

# A simple Mathematical Fuzzy Model of Brain Emotional Learning to Predict $K_p$ Geomagnetic Index

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**Abstract:** In this paper, we propose fuzzy mathematical model of brain limbic system (LS) which is responsible for emotional stimuli. Here the proposed model is utilized to predict the chaotic activity of the earth's magnetosphere. Numerical results show that the correlation of the results obtained from the proposed fuzzy model is higher than non-fuzzy models. Hence, the proposed model can be applied in real time chaotic time series prediction.

**Keywords:** Cognitive science, Amygdala, Computational model, Chaotic time series.

## 1. Introduction

Emotions are cognitive processes and multidisciplinary studies of emotion have a long history. From the psychological point of view, emotions can be derived with reward and punishment received from various real-life situations and studies of the neural basis of emotion culminated in the limbic system (LS) theory of emotion [1-4]. The LS processes the emotional stimuli [2-6] and is located in the cerebral cortex and consists of two main components including: amygdala and orbitofrontal cortex (OFC) (Figure 1). Amygdala is located in subcortical area and its main cognitive functions are long term memory and responsibility for emotional stimuli [7-8]. Amygdala receives connections from the sensory cortical areas [7-8] and also interacts with the OFC that tries to prevent inappropriate responses from the amygdala [7-8]. Recently, researchers have tried to present mathematical models of LS. The first applied mathematical model of LS was proposed by Morén and Balkenius [7-8] which is a neuropsychological motivated mathematical model. This basic model and its modified versions [9-10] have been utilized in various applications including: control application, prediction and alarm systems [11-19]. A control algorithm based on LS model was introduced by Lucas et al. [9-10] which is an action generation mechanism based on sensory inputs and emotional cues. Also LS model was proposed as an alarm system to predict the  $K_p$  index of geomagnetic activity [19-22] and to predict the  $AE$  index of space weather phenomena [23]. These indices characterize the solar winds and geomagnetic storms that is a complex system and can greatly disturb communication systems and damage satellites [23]. The  $K_p$  have chaotic behaviour and can be considered as time series. Recently we proposed a mathematical model of LS for classification and pattern recognition problems [24-25] and in this paper we fuzzify the model and propose fuzzy computational model of LS to predict  $K_p$  index. A fuzzy framework can better explain the brain behaviour. Hence we fuzzify the connections in

the LS model and implement the inhibitory task of OFC as a fuzzy decision making layer. The proposed model is presented in Section 2 and Section 3 presents a comparison between proposed method, Basic LS model and ANN (Artificial Neural Network) [26] which is popular predictor in geomagnetic phenomena forecasting.

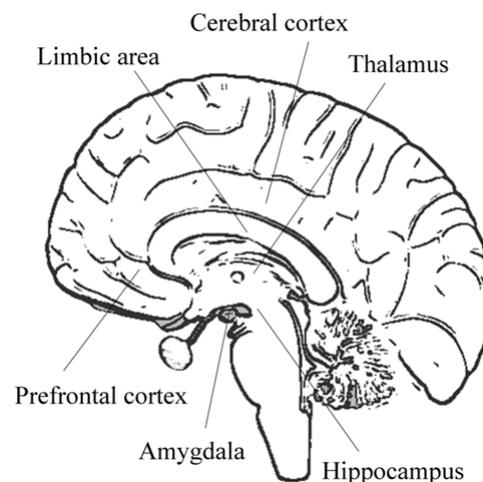


Figure 1. The LS in the brain (from [25])

## 2. Proposed fuzzy computational model of LS

The main modifications introduced here with respect to previous models are considering the plastic connections as some fuzzy rules and defining a fuzzy decision making layer on the final output of LS model as illustrated in Figure 2. In the figure solid lines present the data flow and learning lines are presented as dashed lines. According to the amygdala-orbitofrontal interaction, the proposed computational model named FDBEL (Fuzzy Decay Brain Emotional Learning) is divided into the two parts. The amygdaloidal part receives fuzzy inputs from the thalamus and from cortical areas, while the orbital part receives fuzzy inputs from the sensory cortex only. Also OFC has a fuzzy output that prevents the wrong answers of amygdala. The system also receives a fuzzy reinforcing signal. We improve the performance

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of the model by using decay rate  $\gamma$  in amygdala learning rule. So the learning rules are as follow:

$$V_i^{k+1} = (1-\gamma) \cdot V_i^k + \alpha \cdot \max(T_i^{k+1} - E_a^k, 0) \cdot S_i^k \quad (1)$$

$$W_i^{k+1} = W_i^k + \beta \cdot (S_i^k \cdot R_0) \quad (2)$$

where  $k$  is learning step and  $R_0$  is internal reward calculated by:

$$R_0 = \begin{cases} \max(E_a^k - R^k, 0) - E_a^k, & \text{if } R^k \neq 0 \\ \max(E_a^k - E_o^k), & \text{otherwise} \end{cases} \quad (3)$$

In this model each plastic connection between thalamus and amygdala and between sensory cortex and thalamus, are considered as a fuzzy rule. The Takagi Sugeno fuzzy model for  $i^{\text{th}}$  amygdala connection is as follow:

If ( $S_i$  is  $V_i$ ) then ( $A_i = S_i \cdot v_i$ )

The ( $S_i$ ) is  $i^{\text{th}}$  input and ( $V_i$ ) is  $i^{\text{th}}$  fuzzy set with bell-shaped membership function where the ( $v_i$ ) locates the center of the curve. So the output of amygdala ( $E_a$ ) is calculated by following formula:

$$E_a = \sum_i A_i(S_i; v_i, a, b) \quad (4)$$

And  $E'_a$  in learning rule (see Eq. 8) is:

$$E'_a = \sum_{i,j \neq \text{th}} A_i(S_i; v_i, a, b) \quad (5)$$

where

$$A_i(S_i; v_i, a, b) = \frac{1}{1 + \left| \frac{S_i - v_i}{a} \right|^{2b}} \cdot S_i \cdot v_i \quad (6)$$

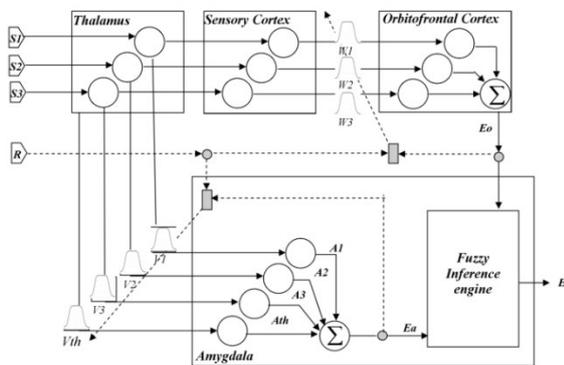


Figure 2. Proposed fuzzy computational model of LS

Also the Takagi Sugeno fuzzy model for  $i^{\text{th}}$  OFC connection is as follow:

If ( $S_i$  is  $W_i$ ) then ( $O_i = S_i \cdot w_i$ )

Where ( $S_i$ ) is  $i^{\text{th}}$  sensory input and ( $W_i$ ) is  $i^{\text{th}}$  fuzzy set with ( $w_i$ ) center bell-shaped membership function. So the output of OFC ( $E_o$ ) is calculated by following formula:

$$E_o = \sum_i O_i(S_i; w_i, a, b) \quad (7)$$

where

$$O_i(S_i; w_i, a, b) = \frac{1}{1 + \left| \frac{S_i - w_i}{a} \right|^{2b}} \cdot S_i \cdot w_i \quad (8)$$

The outputs of amygdala and OFC are crisp values. We fuzzify the output of OFC as a Gaussian membership function with mean  $E_o$  which is input of fuzzy inference engine. So the final output ( $E$ ) fire using following rule:

$$E = 1 - e^{-\frac{(E_a - E_o)^2}{2c^2}} \quad (9)$$

Where the subtraction between amygdala output ( $E_a$ ) and OFC output ( $E_o$ ) implements the inhibitory task of OFC.

### 3. Experimental Results

To test the offered method, the chaotic time series of  $Kp$  characterized the geomagnetic activity of the earth's magnetosphere, was collected from National Space Science Data Center (NSSDC). Totally 184104 hourly samples from 1976 to 1996 has been downloaded. We extract each 4 sequence samples as a pattern and 5th as its target. So 184099 pattern-target pairs of  $Kp$  index extracted. The official values of  $Kp$  index are as following form:

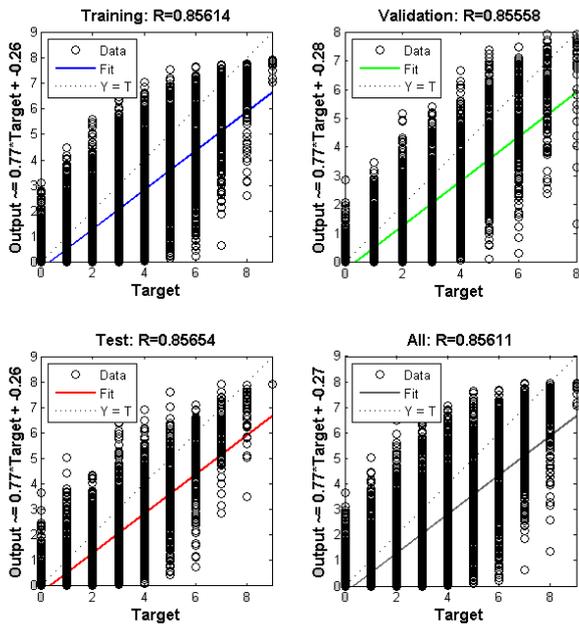
$$0, 0+, 1-, 1, 1+, 2-, 2, 2+, \dots, 9$$

To adjust the weights we scaled all of data between 0 and 1. For all learning scenarios listed below  $\alpha$  and  $\beta$  (Eqs. 6,7) are set at 0.2 and 0.8 respectively. To find optimized decay rate, consider the following scenario: by decay rate 0 system trained the samples in 1988. This training is repeated 10 times and the average of errors recorded. This scenario is repeated by various values (For  $\gamma = 0, 0.05, 0.1, 0.15, 0.2, \dots, 1.0$ ). The highest error is obtained using  $\gamma = 0$  and the lowest error obtained by using  $\gamma = 0.05$ . The parameters values used in learning phase presented in Table 1. In Eq. (6); the values  $a$  and  $b$  are set at  $(v_i - 0.5)$  and  $(v_i - 0.25)$ , respectively. In Eq. (8);  $a = (w_i - 0.5)$ ,  $b = (w_i - 0.25)$  and finally in Eq. 9;  $c = (E_o - 0.25)$ .

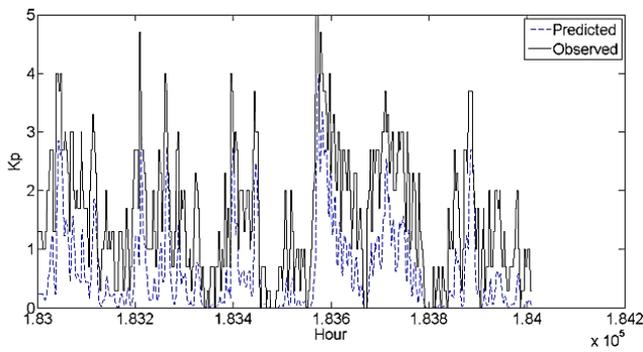
Table 1. the value parameters used in learning phase

Parameter	Value
$\alpha$	0.8
$\beta$	0.2
$\gamma$	0.01

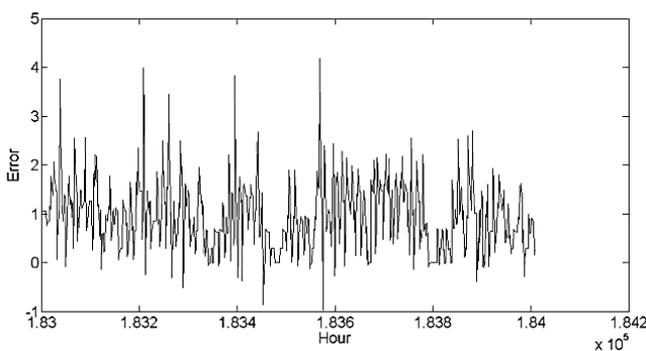
To assess the FDBEL method, 15% of samples are used as validation, 15% as test and 70% as training samples. Figure 3 present the regression plots of the results obtained from FDBEL. In the figures, R is regression value of data. According to the figure the correlations of results in test set, validation and training set are more than 0.85.



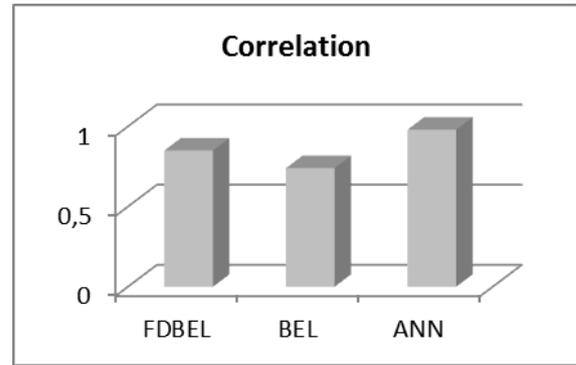
**Figure 3.** The regression plots of the  $K_p$  prediction results in the training set, test set and validation set separately obtained from FDBEL



**Figure 4.** Observed and predicted values at last 1000 hours year 1996 obtained from FDBEL



**Figure 5.** Prediction error at last 1000 hours year 1996 obtained from FDBEL



**Figure 6.** The correlation coefficient comparison between three methods

Figure 4 shows the observed and predicted values of the last 1000 hours  $K_p$  time series obtained from FDBEL. The error size is illustrated in the Figure 5. Finally Figure 6 presents a comparison between FDBEL, BEL and ANN, based on correlation coefficient. The stop criterion in learning process of all methods was validation check and the value  $COR = 0.85$  obtained from FDBEL and significantly increased with respect to the BEL. ANN based predictor shows high correlation in the prediction results. But the number of learning epochs of ANN was 100 while it was just 3 for FDBEL.

#### 4. Conclusions

In this paper we presented fuzzy model of limbic system named FDBEL and utilized to predict  $K_p$  geomagnetic index. This index characterizes solar storms or sub storms that is a complex system with chaotic behavior. The main modifications introduced with respect to the previous models are considering the amygdala and OFC plastic connections as some fuzzy rules and defining inhibitory task of OFC as fuzzy decision maker layer on the final output. The experimental results show that proposed model can forecast the  $K_p$  time series with high correlation and low computational complexity. According to the number of epochs in learning phase, the main feature of FDBEL is fast training. Also the comparison between FDBEL, BEL and the ANN based predictor presents that high correlation in least number of learning epochs is obtained from FDBEL.

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