Modifying Brain Emotional Learning Model for Adaptive Prediction of Chaotic Systems with Limited Data Training Samples

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Abstract. In this paper, new method for learning model, based on the brain emotional learning, is explained, which could use to predicate chaotic system which training data is few in. The method is extracted from prior works; but it is changed to improve performance of brain emotional learning in prediction problems. This approach is proposed with high accuracy rather than other brain emotional learning methods and learning systems; in contrast to low computational and memory resources. In addition, this manner has incremental learning property that causes it to be adapted for new stimuli or input. The scope of paper is explained the method and its advantage to raise the accuracy of BEL model in prediction problems. Therefore, the result of the prediction is made by the enhanced model is compared with other methods such as, (MLP) and (ANFIS). Finally, the proposed modified model is examined on the prediction of average price selling of component in trading agent competition. The obtained results verify the good performance of the proposed model with regard to other methods. In: Shibli K (ed), Proceedings of the 1st International Conference on Applied Operational Research – ICAOR (2008); pp 328–341. Lecture Notes in Management Science Vol. 1. ISSN 2008-0550.

Keywords: Brain emotional learning, chaotic system, few training data, price prediction.

1 Introduction

Recent growing intelligent systems in various areas of science and technology, causes to generate prediction models as an essential component of intelligent systems. The prediction models could comprehend the future state of predicated system; as a result could help intelligent model to make the right decision. In particular, predicting the future of complex system with many variables and chaotic behavior
has been the goal of many researches activity in recent century. It has been shown, the data driven approach, such as, neural networks and neurofuzzy models are capable of approximating any nonlinear multivariate function with arbitrary accuracy [1],[2],[3],[4]. The limitation in number of training data samples causes the accuracy of prediction to decrease [1]. In some environment which there is limitation in time and number of training data samples and system is so dynamic that could use offline learning methods, it is vital to predicate the next state of the system with lack of enough data samples. It seems that, the early prediction even if dose not form very accurate response, better than, there is not any prediction about the next state. Therefore, the predator model could make correct and quick response and use online learning with using few data samples, is very essential.

It is stated that, the best predator models are those with simplest acceptable structures, the smallest number of adjustable parameters and highest generalization [15],[4]. In this article, the emotional models that is stated in neural network structure [7],[8], is changed and proposed as a predator models. It is based on recent theory on modeling emotions in human brain [5]. Learning method based on models of human emotional processing, is recently developed; in particular, it is used by control engineers, robotic designers and decision support systems developers [7],[8],[15]. The effect of emotions on emergent intelligent behavior is not be ignored; even though it is assumed that emotions are negative effect on rational decision making [15],[16],[17]. The emotional learning model in brain could be used to make response to conditional stimuli if it learns the association between conditional stimuli and unconditional stimuli [10],[12].

After this introduction, the related studies to brain emotional learning are described in Sect. 2. The modified model is presented in Sect. 3. Some chaotic time series such as, Lorenz and Ikeda chaotic time series will be predicated by explained prediction model and the result is compared with other learning models, such as ANFIS, MLP, LLNF. In Sect. 4. The result of price prediction of time series of Average selling price of one component in TAC SCM, is proposed in Sect. 5. The remark notes is notified in Sect. 6.

## 2 Related Studies to Brain Emotional Learning

In the Brain limbic system, plays important role in emotional reaction. Limbic system includes several areas such as orbitofrontal cortex, thalamus, amygdala, etc. The amygdala, small area likes almond, take apart to making emotional response [11],[12],[13]. The Amygdala receives input from many areas such as sensory input, orbitofrontal, hypothalamicus. The central of Limbic system is amygdala. The amygdala is consisted of three groups of nuclei, such as, basolateral group (BL), centromedial group (Ce_M), cortical group. In turn, BL has three nuclei; in other words, BI is composed of lateral, basolateral, basal nucleus. In the same way, central and medial nucleus, are part of Ce_M[13]. The basolateral and amygdala connects with many areas of cerebral. Besides, It has strongest and bidirectional connections with the insular cortex, orbital cortex. It is
shown that, neurons in amygdala part respond to reward. But, when the reward converts to punishment signal, the response of amygdala neurons did not change. On the other hand, orbitofrontal makes a quick response to negative signal [11],[12],[13]. One of famous typical of emotional modeling is expert system, is explained as an alternative model for emotional processing. Making a rule base on emotional reaction is proposed as another way to imitate the emotional behavior of human beings to make computational model [12]. Some researches focused on internal representation of emotional brain system, and formalized the brain states to react emotional stimulus, such as, the amygdala-orbitofrontal system, is proposed by Moren and Balkenius [18]. The model learns to reacts the new stimulus on based of generating rewards and punishment signal. Besides, in the model, the amygdala learns to associate between emotionally charged and neutral stimuli. Next, the orbitofrontal cortex inhibits inappropriate experience and learning connection [11]. The reinforcement signal in the model is not determined. But, It is a vital role to adjust weights of the model. The model is proposed as modular neural network with two modules and integrity unit (Fig. 1. shows the model).

![Diagram](attachment:image.png)

**Fig. 1. Graphical Description of Moren’s Computational Model**

The model is consisted of two subsystems which attempt to make a right response to emotional stimuli. Each subsystem has own role to create own output; therefore the final output of the model is summation of the outputs of subsystem. The upper subsystem is orbitofrontal which evaluates the response of amygdale in order to inhibit inappropriate answers of amygdale. The lower subsystem is amygdale that has many roles; but in the model is focused on evaluative property of amygdale which causes the emotional stimuli is measured and produced appropriate reaction.
Each subsystem is consisted of number of nodes which is related to the dimension of each stimulus. Therefore, the stimulus enters the thalamus part of the model.

The thalamus calculates the maximum over the all inputs \([11]\), and sends it to amygdale as one of inputs. The orbitofrontal has not any input from thalamus instead of it receives the output of amygdale to update the weight. The output of each subsystem is clarified by (1),(2),(3),(4),(5),(11). The structure of the model is very simple, and the number of adjustable parameter is low; but the reward signal is not obviously defined.

\[
A_i = S_i V_i . \tag{1}
\]

\[
O_i = S_i W_i . \tag{2}
\]

\[
E = \sum_i A_i - \sum_i O_i . \tag{3}
\]

\[
\Delta W_i = \beta (S_i \sum_j (O_{ij} - \text{Rew})) . \tag{4}
\]

\[
\Delta V_i = \alpha (S_i \max(0, \text{Rew} - \sum_j A_{ij})) . \tag{5}
\]

Some researches propose the reinforcement signal to adapt the weights. It is improved the first model, but the accuracy of it is not as good as the others [5]. The output of orbitofrontal and reinforcement signal for orbitofrontal and amygdale is calculated as (6),(7),(8),(5). The \( r_j \) s is intrduced as the factors of the reinforcement agent [5].

\[
E_{o}(n) = E_{o}(n-1) + \sum_j O_j . \tag{6}
\]

\[
R_o = \max (E_{o}(n) - R_n, 0) - E_{o}(n) . \tag{7}
\]

\[
R_n = \sum_j w_j r_j . \tag{8}
\]
3 Enhancing Brain Emotional Learning

The priori model is introduced in modular form which the final output is difference between amygdala output and orbitofrontal output; besides, the reward signal is not clearly determined in the model. For the propose of improving and using the emotional learning model in prediction task, the function of the nodes and the reward signal is modified. In addition, the connection between the components and the number of components is changed (Fig. 2. shows the enhanced model).

The amygdala has many roles; but the first role of amygdala in emotional learning is information storage that is related to stimuli; indeed, amygdala evaluates the new data based on data stores in its memory. This memory helps to amygdala form association between unconditional stimuli and conditional stimuli. Using this association, emotional learning model could make response if it is confronted with unconditional stimuli without conditional stimuli. If this association is made correctly and appreciably the model could be predicated the answer of new stimuli. Therefore, for constructing the predicated model based on emotional learning, constructing association is very essential. For this aim, in this paper, the model is changed to have a several components. (Fig. 3. shows the enhanced model).

![Enhanced model of moron](image)

**Fig. 2.** Enhanced model of moron
At first, new stimuli is classified by classifier component, therefore the training data is not used to update the weights, they use to classifier data and create association between clusters and target desired. Then, evaluation component, evaluates this input and makes answer based on its function, this unit is responsible to adapt the weights. Finally, the outputs of other components enter the central unit to generate the reward signals and final output.

For each new input, a membership function calculates and based on the first output of amygdale is figured out. In the same way, orbitofrontal uses the membership function to evaluate the response of amygdale. The reward signals is made and the parameters of the membership function is updated by using of it. For example, if \( V \) one of adjustable parameter of amygdale component, the reward signal uses to update it by \( (9) \).

The function of thalamus is changed to be intended to improve the result of the model. The information that thalamus is provided is very vital to evaluative task of amygdale. It is caused that amygdale could classify input data accurately, so the output of thalamus is calculated by \( (10) \).

![Diagram](image_url)

**Fig.2.** Connection between components of enhanced model of moron
\[ \text{REW}_d = \sum 1 - (w'_d E_a + w'_d E). \]  \hspace{1cm} (9)

\[ E = w_m (E_a + E_0) - E_2. \]  \hspace{1cm} (10)

\[ \text{REW}_o = \sum 1 - (w'_o E_a + w'_o E). \]  \hspace{1cm} (11)

\[ V = \alpha \text{REW}_o \nabla V. \]  \hspace{1cm} (12)

\[ O_{TH} = [\text{Max}(S_j), \text{Mean}(S_j), \text{Min}(S_j)]. \]  \hspace{1cm} (13)

4 Predictions of Chaotic Time Series

Chaotic time series are used in different fields of science such as, medicine and economics, fluid mechanics, astrophysics, and they is generated. The chaotic property of this time series caused that they are very sensitive to initial conditions and the number of time steps ahead that they are predicated [1], [5].

It is used of Normalized Mean Square Error (NMSE) for comparing with methods. The measurement is defined by (14). Meaning of \( \hat{Y} \) is observed value, \( Y \) is defined the desired target and \( \bar{Y} \) is the average of desired target.

\[ \text{NMSE} = \frac{\sum_{i=1}^{N} (Y_i - \hat{Y}_i)}{\sum_{i=1}^{N} (Y_i - \bar{Y})}. \]  \hspace{1cm} (14)

4.1 Lorenz time series

The Lorenz chaotic time series [5] is chosen as first example, is predicated with EPM. It is described by (15), (16).
\begin{align}
\dot{x} &= a(y - x) \\
y &= bx - y - xz \\
\dot{z} &= xy - cz
\end{align}
\tag{15}

\begin{align}
a = 10, b = 28, c = 8/3, T = 0.01s
\end{align}
\tag{16}

Fig.3. The correlation between observed value and desired target by various prediction methods

By adjusting suitable parameters above and with 0.01 second sampling a chaotic time series is obtained. The strange attractor is shown in Fig.4. At first, The training set is chosen from the 30th second to 45th. Then, 500 samples, from 45th to 50th are chosen as test set [5]. Table 1, shows the NMSE and correlation of pre-
dicting Lorenz chaotic time series by multilayer perceptron with back propagation learning (MLP), Takagi Sugeno neurofuzzy Inference system (T–S) with orthogonal least square algorithm (OLS). The correlation of observed value which is predicted by enhanced model with desired value is more high than ANFIS method (Fig.3, presents it). The index error (NMSE) of prediction enhanced model is compared with others prediction methods (Fig.4, shows the comparison between NMSE).

Table 1. Correlation and NMSE of predicting Lorena Time Series with different methods

<table>
<thead>
<tr>
<th>Learning method</th>
<th>NMSE Test</th>
<th>Correlation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Enhanced model</td>
<td>0.0032</td>
<td>0.9986</td>
</tr>
<tr>
<td>ANFIS [5]</td>
<td>0.00317</td>
<td>0.925</td>
</tr>
<tr>
<td>Emotional [5]</td>
<td>0.006045</td>
<td>0.875</td>
</tr>
<tr>
<td>MLP [5]</td>
<td>0.00422</td>
<td>0.854</td>
</tr>
</tbody>
</table>

![Bar chart showing comparison between learning methods](image)

Fig.4. The comparison of error index (NMSE) level between proposed model and others
4.2 IKEDA time series

The Ikeda map time series is described by (17)

\[
\begin{align*}
    x(k+1) &= 1 + a(x(k) \cos(\rho) - y(k) \sin(\rho)) + \varepsilon_x \delta(k) \\
    y(k+1) &= a(x(k) \sin(\rho) + y(k) \cos(\rho)) + \varepsilon_y \delta(k)
\end{align*}
\]  

(17)

Where, \( \varepsilon_x, a = 0.9, \rho = 0.6, \varepsilon_y = 0 \) is the magnitude of the internal dynamic noise, and \( \{\delta(k)\} \) is a uniformly distributed random variable in \([-1,1]\). Training data set is 1200 samples and train data are 500 samples and the test data are 700 samples. The time series is extracted from (18). For clear comparison the prediction accuracy between all methods, error index (NMSE) is shown (Fig.5.). Table 2, gives the difference prediction error between several models.

\[
[x(t-30), x(t-20), x(t-10); x(t)].
\]  

(18)

![Bar chart](image)

**Fig.5.** The error index (NMSE) value of predicting 10 step ahead of IKEDA time series via several methods
Table 2. NMSE of various methods in predicting the 10 step ahead of IKEDA

<table>
<thead>
<tr>
<th>Learning method</th>
<th>NMSE Test</th>
</tr>
</thead>
<tbody>
<tr>
<td>Enhanced model</td>
<td>1.0970</td>
</tr>
<tr>
<td>ANFIS</td>
<td>1.1170</td>
</tr>
<tr>
<td>RBF network[6]</td>
<td>1.5334</td>
</tr>
<tr>
<td>MLP [6]</td>
<td>2.2517</td>
</tr>
</tbody>
</table>

5 Average price of selling Time series

5.1 Trading Agent Competition Environment

In this competition the six agents participate to supply components and assemble them to provide computers and then sell them to customers. Trading agent competition supply chain management game provides the competitive environment in which agents could be compete against each other to increase its profit. Therefore, (TAC SCM) is the competition that six agents act as manufactured agent. The game take 220 simulated days to finish, and the time of each day in real time is 15 seconds. Each agent should do three jobs such as buy component from supplier agent, sell computer to customer and management of factory. At the end of competition, the agent with the highest sum of money in the bank is winner [9].

There are many quantities that could be predicted during TAC SCM game. Such as future price of computers, average price at which a specific type of computer sell in future, component prices [10]. In this paper it is focused on average component selling price; but, details are available in the documents [9].

5.2 Prediction one of Time Series related to TAC SCM

In TAC SCM game, prediction prices; in particular, price of selling component is very important to predicate the condition of market and behavior of other agents; therefore, manufacture agent could be able extracts the useful information from receiving data. The time series is explained with (19).

\[ [x(t - 20), x(t - 10), x(t)] \]  \hspace{1cm} (19)

The system is generated this time series is chaotic and it is related to many parameters that is changed in each game; therefore, it is not suitable to learning the system to predicate the system in offline method. For the prediction it is used of the information 93 days of game: therefore, the number of data is 74 samples. Training data are 24 samples and test data are 50 samples. As thus, it is supposed that, the average price of 50 next days is predicated by using the data 24 prior days of game.
It can be seen from Table 3, that the ANFIS neural fuzzy model could not predicate better than the proposed method. In this comparison, ANFIS with different structure and various iteration numbers is made. Therefore, the structure with 25 rules is the best structure found. In each step, there is information about the correct answer after 20 steps from it, therefore the correct answer along the corresponding input could be added to information stored in amygdala and orbitofrontal model for next predication uses them. The correlation value between observed data and real data is shown. (Fig. 5.)

**Table 3.** The comparison of various methods in predicting the Average Price Selling of TAC SCM

<table>
<thead>
<tr>
<th>Learning method</th>
<th>NMSE Test</th>
<th>Correlation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Enhanced model</td>
<td>2.5421</td>
<td>0.4858</td>
</tr>
<tr>
<td>ANFIS</td>
<td>3.5150</td>
<td>0.0934</td>
</tr>
</tbody>
</table>

*Fig. 5.* The correlation value of predicating average price selling time series through ANFIS and Enhanced model
6 Conclusion and Remark Notes

The changes that are proposed in this paper, causes the emotional brain learning could be used in multi-objective prediction. For this propos, there is no need to major change; the multi-objective prediction is done by adding some nodes. In addition, the structure of the model is very simple and it is independent of the dimension of on input; therefore it is possible use the high dimension prediction without worrying about increasing the number of nodes or rules.

The method is proposed in this article, it is ability to make a short term prediction as well as the long term prediction. On the other hand, the model uses past experience to predicate its future behavior. In fact, its adaptive learning property could be used in both prediction terms. If it receives information from environment or the reward nears to defined quantity; the input and corresponding output could add to training data set to improve the produced reaction to new stimuli.

Because the number of adjustable parameter in model is small, and the training data samples are used as data base or memory for associating new data with them, the main advantage of the modified model is emergent; consequently, the enhanced model is could predicate the desired target with a few number of data without needing to adjust weights by using the training data in iterative manner, and particularly the result of prediction model is more accurate than other.

It can be seen that, the proposed model is hybrid model that its learning method is composed of unsupervised learning and reinforcement learning. This method is needed to improve in order to could take part in out associative learning. In addition, it could be predicated more accurate than ANFIS for Macky-Glass time series by changing the function and connection between components [20]. In deed, by adding the changes in proposed model the general approximation learning model is constructed [19].

References


