMLP algorithm implementation is presented. In Section V results are presented and a briefly discussion is made. In Section VI we summarize conclusions.

[1]This research has been partially supported by National Spanish Ministry for Innovation (MICINN) under the following project: PTFNN (MCINN ref: AGL2006-12689/AGR). The authors also wish to thank to The National Foundation of Science Technology and Innovation (FONACIT) of the Bolivarian Republic of Venezuela for its contribution in the development of Marcano's Ph.D studies

II. Synaptic plasticity and Metaplasticity

It is well known in the ANN field that in 1949 Hebb postulated that, in the learning phase, synaptic connections of biological neurons are strengthened due to the correlated activity of presynaptic and postsynaptic neurons [3]. This plasticity property of the synaptic connections is modeled in many ANNs as a change in the connections weights of their artificial neurons or nodes. Likewise, synaptic plasticity of biological neural networks has been simulated in artificial ones by changing their weight values. And these weights are parameters that play the most relevant role in Artificial Neural Network (ANN) learning and performance.

Metaplasticity as a biological concept is widely known in the field of Biology, Medical Computer Science, Neuroscience, Physiology, Neurology and others [4][5]. Synaptic Metaplasticity is defined by many scientists as the plasticity property of synaptic plasticity [6][7]. It has been observed that not only biological synapses strength change with its participation in neurons activity, but also the efficiency of the change is different depends on the stimulus of the neuron involved in. As a direct property of synaptic plasticity, biological and artificial Metaplasticity (AMP) may also play an important role in biological and artificial learning. Both matters are under research, and some very interesting studies have been conducted in the last years [8][9][10].

An understanding of metaplasticity might yield new insights into how the modification of synapses is regulated and how the information is stored by synapses in the brain. And not only Metaplasticity. Nowadays, in this paper authors' opinion, artificial models of biological neurons should benefit of at least these three biological mechanisms:

A. Synaptic plasticity

The Synaptic plasticity refers to the efficacy modulation of information transmission between neurons, being related to the regulation of the number of ionic channels in synapses. The first modell of synaptic plasticity was postulated by Hebb

978-1-4244-2794-9/09/$25.00 ©2009 IEEE

and it is known as the Hebb rule [3]-[11].

B. Synaptic metaplasticity

One of the important biological characteristics of the synaptic rule is that it also models metaplasticity, which is an important homeostatic mechanism of neurons (since it regulates weight variation, down-regulating weight increment in synapses with initially-high weights and up-regulating weight increment in synapses with initially-low weights) [12]. It improves the process of weight change, making more difficult for the neuron to become either inactive or saturated.

C. Intrinsic plasticity

Although synaptic metaplasticity makes it difficult for synaptic weights to become either null or saturated, it does not totally preclude either of these two extreme situations. For totally precluding the possibility of either weight annihilation or saturation, another important homeostatic property of real neurons should be taken into account: the so-called *intrinsic plasticity* [13], [14].

III. AMMLP Neural Network

The Multilayer Perceptron Neural Network (MLP) has been used for the solution of many classification problems in pattern recognition applications [15]. The functionality of the topology of the MLP is in most cases determined by a learning algorithm, the Backpropagation (BP), based on the method of steepest descent. In the process of upgrading the connection weights, is the most commonly used algorithm by the ANN scientific community. The BP algorithm presents some limitations and problems during the MLP training [16]. Many researchers have centered their work in to improve and develop mixed algorithm focused on reduce those problems about the complexity, and increase their advantages. [16]-[17].

Different models and simulations of AMP have resulted in conclusions relevant not only to the cybernetics field, they also feedback to biology and medicine State-of-the-Art [13]. The idea proposed and tested in this paper is based on the hypothesis that biological synaptic metaplasticity could have a direct relation with the information carried by the input stimulus of the neurons, or training patterns in its artificial counterpart. So, we model artificial metaplasticity as proposed in [18], where the ability to change the efficiency of artificial plasticity is modelled by giving more relevance to the less frequent patterns and less relevance to the frequent ones and relates AMP to Shannon's information theory. At the end, in the overall algorithm, the AMP is included in the training algorithm by affecting the weights in each iteration step using a weight function that assumes an estimation or an hypothesis of the real distribution of training patterns. In this paper, we used the following function to weight the weights updates in the learning phase:

$$f_X^*(x) = \frac{A}{\sqrt{(2\pi)^N}.e^{B\sum\limits_{i=1}^{N} x_i^2}} \tag{1}$$

where N is the number of components of input vector X that feeds first hidden layer (for the second hidden layer, X is substituted by first hidden layer output vector, and so on) and A, B parameters that have to be empirically found (A, $B \in R$). This weight function corresponds to the assumption that probabilities of the input patterns follow a Gaussian distribution. Note that although the algorithm is robust to divergences in this assumption [18], if this diverges much from reality, the training is degraded and can even not converge.

IV. The AMMLP algorithm

1) Network structure used in the experiments:
   a) Number of input neurons equal to the number of attributes of the records in the database (plus the bias input).
   b) Number of hidden layers: 1.
   c) hidden neurons: 8 (a compromise solution found empirically to achieve the results with a simple structure)
   d) Output neurons: 1 (all classifications present two classes)
   e) Learning rate η =1
   f) Activation function is sigmoidal with value between [0,1].
2) Initialize all weights in weight matrix W randomly between [- 1,1]
3) Training phase
   a) AMP is modelled by applying the weight function in (1) to the BP weights updating during learning:

$$\omega_{ij}^{(l)}(t+1) = \omega_{ij}^{(l)}(t) + \eta.\delta_j^{(l)}.\hat{y}_i^{(l-1)}/f_X^*(x) \tag{2}$$

   where $\omega_{ij}^{(l)}$ are the weights of the j artificial neurons in layer l during iteration t, being $\hat{y}_i^{(l-1)}$ the outputs of the i neurons in previous layer (x_i for the first hidden layer), and $\delta^{(l)}$ the usual error term back-propagated in BP, that for the sigmoidal activation functions case and layer L, follows the expression:

$$\delta^{(L)} = \left(y - \hat{y}^{(L)}\right).\hat{y}^{(L)}.\left(1 - \hat{y}^{(L)}\right) \tag{3}$$

   being y the desired output

   b) Test training conditions
      i) if epochs = 2000
      stop training

ii) if Mean Squared Error, MSE = 0.01
stop training

Network Structure Selection

Initially, in order to determine the network structure and metaplasticity parameters, we used the same network parameters applied in recent research [10][18][19] (you can see the order of A and B in Tables I, VII and X). We applied two different criteria to decide for the better network structure and metaplasticity parameters such as:

1) Metaplasticity parameters: fixing a number of neurons in the hidden layer sufficiently high to presume that the ANN has sufficient processing units to perform the classification, begin to vary the metaplasticity parameters starting with A and finally with parameter B, until we achieve the mentioned value (MSE $\approx$ 0.01) in the minimum number of iterations.

2) Number of neurons in hidden layers: We vary the number of neurons in hidden layers until we achieve the Mean Squared Error (MSE) of approximately 0.01 (metaplasticity parameters are not changed) with the minimum number of neurons without degrading final performance.

For example, in the first experiment presented in the next section, Table I shows results obtained for different network structures and metaplasticity parameters.

TABLE I
MMLP RESULTS OBTAINED FOR DIFFERENT NETWORK STRUCTURES AND PARAMETERS OF METAPLASTICITY ALGORITHM

Network Structure			Metaplasticity Parameters		Mean Squared Error	Clustering Accuracy (%)	
I	HL	O	A	B		Training	Testing
9	8	1	39	0.5	0.01	99.99 %	99.14 %
9	8	1	41	0.25	0.01	98.89 %	98.71 %
9	7	1	39	0.25	0.01	99.11 %	98.71 %

V. RESULTS AND DISCUSSION

The AMMLP proposed as a classifier was implemented in MATLAB© (software MATLAB version 7.4, R2007a) and computer Pentium IV of 3.4 GHz with 2 GB of RAM. This algorithm was applied to three (3) different well-used databases for Machine Learning.

A. *Wisconsin Breast Cancer DataBase (WBCD)*

The breast cancer database was obtained from the University of Wisconsin Hospital. It contains 699 examples, where 16 samples have missing values which are discarded in a pre-processing step, so only 683 were used. Each sample has one of 2 possible classes: “benign” or “malignant”. The Benign dataset contains 444 samples (65%) and Malignant contains 239 samples (35%). Each record in the database has nine attributes, which are shown in Table II [20].

TABLE II
WISCONSIN BREAST CANCER DATA DESCRIPTION OF ATTRIBUTES

Attrib. Numbers	Attribute Description	Value Attribute Range	Mean	Standard Deviation
1	Clump thickness	1-10	4.44	2.82
2	Uniformity of cell size	1-10	3.15	3.07
3	Uniformity of cell shape	1-10	3.22	2.99
4	Marginal adhesion	1-10	2.83	2.86
5	Single epithelial cell size	1-10	2.23	2.22
6	Bare nuclei	1-10	3.54	3.64
7	Bland chromatin	1-10	3.45	2.45
8	Normal nucleoli	1-10	2.87	3.05
9	Mitoses	1-10	1.60	1.73

As to the AMMLP structure, in Table I, results show that the highest classification accuracy is obtained by the AMMLP with 9 inputs, 8 hidden layer neurons and 1 output neuron. Table III, shows the network structure, metaplasticity parameters, epochs, mean square error (MSE) and numbers of patterns used in training and testing phase. Figure 1 represents the best performing AMMLP architecture of the ANNs. As it could be expected, AMP model does not affect to the structure, that is, to the capacity or performance potential of the ANN.

TABLE III
NETWORK PARAMETERS APPLYING TO THE WBCD

Types Classifiers	Network Structure			MSE	Epochs	Metaplasti. Parameters		Numbers Patterns	
	I	HL	O			A	B	Training	Testing
AMMLPs	9	8	1	0.01	2000	39	0.5	410	273
BPNNs	9	8	1	0.01	2000	NA[2]	NA[2]	410	273

The activation function is sigmoidal with scalar output in the range (0,1) and it is the same for all the neurons. To comparatively evaluate the performance of the classifiers, all the classifiers presented in this particular case were trained with the same training data set and tested with the same evaluation data set. The network was trained with 60% of data, 410 samples, of which 144 malignant and 266 benign records. The testing set, remaining 40% of data, consisted of 233 samples of which 95 malignant and 178 benign records.

For the experiments, we generated 100 AMMLPs with different weights whose values were random with normal distribution (mean 0 and variance 1). In each experiment 100 networks were trained in order to achieve an average result that does not depend on the initial random value of the weights of the ANN. Two different criteria were applied

[2]NA: does not apply

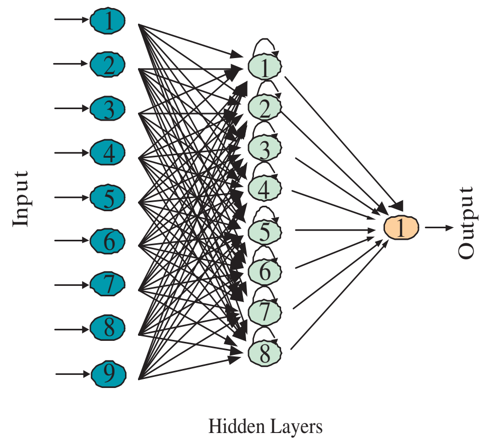

Fig. 1. Best performing AMMLP network architecture for WBCD dataset: 9 input neurons, 8 hidden layer neurons and 1 output neuron.

to stop the training: for one case it was stopped when the error reached 0.01 (the error reduces but cannot converge to 0) and, for the other one, the training was conducted with a fixed number of 2,000 epochs.

Now, we compare AMMLP algorithm with Classical Backpropagation MLP training.

1) Performance evaluation methods: We have used three methods for performance evaluation of breast cancer diagnosis. These methods are classification accuracy, analysis of sensitivity, specificity and confusion matrix. We explain these methods in the following sections.

- Classification accuracy: In this study, the classification accuracy for the datasets were measured using the equation:

$$accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{4}$$

  where TP, TN, FP, and FN denote true positives, true negatives, false positives, and false negatives, respectively.

  True positive (TP): An input is detected as a patient with breast cancer diagnosed by the expert clinicians.

  True negative (TN): An input is detected as normal that is labeled as a healthy person by the expert clinicians.

  False positive (FP): An input is detected as a patient that is labeled as a healthy by the expert clinicians.

  False negative (FN): An input is detected as normal with breast cancer diagnosed by the expert clinicians.

- Sensitivity and specificity: For sensitivity and specificity analysis, we used the following expressions.

$$Sensitivity = \frac{TP}{TP + FN}(\%) \tag{5}$$

$$Specificity = \frac{TN}{FP + TN}(\%) \tag{6}$$

- Confusion matrix: A confusion matrix contains information about actual and predicted classifications done by a classifier. Performance of such a classifiers is commonly evaluated using the data in the matrix. Table IV shows the confusion matrix for a two class classifier:

TABLE IV
CONFUSION MATRICES

Representation of confusion matrix		
Actual	Predicted	
	Positive	Negative
Positive	a	b
Negative	c	d

where:

- *a*: is the number of correct predictions when an instance is positive.
- *b*: is the number of incorrect predictions when an instance is negative.
- *c*: is the number of incorrect predictions when an instance is positive.
- *d*: is the number of correct predictions when an instance is negative.

Table 5 shows the classification results obtained by the classifiers used in this research in a confusion matrix.

TABLE V
CONFUSION MATRICES OF CLASSIFIERS USED FOR DETECTION OF BREAST CANCER

Type Classifiers	Desired Result	Output Results	
		Benign	Malignant
AMMLPs	Benign records	176	2
	Malignant records	1	94
BPNNs	Benign records	175	3
	Malignant records	12	83

As it can be observed, AMMLP is superior to classical MLP in all cases.

B. Comparison with recent results on the same database

Our MMLP algorithm has been compared with algorithms proposed recently by other researches, like: Übeyli in [21] obtained 99.54 % of accuracy using different Neural Networks. Karabatak and Cevdet in [22] reached 97.4% of accuracy applying an Association Rule and Neural Network (AR+NN). Guijarro-Berdias *et al.* in [23] achieve 98.6 % of accuracy applying a linear learning method for MLPs using least-squares. In order to determine the performance of MMLPs and BPNNs used in this research for detection of the breast cancer, the classification accuracy on testing sets are presented in Table VI.

As it can be observed, AMMLP performs more efficiently than the rest on this problem, except in the case of [21].

Nevertheless, AMMLP is a classifier simpler than the one proposed by Übeyli in this last reference.

TABLE VI
THE CLASSIFICATION ACCURACIES OF CLASSIFIERS USED FOR DETECTION OF BREAST CANCER

Type Classifier	Classification Accuracies (%)		
	Specificity	Sensitivity	Total Classification Accuracy
AMMLPs	98.95%	98.88%	98.90%
BPNNs	98.31%	87.37%	94.51%

C. AMMLP performance on Ionosphere and Iris classification cases

1) Ionosphere Database: The Ionosphere case was obtained from Johns Hopkins University Ionosphere database [20]. Contained 351 instances, and classified 2 classes of "good" and "bad". The good dataset contains 225 samples (64.1%) and bad contains (35.9%). Each record in the database has 34 attributes. For this research we will only used 33 attribute, because one attributes only contains zero.

For this case the experimental results show that the highest classification accuracy is obtained for the AMMLP with 33 inputs, 7 hidden layer neurons and 1 output neuron. Table VII shows the network structure, metaplasticity parameters, epochs, MSE and the number of patterns used in training and testing phase.

TABLE VII
NETWORK PARAMETERS APPLYING TO THE IONOSPHERE DATABASE

Types Classifiers	Network Structure			MSE	Epochs	Metaplasti. Parameters		Numbers Patterns	
	I	HL	O			A	B	Training	Testing
AMMLPs	33	7	1	0.01	2000	39	0.5	200	151
BPNNs	33	7	1	0.01	2000	NA[3]	NA[3]	200	151

We applied the same criterion used before in order to decide the network structure and metaplasticity parameters. To comparatively evaluate the performance of the classifiers, all the classifiers presented in this particular case were trained with the same training data set and tested with the same evaluation data set. The network was trained with 57% of data, 200 samples, split in 100 good and 100 bad records. The testing set, remaining 43% of data, consisted of 151 samples of which 26 bad and 125 good records.

Table VIII shows the classification results of the classifiers implemented to the Ionosphere Database. Table IX presents The Classification Accuracies of Classifiers used for Ionosphere Database.

AMMLP once again performs significatively better than MLP trained with BP, being remarkable that AMMLP is able to reach the one hundred per cent specificity.

[3]Does not apply

TABLE VIII
CONFUSION MATRICES OF CLASSIFIERS OF IONOSPHERE DATABASE

Type Classifiers	Desired Result	Output Results	
		Positive	Negative
AMMLPs	Good records	125	0
	Bad records	1	25
BPNNs	Good records	121	4
	Bad records	4	22

TABLE IX
THE CLASSIFICATION ACCURACIES OF CLASSIFIERS USED FOR IONOSPHERE DATABASE

Type Classifier	Classification Accuracies (%)		
	Specificity	Sensitivity	Total Classification Accuracy
AMMLPs	100%	96.15%	99.34%
BPNNs	96.80%	84.62%	97.35%

2) Iris Data Set: The Iris Data Set has been used extensively to evaluate various clustering and classifier problems. The data set contains 3 classes of 50 instances each, where each class refers to a type of iris plant (Iris Setosa, Iris Versicolour, Iris Virginica) [20]. Each record in the database has 4 attributes (petal length, petal width, sepal length and sepal width). Among the 3 classes, setosa and versicolor are linearly separable using petal length and sepal length, whereas virginica and versicolor are non-linearly separable using the same attributes [24], for this reason in this research we only used these last two classes.

For this case the experiment results show that the highest classification accuracy is obtained for the AMMLP with 4 inputs, 9 hidden layer neurons and 1 output neuron, determined empirically. Table X shows the network structure, metaplasticity parameters, epochs, MSE and numbers of patterns used in training and testing phase. Table X shows classification results of the classifiers were displayed by a confusion matrix. Finally, in Table XI the classification accuracies of classifiers used for Iris Data Set are presented.

TABLE X
NETWORK PARAMETERS APPLYING TO THE IRIS DATA SET

Types Classifiers	Network Structure			MSE	Epochs	Metaplasti. Parameters		Numbers Patterns	
	I	HL	O			A	B	Training	Testing
AMMLPs	4	9	1	0.01	2000	39	0.5	70	30
BPNNs	4	9	1	0.01	2000	NA[4]	NA[4]	70	30

These results support the hypothesis that Artificial metaplasticity improves learning of ANNs by allowing a more efficient information extraction from the training patterns, which is much more relevant as less patterns are available to design of ANN [18]. Corresponding to what happens in biology, the synaptic reinforcement is not homogeneous. In AMMLP, the network is more sensitive during learning phase

[4]Does not apply

TABLE XI
CONFUSION MATRICES OF CLASSIFIERS OF IRIS DATA SET

Type Classifiers	Desired Result	Output Results	
		Positive	Negative
AMMLPs	Iris Versicolor	50	0
	Iris Virginica	0	50
BPNNs	Iris Versicolor	50	0
	Iris Virginica	2	48

TABLE XII
THE CLASSIFICATION ACCURACIES OF CLASSIFIERS USED FOR IRIS DATA SET

Type Classifier	Classification Accuracies (%)		
	Specificity	Sensitivity	Total Classification Accuracy
AMMLPs	100%	100%	100%
BPNNs	100%	86.66%	98%

to patterns that are less frequent and therefore carry more information to the ANN internal representation of information. These results do not seem to depend on the application as they have also been obtained on complete different problems [19].

VI. CONCLUSION

The goal of this research work was to compare the accuracy of two types of classifiers: the proposed AMMLP and the Classical MLP with Backpropagation, applied to standard databases. The classification results indicate that the AMMLP achieved considerable success. The AMMLP classifier shows a great performance obtaining the following results average for 100 networks: 98.94% in specificity, 98.87% in sensitivity and the total classification accuracy of 98.91% for the case of WBCD. For Ionosphere Database The AMMLP classifier obtained good performance obtaining the following results: 100% in specificity, 96.15% in sensitivity and the total classification accuracy of 98.08%. And finally for de Iris Data Set our classifier obtaining the following results: 100% in specificity, 100% in sensitivity and the total classification accuracy of 100%. Our AMMLP, proved to be equal or superior to the recent classical algorithms applied to this database. Results do not depend on the application and can improve a wide variety of successful MLP results.

REFERENCES

[1] Salahova S. “Remote sensing and GIS application for earth observation on the base of the neural networks in aerospace image classification”. *Recent Advances in Space Technologies, RAST ’07*, pp. 275-278, 2007.

[2] Übeyli ED. “Modified mixture of experts for diabetes diagnosis”. *J Med Syst*, Springer. pp.1-7, 2008. DOI - 10.1007/s10916-008-9191-3.

[3] Hebb DO. *The Organization of Behavior* Laurence Erlbaum Associates, 2002 (reedition of the 1949 original). ISBN 0805843000, 9780805843002

[4] Kandel ER, Schwartz JH, and Jessell TM. *Principles of neural science*. McGraw-Hill, 2000.

[5] Jedlicka P. “Synaptic plasticity, metaplasticity and BCM theory”. *Institute of Pathophysiology, Medical Faculty. Comenius University*, Vol. 103(4-5), pp. 137-143, Bratislava. Slovakia. 2002.

[6] Abraham WC and Bear MF. “Metaplasticity: the plasticity of synaptic plasticity”. *Trends in Neuroscience*, Vol. 19(4), pp. 126-130, 1996.

[7] Abraham WC and Tate WP. “Metaplasticity: a new vista across the field of synaptic plasticity”. *Progress in Neurobiology*, Vol. 52, pp. 303-323, 1997.

[8] Kinto E, Del-Moral-Hernandez E, Marcano A, and Ropero-Pelaez J. “A preliminary neural model for movement direction recognition based on biologically plausible plasticity rules”. *Lecture Notes in Computer Science*, Springer. Vol. 4528/2007, pp. 628-636, 2007. DOI - 10.1007/978-3-540-73055.

[9] Ropero-Pelaez J and Piqueira JR. “Biological clues for up-to-date artificial neurons”. *In Computational Intelligence for Engineering and Manufacturing*, Andina D and Pham D.T. (Eds), Springer-Verlag, The Nederlands. 2007.

[10] Andina D, Jevtić A, Marcano A, and M. Barrón-Adame MJ. “Error weighting in artificial neural networks learning interpreted as a metaplasticity model” *Lecture Notes in Computer Science*, Springer. pp. 244-252, 2007. DOI - 10.1007/978-3-540-73053-8.

[11] Peréz-Otaño I and Ehlers MD. “Homeostatic plasticity and NMDA receptor trafficking”. *Trends in Neuroscience*, Vol. 28, pp. 229-238, 2005.

[12] Turrigiano GG, Nelson SB. “Homeostatic plasticity in the developing nervous system”. *Nat Rev Neurosci.* Feb;5(2):97-107, 2004.

[13] Monteiro J, Netto ML, Andina D, Pelaez JR. “Using neural networks to simulate the Alzheimer’s Disease”. *Proc. of World Automation Congress 2008 (WAC 2008)*, pp. 1-6, HI, USA, 2008. INSPEC: 10411864

[14] Cudmore, R.H., Turrigiano, G.G. “Long-Term Potentiation of Intrinsic Excitability in LV Visual Cortical Neurons”. *Journal of Neurophysiology*, 92, 2004, pp. 341-348.

[15] Hagan MT, Demuth HB, and Beale M. *Neural network design*. PWS Pub Co, Boston, USA, 1996.

[16] Leung H and Haykin S. “The complex backpropagation algorithm”. *Signal Processing, IEEE Transactions on*, Vol. 39, pp. 2101-2104, 1991.

[17] Orozco-Monteagudo M, Taboada-Crispí A, and Del Toro-Almenares A. “Training of multilayer perceptron neural networks by using cellular genetic algorithms”. *Lecture notes in computer science*, Springer. pp. 389-398, 2006. DOI - 10.1007/11892755.

[18] Andina D, Alvarez-Vellisco Antonio, Jevtić A, and Fombellida J. “Artificial metaplasticity can improve artificial neural network learning”. *In Intelligent Automation and Soft Computing*, Special Issue in Signal Processing and Soft Computing. Guest Editor D. Andina. Vol. 15, No. 4, pp. 681-694. TSI Press, USA, 2009. ISSN: 1079-8587.

[19] Andina D, Fombellida J. ”Metaplasticity Artificial Neural Networks Model Application to Radar Detection”, *Journal of Systemics, Cybernetics and Informatics*, Vol. V, Num. 6 pp 91-96. January 2008. ISSN: 1690-4524.

[20] UCI repository of machine learning database. *http://archive.ics.uci.edu/ml/datasets.html*.

[21] Übeyli ED. “Implementing automated diagnostic systems for breast cancer detection”. *Expert Systems with Applications*, vol. 33(4), pp. 1054-1062, 2007.

[22] Karabatak M and Cevdet-Ince M. “An expert system for detection of breast cancer based on association rules and neural network”. *Expert Systems with Applications*, vol. 36, pp. 3465-3469, 2009.

[23] Guijarro-Berdias B, Fontenla-Romero O, Perez-Sanchez B, and Fraguela P. “A linear learning method for multilayer perceptrons using least-squares”. *Lecture Notes in Computer Science*, Springer. Vol. 4881/2007, pp. 365-374, 2007. DOI - 10.1007/978-3-540-77226-2

[24] Voichiţa C, Khatri P and Drăghici S. “Identifying Uncertainty Regions in Support Vector Machines using Geometric Margin and Convex Hulls”. *Int. Joint Conf. on Neural Networks, IJCNN 2008*, pp. 3319-3324, 2008