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Adaptive brain emotional decayed learning for online prediction of geomagnetic activity indices

Ehsan Lotfi [a,*], M.-R. Akbarzadeh-T. [b]

[a] Department of Computer Engineering, Science and Research Branch, Islamic Azad University, Tehran, Iran
[b] Departments of Electrical Engineering and Computer Engineering, Center of Excellence on Soft Computing and Intelligent Information Processing, Ferdowsi University of Mashhad, Iran

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ABSTRACT

In this paper we propose adaptive brain-inspired emotional decayed learning to predict *Kp*, *AE* and *Dst* indices that characterize the chaotic activity of the earth's magnetosphere by their extreme lows and highs. In mammalian brain, the limbic system processes emotional stimulus and consists of two main components: Amygdala and Orbitofrontal Cortex (OFC). Here, we propose a learning algorithm for the neural basis computational model of Amygdala–OFC in a supervised manner and consider a decay rate in Amygdala learning rule. This added decay rate has in fact a neurobiological basis and yields to better learning and adaptive decision making as illustrated here. In the experimental studies, various comparisons are made between the proposed method named ADBEL, Multilayer Perceptron (MLP), Adaptive Neuro-Fuzzy Inference System (ANFIS) and Locally Linear Neuro-Fuzzy (LLNF). The main features of the presented predictor are the higher accuracy at all points especially at critical points, lower computational complexity and adaptive training. Hence, the presented model can be utilized in adaptive online prediction problems.

1. Introduction

The solar wind and geomagnetic storms resulting from the solar activity are amongst the most important physical phenomena that can considerably disturb communication systems and damage satellites. They also have significant effects on space missions. Therefore predicting the occurrences of the solar wind and geomagnetic storms are very important in space missions, planning and satellite alarm systems. These events can be reasonably characterized by the following three geomagnetic activity indices: *Kp* (Kennziffer planetarisch) index, *AE* (auroral electrojet) index and *Dst* storm time index [71,7,65,72,53] where each index can be considered as a chaotic time series. These indicators are good monitors for the warning and alert systems of satellites. For example, the high values of *Kp* and *AE* and the large variation at low values of *Dst* often correspond to geomagnetic storms or substorms [4,21,67,13].

Various models and learning algorithms have been developed to predict these chaotic time series, such as the real time WINDMI model which is based on six nonlinear differential equations [49], neurofuzzy models such as Adaptive Neuro-Fuzzy Inference Systems (ANFIS), Artificial Neural Networks (ANN [66,15,48]) as well as Locally Linear Neuro-Fuzzy systems (LLNF [54]) that divide the input space into small linear subspaces with fuzzy validity functions. Among these methods, ANNs are inspired by physiological workings of the brain. They resemble the actual networks of neural cells in the brain. MLP is a feedforward ANN that is widely used to predict *Kp*, *AE* and *Dst* indices [48,6]. The learning algorithms of MLP and ANFIS impose high computational complexity that is not suited for online learning on fast-varying environments. This problem is viewed in many other learning algorithms such as Locally Linear Model Tree (LoLiMoT [53,54]). LoLiMoT and Recursive LoLiMoT (RLoLiMoT) are popular incremental learning algorithms for LLNF model. In contrast to LoLiMoT, RLoLiMoT can be used for online applications but still suffers from high computational complexity [53] and has been used only in problems with time increments that are sufficiently long.

Recently, the computational models of Brain Emotional Learning (BEL) have been successfully utilized for solving the prediction problem of geomagnetic indices [25,3]. The main feature of BEL based predictors is low computational complexity. These methods are based on reinforcement learning and, as discussed in Section 2.1, they show high accuracy in predicting peak points but do not show acceptable accuracy at all points [3] especially at low values. Specifically, they do not adequately predict time series such as *Dst* index where the low values are most important.

Our understanding of emotion is minimal and the current computational models are over simplified. Their only justification

* Corresponding author. Tel.: +98 935 570 0102.
E-mail addresses: esilotf@gmail.com (E. Lotfi), Akbarzadeh@ieee.org (M.-R. Akbarzadeh-T.).

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is their great utility in solving difficult problems. Here, adaptive brain emotional supervised learning with decayed rule, simulating the forgetting role of Amygdala, is proposed to predict the *Dst* beside the *Kp* and *AE* indices in real time. This adaptive/forgetting approach to Amygdala, in contrast to the more long term memory perspective, also has a biological basis as reported in several other recent works [24,37]. Specifically, Kim et al. [37] examined the long-term forgetting effect of Amygdala, and Hardt et al. [28] showed that a brain-wide decay mechanism in the brain can systematically remove some memories and increase the life expectancy of a memory.

The proposed approach considers decayed learning in an adaptive-online manner in order to enhance the prediction results against non-stationary behavior of time series. The proposed approach is general and can be applied in various emotion based application domains such as in emotion recognition [74], facial expression recognition [52], affective computing [70,23], human–computer interaction [12], autonomous robot and agent design [69,16,75], improved modern artificial intelligence tools [34–36] as well as understanding the brain's emotional process [47].

1.1. Motivations towards emotional modeling

What motivates employing emotional modeling in engineering applications is the high speed of emotional processing resulting from its effects on inhibitory synapses and existence of short paths between Thalamus and Amygdala in the emotional brain [39,40,27]. Although some of the present neural models indicate that sensory structures, especially hierarchical processing structures play a key role in fast processing [5,20], there are also models which shed light on the effects of emotional learning on inhibitory synapses and the role of inhibitory synapses in fast processing. For example, in his study, Scelfo [63] elaborates on the effects of emotional learning on inhibitory synapses and Bazhenov et al. [9] show that inhibitory synapses can play a pivotal role in fast learning.

The subject of quickness of emotional processing can also be seen from the perspective of psychology. Emotional processing creates emotional intelligence in human brain and according to Goleman [27], emotional intelligence can facilitate learning, especially in children, and it is also accountable for the ability to react quickly in emergencies. Goleman believes humans possess two minds, rational mind and emotional mind: emotional mind is far quicker than the rational mind and emotional stimuli such as fear can bring about quick reactions usually when there is no chance for the rational mind to process the danger. Parts of brain responsible for processing emotions have the ability to produce the required reaction extremely quickly; and consequently the inhibitory connections in cerebral cortex, which are affected by the emotional system, can improve learning speed.

Considering that Limbic system is responsible for processing emotional stimuli, it is not unlikely that the most important characteristic of the practical models produced based on this system and especially the models including the Amygdala–Thalamus short path and the inhibitory connections is fast learning and quick reacting. This can reveal their ability in predicting non-stationary time series. The main motivation behind the existing tendency towards models based on human emotions is the very same fact that emotional stimuli can speed up processing in humans and it is expected that quick learning is the distinctive feature of artificial models of emotional learning. Here we propose a novel brain-inspired emotional model that, because of its fast learning, can be used in real time applications.

The organization of the paper is as follows: Neuropsychological motivation and works related to modeling emotional learning are presented in Section 2. The proposed method is then presented in Section 3. Experimental results on online prediction are evaluated through several simulations in Section 4. Finally, conclusions are made in Section 5.

2. Neuropsychological aspect of emotion and related works

Most human behavior is dictated by emotion. Emotions are cognitive processes [64] that are studied under various disciplines such as psychology, neuroscience and artificial intelligence. Psychological and neural studies of emotion have a long history. From a psychological point of view, emotions can be derived through reward and punishment in various real-life situations [56]. Studies of the neural basis of emotion culminated in the limbic system (LS) theory of emotion. As shown in Fig. 1, LS which is located in the cerebral cortex consists mainly of the following components [41]: Amygdala, Orbitofrontal Cortex (OFC), Thalamus, Sensory Cortex, Hypothalamus and Hippocampus. Amygdala which is located in sub-cortical area is an emotional computer. Attention and permanent memory are the other cognitive functions of Amygdala [60]. Amygdala has extensive interconnections with many other areas. It receives connections from the sensory cortical areas and reward signals in the learning process. Amygdala also interacts with the OFC. OFC receives connections from the sensory cortical area and Amygdala responds to the emotional stimulus. OFC then evaluates the Amygdala's response and tries to prevent inappropriate answers based on the context provided by the hippocampus [8].

For BEL modeling, researchers focus on internal representation of emotional brain system, and formalize the brain states. The Amygdala–OFC system was first proposed by Morén and Balkenius in 2000 [55,8,56]. Amygdala–OFC model learns to react to the new stimulus based on the history of input rewards and punishment signals. Additionally, in the model, Amygdala learns to associate with emotionally charged and neutral stimuli. And the OFC prevents inappropriate experience and learning connections. Amygdala–OFC model consists of two subsystems which attempt to respond correctly to emotional stimuli. Each subsystem consists of a number of nodes which are related to the dimension of each stimulus. At first, the stimulus enters the Thalamus part of the model to calculate the maximum input and submits it to Amygdala as one of the inputs. The OFC does not receive any input from Thalamus. Instead, it receives Amygdala's output in order to update the weights [55].

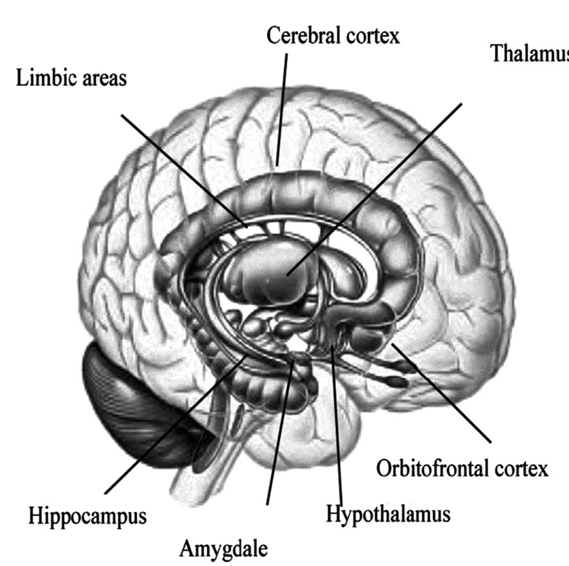

Fig. 1. The limbic system in the brain.