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

Ehsan Lotfi a,n, 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

A R T I C L E  I N F O
Article history:
Received 18 December 2011
Received in revised form
7 February 2013
Accepted 28 February 2013
Available online 31 May 2013

Keywords:
Amygdala
Adaptive BEL
BELLIC
Long-term forgetting
Online learning
Solar winds

A B S T R A C T

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.

© 2013 Elsevier B.V. All rights reserved.

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 [42,1,67,13].

Various models and learning algorithms have been developed to predict these chaotic time series, such as the real time WINDMO 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