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ON QUANTITATIVE MATHEMATICAL EVALUATION OF LONG TERM POTENTAITION AND DEPRESSION PHENOMENA USING NEURAL NETWORK MODELLING

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ABSTRACT

This work adopts a novel quantitative modeling approach for some brain functions analysis and evaluation. More specifically, this paper deals quantitatively with behavioral brain functions prediction on mathematical artificial neural networks (ANNs) bases. That fulfilled by modeling of genetically developed two performances brain functions (learning and memory). It seems relevant to apply mathematical neural modeling to investigate systematically any developmental brain functional performance problems. Consequently, such type of mathematical modeling should be recommended to support quantitatively (rather than qualitatively) brain functional performance evaluation. That is during design, implementation and carrying out precise experimental work assessment of brain performance developmental research work projects.

This paper results in interesting quantitative relationships obtained for (learning and memory) performance evaluation. The two long term phenomena Potentiation (LTP) and depression (LTD) observed at hippocampus brain area, affected by two synaptic plasticity factors (forgetting and learning).Both are introduced following Hebbian learning coincidence detection equation(s). Moreover, these two phenomena (LTP and LTD) shown to be mapped into two separate domains, as two-dimensional feasible learning space. Additionally, another interesting link is deduced relating Hebbian coincidence detection learning process with the well-known sigmoid activation function.

Finally, the obtained results seem to open widely applications of the presented modeling equations, for extended genetically engineering experimental work. Those applications, are mainly aiming to brain functional development on the bases of individual differences, and learning abilities.

1 INTRODUCTION

This paper motivated by obtained results after experimental work based on genetic engineering technology (Joe Z. Tsien 2001, 2000). Such work is mainly concerned with investigational research for some brain functions development (Ezel, C. 2001), (Grossberg, S. (Ed), 1988). More specifically, the objective of that experimental research work is to build up smarter genetically reformed mouse on molecular basis (Joe Z. Tsien, 2001). Therein, brain functions (learning and memory), observed to have better performance following increase of synaptic connectivity (plasticity), in addition to improvement of forgetting factor. The long-term Potentiation phenomena (LTP) observed at hippocampus cortical brain area improves synaptic plasticity as well as memorization factor.

It is noticed that work obtained results were mostly evaluated qualitatively rather than quantitatively,(Bliss, T. V,et.al.1973),(LeDoux, 1999),(Winson,1999). The presented mathematical model obeys the general research direction recommended for ANNs theorists to investigate brain functions phenomena (Sompolinsky, 1988).

2 REVISING OF PAVLOV-HEBBIAN MODEL

Referring to Figure, that shown in below (D.O. Hebb, 1949), and (Hassan H. and Watany M, 2000). The learning process observed to be well performed, after the fulfillment of two input vector events, association. That implies coincidence detection learning process, between input signal vector (X1, X2) to sensory neurons (A, C) and dynamic weight vector (W1, W2), associated with both neurons. The coincidence learning of input signals (with two vector components), is detected as an output salivation signal (Z), that developed by motor neuron (B).

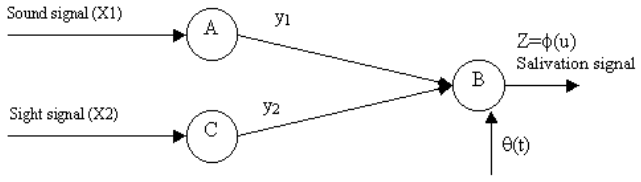

Figure 1: the structure of the Pavlov-Hebbian model.

Referring to the weight dynamics described by the famous Hebbian learning law, (D.O. Hebb, 1949),

adaptation dynamical process for synaptic interconnections given after (T. Kohonen 1988), by the following Eq.:

$$\frac{d\omega_{ij}}{dt} = \eta z_i y_{ij} - a(z_i)\omega_{ij} \qquad (1)$$

Where, The first right term corresponds to learning Hebbian law and η is a positive constant. The second term represents active forgetting; a (z_i) is a scalar function of the output response (z_i). Referring to the structure of the model given at Figure1 the adaptation Eq. of the single stage model is as follows.

$$\dot{w}_{ij} = -aw_{ij} + \eta z_i y_{ij} \qquad (2)$$

Where, the values of η , zi and yij are assumed all to be non-negative quantities (Freeman, J.A, 1994), η is the proportionality constant less than one, a is also a less than one constant.The solution of the above Eq.2 given as follows:

$$w(t) = \frac{\eta}{a}(1 - e^{-at}) \qquad (3)$$

The above solution considered herein, for investigation of two synaptic plasticity factors (forgetting and learning).That is following both long-term phenomena Potentiation (LTP) and depression (LTD) observed at hippocampus brain area.

3 MODELING OF LEARNING CURVES FOR COINCIDENCE DETECTION

The model based on transferring of dot products of coincidence detection vectors, into learning process curve that closely similar to the well-known sigmoid transfer (output) function.

Considering normalized two weight and input vectors, it seems a good presentation of coincidence detection process given as:

$$y = \cos(\theta) \qquad (4)$$

Where… θ is the angle between weight and input vectors. Therefore, the relation given as:

$$x = f(y)$$

Where

$$x = \frac{y}{1-y} \qquad \text{For } (0 <= y<1) \qquad (5)$$

This Eq. inversely equivalently given by inverse y = f(x) as:

$$y = \frac{x}{1+x} \qquad (6)$$

This function could be easily as an approximation of

$$y \approx (1 - e^{-x}) \qquad (7)$$

When only two terms of e^{-x} expansion are considered

However, this exponentially saturated function behaves as the sigmoid function at the range $0 \le x < \infty$ at the next section. Considering generalization of this function, individual differences represented well by relevant choice the parametric value λ in the following Eq.:

$$y = (1 - e^{-\lambda x}) \qquad (8)$$

This value corresponds to the learning rate factor suggested when solving Hebbian learning differential Eq. using Mathematica at (Freeman, J.A, 1994). Considering the view of coincidence detection learning, the angle α is a virtual learning parameter that controlling individual differences factor. So the parametric value λ expressed as:

$$\lambda = \frac{1}{\tan\alpha} \qquad (9)$$

The special case where ($\alpha = \pi/4$), learning is virtually corresponding to the natural state (normalized). Consequently, brainier performance supposed to start at ($\alpha > \pi/4$), and exceeded up to the limit at ($\alpha = \pi/2$). At this limit, learning curve reaches to hard limiter performance, simulating maximum brainier (smartest) performance. Conversely, knockout brain functions cases considered for ($0 \le \alpha < \pi/4$)

These two-brain state functions are well corresponding to practical electrical stimulating at hippocampus brain area. That by either higher or lower frequencies than the normalized learning curve … these two states of frequencies results (after stimulation) in long-term Potentiation (LTP) long term Depression (LTD) respectively Winson,J.1999), (Joe Z. Tsien 2001).

3.1 Graphical illustration of Coincidence Detection learning

The graphical presentation of the previously suggested neural learning models for coincidence detection is briefly given at the following Figures, 2, 3, and 4.

Referring to Figure 2, the three curves shown in the above represents a comparative point of view. That illustrated for the three graphical mapping of different learning performance activities. Coincidence learning detection based on sigmoid activation function (suggested with gain factor equals unity) is shown by curve (a) .At curve (b), the exponentially limited asymptotic graph, following synaptic weight growth

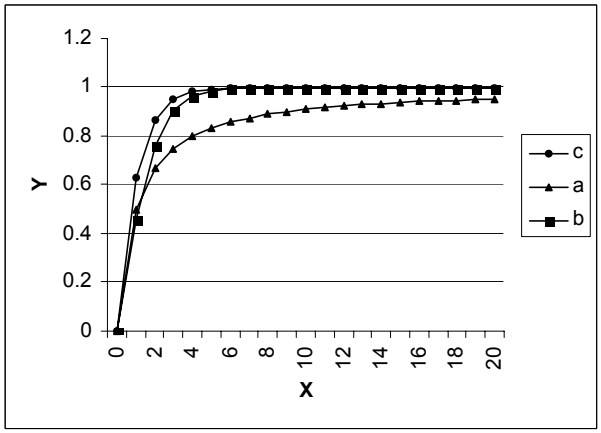

Figure 2: illustrates the relation between different three-coincidence detection Learning curves

(a) $\frac{x}{1-x}$ (b) $\frac{1-e^{-x}}{1+e^{-x}}$, (c) $1-e^{-x}$

That is adopting Hebbian activation rule, representing solution of Eq. (2), as suggested by (Freeman, J.A, 1994), using Mathematica. However, curve (c) represents the solution for Eq. (5) given in the above simulating dot product of coincidence detection vectors.

At Figure3, the graph(Y) shown, represents Eq. (5) in the above section, that may be considered as mapping of both LTP, LTD phenomena into two, separate domains.

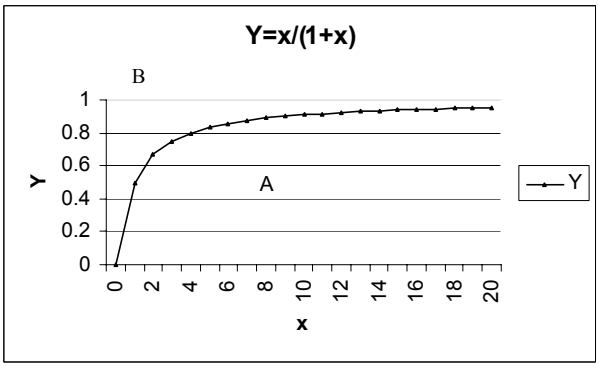

Figure 3: illustrates the division of the learning space into two domains A and B that simulates activities of both, LTD and LTP phenomena respectively.

Finally, referring to Figure4, it represents different three individual levels of learning. Curve Y2 is an equalized representation of both forgetting and learning factors. However, curve Y1 simulates lower level of learning rate, (learning disability). Conversely, the curve Y3 indicates better learning performance than normalized level (of synaptic connectivity), simulated by learning performance curve Y2.

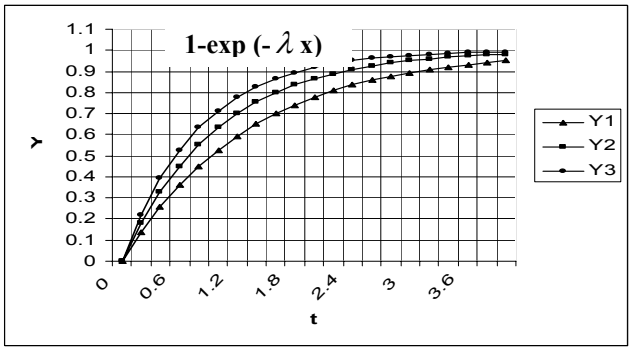

Figure 4: shows three different learning performance curves Y1, Y2 and Y3 that converge at time t1, t2 and t3 considering different NMDA receptor opening time represented at different slope value $\lambda = \frac{1}{\tan\alpha}$

4 RESULTS AND COMMENTS

The learning and memory functions practically observed to be interrelated to each other. For example, the study introduced at (Joe Z. Tsien,2001) considered coincidence detection learning for how to forget the relation between an electrical shock and its associated sound. This implies close relation between learning and memory brain functions .However, herein, learning and memory functions are presented (for simplicity), each at a stand-alone Figure. That Figures 5 and 6 for illustration the effects of both forgetting factor, and learning rate parameter, on learning and memory brain functions, respectively. Noting that horizontal, and vertical axis (for both Figures 4 and 5) represent learning time, and, synaptic connectivity respectively.

Referring to the solution of Eq. (3) introduced at section two in the above, graphical representations for that solution are shown at Figures 5 and 6 given below. In both Figures, virtual opening time for crossing a chemical substance N-methyl-D-aspartate NMDA, is considered as neural receptors at hippocampus brain area. Interestingly, this result verifies numerically values obtained by experimental research work for (learning and memory). (Joe Z. Tsien, 2001).

By details, referring to Figure 5, the normalized curve is given by y3, the learning process is virtually completed, when maximum synaptic connectivity (plasticity)

Approximately the value (0.9).The curve y4, represents in a simulated manner, the two times increase, of opening time for NMDA receptor following Work of (Joe Z. Tsien, 2001).That case implies two time improvement of memorization (better forgetting factor) as given at Eq.s (2), (3) in section two. This means, when lessening of forgetting factor value considered, improvement of learning time observed.

Conversely, when closing receptors period, as shown by graphs y2, y1 until ratios: 0.5, 0.25 respectively (greater forgetting factor), that leads to worst learning performance as illustrated in Figure5 shown below.

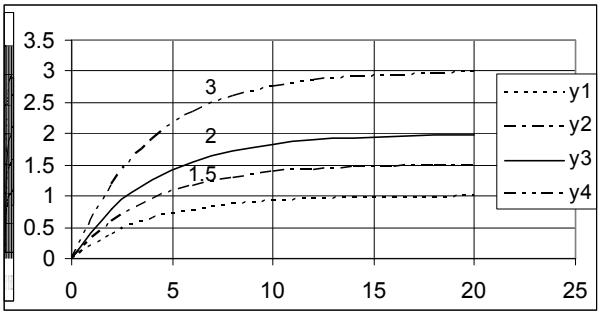

Figure 5: illustrates the effect of forgetting factor on learning period.

For graphs y1, y2, y3, and y4 the relative values of learning periods approximately given as 10:5:2.5:1.2, that corresponds for values of forgetting factor: 0.25, 0.5,1,2, respectively.

Referring to Figure 6, the effect of different values of learning rate parameter illustrated. The shown numerical values, leads to better (memory improvement), supported by results given at experimental research work (Joe Z. Tsien, 2001).The learning rate parameter virtually increased theoretically by factors: 1.5,2,3.However,the experimental results should not exceed practically the unity value as given by Eq.s(2), (3) .

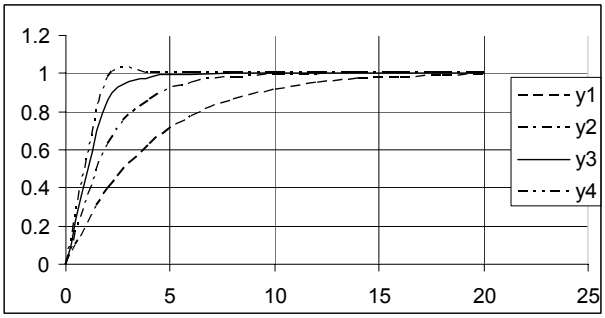

Figure 6: illustrates the effect of learning rate parameter leading to synaptic connectivity saturation, on memorization period (memory brain function). For graphs y1, y2, y3, and y4 the relative values of memorization periods are 12:4:2.5:1.2 that corresponds to learning rates: 1, 1.5,2,3 respectively.

The practical results given at (Joe Z. Tsien, 2001) illustrated the improvement of coincidence detection learning period by factor 2.5.However, the memorization period improved by five times. That when period assigned for crossing a chemical substance N-methyl-D-aspartate NMDA (opening receptor time) duplicated experimentally.

5 CONCLUSIONS AND DISCUSSIONS

Production of mice (or other spices) with genetically reformed brain functions, belongs to an interesting microbiological field of research. However, that research seems considered as an activity of implicitly interested set of diverse research directions. This set comprises computational neurobiology (brain bioinformatics), genetic engineering, neuro microbiology, and the main attention of neurophysiology. Moreover, mathematical neural networks analysis and behavioral modeling attached recently to that set of research directions, (Ezel, C. 2001). Consequently, reforming process of brain functions characterized by interdisciplinary costly experimental work, that inherently very complex and challenging as well.

The presented comments given at the previous section seem to be very promising, for supporting experimental results forecasting, at that interdisciplinary research field. Therefore, future progressive development of experimental research work seems fulfilled by production of other quantitatively distinct level classes of intelligence. Such progressive work motivated by dependence upon analytical models similar to that suggested here. However, the author and others currently carry analytical work that is more elaborate. The currently performed mission herein, includes explicitly quantitative verification of obtained numerical values relating all development of learning and memory brain functions as published at (Joe Z. Tsien, 2001.Additionally, it is worthily to note that analytical model results shown herein may be medically promising for treating cases of brain dysfunction, specially that concerned with learning and memory(D. C. Javitt, and J. T. Coyle, 2004). However, this predicted direction is similar to what previously suggested by the author and others at (Ghonaimy M. A., et al, 1994).

Finally, recommendations of applying neural network modeling at microbiological research field, proved to be very beneficial for opening new development brain functions. Moreover, these functions evaluations and analysis could developed, and being medically promising, on the bases of individual differences, and learning abilities, (Hassan, M., H ,1998), Additionally, more complex elaborated experimental as well as analytical expected when modeling by spike (pulsed) neurons is considered.(Sejnwski,1999).

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