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ON MATHEMATICAL ANALYSIS, AND EVALUATION OF PHONICS METHOD FOR TEACHING OF READING USING ARTIFICIAL NEURAL NETWORK MODELS

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ABSTRACT

Teaching how to read is a critical educational mission (Jeanne S. Chall, 1996). This work introduces a novel approach for evaluation of phonics method selected for learning how to read (keith Rayner, Barbara R. Foorman, Charles A. Perfetti, David Pesetsky, Mark S. Seiedenberg 2003). Herein, neural network modeling is adopted for mathematical analysis and simulation of reading activities rather than other psychological science approaches (keith Rayner, et al.,2001). The main objective of this suggested neural network modeling presented to investigate systematically and to simulate realistically recognizable observations associated with phonics method reading activities. So that selection of two models depending upon neurobiological characterizations is very relevant for realistic simulation –at system level– of reading process activities (Hopfield, J.J, and D.W. Tank, 1986). Consequently, both models are based on biological observations, and derived mainly from original experimental studies of animal learning in psychology (Pavlov, I.P., 1927), (Hampson, S.E , 1990). One of the models is derived from Pavlovian learning adopting Hebbian rule (Hebb, D.O., 1949). While the other is based on Throndikian learning (Thorndike, E.L , 1911), obeying learning by interaction with environment (M.Fukaya, et.al. , 1987).

1 INTRODUCTION

For long time, psycho-linguistics researchers as well as educationalists were trying effectively to find an optimal method for "how reading should be taught?" (Jeanne S. Chall, 1996), (keith Rayner, et al., 2001). Considering an overview presented at following subsection for teaching reading, some motivational points supporting our adopted research are well illustrated.

1.1 An Overview For Teaching How To Read

Learning how to read is an effective and decisive educational mission, specifically for children during their primary school years. So failure in performing that educational mission (during early school years) leads to some nearly permanent learning disabilities during following more advanced educational stages. During last decade phonics method is replaced –at many schools in USA- by other guided reading methods that performed by literature based activities (keith Rayner, Barbara R. Foorman, Charles A. Perfetti, David Pesetsky, Mark S. Seiedenberg: , 2003). Nevertheless, recalling that leaning by phonics is performed directly by coincident association between pronounced sound (phoneme) and its corresponding letter / word. Comparative evaluational analysis for both methodological approaches proved the superiority of phonics method (keith Rayner, Barbara R. Foorman, Charles A. Perfetti, David Pesetsky, Mark S. Seiedenberg 2003). However researches at the field of psychology and linguistic are continuously carried out to support obtained field results. Recently some evaluated field results that tested the progressive outcome from teaching to read processes to proved the optimality of phonic method adopted for teaching children how to read (Jeanne S. Chall 1996).

1.2 The Objective Of This Paper

This paper is motivated by some published research work dealing with the relation between computer and education (Yu, Fancies T., 2002), (Lee, F.L.,1998).additionally this paper is well supported by other recently published papers adopting modeling and simulation of some psycho-educational experiments (Hassan H. and Watany M., 2000), (Hassan H. and Watany M., 2003). The objective of this paper is to justify and support the superiority and optimality of phonic approach over other teaching to read methods. In fulfillment of this objective an elaborated mathematical representation is introduced for two different neuro-biologically based models. Both of models are derived from some experimental work for animal learning psychological studies (Pavlov, I.P., 1927), (Hampson, S.E., 1990). Moreover the two suggested models, herein are designed to simulate realistically detail biological observation concerning with reading process. Also, both models adopt training processes that closely related to learning paradigm known as "learning without a teacher"(Haykin S., 1999).

In figure 1. the generalized concept of artificial neural network modeling is illustrated. Our suggested models obeys that concept as the two inputs I_1, I_2 represent sound (heard) stimulus and visual (sight) stimulus respectively. The outputs O_1, O_2 are representing pronouncing and image recognition processes respectively. 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) (Haykin S., 1999).

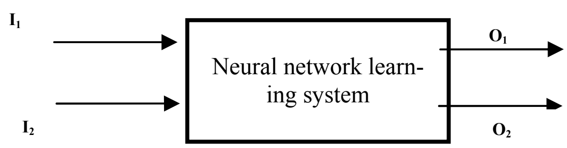


Figure 1: generalized model for ANN learning system considering input stimuli and output responses

1.3 Relation Between Pattern Recognition And Reading Process

In addition to the presented view in the above for teaching to read methods, reading process could be viewed as related to pattern recognition and classification problem. This justifies our adopting of ANN system for modeling biological observations detected during reading activities. A significant proportion of information that absorbed (stored in human brain) is introduced in form of patterns. Reading process is simply viewed as to pronounce any string of visualized letters as a part of varied text patterns. Visual system must solve pattern recognition and classification problem in accordance with cognitive issues. In other words, the seen pattern should be transferred into its corresponding (previously stored) correlated auditory pattern (R. Beale and T. Jackson, 1990).

1.4 Brief View For Suggested Models

The first model obeys the original Hebbian learning rule (Hebb, D.O., 1949). 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 (Hassan H. and Watany M., 2000). Also, the model is modified following general Hebbian algorithm and correlation matrix memory (Haykin S., 1999).

The second model is suggested to adopt reinforcement learning / neurodynamic programming that is equivalently known as learning by interaction with environment (M.Fukaya, et.al., 1987). The model is preceded by two perceptron circuits that develop two logical values (1 or 0) as inputs to the basic considered model. These inputs are provided after performing the classification of both visual and audible patterns following linear separability theory (Minsky, M.I. and S.A. ,1988).

1.5 Paper Organization

This paper is organized as follows : at next two sections detail descriptions of the suggested models are successively presented at sections 2 & 3. That following previously published elaborated results for mathematical analysis and simulation (Hassan H. and Watany M., 2000), (Hassan H. and Watany M., 2003). The obtained results and analysis are given at section 4, they illustrate relation between noisy teacher, learning rates, and individual differences and their effect on learning convergence. At last section some conclusive remarks and discussion are presented.

2 DESCRIPTION OF THE FIRST MODEL

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. Generally, the output response signal varies as shown in the original Pavlov experimental work (Pavlov, I.P., 1927), 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 pronouncing 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 Figure 2, where A and C represent two sensory neurons / areas and B is nervous subsystem developing output response.

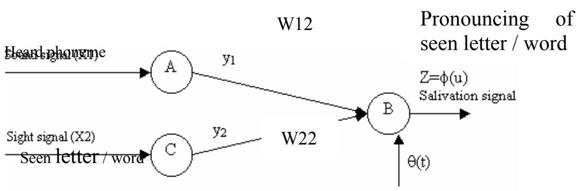


Figure 2: The structure of the first model where reading process is expressed by conditioned response for seen letter / word

The above simple structure drives an output response (pronouncing) that is represented at figure 1 as O_1. However the other output response represented at figure 1 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.

From biological point of view that model considers any activity pattern (sound or visual signal) must be stored in brain memory through learning process. The interaction between learning and memory is will recognized during performing of reading processes. When some activity pattern is learned in brain memory. The recalling process of such reading patterns is recommended to be following long term memory (Grossberg S., 1982). Noting that computations accomplished by hippocampus play the role for transferring short term memory to long term memory after learning convergence (Grossberg S., 1982), (, T.V.P. and T. Lomo, 1973).

2.1 Mathematical Formulation Of The Model

Let the model considers the input (conditioned / unconditioned) stimulus vector X with m dimensionality to be decomposed into two smaller vectors. The first small vector with r dimension simulates the audible sound signal, however the other belongs the rest (m-r) dimensions. Similarly the output response vector Y is decomposed into two smaller vectors representing (conditioned / unconditioned) responses.

With more mathematical details considered q pairs of patterns relating X and Y vectors. The kth pair of patterns is represented by the key vector Xk and the memorized Yk. Let the key vector Xk with m input space dimensionality, which represents implicitly both of heard phoneme (sound signal) stimulus and its corresponding seen letter / word (visual signal) stimulus. Hence, this implicit vector should be decomposed into two smaller vectors each with dimensionality less than (m). Assume that sound signal is represented (simulated) as vector with r dimensionality. Obviously the correlated visual signal is simulated as a vector with dimension (m-r). This means in practical application that vanishing any of two smaller vectors implies non existence of either input stimuli. In other words input conditioned or unconditioned stimulus is detected by measuring input space dimensionality of vector Xk. similarly, the memorized vector Yk represents two unconditioned / conditioned response to the input stimulus vector Xk . However the dimensionality of that memorized response vector differs from that for input vector. Consequently, considering that Yk vector have l dimensionality, hence it decompose into two smaller vectors as unconditioned and / or conditioned responses. Let Yk vector with l dimensionality implicitly includes both output response signals. i.e. when pronouncing signal vector have s dimensionality the other recognizing process of seen letter / word is simulated as a vector with (l-s) dimensionality. As a consequence of the above description of both vectors Xk , Yk the following equations illustrate well memorization process during after completion of learning convergence (reading activity).

2.1.1 Memorization Equations

Consider X'k and X"k are the two vectors simulating heard and seen input stimuli respectively. Similarly Y'k and Y"k are the two vectors simulating pronouncing and visual recognizing output responses respectively. The two expected unconditioned responses are described in matrix form as follows:

$$Y'_k = W(k)\, X'_k \qquad , k = 1, 2, 3, \ldots\ldots, q \tag{1}$$

Where w(k) is a weight matrix determined solely by the input-output pair (X'_k , Y'_k)

$$y_{ki} = \sum_{j=1}^{r} w_{ij}(k) x_{kj}, \qquad i = 1, 2, \ldots, r \tag{2}$$

Where the $w_{ij}(k), j = 1,2,\ldots,r$ are the synaptic weights of neuron i corresponding to the kth pair of associated patterns of the input-output pair (X'_k , Y'_k). we may express y_{ki} in the equivalent form

$$y_{ki} = \left[w_{i1}(k), w_{i2}(k), \ldots, w_{ir}(k)\right] \begin{bmatrix} x_{k1} \\ x_{k2} \\ x_{k3} \\ \vdots \\ x_{kr} \end{bmatrix}, i = 1,2,3,\ldots,s \tag{3}$$

Similarly for visual input stimulus X''_k and recognizing (of seen letter / word) output response Y''_k

$$y_{ki} = [w_{ir+1}(k), w_{ir+2}(k), \ldots, w_{im-r}(k)] \begin{bmatrix} x_{kr+1} \\ x_{kr+2} \\ x_{kr+3} \\ \vdots \\ x_{km-r} \end{bmatrix}, i = s+1,2,3,\ldots,l \tag{4}$$

For conditioned response the input hearing stimulus X'_k results in recognizing of 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

$$y'_{ki} = [w_{ir+1}(k), w_{ir+2}(k), \ldots, w_{im-r}(k)] \begin{bmatrix} x''_{kr+1} \\ x''_{kr+2} \\ x''_{kr+3} \\ \vdots \\ x''_{km-r} \end{bmatrix}, i = 1,2,3,\ldots,s \tag{5}$$

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

$$y''_{ki} = [w_1(k), w_2(k), \ldots, w_r(k)] \begin{bmatrix} x'_{kr+1} \\ x'_{kr+2} \\ x'_{kr+3} \\ \vdots \\ x'_{km-r} \end{bmatrix}, i = s+1,2,3,\ldots,l \tag{6}$$

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

$$W(k) = \begin{bmatrix} w_{11}(k) & w_{12}(k) & \ldots & w_{1m}(k) \\ w_{21}(k) & w_{22}(k) & \cdots & w_{2m}(k) \\ \vdots & \vdots & \vdots & \vdots \\ w_{l1}(k) & w_{l2}(k) & \cdots & w_{lm}(k) \end{bmatrix} \tag{7}$$

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

$$\begin{bmatrix} y_{k1} \\ y_{k2} \\ \vdots \\ y_{kl} \end{bmatrix} = \begin{bmatrix} w_{11}(k) & w_{12}(k) & \ldots & w_{1m}(k) \\ w_{21}(k) & w_{22}(k) & \cdots & w_{2m}(k) \\ \vdots & \vdots & \vdots & \vdots \\ w_{l1}(k) & w_{l2}(k) & \cdots & w_{lm}(k) \end{bmatrix} \begin{bmatrix} x_{k1} \\ x_{k2} \\ \vdots \\ x_{km} \end{bmatrix} \tag{8}$$

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 :

$$M = YX^T \tag{9}$$

Relating key patterns X with stored memorial stored patterns Y.

Considering that the ramp function to represent one output of principle components of any response (of the presented model) due to some input stimulus. This function is mathematically similar to the sigmoid classical activation function. In addition to, its simplified computational processing. The effects of different choices of signal functions on sensory and / or response pattern processing have been classified mathematically, including the important contrast enhancement and noise suppression properties of sigmoid signal functions (Grossberg, S. and Levine, 1987).

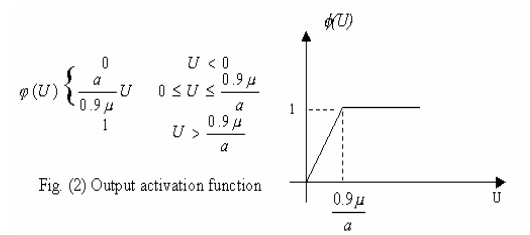


Figure 3: illustrates the output response as ramp function

Consequently, the ramp function shown at Figure 3 is suggested in the simulations because it has similar mathematical properties to the sigmoid function and simple to process.

Referring to the structure of the model given at figure 2 the adaptation equation of the single neuronal model (between *i, j* nodes) is as follows.

$$w_{ij} = -a w_{ij} + \eta y_i x_{ij} \tag{10}$$

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 (Freeman, A.J. 1994), assuming that the ratio of the values of η and a to be $\left(\frac{\eta}{a} = 1\right)$, so a linear neuron model for the output is fulfilled as suggested for generalized Hebbian algorithm (Haykin S., 1999).

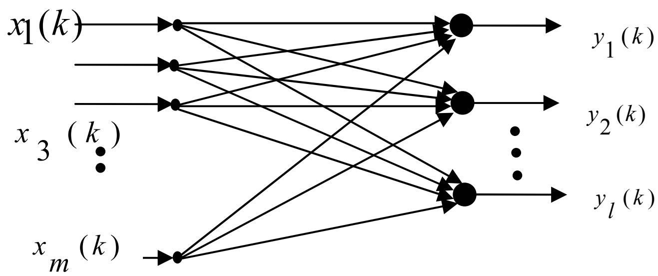


Figure 4: feedforward network with single layer computational nodes (linear neurons) that trained in accordance with generalized Hebbian algorithm (GHA) developing principle components at its output. Noting that input environmental stimulus vector X(k) with m dimensionality giving output response vector Y(k) with l dimensionality.

Consider that the above model with single neuron output is modified basically to form Hebbian neuronal based circuit which functions as maximum eigen filter. So it extracts at its output the principle component of input stimulus vector with arbitrary dimension. The single neuronal model presented in the above Figure 2 is expanded into feedforward with single layer of linear neurons as shown in Figure 4 (Grossberg S., 1982).

3 THE SECOND MODEL

This model is based on neurodynamic programming (reinforcement learning) where two level neural networks that learn by interaction with environment are considered. The inputs and outputs are developed as digital (logical variables) which obeying the generalized structure of ANNs model shown at Figure 1. However, the model is composed of two stages: the first have two perceptron submodel structures, the second is two layers neural network model. Each of perceptron develops one stimulating signal, either visual or auditable. Both of threshold logical values are given to the second two layer model. In figure 5 it is shown both of two perceptron models. The initial and final states of the completed model are given at tables. That is derived by either retina sensory area or by other cochlea area. The perceptron input for the retina area as well as that for cochlea area are vectors represented implicitly as vector X suggested as model given in the above. The input / output relationship of the model are given as a pair of logic function F1 & F2 where initially illustrated of table 1. If output patterns need the desired function for reading convergence process, the input / output relationships is represented as in table 2. in our case the final states of input stimuli and output responses are mathematically given as :

$$F_1 = X_2 \quad , \quad F_2 = X_1$$

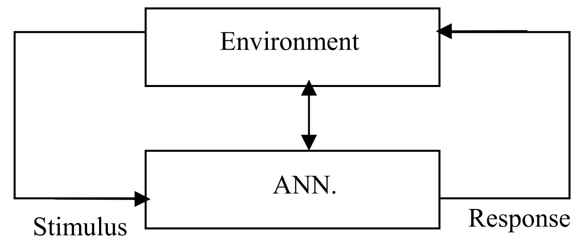


Figure 5: shows how the second ANN model interacts with environmental conditions considering that inputs and outputs are logical variables (1 or 0)

Referring to Figure 6 the intermediate network model states are denoted by m_i (i = 1, 2, .., 4) logical variable. The following relations are expressing the input / output relations desired (modified after M.Fukaya, et.al, 1987).

$$m_1 = x_1 + x_2, \quad m_2 = x_2\bar{x}_1, \quad m_3 = x_2\bar{x}, \quad m_4 = x_1$$
$$y_1 = m_1\overline{m}_2\overline{m}_3, \quad y_2 = m_4$$

Applying Boolean algebra it could be proved the following relationships

$$F_1 = X_2 \quad , \quad F_2 = X_1$$

are valid.

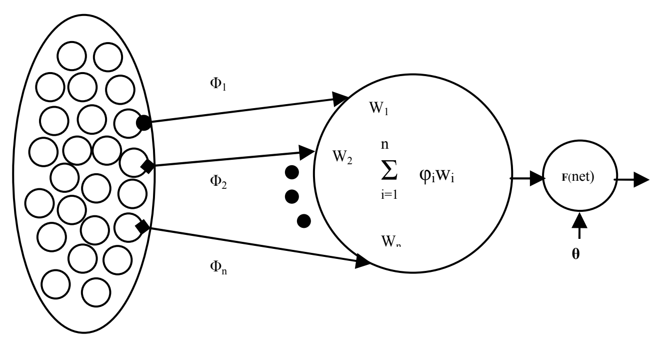


Figure 6-a: illustrates audible pathway that classifies input sound stimuli obeying linear separability

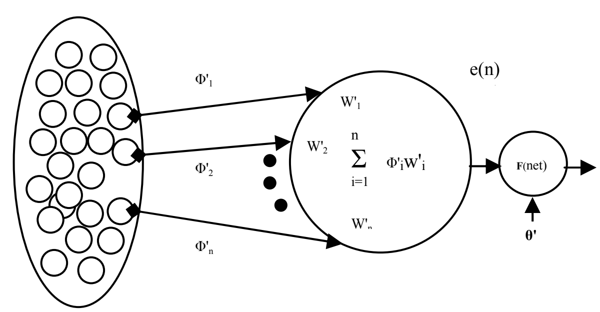


Figure 6-b: illustrates visual pathway that classifies input sight stimuli obeying linear separability

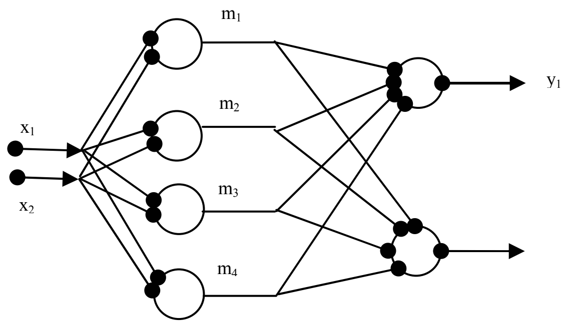


Figure 7: Simulated model for learning by interaction with environment adapted from M.Fukaya, et.al, 1987.

The number of trials (training cycles) needed to get the above final state / action is derived analogously as (286 cycles) (M.Fukaya, et.al, 1987). However this result is basically dependable upon the initial model state (simulating initial conditions of synaptic weights for students under training). Our results for similar analysis of synaptic weights connectivity are previously published at (Ghoaimy M. A., 1994). These results proved that individual differences phenomenon is directly affected by the initial states of synaptic weight connectivity and leading in some special cases to learning disabilities.

Table 1: The initial states and actions for unconditioned stimuli and responses (initial condition)

X1	X2	F1	F2
0	0	0	0
0	1	0	1
1	0	1	0
1	1	1	1

Table 2: The final states and actions for conditioned stimuli and responses (completion of learning phase)

X1	X2	F1	F2
0	0	0	0
0	1	1	0
1	0	0	1
1	1	1	1

Figure 5 represents two perceptrons forming the preceding stage that develops inputs to the second model which learn obeying the principal of reinforcement (learning by interaction with environment).

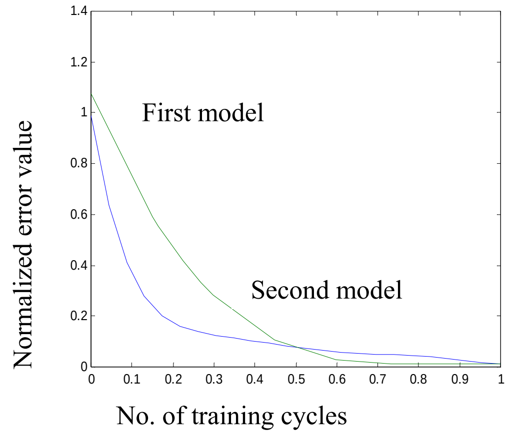


Figure 8: comparison between first and second model learning curves as published at original psycho-experimental work by Pavlov and Throndik considering normalized output values adapted from Hassan H. and Watany M., 2003.

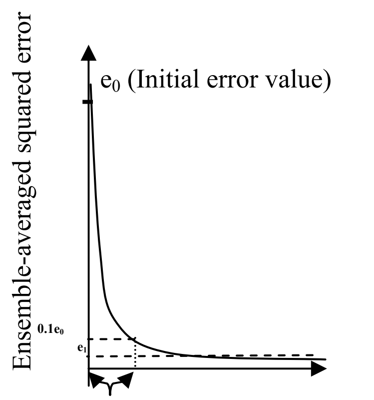


Figure 9: idealized learning curve of the LMS algorithm that seems to be as the above results illustrated in Figure 8 adapted from Haykin S., 1999.

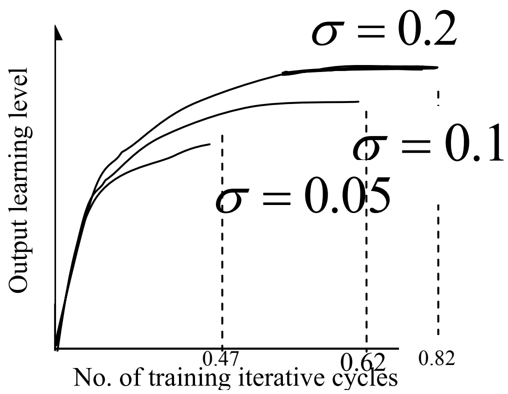
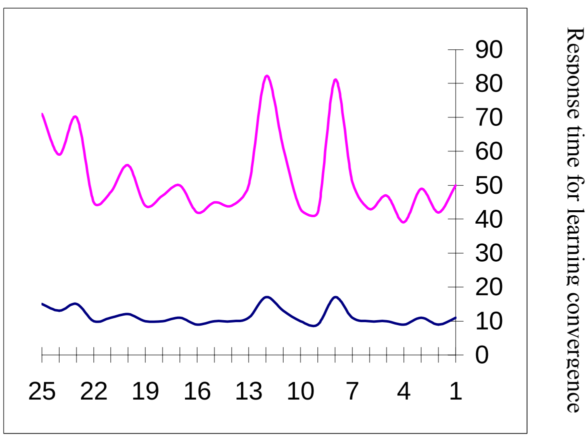
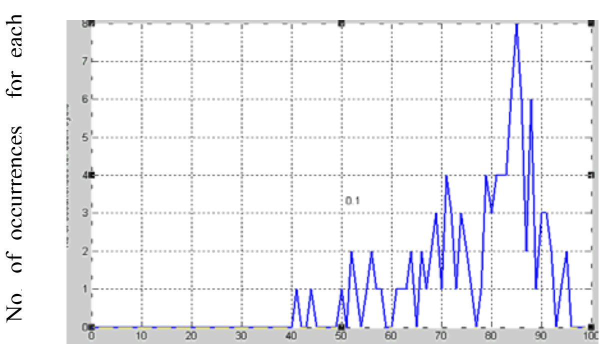


Figure 10: relation between noise power (σ) that represents noisy teacher and learning process convergence. Adapted from Ghoaimy M.A., et.al., 1994



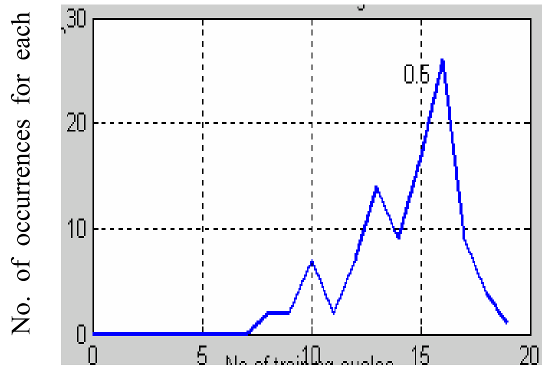
Samples of students group

Figure 11: illustrates the effect of learning rate parameter η on the learning convergence time for two diiferent value 0.1 & 0.5 noting that time response obeys Gaussian distribution in an approximate manner



No. of training cycles

Figure 12a: illustrates the time response for learning convergence for learning rate



No. of training cycles

Figure 12b: illustrates the time response for learning convergence for learning rate 0.5

4 RESULTS AND ANALYSIS

Briefly, some of interesting results are obtained concerning learning curves performance of the two suggested models. The study proved the well analogy between learning performance curves of the two models and fulfill the modeling of learning how to read phenomenon using phonics method. For both models the curves seems to agree well with the idealized curve for LMS algorithm derived and illustrated at figure 8 (Haykin S., 1999). Additionally an interesting relation between different learning rates and the effect of noisy teacher. The statistical analysis of time response – that measured by number of cycles until learning convergence – for some number of students shown to be approximately closed to Gaussian distribution. The study of both models which are based on some psycho-learning experimental processes given in the above results in a set of curves shown at Figure 8, Figure 9, Figure 10, Figure 11 and figure 12.

In more details, referring to Figure 8, for both models these curves seem to be equivalent to each other. These curves agree well with the idealized curve for least mean square (LMS) algorithm derived and presented at (Haykin S., 1999)

Referring to the figure 9 the value $0.1e_0$ represents the minimum possible error after learning convergence. In Pavlov experiment it is the minimum latony time to get desired response, for Thorndike experiment it represents maximum speed response (Pavlov, I.P., 1927), (Thorndike, E.L , 1911)

Referring to figure 10 an interesting remarks that worthy to be evaluated, the relation between learning rate values and noisy data (teacher) considering unsupervised learning. That is convergence time of learning process is inversely proportional to noise power value (Ghoaimy M. A., et al, 1994). However, that convergence time is indirectly proportional to the learning rate values as follows. The convergence time of learning process is reached after

47, 62, 82 training cycles when noise power is, 0.05, 0.1 and 0.2 respectively.

Referring to figure 11, the graphical relation for figure 7 simulated model for learning by interaction with environment adapted from (M.Fukaya, et.al , 1987)

measured values of response time versus some sample group of students seems to be similar to output response results concerning some sample group of students shown therein at (Hassan, M., H.,1998). It is worthy to note that, the statistical analysis of the seen oscillatory performance shown at figure 8 proved that most of values are symmetrically positioned around the average value of time response. For example: for $\eta = 0.1$ approximately half of the obtained values are in the range (39 to 71). In other words the result values' distribution is approximately near to Gaussian (normal distribution).

5 CONCLUSIONS AND DISCUSSIONS

Understanding learning processes carried out in ANNs models is recommended for increasing efficiency and effectiveness of some educational activities (Yu, Fancies T.,2002). Also learning mathematics is simulated using computer adopting harmony theory to evaluate and analysis some teaching mathematics processes (Lee, F.L , 1998). This paper is accomplished following recently research approach concerned with relation between computer and education. More specifically, the represented work herein, provides educationalists as well as psycho-linguistics researchers by a novel and nearly decisive solution concerning the great debate issue for "how reading should be taught?".

This objective is well fulfilled by adopting two neurobiologically ANNs models. Both models are reinforcing each other declaring that phonics method has better optimality and superiority over other approaches for teaching reading. Conclusively, the effective supporting of phonic method is based upon mathematical as well as biological evaluation and analysis of psycho educational experimental studies (Hassan H. and Watany M., 2000), (Hassan H. and Watany M., 2003). Consequently, the adopting of ANNs modeling seems to be a very relevant tool to accomplish simulation of such educational reading activities phenomenon.

The learning curves derived from biological observation of the original work carried by both scientists Pavlov and Throndik (Pavlov, I.P., 1927), (Thorndike, E.L, 1911) agree with computer simulation obtained results so the output errors during proceeding of training for both models are decreased depending upon individual differences. Additionally, the analogy of the Pavlovian response for different inter-stimulus-intervals (ISI) towards the optimized output, and Thorndike repeated trials to achieve the quickest output response (Grossberg, S. and Levine, D.S., 1987). Accordingly to get optimum learning performance (minimum time response) synchronization between two input stimuli is highly recommended as given at (Grossberg, S. and Levine, D.S., 1987).

Thus, environmental changes or otherwise physical supervisor (teacher) – when supervised learning is considered – has to attract neural system / model towards a synchronous state (ISI $\rightarrow$ optimum value) (Hassan H. and Watany M., 2000), (Grossberg, S. and Levine, D.S., 1987). That in order to fulfill desired output optimality. Moreover as this output response is represented in a vector form, Hamming distance could be used to measure classification exactness of the output response (R. Beale and T. Jackson, 1990). Additionally, correlation matrix memory is recursively updated according to successive provided pairs of stimuli until complete storage of all q patterns (referring to equation 9) in the model memory (Haykin S., 1999).

Finally, this work seems to open the research for more evaluation and elaborated studies which aim to achieve better optimized strategies concerned with other educational issues. Moreover it proves the previously suggestion direction at when designing systems "The more biological based models, the more optimality could be reached"(Caudil, M., 1992).

Figures 12a,12b illustrate how the time response fc learning convergence tends to be close as Gaussian distri bution by increasing number of students to one hundre Figure12afor learning rate 0.1 while Figure12b for 0.5

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