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Application of neural networks' modeling on optimal analysis and evaluation of e-learning systems' performance (time response approach)

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ABSTRACT

This piece of research addresses an interdisciplinary challenging issue concerned with dynamical evaluation of e-Learning systems' performance. More precisely, it presents an interdisciplinary work integrating neuronal, psychology, cognitive, and computer sciences into educational environment. That's in order to introduce systematic analysis and dynamical evaluation of the adopted study for e-learners' time response (equivalently convergence time) phenomenon. Specifically, this work concentrates on dynamical evaluation of one measuring parameter fore-learning performance namely: time response. In other words, e-learner's response time has been adopted as an appropriate candidate learning parameter applicable for reaching optimal analysis and evaluation of e-learning systems performance. Herein, that time considered as period of time requested in order to reach correctly a pre-assigned (desired) output answer which determined by an e-learner while examined via Multiple Choice Questions (MCQ). At the macro-level, the paper proposed e-learner's response time affected mostly by two basic extrinsic and intrinsic educational factors. Firstly, that associated to effectiveness of e-learning environment such as communication signal to noise ratio, and learning rate value. Secondly, that tightly coupled with gain factor candidates' brain function and structure (synapses, axons, and dendrites).Such as the number of dynamically contributing neurons, and the gain factor of neuronal response function. Consequently, Artificial Neural Networks (ANNs) simulation has been adopted for realistic evaluation of timely dependent candidate's response till reaching desired correct output solution for any arbitrary MCQ exam. After successful timely updating of dynamical state pattern (synaptic weight vector), pre-assigned (desired) correct response is accomplished in accordance with coincidence learning modeling. The presented simulation has been developed towards quantified analysis of the highly specialized neurons' role performed to select correct answers to MCQ. Furthermore, the time response parameter considers individual differences of learners' brain role (considering various number of neurons), while performing selectivity (MCQ) processes. Finally, after running of suggested realistic simulation programs, some interesting conclusive results introduced.

Introduction

Modeling of human brain functions considered as recent interdisciplinary evaluation trend by educationalists in learning science incorporated Neuro-physiology, psychology, and cognitive science, [1][2].In this context, there is a strong evidence in modern neuroscience that networks of neurons perform a dominant role in performing cognitive brain functioning such as selectivity. Consequently, ensembles of highly specialized neurons (neural networks) in human play the dominant dynamical role in the functioning of developing selectivity function by brain [3][4][5]. More precisely, inside a learner's brain, dynamical changes of synaptic connectivity pattern (weight vector) has to be adaptively modified response time (during selectivity process), in order to develop correctly selected answer

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 [6][7][8].That is carried out by using ANN modeling based on error correction (supervised) learning, supposed output delivery of a pre-assigned learning level. In accordance with referring to contemporary neuroscience evaluation, there are possibly great implications for learners, tutors, and educationalists [9][10]. Recently, Artificial Neural Networks (ANN[s]) combined with cognitive neuroscience considered as an interdisciplinary research direction for optimal learning performance adopting students' time response as learning

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parameter [11][12]. In this presented work, the ANN model proved to be qualified to perform realistic simulation of above mentioned brain functions aiming to proper analysis and evaluation for the e-learning progress and activities.

Generally, practically performed e-learning process - fromneuro-physiological P.O.V. - utilises two essential cognitive functions as follows. Firstly, pattern classification/ recognition function based on visual/audible interactive signals. Secondly, associative memory function is used which is originally based on classical conditioning motivated by Hebbian learning rule. Both functions are required to perform efficiently interactive learning process in accordance with behaviourism [13][14][15].Inputs to the neural network learning model are provided by e-educational environmental stimuli (unsupervised learning). The correction signal in the case of e-learning (face to face tutoring), is given by responsive outputs. The model has to be evaluated by either the e-environmental conditions (unsupervised learning) or by the tutor. He plays a role in improving the input data (stimulating e-learning synaptic pattern), by reducing noise and redundancy of input model pattern. That correction process performed in accordance with tutor's experience, he provides the model with clear data by maximizing its signal to noise ratio [16]. However, that is notadoptedcase herein, which based on unsupervised Hebbian self-organized (autonomous) learning [17].Therefore,evaluation of learning systems performance is an interesting challenging issue, considered under investigations by educational researchers working at interdisciplinary field integrating educational environment with computer technology andneural science[8][11][18].

Some research worker considers thatbasic implementation of e-Learning system isan adaptive paradigm. More specifically, integrating machine intelligence technique such as ANN seems to make e-Learning more attractive by ensuring on flexibility, adaptability and modularity [10]. Essentially educationalists need to know how neurons synapses inside the brain are interconnected together to perform communication among brain regions [13]. By this information they can fully understand how the brain's structure gives rise to perception, behavioral learning. Consequently, they can investigate systematically the very details about how learning phenomenon concerned with brain's response time proceeds?.The presented paper is an interdisciplinary piece of research that aims to simulate appropriately performance evaluation issue in e-learning systems with special attention to face to face tutoring phenomenon. That purpose fulfilled by adopting an appropriate metric parameter to evaluate learners' interaction with e-learning course material(s) during face to face tuition. Herein, e-learner's response time is recommended as metric learning parameter. Practically, it is measured as learner's elapsed time till accomplishment of a pre-assigned/desired achievement level (learning output)[11][16][19]. This paper presents ANN modeling approach for getting insight with e-learning evaluation issue considering learner's response (convergence) time. Mainly, ANN[S] models are inspired by synaptic connectivity dynamics of neuronal pattern (s) inside brain.Which equivalently named as synaptic plasticity performing coincidence detection learning; based on Hebb's rule[14].

The rest of this work composed of three sections rather than the introductory one. At the second section, relevant selectivity criterion based on grandmother selectivity is introduced. Simulation results presented at the third section including the effect of learning rate values and the number of neurons on e-learning systems' performance (Time Response). Finally, at the last fourth section some interesting conclusion remarks have been introduced.

Grandmother selectivity criterion

Single neuron function

At Figure 1, given in below an illustrative schematic drawing is shown for the basic structure of a single biological neuron[20].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. Briefly, a typical biological neuron composed of three basic components {a cell body (soma), dendrites, and an axon Dendrites}. All are characterized by their thin structures that arise from the cell body, often extending for hundreds of micrometers and branching multiple times, "dendritic tree". An axon is a special cellular extension that arises from the cell body at a site called the axon hillock. The soma frequently gives rise to multiple dendrites, but never to more than one axon, although the axon may branch to approximately (10^4) times before its termination in a form of synaptic connectivity pattern inputs to other neurons. 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. This neuron presents the basic building block of learner's brain structure. Accordingly, performance improvement of many building blocks(neurons) conducts inevitably a significant enhancement of global brain based learning function. 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 learning function. Thus, enhancement of learners' intelligence (learning and memory) [21] [22], could be attained via enhancement of neuronal activation (response) function [6]. Moreover, some recently published work (based on neural network modeling) illustrated the tight mutual relation between learning and memory [4]. Additionally, about one decade ago two other published research articles have account respectively to the effect of brain synaptic plasticity on learners' ability [23], and the effect of not well prepared tutors on learning time response [16].

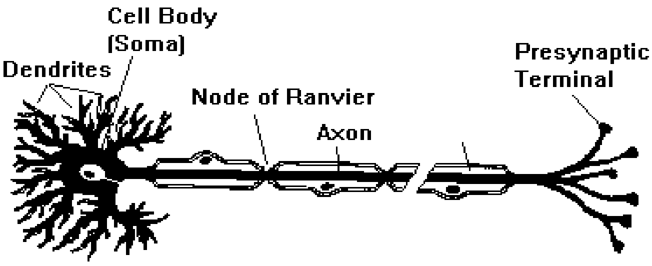

Figure 1: A simplified schematic structure a single biological neuron (adapted from [20]).

Modelling of grandmother selectivity criterion is based on a simple sorting system constructed using a set of grandmother cells (neurons).The basic building block of this model is motivated by biological neuronal model with input synaptic pattern and output axonal signal [24]. That implies, each neuron should be well trained in order to respond exactly (correctly) to one particular input synaptic pattern. In other words, each neuron has become able (after training) to recognize its own grandmother. Appling such models in real world, they have been characterized by two features. Firstly, a lot number of grandmother cells are required to implement such grandmother model. That is due to the fact each cell is dedicated to recognize only one pattern.

Secondly, it is needed to train that simple sorting network possible grandmother pattern to obtain correct output response. Consequently, all synaptic weight values at this model have to be held up unchanged (fixed weights). Hence, it is inevitably required to either add new grandmother cell(s),to recognise additional new patterns or, to modify weights of one or more existing cells to recognise that new patterns. Referring to the electronic MCQ answering system [25]. E-learning systems adopt reliable approach considering computer based multiple choice questions (MCQ) exam. Since there is fairly involvement of a machine, while taking of the exams and the marking became easier and faster. However, performing these processes require assignment a computer for each examinee, so it cannot be held in ordinary classrooms. Specifically, while considering some engineering application associated with combinational logic circuits and readily available ICs have been adopted. That's for building up a hardware setup, engineering candidates could take their exams and obtain corresponding marks with the aid of a single central computer for any number of candidates in any place. That setup approach consists of a single unit of answering console for each candidate, with answering buttons and an in-built memory unit to store the required answer.

The answers are calculated and displayed on screen dynamically for fast feedback to students and ensure effectiveness of classroom e-learning [25]. In close similarity to e-learning systems, most widely used techniques for performance evaluation of complex computer disciplines which use experimental measurement, analysis and statistical modeling, and simulation [26]. Herein, special attention is given to quantitative evaluation of timely updated performance of learners' brain functions. That is carried out by using ANN modeling based on error correction (supervised) learning, supposed output delivery of a pre-assigned learning level. More precisely, inside a learner's brain, dynamical changes of synaptic connectivity pattern (weight vector) modified adaptively after during response time period, so as to develop (output desired answer). Accordingly, superior quality of evaluated e-leaning system performance attained via global decrease of response time (on the average).Consequently, response time value needed - to accomplish pre-assigned learners' achievement- is a relevant indicator towards quality of any -under evaluation- learning system.

Mathematical formulation of grandmother selectivity

The presented formulation originated by some selective criterion given at [26][27]. In this subsection, a special attention is developed to modelling of grandmother selectivity criterion [24][26][27].This criterion is based on a simple sorting system constructed using a set of grandmother cells (neurons).The basic building block of this model is motivated by biological neuronal model shown in the above (Figure 1) with input synaptic pattern and output axonal signal.

Referring to Figure 2, grandmother model could be described well by following mathematical formulation approach. The output of any grandmother cell (neuron) is a quantizing function defined as follows: It is worthy to note that selectivity condition considers a network model adopting artificial neurons with threshold (step) activation function as shown asa quantizing function defined as follows:

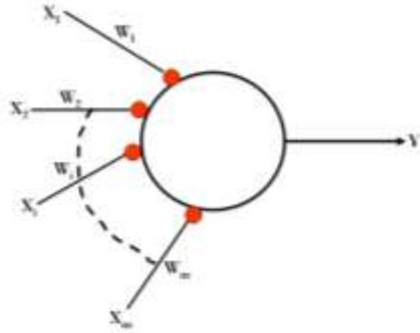

Figure 2. Illustrates a single grandmother cell (artificial neuron), that works as processing element.

$$\phi(a) = \begin{cases} 0 & when \quad a < 0 \\ 1 & when \quad a \geq 1 \end{cases} \qquad (1)$$

Then the output y is represented by

$$y = \phi(U - \Theta) \qquad (2)$$

Where U is defined as

$$U = \sum_{i=1}^{m} w_i x_i \qquad (3)$$

Additionally, Θ is defined as a fixed threshold value controlling firing of selectivity neuron.

The necessary and sufficient condition for some neuron to fire selectively to a particular input data vector (pattern) is formulated mathematically as given in below.

Consider the particular input pattern vector

$$x_c = (x_{c1}, x_{c2}, ... x_{cn}) \qquad (4)$$

$$\Theta < U_c$$

Hence, $$\Theta \geq U_c + W_m$$

for any m satisfying

$$1 = x_{cm} \qquad (5)$$

$0 = x_{cm}$

$0 \geq U_c - W_m$ and $U_c = \sum_{i=1}^{n} W_i x_{ci}$

Simulation Results

Effect of neurons' number on time response

The following simulation results show how the number of neurons may affect the time response performance. Those graphical presented results show that by changing number of neural cells(14 ,11 ,7 ,5 ,and 3); during interaction of students with e-learning environment, the performance observed to be improved by increase of number of neuronal cells (neurons).That is shown at figures (3 , and 4) respectively; for fixed Learning rate = 0.1 and gain factor = 0.5.

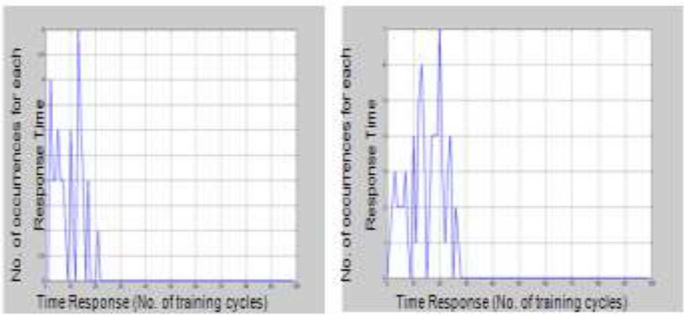

Figure 3: Illustrate time response performance with #neurons = 14 (left) and with #neurons =11 (right).

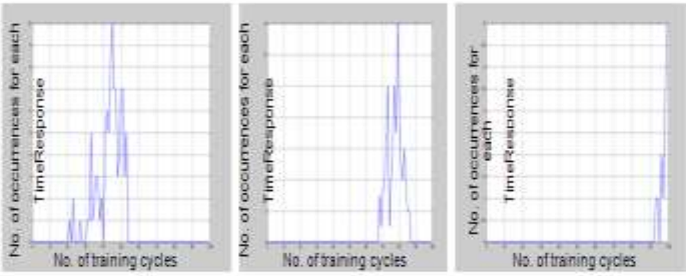

Figure 4: Illustrate time response performance with #neurons = 7 (left),with #neurons = 5 (middle) and with #neurons = 3

3.2Learning rate versus learning time response

Simulation results for different learning rate values versus response time parameter are illustrated by four plotted curves shown in below at Figure 5. At this figure considered learning parameter (Time Response) is associated with various learning rate values (η= 0.1, 0.2, 0.3., and o.4) consideringassuming 1000 virtual number of students [1]. Its bell shape form seems similar to be in agreement with Gaussian (Natural) distribution.Furthermore, by considering various number of neurons contributing to solving MCQ exams the time response improved by increase of learning rate values (η=0.05,0.1, and 0.3), as illustrated at Figure 5 (right). Interestingly, values of learning rate simulate realistically extrinsic effectiveness of e-learning environment technology which associated to communication signal to noise ratio and other impact factors [11][16][19].

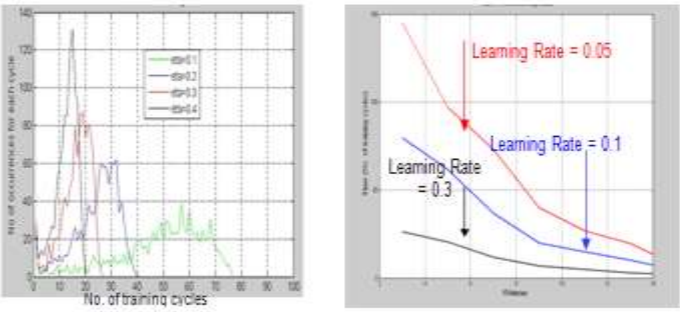

Figure 5. Illustrates the statistical distribution of time response for different learning rate valuesη(0.1, 0.2, 0.3., o.4) (left). The figure (right) Illustrates the performance of e-learning versus response time for three different learning rate valuesη (0.05, 0.1, 0.3), considering increased number of neurons

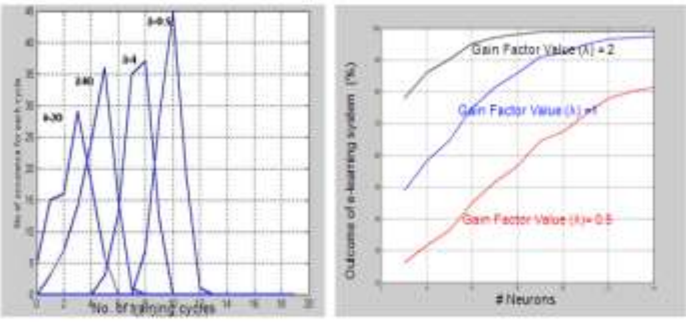

Figure 6: Figure left Illustrates improvement of average response time (no. of training cycles)by increase of the gain factor values adapted from [27]. And the figure right Illustrate Outcome of e-learning system (%) versus number of neurons at different gain factor valueswhen #cycles = 300 and Learning rate = 0.3, considering increased number of neurons

Gain factor versus time response

The graphical results shown in below (at Figure.6) illustrate gain factor effect on improving the value of time response measured after learning process convergence. These four plotted graphs at Figure 10 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 respectively decreased response time (number of training cycles) by values (10,7.7,5,and3) cycles. These values are given (on approximate averages).

In reaching some desired correct learning output Gain Factor Values (λ) and average response (response time) values varies significantly in accordance with learners' individual differences[19][26].Additionally, by referring to Figure 6 (right) it is shown that by various gain values (at fixed time response) the obtained e-learning outcomes are changed. That's besides considered various numbers of neurons contributing into solving MCQ exams.

Conclusions

Through above adopted approach, obtained results are evaluated considering some other results for performance evaluation of some neural system models concerned with time response of learning process. Conclusively, the following four interesting remarks -related to enhancement of e-learning systems' performance quality- have been obtained:

- Following previously suggested measuring approach of learning time response any e-learning system's performance quality could be quantitatively evaluated. So, experimental measurement of time response average values (quantified evaluation), provides educationalists with a fairly unbiased judgment for any e-learning system (considering a pre-assigned desired achievement outcome).
- As consequence of above remark quantified performance evaluation has been considered as two extrinsic and intrinsic factors. They are realistically simulated by e-environment technical characteristics and the individual differences of e-learners' time response.
- Modification of learning systems performance obtained by increment of learning rate value, which is expressed by the ratio between achievement level (testing mark) and the response learning time. This implies that learning rate could be considered as a modifying parameter contributes to both learning parameters (learning achievement level and learning time response) [30][31].
- In future, more elaborate quantitative evaluation of individual differences phenomena expected. By incorporation of Nero-physiology, Psychology, and Cognitive sciences. That elaborate study needsfor modification of e-educational systems' processes [28]. It is carried out considering the effect of initial internal (intrinsic) brain status of learners as well as external environmental factors upon convergence of learning / training processes.

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