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On Simulation of Brain Based Learning Paradigms (Neural Networks Approach)

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ABSTRACT

This piece of research presents an interdisciplinary and challenging research approach originated from mental stimulation and brain based learning paradigms. In more details, it specifically adopts the approach of Artificial neural networks (ANN^{s}) which are conceptually computational systems with increasingly common and sophisticated applications. Furthermore, this work aims to present realistic design of a model integrating ANN^{s} with brain based learning paradigm associated to some educational phenomena. Referring to recent neurological researchers findings that have revealed in order to promote and encourage maximum learning capacity within learners' brains. It is vital to enhance learning performance of arbitrary educational process via mental stimulation of brains' synapses and neurons. In practical educational environment, brain is intimately involved in and connected with, everything instructors and learners do while face to face tutoring sessions. Interestingly , the obtained modeling results support improvement of learning creativity following increase of synaptic connectivity in addition to the neurobiological research work concerned with the other half of the brain (Glial cells).

Introduction

The field of the learning sciences is represented by a growing community internationally. Many experts now recognize that conventional ways of conceiving knowledge, educational systems and technology-mediated learning are facing increasing challenging issues in this time of rapid technological and social changes. Since beginning of last decade, Artificial Neural Networks (ANN^{S}) models have been adopted to investigate systematically mysteries of human brain, the most complex biological neural system, [1]. Furthermore, due to recently excessive progress in information technologies and computer applied at the field of the learning sciences, some complex interdisciplinary educational issues arise in practice. That's motivated by evaluation trend in learning science incorporated Nero-physiology, psychology, and cognitive science, [2][3][4].

More specifically, this paper addresses an investigational and systemic approach associated with interdisciplinary research work originated from mental stimulation and brain-based learning [5][6]. Furthermore, other research fields such as neurology, social science, psycho-immunology; behavioral genetics, psychobiology, cognitive science, neuroscience and physiology play a role in evaluation and analysis of challenging educational issues [5]. Recently, neurological researchers have revealed that in order to promote and encourage maximum learning capacity within learners' brains. It is vital to enhance learning performance of arbitrary educational process via mental stimulation of brains' synapses and neurons. Those are mainly responsible for perception of carried valuable knowledge. Therefore, as tutors adopt brain based learning style, it is needed to be able to stimulate, encourage and hook our learners into increasing of their learning performance capacity about many different subjects and topics [6][7]. In the neural networks context, the perception function in learners' brain is well performed during mental stimulation by interactive engagement of tutors with learners.

This piece of research presents specifically an overview on an interdisciplinary research issue integrating educational field phenomena with the modeling of brain based learning using Artificial Neural Networks (ANN^{s}). In more details, the adopted ANN model simulates realistically the brain based learning style by a supervised with a teacher paradigm. That paradigm proceeds via bidirectional communication between a tutor and his learner(s). Accordingly, it realistically represents interactive engagement learning strategy which observed at our classrooms as (face to face tutoring). In practical educational environment, brain is intimately involved in and connected with, everything instructors and learners do while face to face tutoring sessions. It is an essential premise: face to face tutoring represents about one fourth of total learning achievement at the open learning system's environment [8]. Moreover, it considered as an engagement (interactive) strategy of brain based learning in order to enhance learners' capacity. In other words, in the educational phenomenon context, brain based learning style may be strategically performed by either by interaction engagement with a teacher (face to face tutoring) or with computer aided learning software. Moreover, our obtained results shown to be supported by two recently published research papers. Finally, obtained result supports improvement of learning creativity following increase of synaptic connectivity in addition to the neurobiological research work concerned with the other half of the brain (Glial cells) [9].

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The rest of this presented work is organized as follows. At the next second section, a brief review is introduced about biological function of the basic building block of brain (a single neuron). It's presented as schematic structure of a single neuron, along with the mathematical modeling of its function. The basic principles for modeling of brain based learning are given at the third section. At the fourth section simulation results are presented. Some interesting conclusions are introduced at the last fourth section.

Finally, an appendix is given to illustrate a simplified macro level flowchart describing in brief algorithmic steps for realistic simulation of brain based learning program using Artificial Neural Networks.

Learners' Brain Function

Referring to the White House report about the Decade of the brain [1], neural network theorists as well as neurobiologists have focused their attention on making a contribution to investigate systematically biological neural systems (such as the brain), functions. There is a strong belief that making such contribution could be accomplished by adopting recent direction of interdisciplinary research work, via combining ANN S with neuroscience. Consequently, by construction of biologically inspired artificial neural models it might have become possible to shed light on behavioral principles and functions concerned biological neural systems. By some details about brain based learning, it is tightly coupled to brain function as follows:

1) Learning: is the ability to modify behavior in response to stored experience (inside brain synaptic connections).

2) Memory: is that ability to restore the modified behavioral information over a period of time. As well as the ability to retrieve spontaneously the modified experienced (learned information) patterns distributed inside brain synaptic connections.

Single neuron function

Inside learner's brain structure, patterns of synaptic connectivity among vast number of neurons relies upon information processing conducted through communication between neuronal axonal outputs to synapses. At Fig.1, given in below an illustrative schematic drawing is shown for the basic structure of a single biological neuron. This neuron presents the basic building block of learner's brain structure. Consequently, performance improvement of many building blocks (neurons) conducts inevitably a significant enhancement of global brain based learning function. Thus, enhancement of learners' intelligence (learning and memory) could be attained via enhancement of neuronal activation (response) function. The following subsection presents a detailed mathematical formulation of a single neuron function.

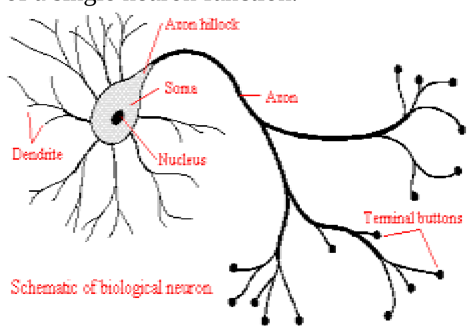


Fig. 1: A simplified schematic structure a single biological neuron (adapted from, [3]).

Mathematical formulation of a single neuron function

Referring to T.Kohenen's work [10], the output neuronal response signal observed to be developed following what so called membrane triggering time dependent equation. This equation is classified as a complex non-linear partial deferential. Its solution works to provide us with the physical description of a single cell (neuron) membrane activity. However, considering its simplified formula, which equation may contain about 24 process variable and 15 non-linear parameters. Following some more simplification of any neuron cell arguments, that differential equation describing electrical neural activity has been suggested, as follows:

$$\frac{dz_i}{dt} = \sum_{j=1}^{n} f\left(y_{ij}\right) - j\left(z_i\right) \tag{1}$$

Where,

y_{ij} represents the activity at the input (j) of neuron (i) ,

$f(y_{ij})$ indicates the effect of input on membrane potential,

$j(z_i)$ is nonlinear loss term combining leakage signals, saturation effects occurring at membrane in addition to the dead time till observing output activity signal.

The steady state solution of the above simplified differential equation (1), proved to be presented as transfer functions. Assuming, the linearity of synaptic control effect, the output response signal is given by the equation:

$$Z_i = \phi\left(\sum_{j=1}^{n} w_{ij} y_{ij} - \theta_i\right) \tag{2}$$

Where, ϕ is the activation function having two saturation limits. That ϕ may be linear above a threshold and zero below or linear within a range but flat above.

θ_i is the threshold (offset) parameter , and

w_{ij} synaptic weight coupling between two neuron *(i)* and *(j)*.

Considering realistic nonlinearity of neuron's signal activation function *(ϕ_i), it* has been recommended specifically to obey +ive behavioral segment of tangent sigmoid function. It is presented for any arbitrary neuron by the following equation

$$y(V) = \left| 1 - e^{-\lambda(V-\theta)} \Big/ 1 + e^{-\lambda(V-\theta)} \right| \tag{3}$$

Where

$$V = \sum_{i=1}^{m} w_i x_i$$

λ …… is the gain factor value.

θ…… is the threshold value.

m……is the number of synaptic inputs (from other neurons) to assigned neuron.

By referring, to the weight dynamics described by the famous Hebb's learning law, the adaptation process for synaptic interconnections is given by the following modified equation:

$$\frac{d\omega_{ij}}{dt} = \eta z_i y_{ij} - a(z_i)\omega_{ij} \tag{4}$$

Where, the first right term corresponds to the unmodified learning (Hebb's law) and η is the *a* positive constant representing learning rate value. The second term represents active forgetting; a (z_i) is a scalar function of the output response (z_i). The adaptation equation of the single stage model is as follows.

$$\dot{w}_{ij} = -a w_{ij} + \eta z_i y_{ij} \tag{5}$$

Where, the values of η , z_i and y_{ij} are assumed all to be non-negative quantities. The constant of proportionality η is less than one represents learning rate value, However, *a* is a constant factor indicates forgetting of learnt output; (it is also a less than one).

Modelling of brain based leaning

At Fig.1& Fig.2 shown in below, adopted interdisciplinary approach concerned with learning creativity phenomenon is illustrated. Detailed illustrations for both figures are given at subsections (A, B) as follows:

Interactive Brain Based Learning Process

In Fig.2, presents an interactive brain based learning model through stimulating signals (by learning environment). This figure is well qualified in performing simulation of human brain based learning and /or cognitive functions. At that figure, Inputs to the neural network learning model are provided by environmental stimuli (unsupervised learning).The correction signal for the case of brain based learning with a tutor is given by responses outputs of the model will be evaluated by either the learning environmental conditions. Finally, the tutor plays a role in improving the input data (mental stimulating learning pattern), by reducing noise and redundancy of model pattern input. That is according to tutor's experience, he provides the model with clear data by maximizing its signal to noise ratio.

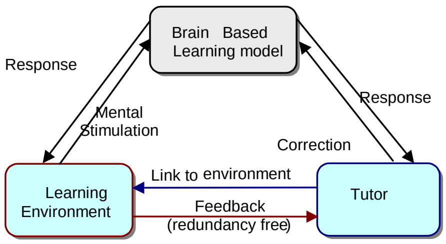


Fig. 2: Illustrates a general view for interactive brain based learning process.

ANNs and Brain Based Learning Phenomenon

In Fig. 3, it illustrates generally the performance simulation of two diverse learning paradigms. Both paradigms have been : interactive brain based learning process, other self organized (autonomous) learning. By some details, firstly is concerned with classical supervised learning observed at our classrooms (face to face tutoring). Accordingly, this paradigm proceeds interactively via bidirectional communication process between tutor and his learner(s)].However, secondly other learning paradigm performs self-organized (autonomously unsupervised) tutoring process [11].

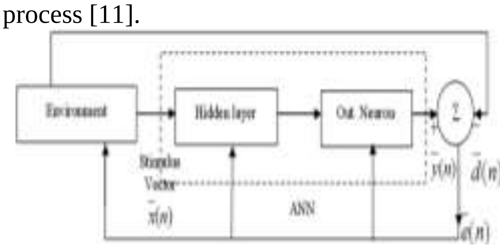


Fig.3: Generalized ANN block diagram simulating two diverse brain based learning paradigms, adapted from [4].

The mathematical formulation of the ANN brain based learning model given at figure 3 is given by follows. The error vector $\bar{e}(n)$ at any time instant (n) is observed during learning processes given by:

$$\bar{e}(n) = \bar{y}(n) - \bar{d}(n) \quad (6)$$

Referring to above Fig.1; following four equations are deduced:

$$V_k(n)=X_j(n)W^T_{kj}(n) \quad (7)$$

will be evaluated by either the environmental conditions (unsupervised learning) or by the teacher. Finally, the tutor plays a role in improving the input data (stimulating learning pattern), by reducing noise and redundancy of model pattern input. That is according to tutor's experience, he provides the model with clear data by maximizing its signal to noise ratio. Detail results about the effect of noisy learning environment are presented at next section (IV).

$$y_k(n)=\varphi(V_k(n))=(1-e^{-\lambda v_k(n)})/(1+e^{-\lambda v_k(n)}) \quad (8)$$

$$e_k(n)=|d_k(n)-y_k(n)| \quad (9)$$

$$W_{kj}(n+1)=W_{kj}(n)+\Delta W_{kj}(n) \quad (10)$$

Where: X……. input vector, W…….weight vector,
φ……. is the activation function, y……. is the output,
e_k……. the error value , and d_k…… is the desired output.

Noting that $\Delta W_{kj}(n)$ the dynamical change of weight vector value .

Above four equations are commonly applied for both learning paradigms: supervised (interactive learning with a tutor), and unsupervised (learning though students' self-study).

The dynamical changes of weight vector value specifically for supervised face to face learning phase (learning under guidance of a tutor). is given by equation:

$$\Delta W_{kj}(n)=\eta\, e_k(n)\, x_j(n) \quad (11)$$

Where η is the learning rate value during learning process for both learning paradigms. However, for unsupervised paradigm, dynamical change of weight vector value is given by equation:

$$\Delta W_{kj}(n)=\eta\, y_k(n)\, x_j(n) \quad (12)$$

Noting that $e_k(n)$ presented at equation (11) is substituted at equation (12) by $y_k(n)$ at any arbitrary time instant (n) during brain based learning process.

Simulation Results

The following five subsections present some obtained simulation results using ANN[s] learning paradigms. These presented results are mainly concerned with students' brain based response time. In more details, these results consider the effect of five various factors on brain based learning performance given at subsections (*A, B, C, D, and E*). These subsections present the effect five factors respectively as follows. The effect of noisy learning environment; and its relation with learning rate factor (η); effect of gain factor (λ); comparison between the effect of two neural networks design factors (η) & (λ); effect of number of neurons; and effect of number of Glial cells on brain based learning performance.

Effect of Noisy Learning Environment

At educational field practice, it has been found that children learn in a variety of ways such as teacher- centered learning and teaching style [12] Traditional teaching is concerned with the teacher being the controller of the learning environment.. A major factor in determining the nature of the physical classroom environment is the type of learning that the teacher wishes to encourage. This is directly related to teaching style. [13].These different ways in which a child learns is partially related to the type of learning environment available [14]. These learning environments may also affect the child's ability and motivation to learn.

In nature, ideal (noiseless) learning environment is not available in practice. Usually, it is environmental learning data is vulnerable to contaminations by either external or internal noisy conditions. So, learning/teaching processes in our classrooms, for either suggested topics, have to be accomplished under influenced effect of some environmental noise [15]. Therefore considerable attention has been paid in this subsection to report the effect of either noisy CAL environment or noisy teacher on learning convergence time. The simulation results were obtained via association between the two input stimuli (visual and auditory) following classical conditioning learning [16][17]. Obtained results for Optical Character Recognition (OCR) under different noise levels are given in a tabulated form as in Table 1. Practically, the best way to teach children how to read is carried out under the effect of less noisy data. The noise effect is measured by signal to noise ratio value (s/n) versus the number of training cycle**s** (t). Conclusively, an interesting remark observed considering relation between number of training cycles values (convergence learning time), and noisy environmental data in case of application of adopted ANN learning model. The convergence time cycles (t), of learning process is inversely proportional to signal to noise ratio values, (s/n) and learning rate values. On the other hand, it is directly proportional to noise power value(s) [15][18]. Additionally, the evaluated relation between learning rate values and noisy data (tutor) appeared considering unsupervised learning. The convergence time of learning process is reached after 47, 62, and 85 training cycles when noise power is 0.05, 0.1 and 0.2, respectively, as shown at Table 1. Running the ANN simulation program with three numerical learning rate values (0.2, 0.1 and 0.05) resulted in the training cycles (3, 5, and 10) respectively. Fig.7 shows the statistical distribution for the relation between number of training cycles and learning rates. This distribution is seems to be similar to Gaussian (normal) as it has a bell shape, which proved the realistic of the developed model.

Table 1: Effect of noisy environment on learning of reading convergence

Noise Power	0.2	0.1	0.05
(s/n) Ratio	5	10	20
t (cycles)	85	62	47

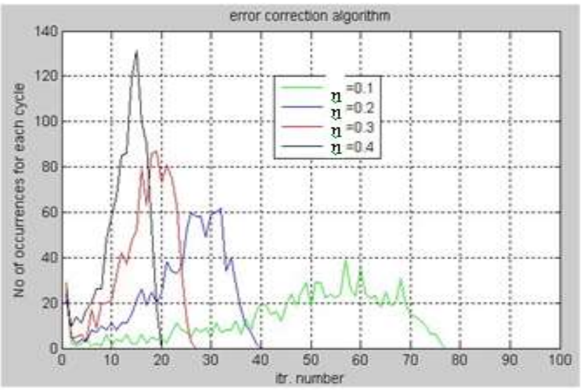


Fig.4: Statistical distribution of learning convergence time for different learning rate values.

Effect of Gain Factor (λ)

The graphical results shown in below (at Fig.5); illustrate gain factor effect on improving the value of time response measured after learning process convergence. These four graphs at Fig.6 are concerned with the improvement of the learning parameter response time (number of training cycles). That improvement observed by increasing of gain factor values (0.5, 1, 10,and 20) that corresponds to decreasing respectively number of training cycles by values (10,7.7,5,and3) cycles, (on approximate averages). Gain Factor Value (λ) and average response (learning convergence time) in reaching some desired output learning level.

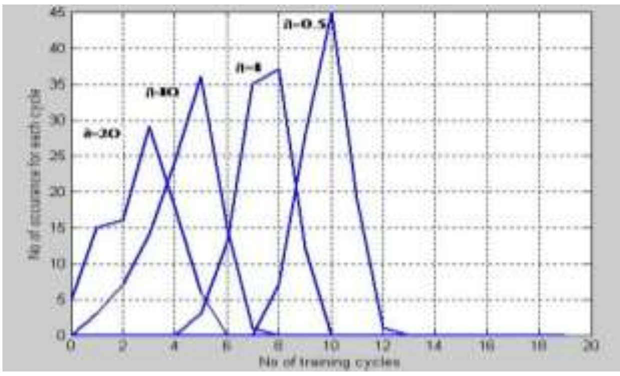


Fig.5. Illustrates improvement of average response time (no. of training cycles) by increase of the gain factor [4]

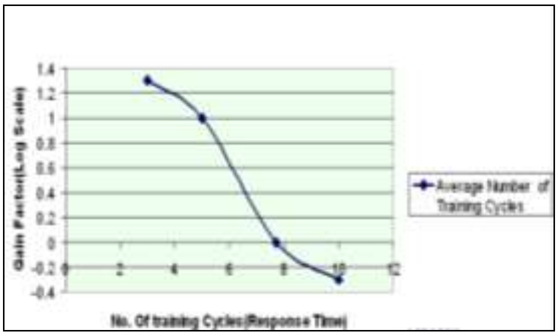


Fig.6. Illustrates improvement of average response time (number of training cycles) by increase of average gain factor values (considering Log- scale description)

Comparing of two ANNs Design factors (η) & (λ)

Four samples comparing both deign factors of ANN models are shown as follows:

1- Firstly, two samples are given in the below at (Fig.7), and (Fig.8).These two figures are concerned with the improvement of the learning parameter response time (number of training cycles), observed by increasing of gain factor (from 0.5 to 1), for fixed learning rate value (0.1). Respectively, the number of training cycles decreased approximately -on the average- (from 80 to 30) cycles. Both figures indicate gain factor effect on improving time response values measured (after learning process convergence).

2- Secondly, other two samples are shown in below at (Fig.9), and (Fig.10) .Both figures consider changes of learning rate parameter (for fixed gain factor value (0.5)). By some details, as the value of learning rate parameter increases from 0.2 (Fig.9), to 0.6 (Fig.10), the average (normalized) number of training cycles, decreases approximately (on the average), (from 38 to 12) cycles.

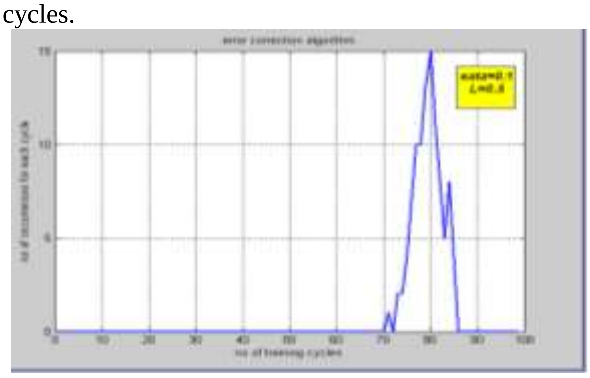


Fig.7. Illustrates the statistical distribution of learning convergence time for learning rate values =0.1, gain factor =0.5.

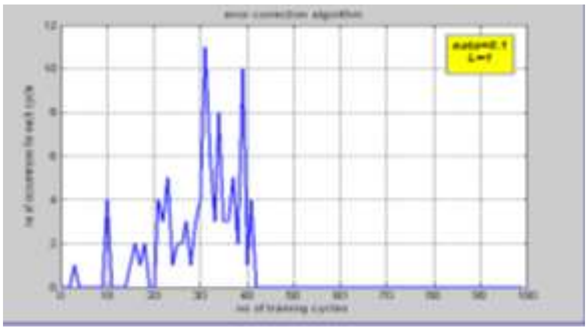


Fig.8.Illustrates the statistical distribution of learning convergence time for learning rate values =0.1, gain factor =1.

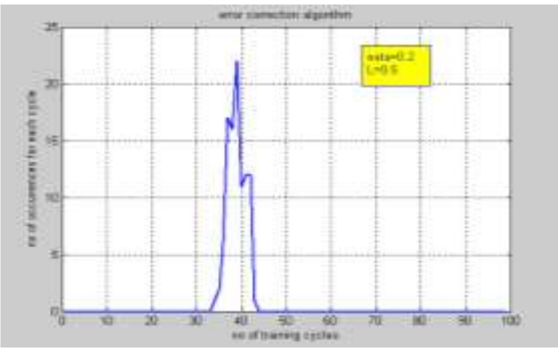


Fig.9: Illustrates the statistical distribution of learning convergence time for learning rate values =0.2, gain factor =0.5.

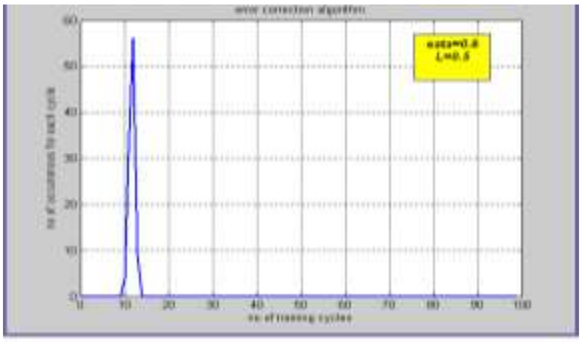


Fig.10: Illustrates the statistical distribution of learning convergence time for learning rate value =0.6, gain factor =0.5.

The effect of number of neural cells

The following simulation results show how the number of neurons may affect the learning performance. Those graphical presented results show that by increasing number of neural cells in brain based learning, the performance observed to be improved. That is shown at figures (11 up to 15).

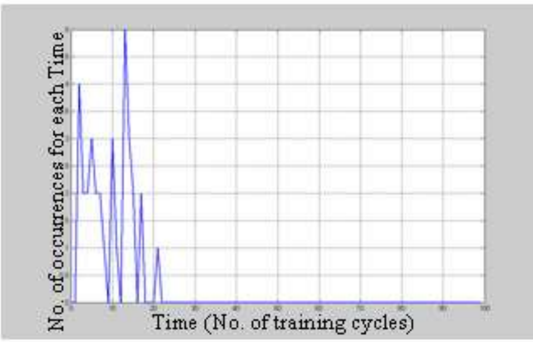


Fig. 11: Illustrate error correction performance with time factor when #neurons = 14, Learning rate = 0.1 and gain factor = 0.5

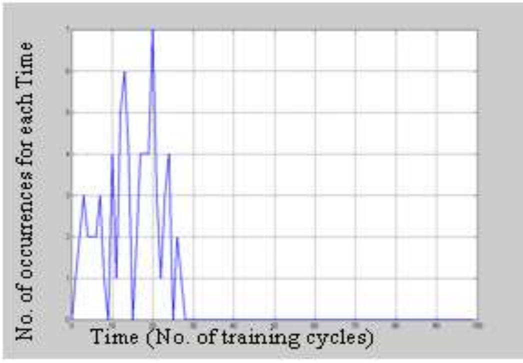


Fig. 12: Illustrate error correction performance with time factor when #neurons = 11, Learning rate = 0.1 and gain factor = 0.5

Fig. 13: Illustrate error correction performance with time factor when #neurons = 7, Learning rate = 0.1 and gain factor = 0.5

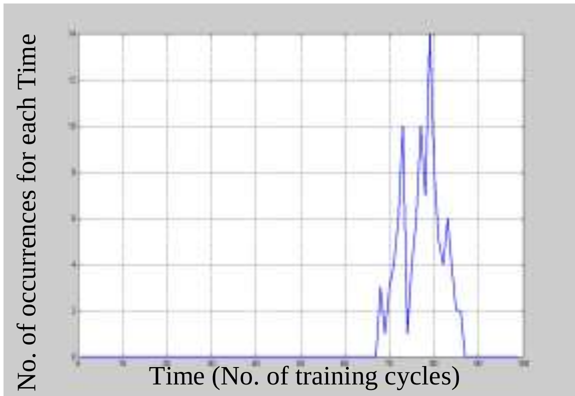


Fig. 14: Illustrate error correction performance with time factor when #neurons = 5, Learning rate = 0.1 and gain factor = 0.5

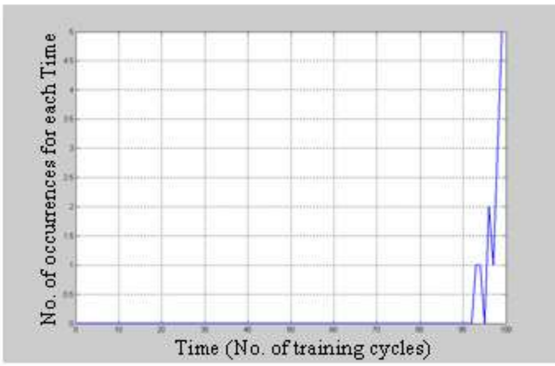


Fig .15: Illustrate error correction performance with time factor when #neurons = 3, Learning rate = 0.1 and gain factor = 0.5

The effect of number of Glial cell

In addition to above clarifications about the effect of number neuronal cells applied for brain based learning (at hippocampus brain area) , interesting analysis for the effect of brain Glial cells on learning performance (convergence time factor) is shown at Fig.16, in below . It illustrates mutual inter-communication among Glial cells and typical neuronal brain cells. Noticeably, increasing of synaptic connectivity value is measured as ratio between number of Glial cells versus number of typical neurons. This ratio leads to improvement of learning performance time factor, [19] that considered as number of training cycles. For more details about other half of the brain, it is recommended to consult two references [9] [20].

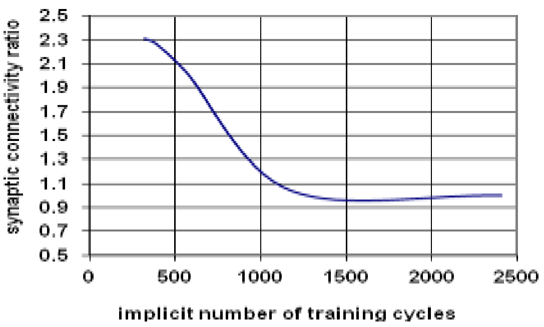


Fig.16: Illustrates the relation between number of training cycles during learning process and the synaptic connectivity (weights) values.

Conclusion

This article presents some interesting simulation results associated with reaching optimal based learning for the effect of learning environment as well as the number of neurons on learning performance. More precisely, the effect of the other half of the brain is given via simulation of glial cells effect. Interestingly, this research work adopts the supervised ANN paradigm based on cognitive associative learning of Pavlov's experimental work. After running the suggested simulation program, obtained supported the following three findings:

1-The statistical distribution for relation between number of training cycles and learning rates seems to be similar to Gaussian (normal) as it has a bell shape, which proved realistically of the developed model. That observed learning phenomenon has been considered for quantitative creativity analysis and evaluation [4] [21].

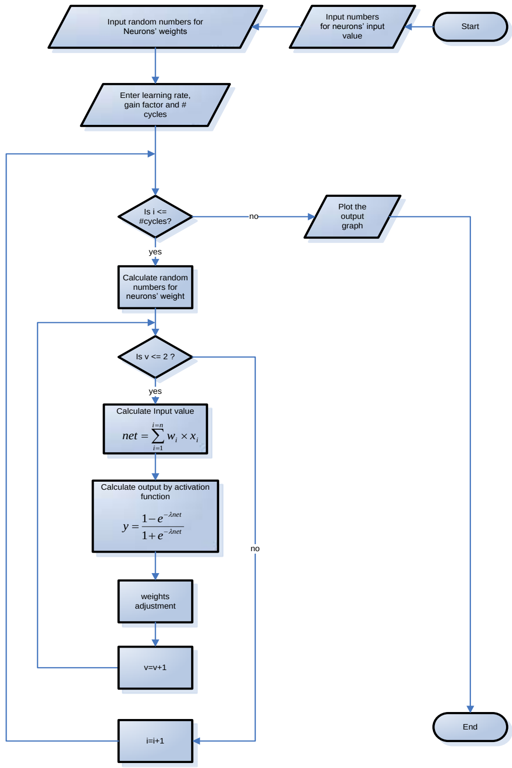
2-More recently, an interesting published work deals with the simulation of quantitative learning creativity using ANN [22].

3-The learning rate parameter is analogously proportional to the signal to noise ratio (as communication parameter).Furthermore, that parameter is associated to diverse educational technology methodologies adopted for brain based learning systems [23].

4-As future expected extension of presented paper, it is highly recommended to consider more elaborate investigational analysis and evaluations for other behavioral and cognitive learning phenomena observed at educational field (such as learning creativity, improvement of learning performance, learning styles,……etc.) using ANNs modeling.

Appendix A

The shown figure in below presents a simplified macro level flowchart describing in brief algorithmic steps for realistic simulation of brain based learning program using Artificial Neural Networks. After running that program, a set of graphs of time response versus number of neuron cells are obtained as shown at simulation results at figures (11, 12, 13, 14, and 15).



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