On Mathematical Modeling of Cooperative e-Learning Performance During Face to Face Tutoring Sessions (Ant Colony System Approach)

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Abstract—Investigational analysis and evaluation of cooperative learning phenomenon is a challenging educational issue. Recently, educationalists have adopted interesting research work concerned with realistic modeling of human’s cooperative learning phenomenon. That’s by investigation of its analogy with natural behavioral learning aspects, observed by swarm intelligence of social insects colonies. Herein, this paper presents a realistic mathematical modeling of cooperative e-learning which inspired from cooperative behavioral learning observed by one type of Ant Colony System (ACS). More specifically, presented modeling motivated by qualitative analysis of observed behavioral learning performance of ACS type namely: Temnothorax albipennis. In nature, this ACS type observed to perform cooperative behavioural learning on the basis of tandem running technique. Objectively, this colony agents (ants) search for optimal algorithmic solution of foraging process by performing interactive technique. That’s involves learning by interactive communication (positive feedback) between two ants (Follower/Leader) controlling trade-off between speed and accuracy. Interestingly, the analogy between introduced ACS models and corresponding Artificial Neural Networks models is presented.

Keywords—e-learning systems; Cooperative learning; Ant Colony System Optimization; Computational Intelligence; Traveling Sales Man Problem.

I. INTRODUCTION

In face to face tutoring, the phase of interactive cooperative learning is an essential paradigm aiming to improve any of Open Learning Systems’ performance. In some details, it has been recently, declared that cooperative interactive learning among studying agents fellows (learners), contributes about one fourth of learning achievement (output) attained at face to face tutoring sessions [1]. The presented work develops educationalists’ special attention towards addressing of learning convergence speed considering metric time measurement (as one of main learning parameters). Referring to realistic Ant Colony System (ACS) approach, that time measurement equivalently considered as natural analogy to learning response time. That’s in fulfillment of a pre-assigned learning output level observed practically - at educational field - to be attained after time period defined as learning response time.

Herein, cooperative interaction among e-learning agents (students) adopted for realistic analogical modeling in accordance with ACS agents (ants) behavior. Consequently, by referring to cooperative tutoring sessions and on the bases optimal solution of Traveling Sales-man Problem (TSP) reached by (ACS), cooperative learning process is mathematically modeled. It is noticed that optimal solution of TSP obtained-by some speed- with dependence upon different values of inter-communication levels among ACS agents (ants). So, consecutive steps performed by Open Learning Systems analogously accumulate cooperative learning function as that happens at ACS with and without communication[2-4]. Adopted mathematical model herein is well supported by some recently published papers. Such as that deals with Biological Information Processing Mechanism in Neural and Non-Neural Bio-Systems [5]. And others associated with comparative study of behavioral learning in human versus some non-human creatures [6-9]. Moreover, presented model inspired by interesting analogy shown between cooperative ACS performance(ants), and cooperative behavioral learning among number of place field neuronal cells(at hippocampus rat’s brain area), for solving
reconstruction problem [9-12]. This rat's behavioral learning model illustrated the effect of increasing number of neuronal cells upon better performance in reaching more accurate result when solving pattern recognition problem. In other words, results for interesting comparative analogy between two distinct types of computational intelligence agents illustrated the effect of increasing number of agents (either neuronal cells or ants), on cooperative learning performance. Finally, suggested mathematical model proved to perform realistically natural as that expected for mutual cooperative learning interaction among learning agents. Objectively, presented comparative study may results in optimal improvement of learning achievement performance (during open learning function).

The rest of this paper composed of five sections organized as follows. At the next second section, an overview revising of foraging process at ACS, i.e. transportation process of food back and fro, (from food source) to food store (nest) is presented. This process adopts autocatalytic behavioural learning algorithm among agents [3]. One type of Ant Colony System adopting tandem running technique is introduced at this section. This type is namely: Temnothorax albipennis (formerly Leptothorax albipennis). It performs during foraging process a paradigmatic decentralized decision-making in correspondence with positive feedback between leader and follower ants [13][14]. At the fourth section, realistic ANN model of the (Follower/Leader) performance considered as teacher and pupil guided-error correction algorithm [15][16]. Modeling of foraging process of Leptothorax albipennis ACS is presented at the fifth section as an unsupervised ANN model (Hebbian learning rule) [16][17]. At the sixth section, mathematical formulation of cooperative learning performance considering the two supervised and unsupervised learning paradigms is given in details. Some interesting conclusive remarks and suggestions for future work are presented At the last seventh section. Finally, three appendices are attached at the end of this paper.

The relation of presented research work with general interdisciplinary plan of other framework (APPENDIX I). Two computer program codes for ANN supervised and unsupervised learning models are given at APPENDIX II & APPENDIX III respectively.

II. REVISIGN OF FORAGING PROCESS PERFORMED BY ANT COLONY SYSTEM

In natural environment, ants observed to perform foraging process by storing food via repetitive straight line movement connecting any food source to their nest (Figure 1). Illustrates the foraging process of transportation of food (i.e., from food source) to food store (i.e., nest). This process is adapted with the existence of an obstacle through the pathway from nest to source and vice versa. The details are given through the text adapted from [4]. The primary means for ants to maintain bidirectional walking (back and fro) in straight line is a pheromone trail. Ants deposit a certain amount of pheromone while walking, and each ant probabilistically prefers to follow a direction rich in pheromone. Referring to Figure 1B, this elementary behaviour of real ants can be used to explain how they can find the shortest path that reconnects a broken line after the sudden appearance of an unexpected obstacle has interrupted the initial path. In fact, once the obstacle has appeared, those ants which are just in front of the obstacle cannot continue to follow the pheromone trail and therefore they have to choose between turning right or left. In this situation we can expect half the ants to choose to turn right and the other half to turn left. A very similar situation can be found on the other side of the obstacle (Figure 1C). It is interesting to note that those ants which choose, by chance, the shorter path around the obstacle will more rapidly reconstitute the interrupted pheromone trail compared to those which choose the longer path. Thus, the shorter path will receive a greater amount of pheromone per time unit and in turn a larger number of ants will choose the shorter path. Due to this positive feedback (autocatalytic) process, all the ants will rapidly choose the shorter path (Figure 1D). The most interesting aspect of this autocatalytic process is that finding the shortest path around the obstacle seems to be an emergent property of the interaction between the obstacle shape and ants distributed behaviour: Although all ants move at approximately the same speed and deposit a pheromone trail at approximately the same rate, it is a fact that it takes longer to contour obstacles on their longer side than on their shorter side which makes the pheromone trail accumulate quicker on the shorter side. It is the ants’ preference for higher pheromone trail levels which makes this accumulation still quicker on the shorter path.

This process is adapted with the existence of an obstacle through the pathway from nest to source and vice versa, however, more detailed illustrations are given through other published research work [2][3]. Therein, ACS performance obeys computational biology algorithm used for solving optimally travelling salesman problem TSP [2]. The most interesting aspect of this autocatalytic process is that finding the shortest path around the obstacle seems to be an emergent property of the interaction between the obstacle shape and ants distributed behaviour: Although all ants move at approximately the same speed and deposit a pheromone trail at approximately the same rate, it is a fact that it takes longer to contour obstacles on their longer side than on their shorter side which makes the pheromone trail accumulate quicker on the shorter side. It is the ant’s preference for higher pheromone trail levels which makes this accumulation still quicker on the shorter path.
III. LEPTOTHORAX ALBIPENNIS PERFORMANCE

A specific type of ant colony systems formerly called Leptothorax albipennis performs a paradigmatic decentralized decision-making based on learning/teaching technique known as tandem running. Briefly, this type of ACS adopts (tandem running technique) and performs its behavioral learning function sequentially (in stepwise) as follows. In case of one ant running to lead another ant moving from the nest to food, both leader and follower (teacher and pupil) are acutely adaptive sensitively to the progress of their partner. To the best of our knowledge; agents of Leptothorax albipennis ACS perform a creative inter-communication technique among ants. That's involves teaching by interactive feedback between two ants controlling trade-off between speed and accuracy [7][9][13]. Its individual agents (ants) adopt tandem running which is an intelligent behavioral teaching technique [13]. Colonies of that ant type have been shown flexibly to compromise accuracy for speed. Briefly, in case of one ant running to lead another ant moving from the nest to food, both leader and follower are analogous to teacher and pupil. Both are acutely sensitively adaptive to progressing of their partner. This learning technique involves teaching by interactive feedback between two ants controlling trade-off between speed and accuracy[14].

A. Tandem running technique

Referring to Figure 2, it illustrates schematically the learning paradigm inspires from tandem running technique. This technique involves interactive bidirectional feedback between teacher and pupil corresponding to leader and follower ants respectively. Furthermore, at this figure, depicted block named as (Follower/Leader) suggests that tandem followers after learning their lessons so well, that they often become tandem leaders[13][14].

In cooperative learning context, the above type of ACS behavioral learning performance [14][18] is analogous to what could be observed in classrooms; if one agent (student) behaves independently upon other agents' achievements [19]. So, it described as teacher-centered providing Individual learning which implies that leader ant (teacher) can transfer knowledge and cognitive skill to the learner (another ant) [19][20]. Accordingly, via that teacher-centered type of learning the teacher provides the major source of information, and feedback [21]. Conclusively , ANN models based on supervised learning paradigm are relevant for realistic simulation of cooperative teacher-centered learning performance [19][20].

B. Performance of ACS optimization

By following another ANT-density algorithm, the same ACS type (Leptothorax albipennis), is capable of solving TSP optimally. Simulation results are shown at Figure 3, adapted from[22].Therein, at [22] it is shown that efficiency per ant (required to reach optimal TSP solution), is well improved as number of ants increase. Furthermore, it could be observed that number of trials increase at Thorndike's psycho-learning experimental model, is analogous to number of ants at ANT-density algorithm [9] . Finally, the presented model seems to take into account the mixed learning paradigms in accordance with the performed functions either at the level of Follower/Leader or at the global ACS agents to perform main objective foraging function. At the bidirectional feedback between teacher and pupil respectively corresponding to leader and follower ants, error correction (supervised) learning is considered [17].However, learning by interaction with environmental conditions is considered for performing main ACS foraging function[22][23].
IV. FOLLOWER/LEADER LEARNING MODEL

According to presented analysis of the learning behaviour of the Leptothorax albipennis ACS given at the above subsections. This section is dedicated to presents a relevant leaning with supervisor ANN model following.

Referring to Figure 4, given in below, it simulates realistically the (Follower/Leader) performance according to adopted tandem running technique [13][14]. So, is well analogous to ACS learning processes considering teacher and pupil guided-error correction algorithm[17].

![Block diagram for suggested ANN model presenting two supervised and unsupervised learning paradigm](image)

The error vector at any time instant \( n \) observed during learning processes is given by:

\[
\vec{e}(n) = \vec{y}(n) - \vec{d}(n)
\]

(1)

Where:

\( \vec{e}(n) \): Error correcting signal controlling adaptively

\( \vec{y}(n) \): The output signal of the model

\( \vec{d}(n) \): Numerical value(s) of the desired/objective parameter of learning process (generally as a vector).

Referring to above figure 3., the following equations are considered:

\[
V_k(n) = W_{kj}(n) W_{j}(n) \tag{2}
\]

\[
y_k(n) = \varphi(V_k(n)) = (1 + e^{-V_k(n)})/(1 + e^{V_k(n)}) \tag{3}
\]

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

\[
W_k(n+1) = W_k(n) + \Delta W_k(n) \tag{5}
\]

Where: \( X \) is input vector, \( W \) is the synaptic weight vector, and \( \varphi(.) \) is an activation (Hyperbolic tangent) function associated to the \( k^{th} \) neuron. It is characterized by its argument \( \varphi \).

\( \lambda \) is gain factor, \( \eta \) is learning rate value during performing of learning process. Moreover, it is worthy to note that above equations (2-5) are commonly valid for two diverse ANN learning paradigms namely; supervised (interactive learning with a tutor), and unsupervised (learning though students’ self-study). Specifically, in this work supervised (interactive) learning paradigm is considered. So, dynamical changes of weight vector value (connecting the \( k^{th} \) and \( i^{th} \) neurons) for supervised learning process is given by following equation:

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

where, \( \eta \) is learning rate value during performing of learning process. However, dynamical changes of weight vector value unsupervised learning (Hebian rule)[17], is given by equation:

\[
\Delta W_{kj}(n) = \eta y_k(n) X_j(n) \tag{7}
\]

V. FORAGING BEHAVIORAL LEARNING PROCESS BY INTERACTION WITH ENVIRONMENT

The introduced ACS type performs its foraging process following principle of learning by interaction with environment. With dependence upon pattern recognition technique of food sources. In accordance with adopted decentralized decision making discipline, distributed food sources were optimally recognized by Leptothorax albipennis ACS. Interestingly, that foraging behavioral learning performed analogously to rat's learning model solving reconstruction problem inside 8-Figure maze. Accordingly, this section introduces at the following subsections(A&B); the effect of increasing number of neuronal cells (corresponding to number of ants) upon better performance in reaching more accurate result (optimal minimum error), when solving pattern recognition problem (corresponding to optimal foraging process).

A. Rat’s Behavioral Learning Model While Solving Reconstruction Problem Inside 8-Figure Maze

Referring to psycho-experimental work concerned with behavioral learning of a mouse inside 8-Figure maze, results obtained while solving the reconstruction problem presented in two (graphical and tabulated) forms. Graphical results are shown by convergence curve at Figure 5, however that tabulated are given at Table I. Modeling of the suggested reconstruction problem verification on the basis of Bayesian reconstruction to estimate the position of the rat in 8-figure maze (more details are introduced at the fifth section). Noting the value of mean error converges (by increase of number of cells) to some limit, excluded as Cramer-Rao bound. That limiting bound is based on Fisher’s information given as
tabulated results in the above and derived from [11]. That implies LMS algorithm is valid and obeys the curve shown at in blow.

The value of mean error converges (i.e. by the increase of number of cells) to some limit, excluded as Cramer-Rao bound. The limited bound is based on Fisher's information as given at Table I, that's derived from [11]. This implies the curve as shown in Figure 5 obeys the validity of Least Mean Square (LMS) algorithm [8][24].

![Figure 5](image)

**Figure 5.** The dashed line indicate the approach to Cramer-Rao bound based on Fisher information [11].

<table>
<thead>
<tr>
<th>No. of neuron cells</th>
<th>10</th>
<th>14</th>
<th>18</th>
<th>22</th>
<th>26</th>
<th>30</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean error (cm)</td>
<td>9</td>
<td>6.6</td>
<td>5.4</td>
<td>5</td>
<td>4.5</td>
<td>4</td>
</tr>
</tbody>
</table>

**TABLE I. RELATION BETWEEN NUMBER OF CELLS AND MEAN ERROR IN SOLVING RECONSTRUCTION PROBLEM**

**B. Rat's Reconstruction Problem Versus ACS foraging function**

The experimentally measured results shown at Figure 5 in the above, illustrated that error value decrease similarly to an exponential curve decays to some limit value versus the increase of place field cells (at hippocampus of the mouse brain). These results seem to be closely similar to the obtained simulation results shown in the above at Figure 3. This figure illustrated that efficiency per ant improved as number of ants increase. Referring to[11], 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-terms of 25 cells were simultaneously recorded from a freely moving rat. [10]. 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 above figure 2, that according to [11]. Assume that a population of N neurons encodes several variables (x1, x2,…….), which will be written as vector x. From the number of spikes n=(n1,n2,……,nN) 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:

\[
P(x|n) = \frac{P(n|x)P(x)}{P(n)}
\]

Assuming independent Poisson spike statistics. The final formula reads

\[
P(x | n) = kP(x) \prod_{i=1}^{N} f_i(x)^n \exp\left(-\sum_{i=1}^{N} f_i(x)\right)
\]

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,

\[
\hat{x} = \arg\max P(x | n)
\]

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 above equation for solving reconstruction problem (corresponding to the most probable value of \(x\)) seems to be very similar to the equation searching for optimum solution considering TSP reached by ACS (for random variable \(S\)) as follows.

\[
S = \begin{cases} 
\arg\max_{x \in D} \left[ (\tau(r,u))^{[\beta] \left[ \eta(r,u) \right]} \right] & \text{if } q \leq q_0 \\
\text{otherwise} & 
\end{cases}
\]

where \(\tau(r,u)\) is the amount of pheromone trail on edge \((r,u)\), \(\eta(r,u)\) is a heuristic function, which was chosen to be the inverse of the distance between cities \(r\) and \(u\), \(\beta\) is a parameter which weighs the relative importance of pheromone trail and of closeness, \(q\) is value chosen randomly with uniform probability in [0, 1], \(q_0 (0 \leq q_0 \leq 1)\) is a parameter, \(M_i\) is memory storage for \(k\) ants activities, and \(S\) is a random variable selected according to some probability distribution [2][3].

**VI. MATHEMATICAL FORMULATION OF COOPERATIVE LEARNING PERFORMANCE**

The following two subsections(A&B) illustrate conclusively the mathematical formulation of cooperative learning performance. That’s by referring to ANN models’ analogy, and considering both supervised and unsupervised learning paradigms. By some details, presented Figure 6. illustrates set of performance curves of ANN model after running program (unsupervised learning) given at APPENDIX III. However, Figure 7 presents set of curves after running program (supervised learning) given at APPENDIX II. Both figure considered for different number of agents (neurons), different gain factor values, and different learning rate values. The mathematical formulation given by equations (12)&(13) are described generally by set of curves given at Figure 7 and Figure 10 respectively. Conclusively, presented mathematical formulation model proved to perform as realistically natural as expected performance for mutual cooperative learning.
interaction among learning agents (either neuronal cells or ants).

A. Generalized Model Of Learning Performance Curves (Learning Achievement Measurement)

Referring to Figures (8&9), the effect of gain factor as well as learning rate changes on cooperative learning performance is introduced graphically. It is very interesting to note that analysis of introduced effect is supported well by the exponentially decayed graphs described by equation (13) and illustrated by set of curves at Figure 10.

Normalized behavioral model of ACS (Optimization Algorithm), adopted for solving TSP[6]. It considers the changes of communication levels (indicated by $\lambda$ parameter). This parameter value causes changing of the speeds for reaching optimum solutions following the equation:

$$y(n)= \frac{1-\exp(-\lambda i(n-1))}{1+\exp(-\lambda i(n-1))}$$

where $\lambda i$ represents one of gain factors (slopes) for sigmoid function.

$$\eta_i$$ represents one of learning rate factor values.

B. Generalized Model Of Learning Performance Curves (Error-rate measurement)

In agreement with all of the above set of curves shown at three figures (6, 7, and 8), they are all with close similarity to exponentially decayed performance curves. A normalized abstract set of decayed exponential curves are given in below at Figure 7. That's following the mathematical formula where suggested ($\eta_i$) to be defined as a value learning rate factor. The set of various learning rate factor values are denoted by ($\eta_i$). These factor values are mathematically presented after normalization of different learning performance curves (at Figure 10) as follows:

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

where (n) is the number of training cycles.
VI. CONCLUSIONS AND DISCUSSIONS

In nature, response time needed to perform some desired goal (leaning achievement) by an animal’s brain dependent upon stored experience inside its brain. Accordingly, measured learning achievement, and conversely measured error rate are well relevant for performance evaluation of simulated cooperative educational phenomena. So, adopted models of cooperative learning paradigms (in e-learning systems) aim to improve output learning achievements. That's considering their positive correlation with cooperating students who work collaboratively, in good level of intercommunication towards accomplishment of a common goal. Usually, students suggested to work together in small clusters or groups with good level of communication among them. This approach in good resemblance to ants' behavior at ACS where effectiveness of cooperative learning promotes mainly positive interdependence. Interestingly, the following two interesting conclusive remarks are valuable:

1-The existence of an obstacle at some point of ants' pathway is analogous to noisy data applied when training some artificial neural model[26]. In accordance with the asymmetry degree of obstacles' shape, signal to noise ratio is inversely proportional. Consequently, the time needed to find the shorter pathway (analogous to cooperative learning convergence) is directly proportional to degree of obstacle asymmetry [27][28].

2-The stored experience during Hebbian learning process, and computational intelligence of ACS are both analogues to the needed CPU time in order to develop minimum error for reaching optimum learning achievement[5][29].

Finally, presented analysis and evaluation herein based on suggested mathematical modelling- may shed light on promising enhancement of cooperative learning performance. That's by considering obtained interesting resemblance of cooperative learning phenomenon (foraging process), with unsupervised (Hebbian) learning rule, (presented by equation (7)). However, supervised ANN learning model simulates realistically the (Follower/Leader) performance considered as teacher and pupil guided-error correction algorithm (presented by equation(6)). Noting that both equations (6&7) are simulated by teacher and pupil guided-error correction algorithm (presented by equation (6)). Noting that both equations (6&7) are simulated by teacher and pupil guided-error correction algorithm (presented by equation (6)). Noting that both equations (6&7) are simulated by teacher and pupil guided-error correction algorithm (presented by equation (6)). Noting that both equations (6&7) are simulated by teacher and pupil guided-error correction algorithm (presented by equation (6)).

REFERENCES


[18] Simon Garnier, Jacques Gauthrais, and Guy Theraulaz” The biological principles of swarm intelligence "Swarm Intelligence Journal Volume 1, Number 1 / June, 2007 pp.3-31


APPENDIX I

Research Frame Work Suggested by Arab Open University (KSA)

Building Up Bridges For Natural Inspired Computational Models Across Behavioral Brain Functional Phenomena; And Open Learning Systems

Presented frame work belong to some recently adopted interdisciplinary research direction. Namely, building up theoretical bridge connections between neuroscience cognitive science, and swarm intelligence to enhance educational decisions and learning performance quality. In particular, such theories would be capable of analysis and evaluation of learning performance issues, in addition to implement complex educational decisions. So, by adopting Artificial Neural Networks discipline, dynamical modeling of observed educational/learning phenomena issues associated with basic two brain functions (Learning & memory) could be realistically implemented. Examples of such learning phenomena issues are: learning creativity, individual differences, and different cognitive learning styles. By some details, the frame work timely planned as to be composed of three phases. These phases are motivated by dynamical learning mechanism(s), and technologies and started by June 2007. Each of frame work phases, planned to elapsed for (approximately) 8-10 months as follows:

1- Simulation and Modeling of Behavioral Learning Performance, individual differences and Quantified Creativity Phenomenon Using Artificial Neural Networks

2- Modeling of Creativity Phenomenon observed in Ant Colony Systems and comparison with human learning creativity.

3-Comparison between obtained results by the above two phases with recent research work related to modeling of brain functions. That is considering analysis and comparisons among various Learning phenomena considering Ant Colony System Optimization and Artificial Neural Network modeling of behavioral learning. That above work started by July 2007, it is planned to be performed by IT& Computer Department at A.O.U. KSA. That's to elapse for (24 up to 30) months. That plan results in a set of recently published papers. A sample of such papers are given as follows:

-H.M.Hassan, Ayoub Al-Hamadi, "On Quantifying Learning Creativity Using Artificial Neural Networks (A Mathematical Programming Approach)" Published at CCCT 2007 conference held on July 12-17, 2007 – Orlando, Florida, USA.


-H.M.Hassan, Bobby Al-Mohaya “On Quantifying Learning Creativity Using Artificial Neural Networks (A Neuro-physiological Cognitive Approach)” Published at the 7th International Conference on Education and Information Systems, Technologies and Applications (EISTA) to held in Orlando, USA, on July 10-13, 2009.

APPENDIX II

Supervised Learning Code

w = rand(14,1000);
x1 = 0.8; x2 = 0.7; x3 = 0.6;
L = 0.5; eata = 0.3;
h = 0; s = 0; f = 0; m=0;
for i = 1:100
w1=w(1,i); w2=w(2,i); w3=w(3,i);
net=w1*x1+w2*x2+w3*x3;
y=(1-exp(-L*net))/(1+exp(-L*net));
e=0.8-y;
no(i)=0;
while e>0.05
no(i)=no(i)+1;
w1=w1+eata*e*x1;
w2=w2+eata*e*x2;
w3=w3+eata*e*x3;
net=w1*x1+w2*x2+w3*x3;
y=(1-exp(-L*net))/(1+exp(-L*net));
e=0.8-y;
no(i)=0;
end

for i = 1:100
nog(i) = 0;
end
for x = 1:100
if no(x) == i
nog(i) = nog(i) + 1;
end
end

for i = 1:99
m = s / f;
i = 0.99;

APPENDIX III

Unsupervised Learning Code

w = rand(14,1000);
x1 = 0.8; x2 = 0.7; x3 = 0.6;
h = 0; s = 0; f = 0;
cycles = 200;
L = 1;
eata = 0.3;
for g = 1:100
  nog(g) = 0;
end
for i = 1:cycles
  w1 = w(1,i); w2 = w(2,i); w3 = w(3,i);
  for v = 1:2
    net = w1*x1 + w2*x2 + w3*x3;
    y = (1-exp(-L*net))/(1+exp(-L*net));
    e = 0.9-y;
    w1=w1+eata*y*x1;
    w2=w2+eata*y*x2;
    w3=w3+eata*y*x3;
  end
  P = uint8((y/0.9)*90);
  nog(p) = nog(p)+1;
end
for i = 1:99
  h = i * nog(i);
  s = s + h;
  f = f + nog(i);
end
m = s / f;
i = 0:99;
plot(i,nog(i+1),'linewidth',1.5,'color','blue')
plot((i+1)/100,nog(i+1),'linewidth',1.5,'color','black')
xlabel('Time (No. of training cycles')
ylabel('No of occurrences for each Time')
title('Error Correction algorithm')
grid on
hold on