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**Performance Improvement of Reading Brain Function Considering Quantified Analysis of
Highly Specialized Neurons (Neural Networks Approach)**

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Abstracts

This piece of research adopts the conceptual approach of (ANN) models inspired by functioning of highly specialized biological neurons in reading brain based on the organization the brain's structures/substructures. Additionally, in accordance with the prevailing concept of individual intrinsic characterized properties of highly specialized neurons, presented models closely correspond to performance of these neurons for developing reading brain in a significant way. More specifically, introduced models concerned with their important role played in carrying out cognitive brain function' outcomes. The cognitive goal for reading brain is to translate that orthographic word-from into a spoken word (phonological word-form). In this context herein, the presented work illustrates via ANN simulation results: How ensembles of highly specialized neurons could be dynamically involved in performing the cognitive function of developing reading brain.

Keywords: Artificial neural network modeling; Reading brain Performance; Associative memory; Self-organized learning.

Introduction

The field of learning sciences is represented by a growing community conceiving knowledge associated with educational system performance as well as assessment of technology-mediated learning processes [1]. Accordingly, a recent evolutionary trend has been adopted by educationalists as well as learners due to rapid technological and social changes. Moreover, they are facing increasingly challenges arise in this time considering modifications of educational field applications. During last decade of previous twentieth century (1990-2000), educationalists have adopted recent Computer generation namely as natural intelligence as well as Information technology aiming to reach optimality of learning processes' performance. By more details, it is worthy to refer to WHITE HOUSE REPORT (U.S.A.) in 1989; therein, it has been announced that decade (1990-2000) called: the 1st DECADE OF THE BRAIN [2]. However, recently this decade has been continuously reborn during current decade (2010-2020). That for trying to reach completed answer of the mysterious big question "HOW THE BRAIN WORK" [3][4]. Noting that research work about brain has not always been esteemed as the locus of that highly complex and contradictory entity, the human mind [4][5]. Furthermore, overwhelming majority of neuroscientists have adopted motivational concept that huge number of neurons besides their synaptic

interconnections constituting the central nervous system. And synaptic interconnectivity perform dominant roles for learning processes in mammals such as behavioral learning (such as: cats, dogs, ants, and rats), besides humans [6][7]. Recently that concept is specifically motivated and supported by what has been revealed by National Institutes of Health (NIH) in U.S.A. that children in elementary school, may be qualified to learn "basic building blocks" of cognition and that after about 11 years of age, children take these building blocks and use them [8]. In the context of learning how to read phenomenon, some interesting findings have been revealed that ensembles of highly specialized neurons (neural networks) in human play the dominant dynamical role in the functioning for developing of reading brain [9]. More specifically, neurological researchers have recently revealed findings associated with the increase of commonly sophisticated role of (ANN). In realistic and systematic modeling of interdisciplinary discipline integrating neuroscience, education, and cognitive sciences. Therefore, such ANN Modeling processes have been widely varied. In accordance with the nature of assigned brain function and/or educational phenomenon to be modeled.

Major challenges concerned with this modeling issue involve characterizing the nature of the progressive

changes that occur over the early childhood years' reading time [10]. And understanding how reading abilities emerge from preexisting visual perception and language abilities. For example, interpretation of orthography, the written form of language, places unique demands on the brain's visual object-processing systems. Linking orthography with phonology, the sound structure of language, is the *sine qua non* of reading acquisition [11][12].

In other word, referring to contemporary neuroscience evaluation, there are possibly great implications for learners, tutors, and educationalists. That's by considering the cognitive goal for reading brain processes is to translate that seen word (orthographic word-form) into a spoken word (phonological word-form). Herein, the presented work illustrates via ANN simulation results presented by the end of this paper. Accordingly, obtained resulted have been concluded via Modeling of the popular and sophisticated type of complex system named "Artificial Neural Network"(ANN) has been adopted at this piece of research. Where collection of artificial neurons (nodes) are linked up in various ways, and the network then processes "synapses" according to a distribution of weights for the connections between the neurons and transfer functions for each individual neuron [13]. The synaptic connectivity patterns among artificial neurons has implication on learning ability [14], and also on the human learning creativity [7] [15]. The extremely composite biological structure of human brain results in everyday behavioral brain functions. At the educational field, it is observable that learning process performed by human brain is affected with the simple neuronal performance mechanism [16]. Accordingly, in general sense, the human ability to speak (read) English language is motivated by associative features of human brain. That association considered between two stimulating signals (heard voice and seen written words) via brain receptor neurons. In brief, artificial neural networks were originally conceived of in relation to how systems according to the stimuli they receive [17][18]. Moreover a recently published research work revealed that using some pauses while talking, may enhance the teaching methodology of children how to read English language [19][20]. Recently, a related research work has been published. That addressed the issue of how ensembles of highly specialized neurons could be dynamically involved in performing the cognitive function of recognizing words' vocabulary during early infancy development of human reading brain [4]. Finally, it is worthy to note that presented study motivated by some recently other published interdisciplinary work dealing with the intrinsic

properties of neurons associated with learning creativity [21][22], and brain-based learning [23]. The rest of this paper is composed of nine sections including the introductory one organized as follows. At the second next section, generalized learning models are revised via some detailed descriptions of two paradigms (supervised and unsupervised) learning adopted by ANN. Basic concepts of presented reading brain modeling is introduced at the third section. At the fourth section revising generalized Hebbian algorithm generalized is given. Simulation algorithm analysis and its flowchart are introduced at the fifth section. At the sixth section, more detailed mathematical analysis for reading brain memory function are given. The simulation results are introduced at the seventh and eighth section. Finally, the last ninth section presents some conclusive remarks and future work discussions.

Generalized interactive learning model

This section presents by its two subsections (A&B) respectively: details for basic realistic ANN modeling of interactive learning processes. In addition to mathematical formulation of natural Learning Phenomenon

A. Simplified Overview for Interactive Learning Process

At Figure 1, an interactive learning model through stimulating signals is well qualified in performing realistic simulation for evaluating learner's performance. That Figure, illustrates inputs to the neural network learning model which provided by stimuli unsupervised learning environment [25].The correction signal for the case of learning with a teacher is given by responses outputs of the model will be evaluated by either the environmental conditions (unsupervised learning) [26] or by the instructor. The instructor plays a role in improving the input data (stimulating learning pattern), by reducing noise and redundancy of learning model pattern input [27]. In accordance with instructor's experience, he provides illustrated model with clear data by maximizing learning environment signal to noise ratio [26].

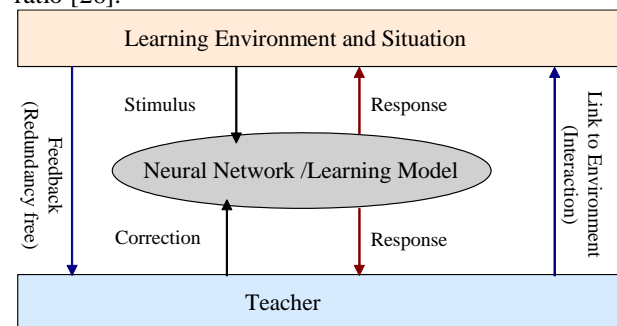


Fig. 1. A simplified view for an interactive learning process.

B. Mathematical Formulae of Natural Learning Phenomenon

Figure 2 illustrates generalized simulation of two diverse learning paradigms. It presents realistically both paradigms: by interactive learning / teaching process, as well as other self-organized (autonomous) learning. By some details, firstly is concerned with classical (supervised by tutor) learning observed at our classrooms (face to face tutoring). Accordingly, this paradigm proceeds interactively via bidirectional communication process between teacher and his learner (s). However, secondly other learning paradigm performs self-organized (autonomously unsupervised) tutoring process.

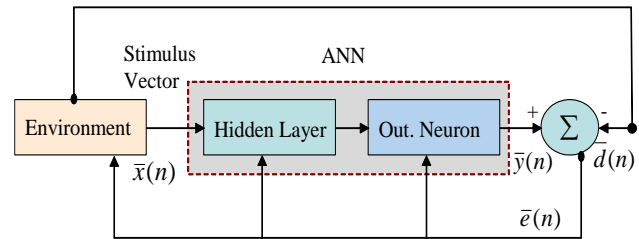


Fig. 2. Generalized ANN block diagram simulating two diverse learning paradigms adapted from [1]

Referring to above Figure 2; the error vector $\bar{e}(n)$ at any time instant (n) observed during learning processes is given by:

$$\bar{e}(n) = \bar{y}(n) - \bar{d}(n) \tag{1}$$

where $\bar{e}(n)$ is the error correcting signal which is controlling adaptively the learning process, and $\bar{y}(n)$ is the output signal of the model. $\bar{d}(n)$ is the desired numeric value(s). Moreover, the following four equations are deduced:

$$V_k(n) = X_j(n)W_{kj}^T(n) \tag{2}$$

$$Y_k(n) = \varphi(V_k(n)) = (1 - e^{-\lambda V_k(n)}) / (1 + e^{-\lambda V_k(n)}) \tag{3}$$

$$e_k(n) = |d_k(n) - y_k(n)| \tag{4}$$

$$W_{kj}(n+1) = W_{kj}(n) + \Delta W_{kj}(n) \tag{5}$$

where X is input vector and W is the weight vector. φ is the activation function. Y is the output. e_k is the error value and d_k is the desired output. Note that $\Delta W_{kj}(n)$ is 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 through student's self-study). The dynamical changes of weight vector value specifically for supervised phase is given by:

$$\Delta W_{kj}(n) = \eta e_k(n) X_j(n) \tag{6}$$

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

$$\Delta W_{kj}(n) = \eta Y_k(n) X_j(n) \tag{7}$$

Noting that $e_k(n)$ in (6) is substituted by $y_k(n)$ at any arbitrary time instant (n) during the learning process.

Reading brain modeling

In accordance with biology, the strength of response signal is dependent upon the transfer properties of the output motor neuron stimulating salivation gland. The structure of the model following the original Hebbian learning rule in its simplified form is represented at Fig 3.

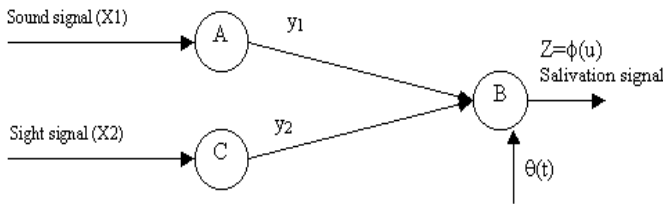


Fig. 3. The structure of simplified Hebbian model form.

Referring to the two figures (Fig.4&Fig.5) shown in below, suggested models obeys that concept as the two inputs I_1, I_2 represent sound (heard) stimulus which simulates *phonological word-form* and visual (sight) stimulus which simulates *orthographic word-form* respectively. The outputs O_1, O_2 are representing pronouncing and image recognition processes respectively. In order to justify the superiority and optimality of phonic approach over other teaching to read methods, an elaborated mathematical representation is introduced for two different neuro-biologically based models. Any of models needs to learn how to behave (to perform reading tasks). Somebody has to teach (for supervised learning) - not in our case - or rather for our learning process is carried out on the base of former knowledge of environment problem (learning without a teacher). The model obeys the original Hebbian learning rule. The reading process is simulated at that model in analogues manner to the previous simulation for Pavlovian conditioning learning. The input stimuli to the model are considered as either conditioned or unconditioned stimuli. Visual and audible signals are considered interchangeably for training the model to get desired responses at the output of the model. Moreover the model obeys more elaborate mathematical analysis for Pavlovian learning process [24]. Also, the model is modified following general Hebbian algorithm (GHA) and correlation matrix memory [25][26][28][29][30]. The adopted model is designed basically following after simulation of the previously measured performance of classical conditioning experiments. The model design concept is presented after the mathematical transformation of some biological hypotheses. In fact, these hypotheses are derived according to cognitive/behavioral tasks observed during the experimental learning process [31]. Generally, the output response signal varies as shown in the original Pavlov experimental work [24], where the output response signal is measured quantitatively in the exactness of pronouncing letter/ word. In accordance with biology, the output of response signal is dependent upon the transfer properties of the output motor neuron stimulating salivating as unconditioned response (UCR) for heard phoneme (sound signal). However, this pronouncing output is considered as conditioned response (CR) when

input stimulus is given by only sight (seen letter/ word). The structure of the model following the original Hebbian learning rule in its simplified form (single neuronal output) is given in Fig.3, where A and C represent two sensory neurons (receptors)/ areas and B is nervous subsystem developing output response. The below simple structure at

Fig. 5 drives an output response reading function (pronouncing) that is represented as O_1 . However the other output response represented as O_2 is obtained when input sound is considered as conditioned stimulus. Hence visual recognition as condition response of the heard letter/ word is obtained as output O_2 . In accordance with biology, the strength of response signal is dependent upon the transfer properties of the output motor neuron stimulating salivating gland. The structure of the model following the original Hebbian learning rule in its simplified form is given in Fig.3. That figure represents the classical conditioning learning process where each of lettered circles A, B, and C represents a neuron cell body. The line connecting cell bodies are the axons that terminate synaptic junctions. The signals released out from sound and sight sensor neurons A and C are represented by y_1 and y_2 respectively.

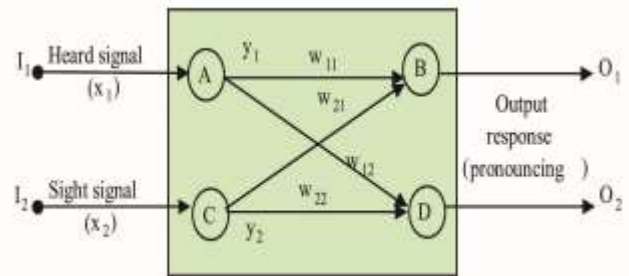


Fig. 4. Generalized reading model which predented as pronouncing of some word (s) considering input stimuli and output responses.

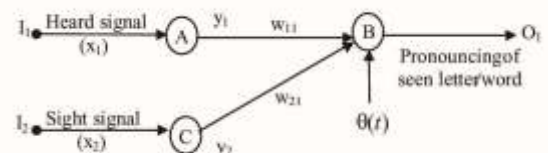


Fig.5. The structure of the first model where reading process is expressed by conditioned response for seen letter/ word

The activation function of neurons A and C are considered as a fraction of signum function. Considering, some more simplification of any neuron cell arguments, the differential equation describing electrical neural activity has been suggested, as follows:

$$\frac{do_i}{dt} = \sum_{j=1}^n f(y_{ij}) - j(o_i) \quad (8)$$

where, y_{ij} represents the activity at the input (j) of neuron (i), $f(y_{ij})$ indicates the effect of input on membrane potential, $j(o_i)$ 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 differential equation (8), proved to be presented as transfer functions. Assuming, the linearity of synaptic control effect, the output response signal is given as:

$$O_i = \phi \left(\sum_{j=1}^n w_{ij} y_{ij} - \theta_i \right) \quad (9)$$

where, ϕ has two saturation limits, the function 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). Specifically, the function (ϕ) is recommended to be chosen as a ramp or sigmoid activation signal function [10]. However, the ramp function was used to represent the output response of the presented model, because of its mathematical similarity to sigmoid function. 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:

$$\frac{dw_{ij}}{dt} = \eta z_i y_{ij} - a(o_i) w_{ij} \quad (10)$$

Where, the first right term corresponds to the unmodified learning (Hebb's law) and η is a positive constant. The second term represents active forgetting, $a(o_i)$ is a scalar function of the output response (o_i). Referring to the structure of the model given at Fig.3, the adaptation equation of the single stage model is as follows.

$$w'_{ij} = -aw_{ij} + \eta y_i x_{ij} \quad (11)$$

Where w_{ij} represents synaptic connectivity between node i and node j . y_i is the output obtained from node i . Where, the values of η , y_i and x_{ij} are assumed all to be non-negative quantities, η is the proportionality constant less than one, and a is also a constant less than one. The solution of the above equation is given graphically as it solved at [19] assuming that the ratio of the values of η and a to be $(\eta/a = 1)$, so a linear neuron model for the output is fulfilled as suggested for

Revising generalized hebbian algorithm (gha) [25]

The Generalized Hebbian Algorithm (GHA) [25] also known in the literature as Sanger's rule, is a linear feed forward neural network model for unsupervised learning with applications primarily in principal components analysis. First defined in 1989 [28] it is similar to Oja's rule in its formulation and stability, except it can be applied to networks with multiple outputs [30]. The name originates because of the similarity between the algorithm and a hypothesis made by Donald Hebb [26] about the way in which synaptic strengths in the brain are modified in response to experience, i.e., that changes are proportional to the correlation between the firing of pre- and post-synaptic neurons [29]

A. Theory

GHA combines Oja's rule with the **Gram-Schmidt process** to produce a learning rule of the form

$$\Delta w_{ij} = \eta \left(y_j x_i - y_j \sum_{k=1}^j w_{ik} y_k \right) \quad (12)$$

where w_{ij} defines the **synaptic weight** or connection strength between the i th input and j th output neurons, x and y are the input and output vectors, respectively, and η is the *learning rate* parameter.

B. Derivation

In matrix form, Oja's rule can be written

$$\frac{dw(t)}{dt} = w(t)Q - \text{diag}[w(t)Qw(t)^T]w(t) \quad (13)$$

and the Gram-Schmidt algorithm is

$$\Delta w(t) = -\text{lower}[w(t)w(t)^T]w(t) \quad (14)$$

where $w(t)$ is any matrix, in this case representing synaptic weights, $Q = \eta \mathbf{x} \mathbf{x}^T$ is the autocorrelation matrix, simply the outer product of inputs, **diag** is the function that **diagonalizes** a matrix, and **lower** is the function that sets all matrix elements on or above the diagonal equal to 0. We can combine these equations to get our original rule in matrix form,

$$\Delta w(t) = \eta(t) \left(\mathbf{y}(t)\mathbf{x}(t)^T - \text{LT}[\mathbf{y}(t)\mathbf{y}(t)^T]w(t) \right) \quad (15)$$

Where the function **LT** sets all matrix elements above the diagonal equal to 0, and note that our output $\mathbf{y}(t) = w(t) \mathbf{x}(t)$ is a linear neuron [28].

C. Applications

GHA is used in applications where a self-organizing map is necessary, or where a feature or principal components analysis can be used. Examples of such cases include artificial intelligence and speech and image processing. Its importance comes from the fact that learning is a single-layer process—that is, a synaptic weight changes only depending on the response of the

inputs and outputs of that layer, thus avoiding the multi-layer dependence associated with the [back propagation](#) algorithm. It also has a simple and predictable trade-off between learning speed and accuracy of convergence as set by the learning rate parameter η [25].

Simulation algorithm flowchart

This section gives an illustration of a simplified macro level flowchart describing briefly algorithmic steps using Artificial Neural Networks modeling of infant's brain performing vocabulary words' acquisition (Fig.6). That figure presents realistic simulation learning program using Artificial Neural Networks following equation (3) in above section.

D. parametric relations deduced from equation (3):

The effect of increased neurons' number at the suggested ANN model considered effectively observed by the output of simulation program after considering following parameters:

$$V = net - \Theta \quad , \quad net = \sum_{i=1}^m w_i x_i \quad \Theta = 0,$$

$$V = \sum_{i=1}^m w_i x_i \quad , \quad Y(net) = \frac{(1 - e^{-\lambda(net)})}{(1 + e^{-\lambda(net)})}$$

Noting that obtained results are plotted as given at the seventh section at (Fig.

E. Algorithmic steps for micro level flowchart of suggested ANN model.

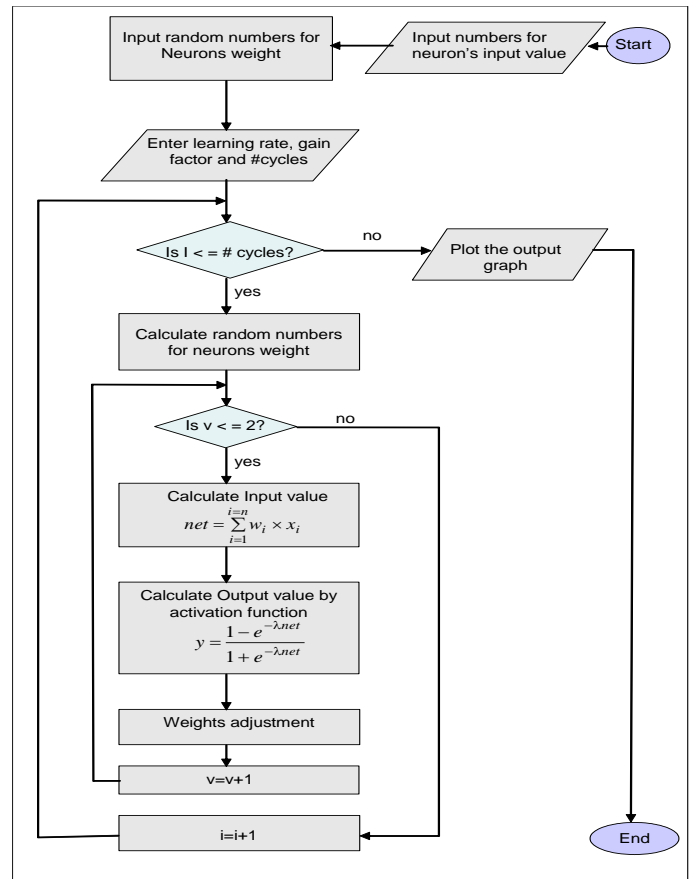


Fig. 6 A simplified macro level flowchart describing algorithmic steps using Artificial Neural Networks modeling

F. Revising of reading ability characteristic modeling

- Reading ability has served as a model system within cognitive science for linking cognitive operations associated with lower level perceptual processes and higher level language function to specific brain systems [32]. More recently, developmental cognitive neuroscience investigations have begun to examine the transformations in functional brain organization that support the emergence of reading skill. This work is beginning to address questions concerning how this evolutionarily recent human ability emerges from changes within and between brain systems associated with visual perception and language abilities, how learning experiences and maturation impact these neural changes, and the way in which individual differences at the genetic and neural systems level impact the emergence of this skill.[33].
- Developmental reading studies have used specific type of recordings to examine more

directly the experience-dependent nature of response to visual word forms, and the relationship between these signals and the rise of fast perceptual specializations for reading [34][35]. To learn how to read is an interesting critical issue, children must code written words and letters into working memory; this code is called orthographic word-form. The goal is to translate that orthographic seen word-form into a pronounced spoken word (phonological word-form). In this context, ensembles of highly specialized neurons inside human brain considered as a neural network. Which dominantly plays a dynamic role in performing developing function of reading process in brain [9]. In other words, the visually recognized written pattern should be transferred and pronounced as its correspondingly associated correlated auditory pattern (previously stored) [36].

- Furthermore, individual intrinsic characteristics of such highly specialized neurons (in visual brain area) influence directly on the correctness of identified images associated with orthographic word-form [37] [38]. How our minds emerge from our flock of neurons remains deeply mysterious. It's the kind of question that neuroscience, for all its triumphs, has been ill equipped to answer. Some neuroscientists dedicate their careers to the workings of individual neurons. Others choose a higher scale:

they might, for example, look at how the hippocampus, a cluster of millions of neurons, encodes memories. Others might look at the brain at an even higher scale, observing all the regions that become active when we perform a particular task, such as reading or feeling fear [39].

- Functional and structural neuroimaging studies of adult readers have provided a deeper understanding of the neural basis of reading, yet such findings also open new questions about how developing neural systems come to support this learned ability. A developmental cognitive neuroscience approach provides insights into how skilled reading emerges in the developing brain, yet also raises new methodological challenges. This review focuses on functional changes that occur during reading acquisition in cortical regions associated with both the perception of visual words and spoken language, and examines how such functional changes differ within developmental reading disabilities. We integrate these findings within an *interactive specialization* framework of functional development, and propose that such a framework may provide insights into how individual differences at several levels of observation (genetics, white matter tract structure, functional organization of language, cultural organization of writing systems) impact the emergence of neural systems involved in reading ability and disability. [11]

Associative reading brain memory function

This section introduces the mathematical formulation of the reading brain association function between seen word (orthographic word-form) into a spoken word (phonological word-form) as follows:

Consider X_k' and X_k'' are the two vectors simulating phonological word-form (heard phonological voice word signal) and orthographic word-form (seen written orthographic word form) by input stimuli patterns respectively. Similarly Y_k' and Y_k'' are the two vectors simulating reading (pronouncing) and visual recognizing output responses respectively. The two expected unconditioned responses are described in matrix form as follows:

$$Y_k' = W(k) \cdot X_k', k = 1, 2, 3, \dots, q \tag{16}$$

where $W(k)$ is a weight matrix determined solely by the input-output pair (X_k', Y_k')

$$y_{ki} = \sum_{j=1}^r w_{ij}(k) \cdot x_{kj}, i = 1, 2, \dots, r \tag{17} \quad \square$$

where $w_{ij}(k)$, $j = 1, 2, \dots, r$ are the synaptic weights of neuron i corresponding to the k^{th} pair of associated patterns of input -output pair (X_k', Y_k') . We may express y_{ki} in equivalent form.

$$y_{ki} = [w_{i1}(k), w_{i2}(k), \dots, w_{ir}(k)] \begin{bmatrix} x_{k1} \\ x_{k2} \\ \dots \\ x_{kr} \end{bmatrix}; i = 1, 2, \dots, s \quad (18)$$

Similarly, for visual input stimulus X_k'' and recognizing (of seen letter/ word) output response Y_k''

$$y_{ki} = [w_{ir+1}(k), w_{ir+2}(k), \dots, w_{im-r}(k)] \begin{bmatrix} x_{kr+1} \\ x_{kr+2} \\ \dots \\ x_{km-r} \end{bmatrix} \quad (19)$$

$i = s + 1, 2, 3, \dots, l$

For conditioned response, the input hearing stimulus X_k' results in recognizing visual signal Y_k'' . However, input seen letter/word stimulus X_k'' results in pronouncing that letter/ word as conditioned response vector Y_k' which expresses the reading activity given by the equation

$$y_{ki}' = [w_{ir+1}(k), w_{ir+2}(k), \dots, w_{im-r}(k)] \begin{bmatrix} x_{kr+1}'' \\ x_{kr+2}'' \\ \dots \\ x_{km-r}'' \end{bmatrix} \quad (20)$$

$i = 1, 2, 3, \dots, s$

In a similar manner, the other conditioned response for recognizing heard phoneme is described by the equation:

$$y_{ki}'' = [w_1(k), w_2(k), \dots, w_r(k)] \begin{bmatrix} x_{kr+1}' \\ x_{kr+2}' \\ \dots \\ x_{km-r}' \end{bmatrix}; i = 1, 2, \dots, s \quad (21)$$

As a result of the above equation, the memory matrix that represents all q- pairs of pattern associations is given by $m * l$ memory correlation matrix as follows:

$M = \sum_{k=1}^q W(k)$, where $W(k)$ weight matrix is defined by

$$W(k) = \begin{bmatrix} w_{11}(k) & w_{12}(k) & \dots & w_{1m}(k) \\ w_{21}(k) & w_{22}(k) & \dots & w_{11}(k) \\ \dots & \dots & \dots & \dots \\ w_{l1}(k) & w_{l2}(k) & \dots & w_{lm}(k) \end{bmatrix} \quad (22)$$

This weight matrix relating input stimulus vector with m-dimensionality X_k connected by synaptic with output response vector Y_k with l-dimensionality. The complete relation for input/ output relation is given by the following equation.

$$\begin{bmatrix} y_{k1} \\ y_{k2} \\ \dots \\ y_{kl} \end{bmatrix} = \begin{bmatrix} w_{11}(k) & w_{12}(k) & \dots & w_{1m}(k) \\ w_{21}(k) & w_{22}(k) & \dots & w_{11}(k) \\ \dots & \dots & \dots & \dots \\ w_{l1}(k) & w_{l2}(k) & \dots & w_{lm}(k) \end{bmatrix} \begin{bmatrix} x_{k1} \\ x_{k2} \\ \dots \\ x_{km} \end{bmatrix} \quad (23)$$

It is worthy to note that the above equation represents memory correlation matrix after learning convergence. So, this matrix is given in other way as:

$$M = Y \cdot X^T \tag{24}$$

The last above equation (24) illustrates that all the values of memory matrix M elements present synaptic weights relating key pattern X with memorized stored patterns Y. In other words, the relation between input patterns to the proposed model and that model's output patterns is tightly closed by the steady state values of the memory matrix M after reaching of learning convergence. Noting, that learning process obeys well the presented ANN model performance given in the above at Fig. 2 by generalized block diagram. Number of highly specialized neurons at corresponding visual brain area contribute to the perceived sight (seen) signal is in direct proportionality with the correctness of identified depicted / printed images. These images represent the orthographic word-form has to be transferred subsequently into a spoken word (phonological word-form) during reading process. Furthermore, in visual brain area individual intrinsic characteristics (Gain Factor) of such highly specialized neurons have direct influence on the correctness percentage [%] of identified images associated with orthographic word-form. Those results given at Fig.7 are analogous to obtained simulation results shown at Fig.8.

Simulation results

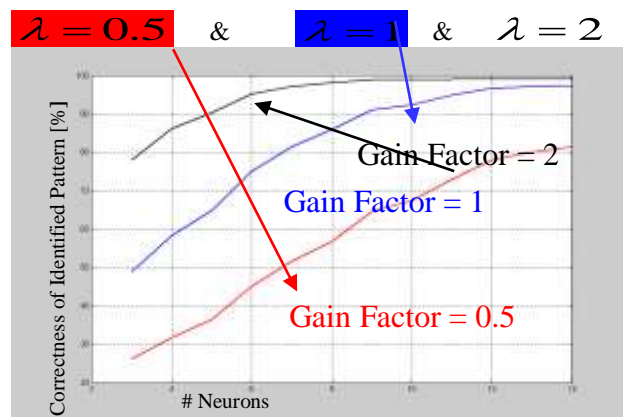


Fig.7 Illustrate students' learning achievement for different gain factors and various number of neurons (measured for learning rate value = 0.3,

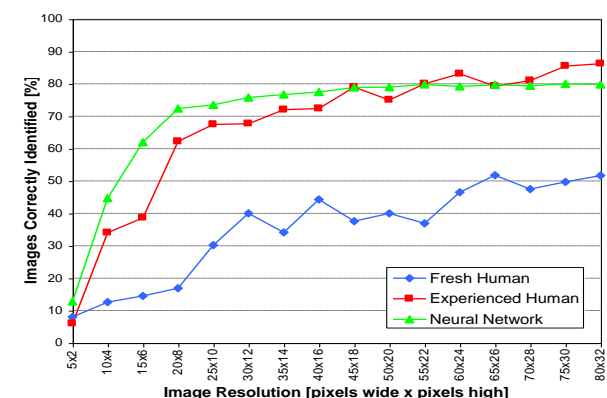


Fig. 8 Simulation results obtained after running of neural network model compared versus measured human results considering basic images with different images' resolution (number of pixels) {adapted from [37]}

In Fig.9, a set of performance curves is shown for general normalized ANN learning model, it represents

considers various gain factor values (denoted by λ parameter). By changing values of this parameter, results in various response time (speeds) in reaching optimum (desired) achievements in accordance with the following equation:

$$y(n) = (1 - \exp(-\lambda_i(n-1))) / (1 + \exp(-\lambda_i(n-1))) \tag{25}$$

Where λ_i represents one of gain factors (slopes) for odd sigmoid function given by equation (25) and n represents the response time expressed in number of cycles (epochs).

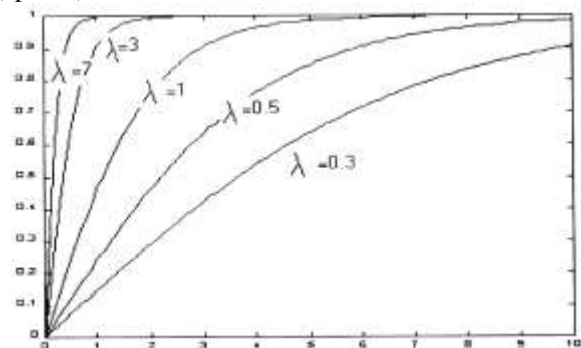


Fig.9. A set of learning performance curves of model with various values of gain factor (λ) versus learning response time.

The effect of number of neural cells

The following simulation results show how the number of neurons may affect the learning performance. The considered learning parameters are for any number

of neurons Activation function = $\frac{1 - e^{-net}}{1 + e^{-net}}$ & Learning

rate = 0.3 & and learning time given as number of training cycles = 300.

Those graphical presented results show that by increasing number of neural cells in brain based

learning, the performance observed to be improved. That is illustrated at the set of figures (8 up to 15). In all of these figures, measuring of the Correctness of Identified Pattern [%] at Fig. 6 and the correct image identification [%] at Fig.8 scaled at vertical (y-axis). Both are corresponded well to horizontal x-axis which presents the nearness to the balance point between 0 & [90%]. In other words, scaling of vertical (y-axis) which scaled between the zero value till 100 [%] at Fig.7 & Fig.8) are analogously mapped to corresponding scaling at the horizontal x-axis at all set of figures (8-13) between 0 & [90%].

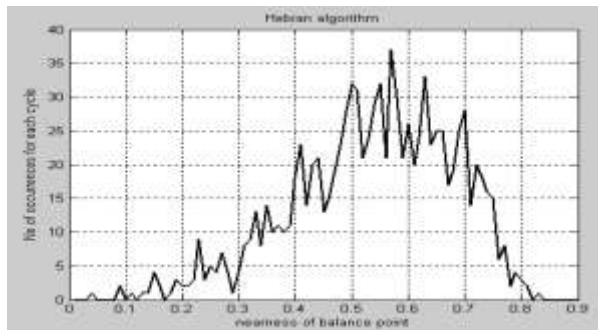


Fig .10 Illustrate nearness to the balance point performance with time factor when #neurons = 3, Learning rate = 0.3 and gain factor = 0.5

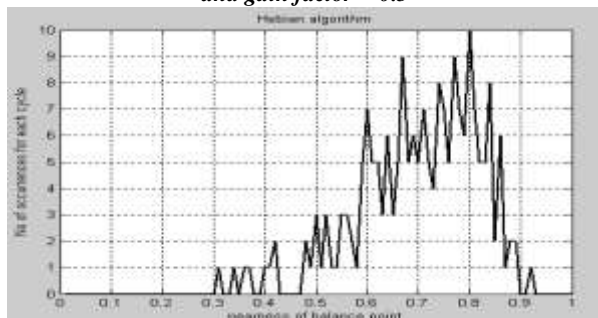


Fig .11 Illustrate nearness to the balance point performance with time factor when #neurons = 5 & Learning rate = 0.3 and gain factor = 0.5

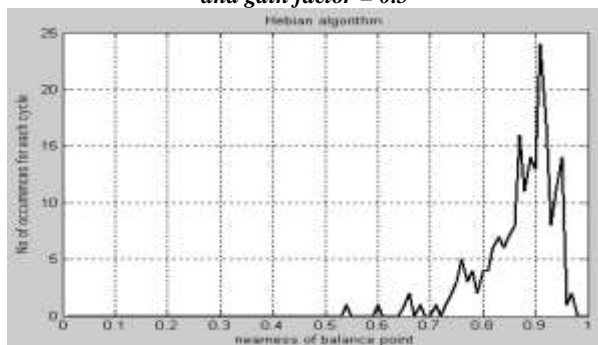


Fig .12 Illustrate nearness to the balance point performance with time factor when #neurons = 7, Learning rate = 0.1 and gain factor = 0.5

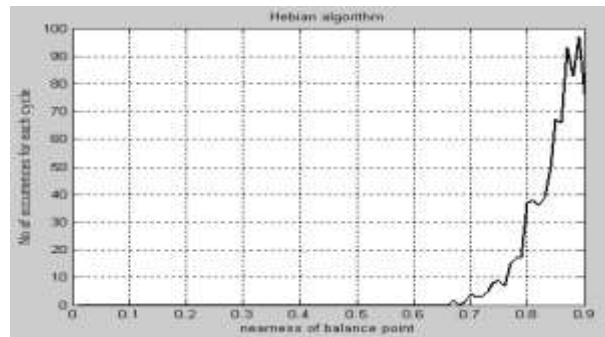


Fig .13 Illustrate nearness to the balance point performance with time factor when #neurons = 9 & Learning rate = 0.3 and gain factor = 0.5

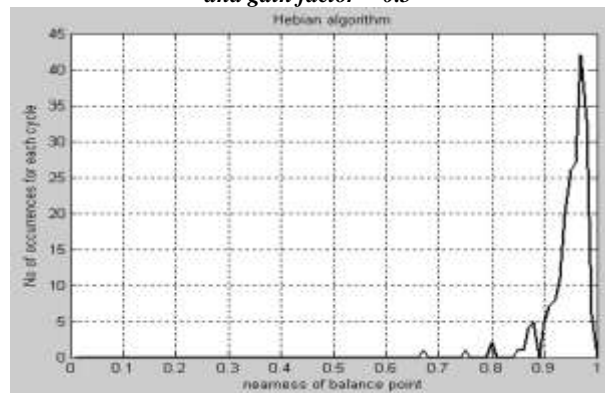


Fig .14 Illustrate nearness to the balance point performance with time factor when #neurons = 12, Learning rate = 0.3 and gain factor = 0.5

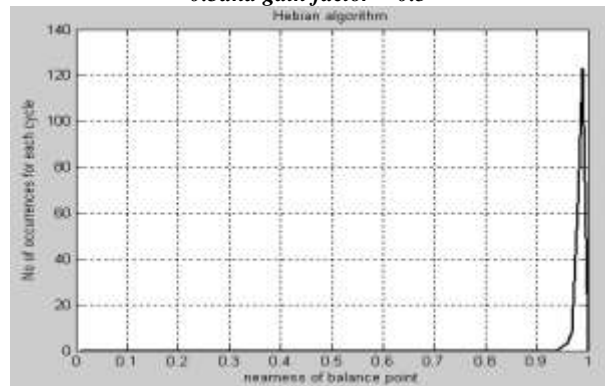


Fig .15 Illustrate nearness to the balance point performance with time factor when #neurons =14, Learning rate = 0.1 and gain factor = 0.5.

Conclusions

This study of presents how highly specialized neurons could be dynamically simulated realistically. It shows that flock of neurons interacts together among the flock's agents to perform a specific common role (Reading function) via visual and auditory brain areas. The following remarks could be concluded:

a) Interesting analogy between number of highly specified flock of neurons contributing to reading function and quality of identified images is observed clearly considering Fig.7 versus Fig.8 respectively.

b) Furthermore, the increased number (at Fig.7) of highly specified neurons corresponds to increasing number of training cycles (epochs) at Fig.9.

c) The gain factor parameter of ANN represents the commonly individual intrinsic differences among flock of highly specified neurons.

d) This work motivated by associative memorization based upon pavlovian experimental work as shown at Fig.3. in addition to adopting GENERALIZED HEBBIAN ALGORITHM (GHA) equivalently Sanger's Rule Approach. However for future extension of this work it is recommended to adopt Hopfield neural network for associative memorization between seen word (orthographic word-form) and a spoken word (phonological word-form).

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