A New Computational Intelligence Model
for Long-Term Prediction of Solar and Geomagnetic Activity

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Abstract

This paper briefly describes how the neural structure of fear conditioning has inspired to develop a computational intelligence model that is referred to as the brain emotional learning-inspired model (BELIM). The model is applied to predict long step ahead of solar activity and geomagnetic storms.

Introduction

Solar and geomagnetic activity are the main causes of space weather phenomena that have harmful effects on satellites, space missions, ground-based communication, power grids, and human life (Hathaway, 2010, Gonzalez et al. 1994). Accurate prediction of solar and geomagnetic activity is necessary in order to develop alert systems of solar and geophysical events and to mitigate these adverse effects. However, long-term prediction of solar and geomagnetic activity is a challenging task due to their chaotic and nonlinear behaviors. Thus, no data-driven models, such as neuro-fuzzy and neural networks (Mirmomeni et al. 2009), or physical-based methods, such as precursor methods (Gholipour et al. 2007), have been able to accurately predict long-term steps within these chaotic systems. Moreover, the results of long-term prediction of these systems are worse when the number of training samples is small. In order to improve the results obtained from applying data-driven models on long-term prediction of solar activity, some efforts have been made by adding preprocessing techniques such as single spectrum analysis(Mirmomeni et al. 2009 , Gholipour et al. 2007). Developing a new model with the capability to predict long-term horizon in these systems is an interesting research topic. This study suggests a new computational intelligence (CI) model for the long-term prediction of solar and geomagnetic activity. The CI model has been developed through inspiration from the emotional aspect instead of the rational aspect of a biological system; the CI model is on the basis of the neural structure of fear conditioning (Ledoux, 1998, Moren et al. 2000) that is a mechanism by which a biological system learns fearful stimuli to predict aversive events. The CI model is a new type of Brain Emotional Learning Inspired Models (BELIMs) that have been developed by taking inspiration from the neural structure underlying the fearful circuit of mammals. So far two types of BELIMs (Parsapoor 2014) have been evaluated on short-term prediction of solar activity and geomagnetic storms. The obtained results of them have been excellent and have provided great motivation to develop a new version of BELIM focusing on long-term prediction of chaotic systems with a small number of training samples. The main contribution of this study is the development of a new version of BELIM with low model complexity in order to overcome both over-fitting and under-fitting issues. In addition to the above contribution, this study contributes by introducing a new CI model that aims to outperform the traditional CI models such as neuro-fuzzy and neural networks. The rest of this paper is organized as follows. First, the challenges related to the development of a new model will be presented. Second, the structural, functional, and learning aspects of the model are described. Third, notable conclusions are discussed.

Challenges

Developing a new CI model involves choosing a suitable biological system, selecting an appropriate theory to explain the biological system, and using simple and efficient mathematical formulations to implement the functionality of the new CI model. Moreover, the answers to the above questions propose new sets of challenging questions.
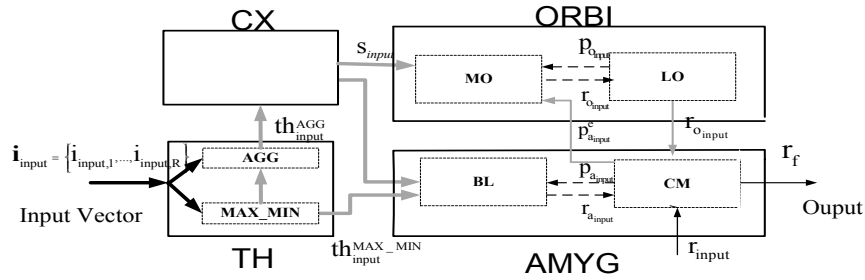
Figure.1. The structural aspect of BELIM.

For example, choosing the emotional system as a biological system to develop a new CI model proposes the question of which emotional theory should be considered to explain the emotional system. This study considers the conditioning theory of fear that proposes a neural structure of the fearful circuit in mammals. However, considering the neural structure of fear for developing the general structure of the new CI model raises other questions.

New Computational Intelligence Model

The CI model can be described according to its structural, functional, and learning aspects.

Structural Aspect of CI Model

Figure 1 describes the structure of a BELIM that consists of four main parts, the THalamus (TH), the sensory CorteX (CX), the AMYGdala (AMYG) and the ORBItofrontal cortex (ORBI). The internal structure of each component and its connections have been summarized as the following. Let us assume that an input of $\mathbf{i}_{input}$ from the training data set $\{\mathbf{i}_{input}\}_{input=1}^{N_u}$ (N_u indicate the number of training data samples) is entered into the model, the input and structure of each part have been explained in the following. 1) The TH, which consists of two subparts:MAX_MIN (maximum_minimum) and AGG (aggregation) is the first part of the model that receives $\mathbf{i}_{input}$. The TH provides two outputs $\mathbf{th}_{input}^{Max\_Min}$ and $\mathbf{th}_{input}^{AGG}$ that are sent to the AMYG and the CX, respectively. 2) The CX provides $\mathbf{s}_{input}$ as an output and sends it to both the AMYG and the ORBI. 3) The AMYG, is divided into the BL (corresponds to the set of the Basal and Lateral of the amygdala) and CM (corresponds to the set of accessory basal and centromedial of the amygdala). The AMYG receives $\mathbf{th}_{input}^{Max\_Min}$ and $\mathbf{s}_{input}$ and provides the primary output r_e and the expected punishment $p_{a_{input}}$. The latter is sent to the ORBI (the subscript a has been used to show the output of the AMYG). 4) The ORBI consists of the MO (medial of orbitofrontal) and LO (lateral of orbitofrontal). The ORBI has a bidirectional connection to the AMYG and receives $\mathbf{s}_{input}$ and $p_{a_{input}}^e$. It provides the secondary output $r_{o_{input}}$ and sends it to the AMYG. 5) The AMYG receives $r_{o_{u,j}}$ and provides the final output r_f (the subscript f has been used to show the final outputs).

Functional and Learning Aspects of CI Model

The function of the CI model is implemented by assigning different adaptive networks to different parts of the model. In this study, the functions of the ORBI and the AMYG will be implemented by assigning weighted-k nearest neighbour-based adaptive networks (Parsapoor et al 2014). Note that a W-kNN based adaptive network is simple with low model complexity; thus it could be useful for the suggested CI model. The suggested CI model uses the combination of two learning methods, Steepest Descent (SD) and Least Square Estimator (LSE), to update the linear and nonlinear learning parameters.

Discussion and Conclusion

This study introduces a new CI model that could be utilized for long-term prediction of solar and geomagnetic activities. For long-term prediction of solar activity, the model is used to predict solar cycles #24 and #25. For geomagnetic activity, the model is used to predict the daily disturbance-time index (Dst). The obtained results will be compared with neuro-fuzzy models.

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