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RESEARCH ARTICLE

Performance and Algorithmic Analogy of Behavioral Learning phenomenon in Neural Network Versus Ant Colony Optimization Systems

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Abstract

This work introduces an investigational study for quantitative analytical analogy comparing between two naturally inspired systems. It takes into consideration interdisciplinary comparative study of observed behavioral learning models for two distinct biological systems. Namely, these systems are associated with mammalian animals and Ant Colony System ACS. Introduced investigations have included behavioral responsive functions, for learning process contributed inside brain neural system (number of neurons), as well as Ant Colony Optimization ACO. Furthermore, presentation of adaptive mathematical learning equations and algorithms revealed an interesting analogy between both suggested systems. Finally, some analogy between suggested system is also introduced versus some animal learning performance, considering spikes (pulsed) neurons approach.

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Introduction

I. INTRODUCTION

Herein an investigational approach is presented an analogy between two simulated naturally inspired systems originated from computational intelligence [1]. In other words, it presents analogy between two naturally inspired computational examples belong to the field of reinforcement learning (RL). One example is characterized by methods of temporal differences (TD). However, the other is classified to evolutionary algorithm (EA) approach [2]. Both have been studied comparatively via their mutual (in-between) analogy. That's exemplified by adaptive equations of Pavlovian experimental learning process versus ant colony system (ACS); considering their computational biology performance.

More specifically, this analogy concerned with adaptive equations for weight dynamics laws at artificial neural network (ANNs) and pheromone updating rules at ACS. Commonly, both examples appeared to obey original natural principles for biological information processing derived from rules for animal learning by interaction with environment. Through simulation experimental work applied for solving of reconstruction problem during rat's movement inside figure 8 maze. It shows how pulsed neural system behaves during prediction of animal free movement, aiming to perform spikes' pattern recognition process. These spikes are recorded from animals' motor system at its hippocampus brain area, and supported the principal of learning by interaction with environment. By some details, this paper deals with the effect of neurons' number on learning time response for both ACS, and ANN^s (ecological and neural systems). That includes, comparison between

adaptive dynamical equations for ant colony optimization, and Hebbian learning rule paradigm. All comparison elements are viewed as reinforcement learning behavioral algorithm. That searches for space value function as temporal difference, [2].

The rest of this paper composed of six sections, other than introductory one. Its organization is given as follows. At the second section II., adaptive learning analogy is introduced. It considers Hebbian learning rule adopted for representation of adaptive process observed at Pavlov's experimental work versus ACS for optimized solution of Travelling Sales Man Problem (TSP). The neuronal population performance observed during animal's behavioral learning is presented by considering pulsed neural system at the third section [3][4]. Along with some other results taken into consideration for optimal solution of reconstruction problem carried out by a rat running on elevated figure 8 maze. This results supported by Least Mean Square (LMS) algorithm [5], applied for learning convergence to Cramer Rao's bound after Fisher information [4]. Furthermore, at the fourth section IV. , some obtained simulation results illustrate how the number of neurons may affect the time response of learning process performance are presented. The algorithmic analogy of ANN system versus ACO is introduced At the fifth section V. At the sixth section VI. Adaptive mathematical learning equations for both ANN and ACO systems are presented. Finally, at last seventh section VII. , some valuable and interesting conclusions and comments are given. An Appendix is attached by the end of this paper.

II. LEARNING ADAPTIVETY ANALOGY

By referring to ACO process, dynamical adaptation process is controlled by pheromone density on different pathways during ACS foraging. Therefore, reaching the end of learning iterative cyclic steps (through two forward and backward paths). The density of deposited pheromone converges to some steady state static distribution. That indicates the optimality obtained of chosen pathways [6][7]. At Figure 1, it is shown that foraging process is adaptively performed by ACS. That by existence of an obstacle (at D) through the pathway from nest to source and vice versa. Asymmetrical state given by different eccentricity across nest towards food axis. The considered eccentricity is analogously represented by two factor values (δ & $1-\delta$) where ($0 \leq \delta < 1$). Accordingly, the increase of pheromone at one of pathways leading to be dominant rather than the other pathway following the two factor values (δ & $1-\delta$). This pheromone is observed as shown at Fig. 2-D given in blow.

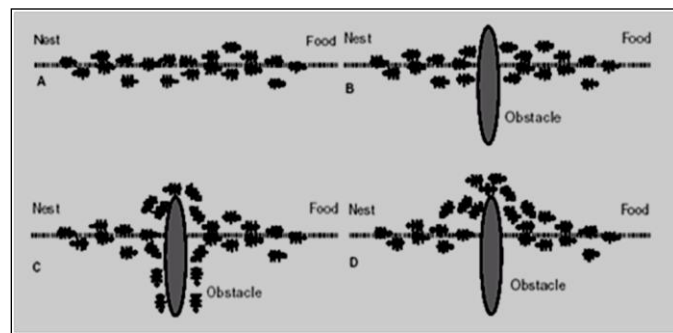


Fig.1 Illustrates the process of transportation of food (from food source) to food store (nest), adapted from [6].

Analogously, by referring to [8][9] neural pathways for visual and audible neuronal signals have two complementing updating factors during training phase. Namely, when considering the value $\square\square\square$ (this value is dynamically changes within range zero up to unity as shown in below) . i.e. the two factors are time dependent following training cycles, and any of both is a complement of the other. Considering that $\square\square\square$ is the factor for audible pathway, hence, during training phase this factor increases following reinforce learning paradigm. Consequently, complemented ($1-\square\square\square$) as visual pathway factor decreases. So, it tends to have no contribution to stimulate motor neuron for salivation. I.e. by learning convergence, as the value of delta reaches unity, and audible signal comes so efficient as to fire motor output neuron. Consequently, salivation drops obtained resulting from stimulation by audible signal only. In other words, reinforcement learning attained by reaching the values zero and unity for visual and audible pathways factors respectively [8].

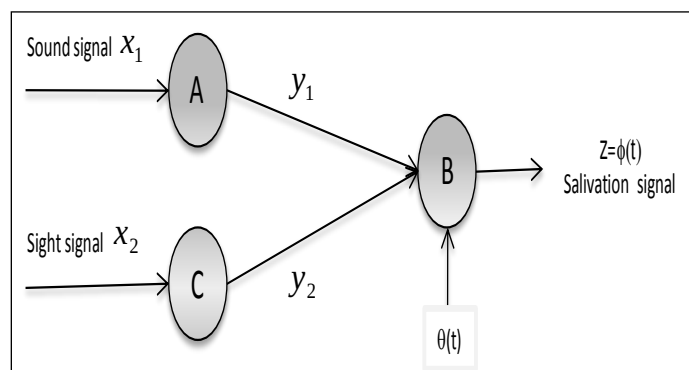


Fig. 2. The structure of the Hebbian learning rule model representing Pavlov's experimental work adapted from [9] .

By some details, and referring to Fig. 2 in the above, it represents the classical conditioning learning process where each of lettered circles A, B, and C represents a neuronal cell body [8]. The line connecting cell bodies are the axons terminating synaptic junctions. The signals released out from sound and sight sensory neurons A and C are represented by y_1 and y_2 respectively. The activation function of neurons A and C are considered as a fraction of sigmoid function as follows :

Such that $0 \leq \delta < 1$

Where: δ is an implicit factor representing the interrelation between motivational and reinforcement learning. However this factor seems to be time dependent during training phases, herein it is considered as a constant for average signal decay through auditory and visual nervous pathways (1 and $1-\delta$) respectively. Noting that value of δ is increasingly changed by time leading to audible path to be dominant rather than the visual one.

$$\Phi_A(\lambda) = \begin{cases} \delta & \lambda \geq 0 \\ -\delta & \lambda < 0 \end{cases}$$

and

$$\Phi_C(\lambda) = \begin{cases} (1-\delta) & \lambda \geq 0 \\ -(1-\delta) & \lambda < 0 \end{cases}$$

III. NEURONAL POPULATION ACTIVITY

Referring to [10], and [4]; therein, the analogy is clear for two folds. Those folds are: learning performance, and dynamical adaptation equations. In details, according to Fisher's information [4], the performance of pulsed neural system is carried as exponential decrease bounded to minimum value that is namely, Cramer Rao's limit. So, that is similar to ACS, optimization processes following as LMS error algorithm when performing solution TSP. Also, the equations describing reconstruction problem solving, on Bayesian rule base, is analogous to probabilistic formula named as Pesdeuo-random proportional action choice rule. Both rules are applied following reinforcement learning paradigm[2]. Additionally, the algorithmic steps to reach solutions for both pulsed neural system and ACS, optimization seems well to be analogous to each other.

Referring to [11] and [12], a pattern recognition problem is suggested as an example for reconstruction process. This example is given briefly as to reveal how the timing of spikes in a population of neurons can be used to reconstruct a physical variable is the reconstruction of the location of a rat in its environment from the place fields of neurons in the hippocampus of the rat. In the experiment reported here, the firing part-terns of 25 cells were

simultaneously recorded from a freely moving rat [4]. The place cells were silent most of the time, and they fired maximally only when the animal's head was within restricted region in the environment called its place field [12]. The reconstruction problem was to determine the rat's position based on the spike firing times of the place cells.

Bayesian reconstruction was used to estimate the position of the rat in the figure-8 maze shown in figure 1. Assume that a population of N neurons encodes several variables ($x_1, x_2, \dots$), which will be written as vector x . From the number of spikes $n = (n_1, n_2, \dots, n_N)$ fired by the N neurons within a time interval τ , we want to estimate the value of x using the Bayes rule for conditional probability:

$$P(x | n) = P(n | x) P(x) / P(n) \quad (1)$$

Assuming independent Poisson spike statistics. The final formula reads

$$P(x | n) = k P(x) \left(\prod_{i=1}^N f_i(x)^{n_i} \right) \exp \left(-\tau \sum_{i=1}^N f_i(x) \right) \quad (2)$$

Where k is a normalization constant, $P(x)$ is the prior probability, and $f_i(x)$ is the measured tuning function, i.e. the average firing rate of neuron i for each variable value x . The most probable value of x can thus be obtained by finding the x that maximizes $P(x | n)$, namely,

$$\hat{x} = \arg \max_x P(x | n) \quad (3)$$

By sliding the time window forward, the entire time course of x can be reconstructed from the time varying-activity of the neural population. The effect of number of neurons at rat's brain hippocampus is similar to the consecutive iterative trials observed by Pavlov's experimental work result (given at Fig. 4)

IV. NEURON'S NUMBER EFFECT ON LEARNING TIME RESPONSE

According to some obtained simulation results, it is shown how the number of neurons may affect the time response of learning process performance. Graphically, obtained results presented by changing number of neuronal cells (14, 11, 7, 5, and 3); brain based learning response during interaction of mammals with their environment [13]. The time response performance observed to be improved by increasing number of neurons (neuronal cells). That is shown at figures (5, 6, 7, 8, and 9) respectively; for fixed Learning rate = 0.1 and gain factor = 0.5.

Fig. 3, The dashed line indicate the approach to Cramer-Rao bound based on Fisher information adapted from [4]

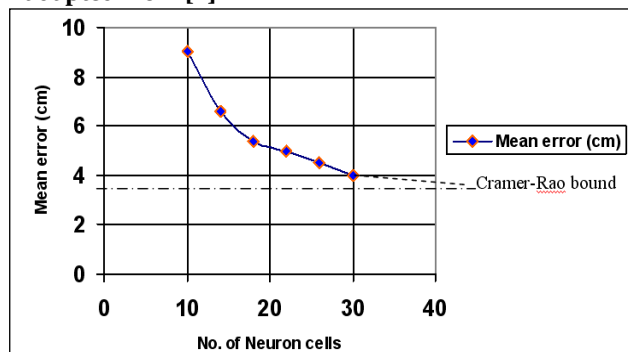


Fig. 4, Fitting curve of Pavlov results adapted from [8]

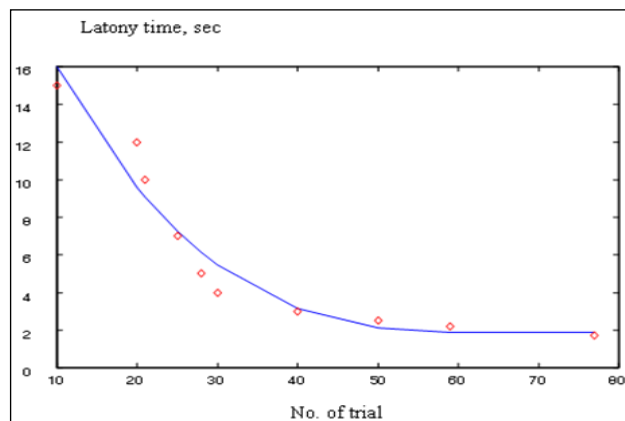


Fig 5. Time Response (No. of training cycles)

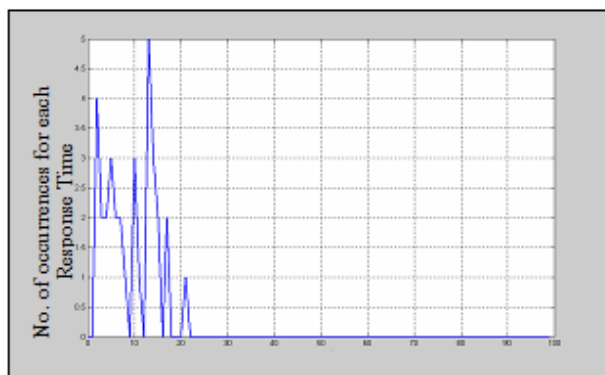


Fig.6. Time Response (No. of training cycles)

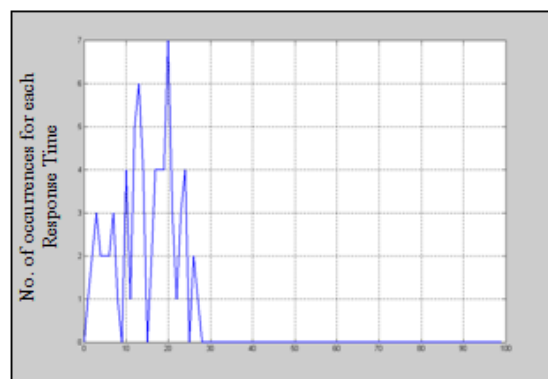


Fig.7. Time Response (No. of training cycles)

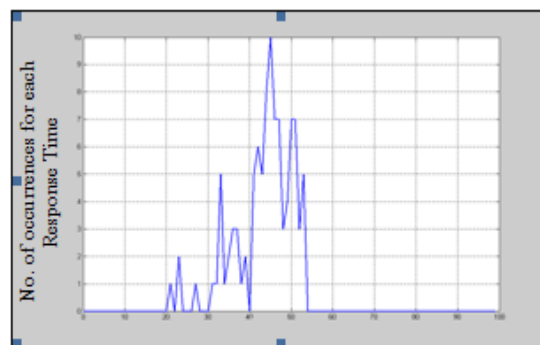


Fig.8. Time Response (No. of training cycles)

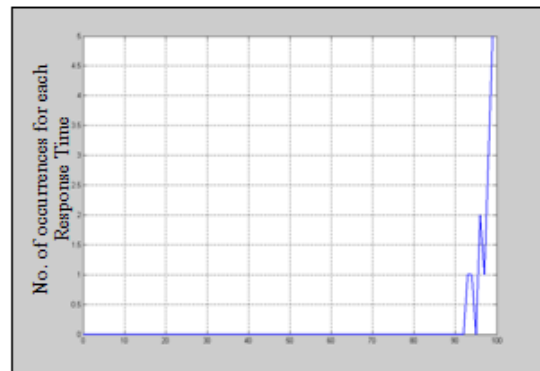
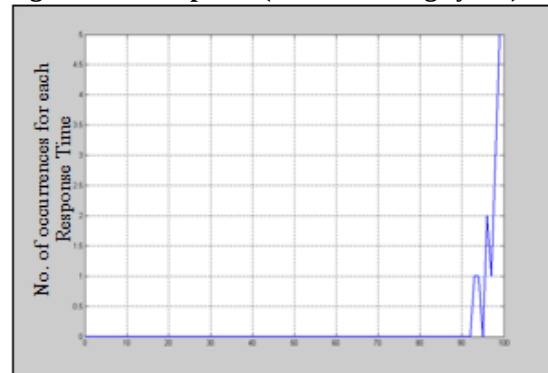


Fig. 9. Time Response (No. of training cycles)



V. LEARNING ALGORITHMS ANALOGY

Figure 10 gives the algorithmic steps for solving basically the Travelling Sales Man (TSP) considering Figure1. Interestingly, it clear that both algorithmic steps illustrated at Figure 10 and Figure 11 are well analogous to each other. Furthermore, the algorithmic steps shown at Figure 11 are describing behavioural training in Pavlov's iterative work processes based on neural network model presenting Hebbian learning (given at Figure 4) [8].

Initialize
Loop /* at this level each loop is called an iteration */
Each ant is positioned on a starting node
Loop /* at this level each loop is called a step */
Each ant applies a state transition rule to incrementally build a solution and a local pheromone updating rule
Until all ants have built a complete solution
A global pheromone updating rule is applied // Until
End_condition
Fig. 10 illustrates ant colony algorithm in two loops with iterative learning cycles.
Initialize
Loop /* at this level each loop is called an iteration that completed by the end of learning process*/
Each pairing stimulus is positioned on a starting latony time cycle
Loop /* at this level each loop is called a step which completed by developing some output by the motor neuron */
Each weight is changed dynamically according to Hebbian learning law
Until developing output signal corresponding to any arbitrary latony time
A maximum salivation signal is obtained when threshold value reaches to zero // Until
End_condition
Fig.11 illustrates training process in ANN models considering latency time phenomenon having two loops with iterative learning cycles.

VI. MATHEMATICAL FORMULATION ANALOGY

This section aims to formulate mathematically effective contributions of two specific ANN design parameters. So, it considers deferent values of gain factors, and learning rates presented by Greek letters (λ, η) respectively. Moreover, graphical presentations for suggested mathematical formulation contributed with different values of both parameters are shown at Fig.1, and Fig.2 given in below. Additionally, the effect of both design parameters is observed either implicitly or explicitly on dynamical synaptic plasticity illustrated at weigh dynamics equations

[14][15]. Additionally, normalized behavior model considers the changes of communication levels (indicated by λ parameter). This parameter value causes changing of the speeds for reaching optimum solutions for Travelling Salesman Problem (TSP) using Ant colony System (ACS) [14][6]. The following equation presents a set of curves changes in accordance with different gain factor values (λ).

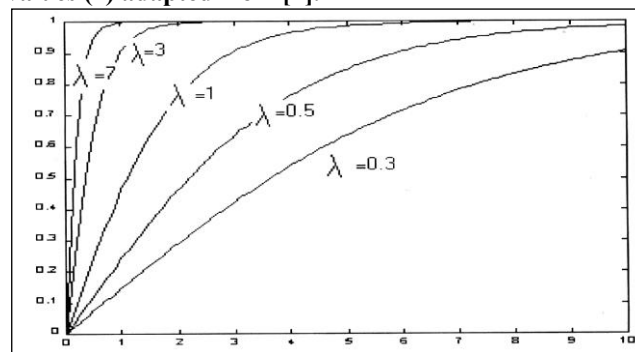
$$y(n) = (1 - \exp(-\lambda i(n-1))) / (1 + \exp(-\lambda i(n-1))) \quad (4)$$

Where λi represents one of gain factors (slopes) of sigmoid function.

These curves represent a set of sigmoid functions to reach by time maximum achievement. Conversely, following formula where suggested (η_i). It presents a set of normalized decay (negative exponential curves) for different learning rate values given by as follows:

$$y(n) = \exp(-\eta_i(n-1)) \quad (5)$$

Fig. 12 Graphical representation of learning performance of model with different gain factor values (λ) adapted from [2].



Where (n) is the number of training cycles. That set of curves is illustrated graphically at figure 8 given in blow. the examples given considering normalization of output response values.

Fig. 13 Illustrates different learning performance curves for different learning rate values (η), adapted from [1].

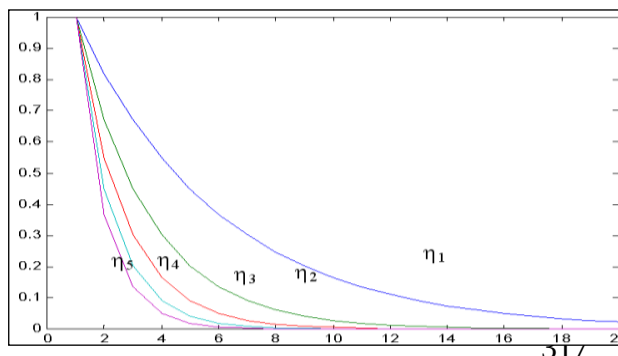


Fig 14 Illustrate performance of ACS with and without communication between ants, adapted from [3].

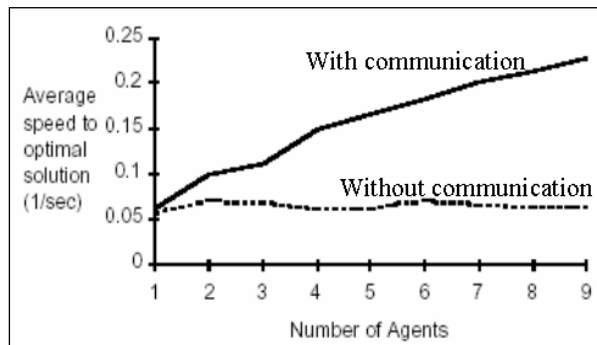
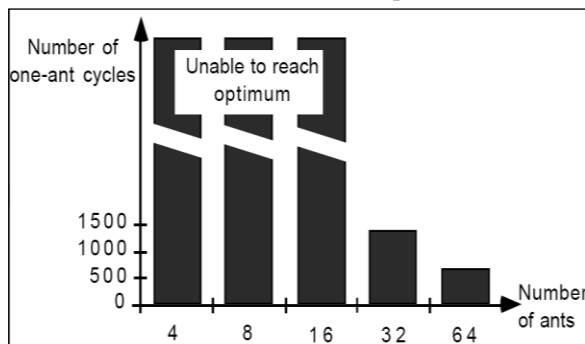


Fig.15 Number of cycles required to reach optimum rated to the total number of ants adapted from [9].



Interestingly, referring to above Fig.12, and Fig.13 both are analogous to Fig.14 and Fig.15 respectively. Similarly, the ants behavior given at figure 15 is analogous to the Pavlov's experimental results at figure 4. Also, it is noticed better synaptic connectivity dynamics resulting in improving of learning systems' performance due to increase of both values (λ , η). Moreover, dynamics of synaptic connectivity among neurons is analogous to synergistic effect observed by Ant colony intercommunications among number of agents (ants), for reaching TSP optimization as shown at Fig.14.

VII. CONCLUSIONS AND DISCUSSIONS

According to above animal learning experiments (dogs, and rats), and their analysis and evaluation by Ann's modeling, all of them agree well as for ACS, optimization process. Also, the performance of both (ant and animals) is similar to that for latency time minimized by increasing of number of trials.

Referring to [3], therein, shown that both work for Thorndike and Pavlov are supporting each other for learning performance. So, it is obvious that both obeys generalize (LMS) for error minimization by learning convergence [5]. Also, that algorithm agrees with the behavior of brainier mouse behavior (that is genetically reformed) as given at [17][18].

Generally, the three introduced systems in this work (along its two parts) perform their function well similar to LMS error algorithm. By some details, artificial neural network models either performing computation on analogue signaling base or on pulsed spikes decoding criterion, they both leads to learning convergence following LMS error algorithm. Noting that, reconstruction method following Bayesian rule is bounded to Cramer Rao's limit. This limit is analogous to minimum response time in Pavlov experiment, and Thorndike work as well. Similarly, for ACS, optimization processes are following as LMS error algorithm when performing solution TSP. Additionally; adaptation equations for all of three systems are running in agreement with dynamic behavior of each other. Moreover, the learning algorithms for three systems are close to each other with similar iterative steps (either explicitly or implicitly).

Finally, it is worthy to note that the rate of increase of salivation drops is analogous to rate for reaching optimum average speed in ACS optimization process. Similarly, this rate is also analogous to speed of cat getting out from cage in Thorndale's experiment. Moreover, the increase on number of artificial ants is analogous to number of trials in Pavlov's work.

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