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An Improved Model of Brain Emotional Learning Algorithm Based on Interval Knowledge

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Abstract

The brain emotional learning algorithm inspired by a reduced system of a computational model simulates the brain learning performance quite simply with mimicking mammalian brains. The present paper endeavors to come forward to an improved model of the emotional learning algorithm based on the interval knowledge. In this proposed model, based on the interval knowledge, the weights of the amygdala and orbitofrontal sections will be updated. Eventually, the results of implementing and performing the improved brain emotional learning algorithm will be presented to be compared with the original version of the algorithm to Prediction the chaotic time series, Lorenz and Rossler, about which a noticeable improvement in its precision, accuracy and speed of convergence of the final results is reported.

Keywords: Brain Emotional Learning Algorithm, Interval Knowledge, Chaotic Time Series, Prediction

1. Introduction

Emotional computation is considered as an interdisciplinary field, including computer science, psychology and cognitive science. In the decision-making process not only computations and logic which are performed by the upper tissue of the brain but the sensations whose origins are in the cerebellum, and midbrain is involved. The brain learning and its applications can be considered as an almost new field of research. The undertaken researches about the aforementioned area reveal that the advocates' claims and contentions about brain learning, without a doubt, were of great value and were worth devoting some time and energy. With regard to above mentioned issue, various methods of education based on the brain learning have been proposed. The brain can act in different ways simultaneously. Additionally, the brain constantly processes and monitors the thoughts, excitements, and images. The brain is a physiological-neural system, which interacting and exchanging information with the environment. Human being is not aware of some brain applications, take control of breathing and some other inevitable activities as examples. Some of the applications of neural networks are for use in stock price prediction [1], bankruptcy Prediction [2], Detect dos-attacks [3] and controlling the False Alarm in an Intrusion Tolerant Database System [4]. Since the brain has various performances, learning process can be complex and different as well. Neural networks trained with gradient descent based algorithms [5] and evolutionary algorithms [6-7]. In this regard, not only the considerable importance of learning fields and material, but also learning methodologies are being stressed. Reptiles react to symbols of chemical, touch, and sight senses and their reactions have already been determined in accordance with their bodies. There are some excitements originated from determined activities in specific areas of the brain called Limbic System. Some significant areas are located in the cortex of the brain, namely Amygdala, Orbitofrontal, hypothalamus, hippocampus, thalamus, etc. Not only are not all excitements merely related to Limbic, but also it has been shown that some Limbic systems are not related to the excitements directly [8-11]. In this paper, applying the interval knowledge, it is being endeavored to introduce a version of the brain emotional learning algorithm which shows better results in prediction the chaotic time series in comparison with the original version of the brain emotional learning algorithm. This paper is organized as follows: Firstly, the interval knowledge will be reviewed, and then the brain emotional learning algorithm will be investigated and the proposed method will be suggested, and eventually the results of the proposed method will be compared with the original version of the brain emotional learning algorithm so that Lorenz and Rossler chaotic time series will be forecasted.

2. Interval Knowledge

In this section, a type of application of interval knowledge in neural network is being presented whose concepts are going to be used to create the improved proposed algorithm. Rough Neural Network is being utilized to estimate the functions based on Lingras model. With any input data and real output values, Rough Neural Network can be implemented [13], figures 1 and 2 shows the structure of the Rough Neuron.

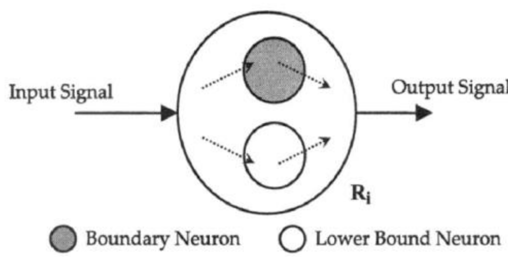

Figure 1. Rough Neuron [14]

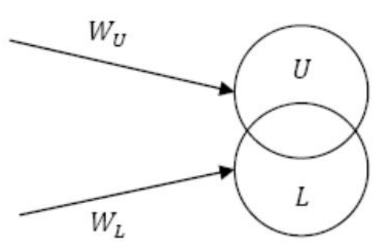

Figure 2. The Structure of the rough neuron with upper weight and lower weight

Where *U* is the upper boundary neuron and *L* represents the lower boundary neuron. One sample of Rough Neural Network is being shown in figure 3. Rough hidden layer neurons consist of upper and lower boundary neurons. Having calculated the average, the output of each rough neuron in this layer is obtained. The single neuron of the output layer in this model is a conventional one. In this model, having announced the error based on first rank gradient descent, learning takes place [13].

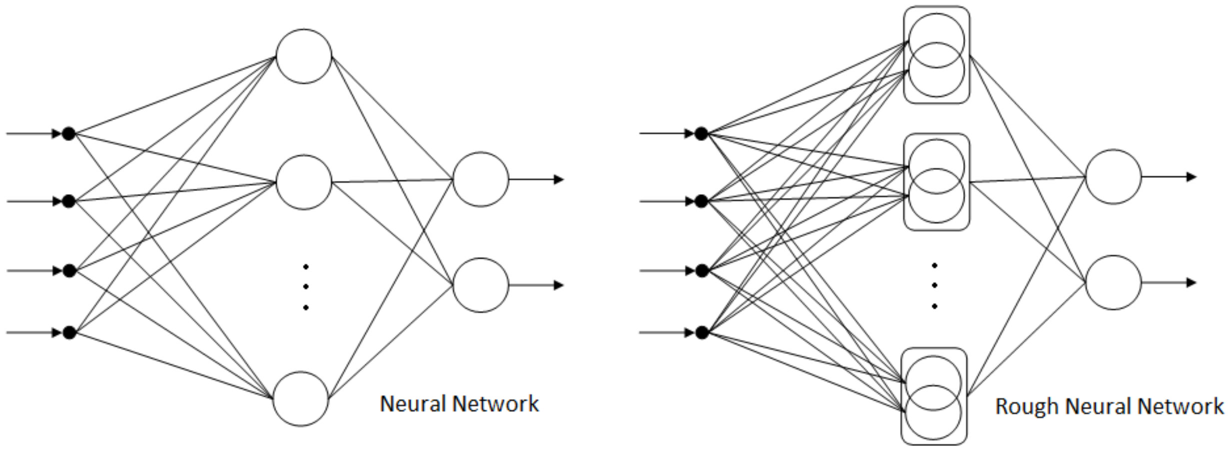

Figure 3. Comparison between the conventional neural networks and rough neural networks

3. Brain Emotional Learning Algorithm

Limbic system is shown in figure 4 and computational model of the brain emotional learning algorithm is shown in figure 5.

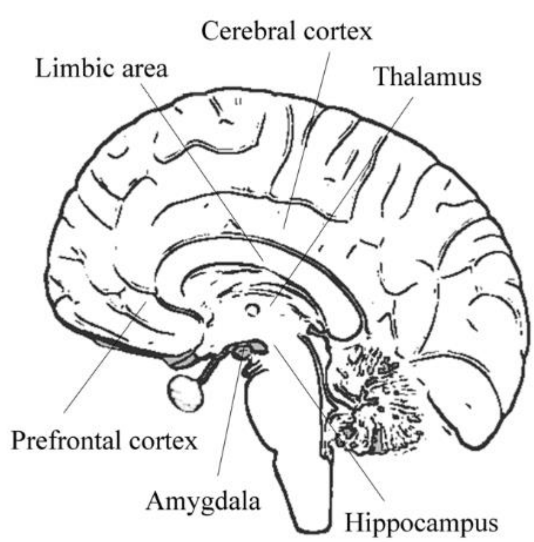

Figure 4. The limbic system in the brain [17]

The given system is categorized into two sections, namely orbitofrontal cortex and amygdala. Confirmatory reward signal is applied to the system, and for each *S* stimulation like thalamic stimulation tie, an *A* tie exists. In addition, an *O* tie exists for everyone except for the thalamic stimulation tie. *E* tie is the output tie of the model which in actual fact collects the outputs of all *A* ties and then subtract the total amount of deterrent ties. The amygdala section plays a crucial role in controlling the emotional activities such as friendship, love and kindness, temper, fear, invasion and anger. The amygdala is the center of noticing the dangers and is of a great importance for human's survival. The amygdala section is trained to predict the next reactions and react to the reward. Orbitofrontal interferes when the prediction made by the amygdala and the reward are not consonant with each other. Consequently, based on the former learning, it endeavors to remove this dissonance. The most significant part of learning algorithm is defining the reward function. Reinforced reward signal is a function of other signals considered as an evaluation function ([12], [15], and [16]).

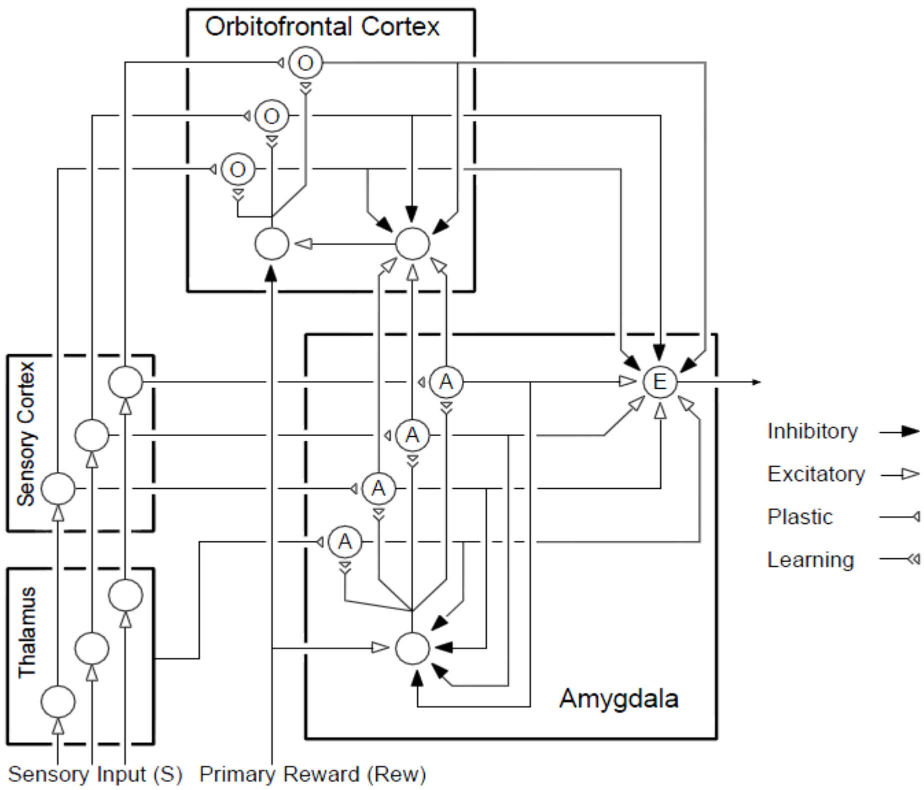

Figure 5. Computational model for brain emotional learning [12]

The output of ties in the amygdala and the orbitofrontal tissue, and the final output of the computational model of the brain emotional learning algorithm are calculated by equations 1-3 respectively.

$$O_i = S_i * W_i \tag{1}$$

$$A_i = S_i * V_i \tag{2}$$

$$E = \sum_i A_i - \sum_i O_i \tag{3}$$

The amygdala is responsible for stimulation and orbitofrontal has a deterrent role. In this model, these V_i are the weights of amygdala and W_i are the weights of Orbitofrontal; A_i and O_i are the output of the ties in the amygdala and orbitofrontal tissue respectively; S_i are the sensory input, E is the final output of the computational model. Equations 4 and 5 are being used to reconcile the weights in learning process [12].

$$\Delta V_i = \alpha(\mathrm{S}_i \max(0, \mathrm{REW} - \sum_j A_j) \tag{4}$$

$$\Delta W_i = \beta(\mathrm{S}_i \sum_j (\mathrm{O}_j - \mathrm{REW})) \tag{5}$$

According to the abovementioned equations, α and β are the coefficients of the weights of the amygdala and orbitofrontal and *REW* is the reward. A_{th} Which can be calculated by equation 6 is the value which moves from thalamus towards amygdala [12].

$$A_{th} = \max(S_1, S_2, ..., S_n) \tag{6}$$

n is the number of inputs of thalamus section; S_i is the i-th sensory input. In figure 6, a very simple structure of connections among the major sections of learning computational system is easily seen. In proposed method, applying the interval knowledge, the weights of the amygdala and orbitofrontal are being taught.

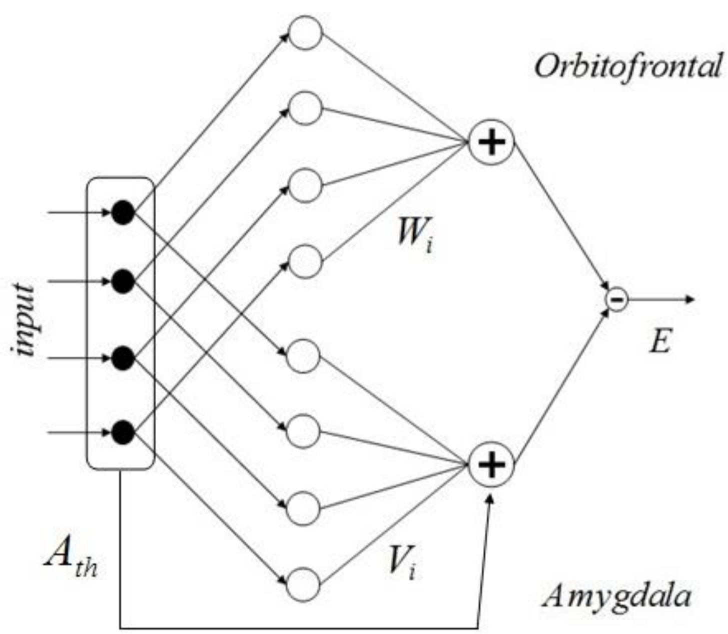

Figure 6. Simple structure of the brain emotional learning

4. The Propose Method

As can be seen in figure 7, the weights of amygdala and orbitofrontal are changed into intervals. V_i is the weight of the amygdala and W_i is the weight of orbitofrontal which have lower and upper boundaries. According to figure 8,

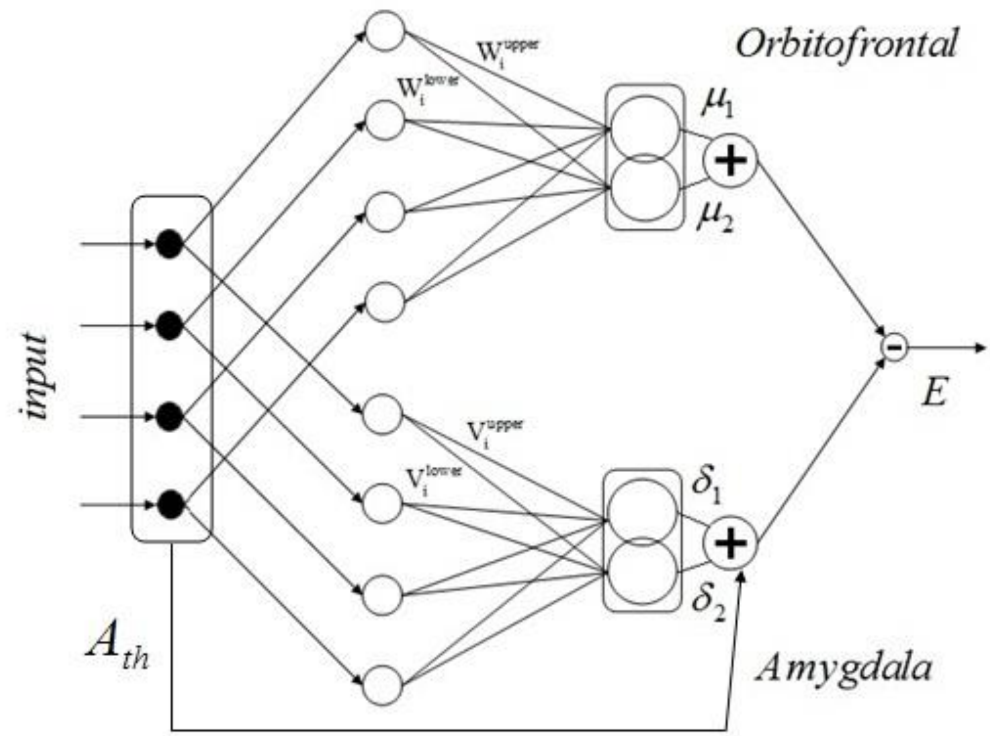

Figure 7. The Structure of the proposed method for brain emotional Learning

Therefore, the outputs of the amygdala and orbitofrontal tissue will include lower and upper boundaries.

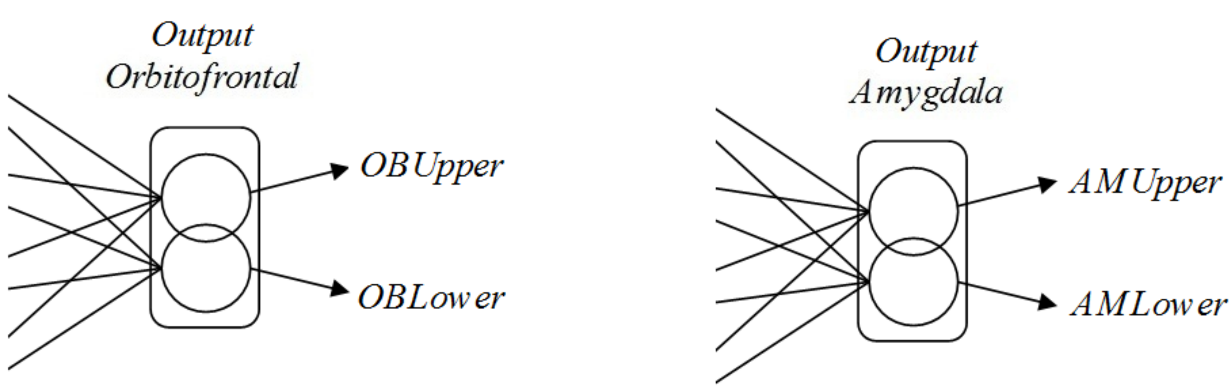

Figure 8. The output neurons of the amygdala and orbitofrontal

On the other hand, the lower and upper outputs of the amygdala will multiply by δ_1 and δ_2 respectively, and eventually with accordance with equation 10, their total will be considered as the output of the amygdala. Similarly, the lower and upper outputs of orbitofrontal will multiply by μ_1 and μ_2 respectively and eventually with accordance with equation 9, their total will be considered as the output of orbitofrontal.

$$OBUpper = \sum_i S_i * W_i^{Upper} \tag{7}$$

$$OBLower = \sum_i S_i * W_i^{Lower} \tag{8}$$

$$OutputOB = OBUpper * \delta_1 + OBLower * \delta_2 \tag{9}$$

$$OutputAM = AMUpper * \mu_1 + AMLower * \mu_2 \tag{10}$$

To update δ_1 and δ_2 parameters in the amygdala, μ_1 and μ_2 in orbitofrontal section, equations 11-16 must be followed. η_1 , η_2 , η_3 and η_4 are the rates of the output parameters of the amygdala and orbitofrontal.

$$e = \mathrm{Target} - \mathrm{E} \tag{11}$$

$$p = \frac{1}{2}(\mathrm{e})^2 \tag{12}$$

$$\begin{aligned}\delta_1(t) = \delta_1(t-1) + \eta_1 * \frac{\partial p}{\partial \delta_1} = \delta_1(t-1) + \eta_1 * \frac{\partial p}{\partial e} * \frac{\partial e}{\partial E} * \frac{\partial E}{\partial AM} * \frac{\partial AM}{\partial \delta_1} = \\ \delta_1(t-1) + \eta_1 * (e) * (-1) * (1) * (AMUpper)\end{aligned} \tag{13}$$

$$\begin{aligned}\delta_2(t) = \delta_2(t-1) + \eta_2 * \frac{\partial p}{\partial \delta_2} = \delta_2(t-1) + \eta_2 * \frac{\partial p}{\partial e} * \frac{\partial e}{\partial E} * \frac{\partial E}{\partial AM} * \frac{\partial AM}{\partial \delta_2} = \\ \delta_2(t-1) + \eta_2 * (e) * (-1) * (1) * (AMLower)\end{aligned} \tag{14}$$

$$\begin{aligned}\mu_1(t) = \mu_1(t-1) + \eta_3 * \frac{\partial p}{\partial \mu_1} = \mu_1(t-1) + \eta_3 * \frac{\partial p}{\partial e} * \frac{\partial e}{\partial E} * \frac{\partial E}{\partial OB} * \frac{\partial OB}{\partial \mu_1} = \\ \mu_1(t-1) + \eta_3 * (e) * (-1) * (1) * (OBUpper)\end{aligned} \tag{15}$$

$$\begin{aligned}\mu_2(t) = \mu_2(t-1) + \eta_4 * \frac{\partial p}{\partial \mu_2} = \mu_2(t-1) + \eta_4 * \frac{\partial p}{\partial e} * \frac{\partial e}{\partial E} * \frac{\partial E}{\partial OB} * \frac{\partial OB}{\partial \mu_2} = \\ \mu_2(t-1) + \eta_4 * (e) * (-1) * (1) * (OBLower)\end{aligned} \tag{16}$$

To learn the weights of lower and upper bounds of amygdala and orbitofrontal, equations 4 and 5 must be followed. The only difference is that the V_i weight can be taught by learning the weights of V_i^{Upper} and V_i^{Lower} separately, and W_i weight is also the same.

5. Experimental Results

In this part of the paper, the results of implementing and performing the improved algorithm to the Prediction of the Lorenz attractor and Rossler attractor chaotic time series are investigated, and eventually there will be a comparison between the improved algorithm and the original version of this algorithm. Rossler attractor chaotic time series are presented by the following equations,

$$\frac{dx(t)}{dt} = -\sigma_L x(t) + \sigma_L y(t) \tag{17}$$

$$\frac{dy(t)}{dt} = \gamma_L x(t) - y(t) + \mathrm{x(t)\,z(t)} \tag{18}$$

$$\frac{dz(t)}{dt} = -b_L z(t) + x(t) y(t) \tag{19}$$

where σ_L , γ_L , b_L and do not have dimensions and present the dynamic Lorenz attractor. If the value of γ_L is 24.74 more than a critical value, $\sigma_L = 10$ and $b_L = 3/8$ will have the chaotic behavior system. Almost 8000 samples of Lorenz attractor time series are shown in figure 9.

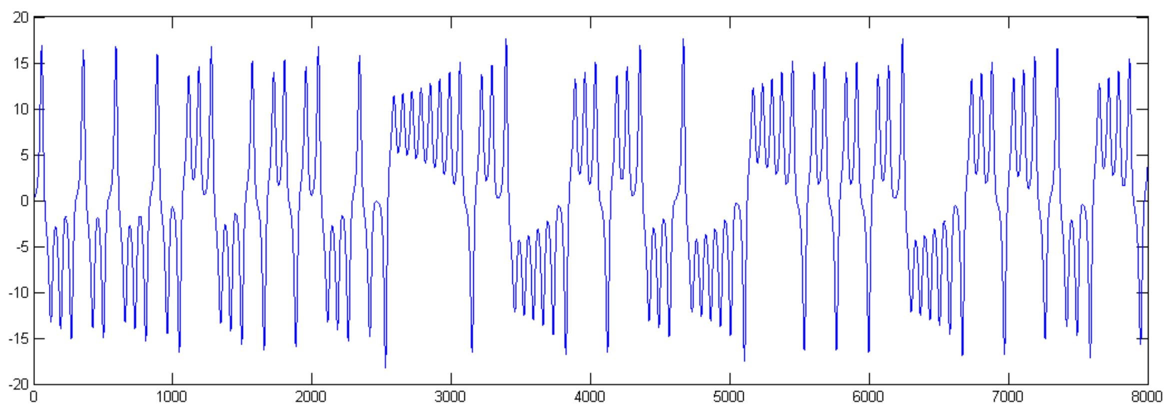

Figure 9. Lorenz chaotic time series

Another time series which has been studied is the Rossler attractor presented by the following equations,

$$\frac{dx(t)}{dt} = -z(t) - y(t) \tag{20}$$

$$\frac{dy(t)}{dt} = x(t) + a * y(t) \tag{21}$$

$$\frac{dz(t)}{dt} = b + z(t) * (x(t) - c) \tag{22}$$

Where $a = 0.15$, $b = 0.20$, $c = 10$ and do not have dimensions. 8000 samples of Rossler attractor time series are shown in figure 10.

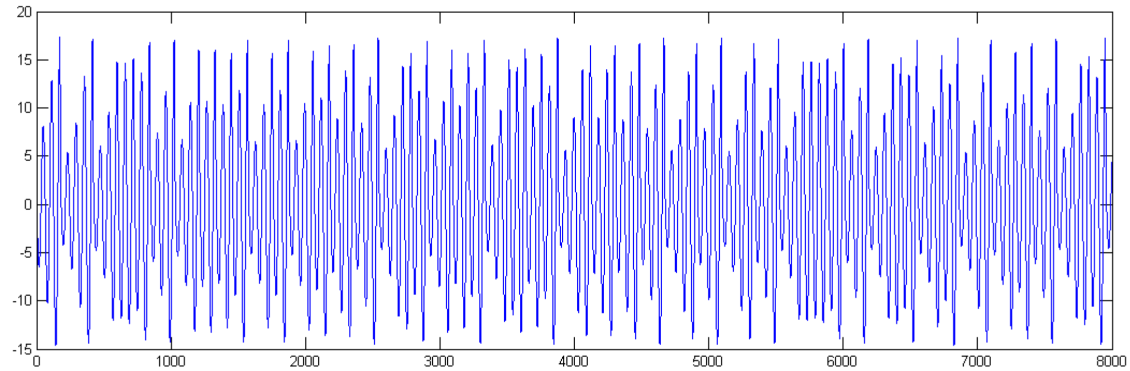

Figure 10. Rossler chaotic time series

The results of comparing the proposed algorithm and the original version [12] to prediction the Lorenz and Rossler time series are reported in tables 1-2 and figures 11-14. One of the noticeable points in the reported results of this paper is the point that with the fewest testing samples, prediction is done carefully.

Table 1. The results of comparison of the proposed method and moren[12] for prediction of lorenz chaotic time series

Algorithm	Max Epoch	Train	Test	Number of Sample	MSE - Train	MSE - Test
Moren[12]	150	5%	95%	8000	0.000561865000	0.000541915300
Proposed	150	5%	95%	8000	**0.000236798300**	**0.000229888300**
Moren[12]	150	10%	90%	8000	0.000277757000	0.000303022100
Proposed	150	10%	90%	8000	**0.000134218800**	**0.000140804800**
Moren[12]	150	15%	85%	8000	0.000138474100	0.000130332100
roposed	150	15%	85%	8000	**0.000099838300**	**0.000091604100**

Table 2. The results of comparison of the proposed method and moren[12] for prediction of rossler chaotic time series

Algorithm	Max Epoch	Train	Test	Number of Sample	MSE - Train	MSE - Test
Moren[12]	150	5%	95%	8000	0.000215253600	0.000225777400
Proposed	150	5%	95%	8000	**0.000154333100**	**0.000160336400**
Moren[12]	150	10%	90%	8000	0.000109057700	0.000111138200
Proposed	150	10%	90%	8000	**0.000084314000**	**0.000086343200**
Moren[12]	150	15%	85%	8000	0.000062907700	0.000062565300
Proposed	150	15%	85%	8000	**0.000060354200**	**0.000061547210**

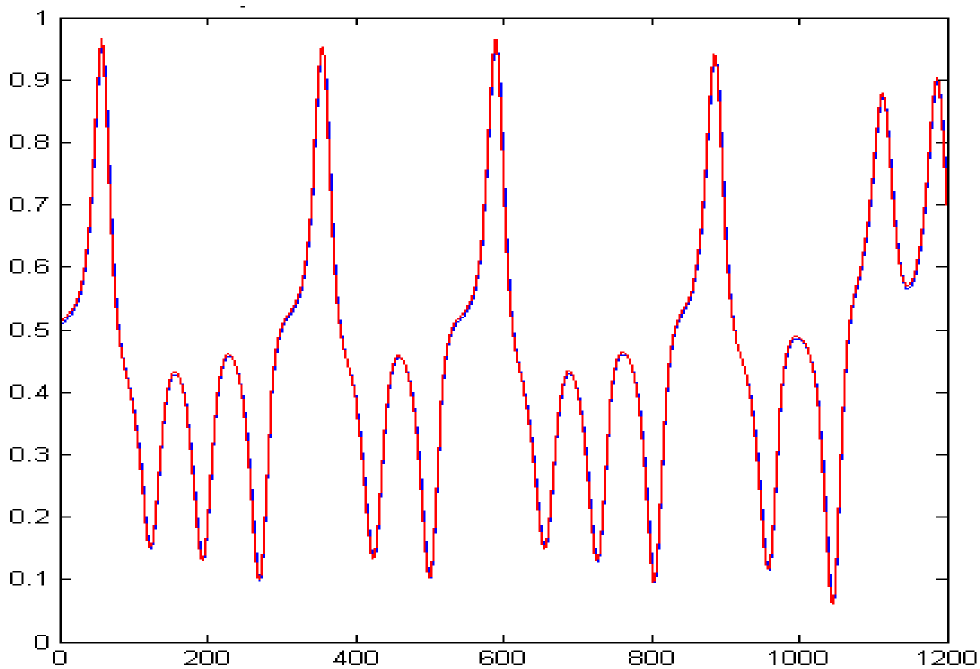

Figure 11. The predicted values and the target values of lorenz time series (Train)

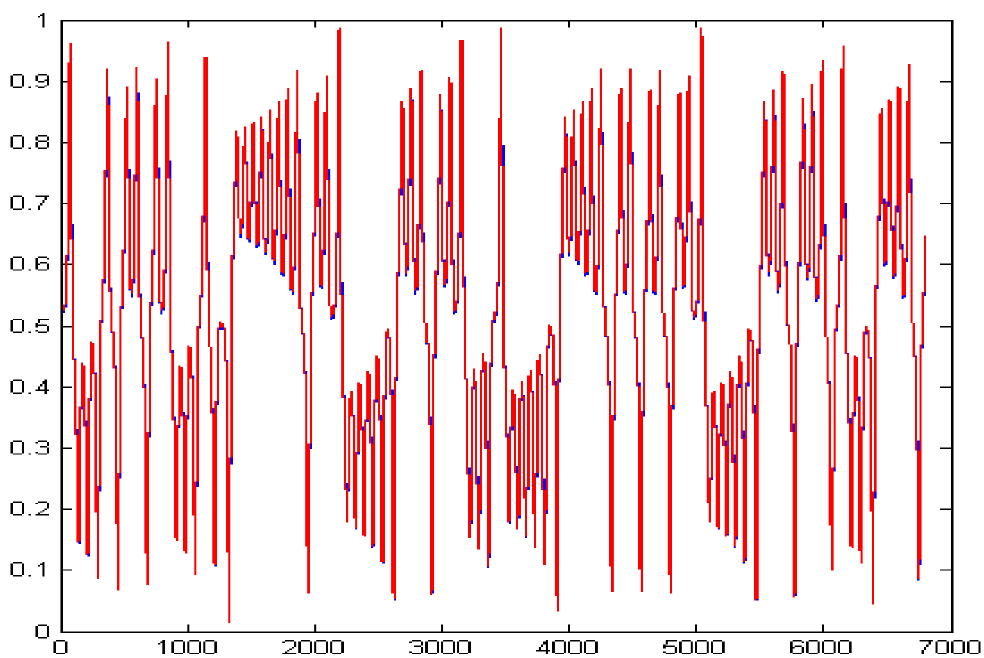

Figure 12. The predicted values and the target values of lorenz time series (Test)

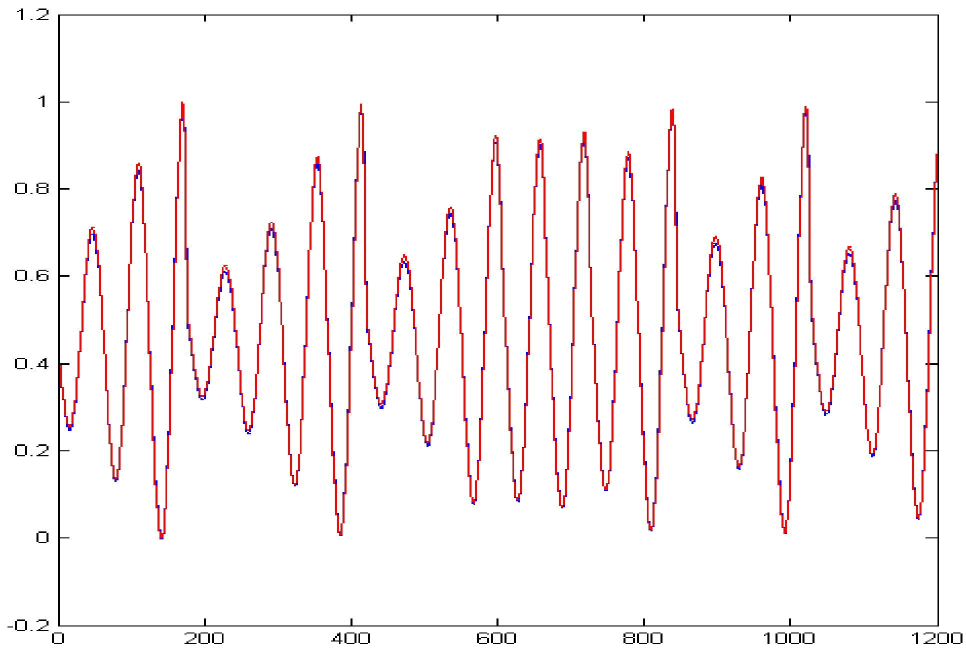

Figure 13. The predicted values and the target values of rossler time series (Train)

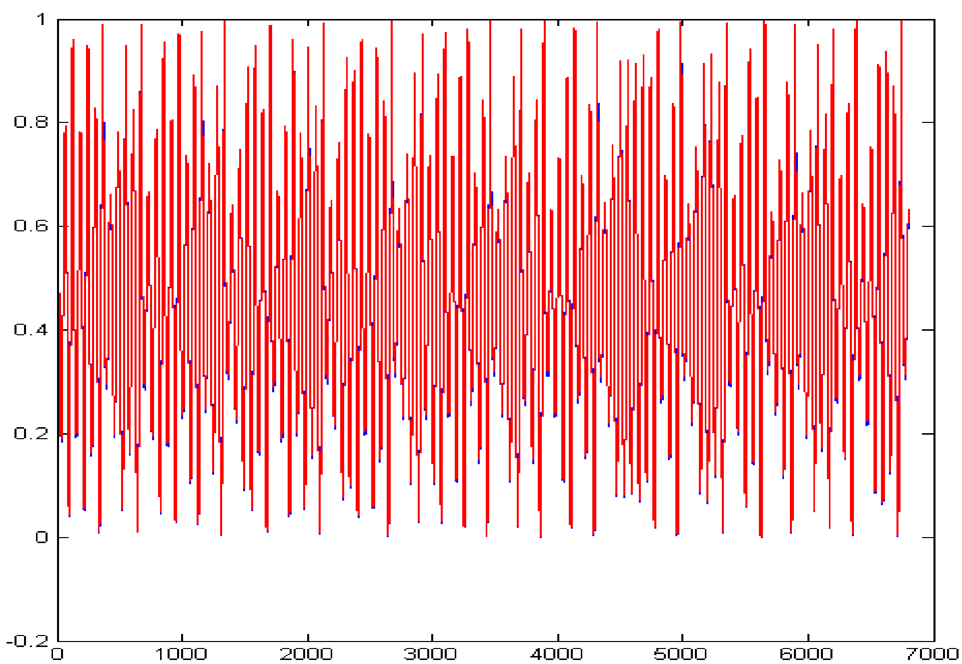

Figure 14. The predicted values and the target values of rossler time series (Test)

6. Conclusion

In this paper, an improved version of brain emotional learning algorithm based on the interval knowledge has been presented. The weights of the amygdala and orbitofrontal are updated based on interval knowledge. With regard to the implementation and performance of the improved brain emotional algorithm and its comparison with the original version to prediction the Lorenz and Rossler chaotic time series, a noticeable improvement in precision, accuracy and speed of convergence of the final results is reported.

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