Brain Emotional Learning for Classification Problem

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Abstract
Emotional learning is new tool in the field of machine learning that the inspired from limbic system. The various models of emotional learning (BEL) have been successfully utilized in many learning problems. For example, control applications and prediction problems. In this paper a new architecture based on a brain emotional learning model that can be used in classification problem (BELC). This model is suitable for high dimensional classification applications. To evaluate the proposed method have been compare it with the Multilayer Perceptron (MLP), K-Nearest Neighbor (KNN), Naive Bayes classifier and Brain Emotional Learning-Based Pattern Recognizer (BELPR) methods. The obtained results show the effectiveness and efficiency of the proposed method for classification problems.

Keywords: brain emotional learning, classification, orbitofrontal cortex, amygdala, machine learning

1. Introduction

Nowadays classification methods have been widely used in the area of science, engineering, industry, business and medicine [1]. Numerous methods have been proposed for classification problems that can be refer to statistical and mathematical methods and intelligence-based methods. They can be categorized as: inductive or transductive, statistical-based or non-statistical–based, supervised or unsupervised methods [2]. Artificial intelligence-based models often bio-inspired, such as neural networks and evolutionary computing techniques have a long tradition of being used as data-driven approaches for complex system modeling. Neural networks are one of the powerful classifiers method which have been extensively used for classification purposes. Emotional learning based computational models [3-5] is a fairly new area in machine learning that of bio-inspired models. Recently, researchers in artificial intelligence try to present computational models of Limbic System (LS). The first a computational model of the LS model was proposed by Lucas [4]. Furthermore, numerous methods of emotional learning have been proposed for various applications. Lucas et al. [6] explicitly determined the reward signal and proposed the Brain Emotional Learning (BEL) base controller which has been successfully modified and utilized in various control applications [7, 8] and prediction problems [9, 10]. In this model, the reward signal is vital for updating the learning weights of system. BEL is a simple composition of Amygdala and Orbitofrontal cortex in the brain. Another model inspired emotional learning is brain emotional learning based intelligent controller (BELBIC) [6] that has been proven to overcome uncertainty and complexity issues of other intelligent controllers. In the BELBIC algorithm, the emotional decision making is neither completely cognitive nor behavioral. This emotional controller is widely used in different fields such as decision making and control engineering applications and robotics [8, 11]. Other models, such as Brain Emotional Learning Based Fuzzy Inference System (BELFIS) [12]. All reviewed BEL models are based on monotonic reinforcement learning and need an input reward extracted from input data [13]. In this paper a new architecture based on a brain emotional learning model that can be used in classification problem (BELC). Other models are developed based on brain emotional learning for classification problems. Such as [17] that is proposed brain emotional learning-based pattern recognizer (BELPR) to solve multiple input–multiple output classification and chaotic time series prediction problems. Also, in [18] the proposed a classifier (ELiEC) based on brain emotional learning that can be considered as an ensemble classification with a different integration mechanism and combination algorithm.

Numerous efforts have been put into developing regularization methods to increase the generalization of supervised classification algorithms and reduce the time complexity of the learning procedure. The properties of emotional learning as low computational complexity and fast training, and its simplicity has made it a powerful methodology in supervised learning. Where the gradient based methods and evolutionary algorithms are hard to be used due to their high computational complexity.

The paper is organized as follows: the brain emotional learning is presented in Sections 2 and proposed method is presented in Section 3 .Section 4 presents the Experimental results where the proposed method is compared with multilayer perceptron (MLP), K-Nearest Neighbor (KNN), Naive Bayes classifier and BELPR. In multilayer perceptron are various versions of backpropagation algorithm; the gradient descent backpropagation (GDBP) [16]. And finally conclusions are made in Section 5.

2. Brain Emotional Learning

The emotional learning method is an intelligent algorithm in the field of machine learning that developed to reduce the complexity of computations and reduce the time complexity in learning problems [3, 4]. Emotional learning is inspired from limbic system. The emotional learning models that first introduced by Moren and Balkenius in his Ph.D. thesis and developed a network representation as a computational model that mimics the amygdala, the orbitofrontal cortex, the thalamus, the sensory input cortex, and, generally, those parts of the brain thought to be responsible for processing emotions [4, 5]. Limbic system is the central base of emotional intelligence that has several sub modules that each has its special functionality and the emotional learning occurs mainly in the amygdala. Two important parts of the limbic system, amygdala and orbito-frontal cortex (OFC), are responsible for processing the emotional signals. The main feature of the limbic system is that the weights of amygdala cannot decrease (called monotonic learning).

Figure 1 shows the graphical model of the sensory signal and learning network connection model inside the brain [3]. In Thalamus, some poor pre-processing on sensory input signals such as noise reduction or filtering can be done in this part. The amygdala, is very well placed to receive stimuli from all sensory cortices and the orbitofrontal cortex is thought to inhibit inappropriate responses from the amygdala, based on the context given by the hippocampus [3].

Tables and Figures are presented center, as shown below and cited in the manuscript.
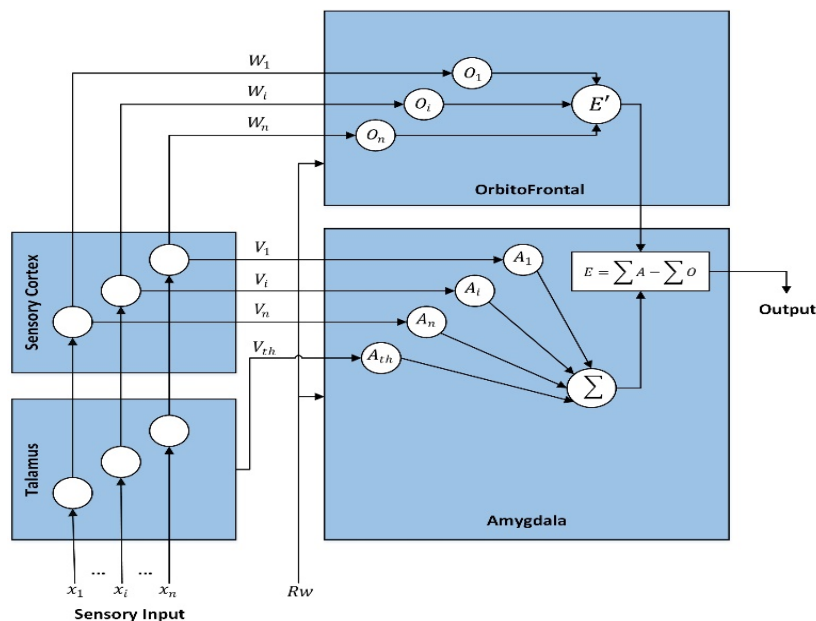

Figure 1. Graphical Model of the Brain Emotional Learning Process

The following limbic system structures are currently thought to be most involved in emotion:

a) Amygdala
b) Hippocampus
c) Fornicate gyrus
d) Hypothalamus
e) Orbitofrontal cortex

a) Amygdala

The amygdala is part of the limbic system [3] which based on the brain emotional learning (BEL) creates emotional intelligence. Amygdala receives plastic connections from sensory cortex and thalamus and the internal reinforce caused by external reward and punishment [3]. The amygdala are related in detecting and learning of our surroundings are important and have emotional significance. There are several inputs to the amygdala that are coming straight from the sensory areas. Outputs from the amygdala are the conditioned signals to the OFC, and the emotional conditioning.

b) Orbitofrontal Cortex

Biological Foundations Working closely with the amygdala is the orbitofrontal cortex (OFC), which will evaluate the activity of the amygdala in context. The orbitofrontal cortex (OFC) is a region of association cortex of the human brain involved in cognitive processes such as decision making. It is critically engaged in emotional processing and inhibitory control for behavior monitoring by assigning value in decision making mechanism whereas orbitofrontal cortex lesions are known to have abnormal behavior and emotional irregularities. The main function of orbitofrontal cortex is thought to be inhibitory whenever the emotional reaction is assumed to be inconvenient due to reinforcement, in fact orbitofrontal cortex has interconnections with hippocampus, and also it has bidirectional connections with amygdala.

In Figure 1, there is one A node for every stimulus X, including one for the thalamic stimulus. There is also one O node for each of the stimuli, except for the thalamic node. There is one output node E that is common for all the outputs of the model. The E node simply sums the outputs from the A nodes and then subtracts the inhibitory outputs from the O nodes. The result is the output from the model. In other words, E can be obtained from:

$$E = \sum_i A_i - \sum_i O_i (include\ A_{th}) \tag{1}$$

One of amygdala inputs is called thalamic connection and calculated as the $A_{th} = [\max(x_i)\ or\ \min(x_i)\ or\ mean(x_i)]$ overall Sensory Input X as equation. Likewise, the E node sums the outputs from A, except A_{th} and then subtracts from inhibitory outputs from the O nodes. The learning rule of the amygdala is given as:

$$A_i = x_i v_i \tag{2}$$

$$\Delta v_i = k_a(x_i \times \max(0, Rw - \sum_j A_j)) \tag{3}$$

Where v_i the weight in the amygdala connection is, k_a is the learning step in the amygdala, and Rw is the value of reward signal. The term max in (3) is for making the learning changes monotonic, implying that the amygdala weight can never be decreased. This rule is for modeling the incapability of unlearning the emotion signal previously learned in the amygdala. Similarly, the learning rule in the orbitofrontal cortex is given as:

$$O_i = x_i w_i \tag{4}$$

$$\Delta w_i = k_o \left(x_i (E' - Rw) \right) \tag{5}$$

Where w_i is the weight in the orbitofrontal connection, and k_o is the learning step in the orbitofrontal cortex. Also E' is:

$$E' = \sum_i A_i - \sum_i O_i (without\ A_{th}) \qquad (6)$$

In Figure 1, the top is the orbitofrontal, the bottom right is the amygdala, and the left contains the thalamic and sensory cortical modules. The sensory inputs X enter the thalamic part, where a thalamic input to the amygdala is calculated as the maximum or minimum or mean over all inputs. A primary reward signal Rw enters both the amygdaloid and orbitofrontal parts. In fact, by receiving the sensory input X, the model calculates the internal signals of amygdala (A) and orbitofrontal cortex (O). Since the amygdala does not have the capability to unlearn any emotional response that it ever learned, inhibition of any inappropriate response is the duty of the orbitofrontal cortex. The amygdala part receives inputs from the thalamus and from the cortical areas, while the orbitofrontal part receives inputs from the cortical areas and the amygdala only.

Tables and Figures are presented center, as shown below and cited in the manuscript.

3. Proposed Model

In this section, the structure of proposed method is introduced. In this paper a new architecture based on a brain emotional learning model that can be used in classification problem (BELC). Proposed method can be used in classification and prediction problems. In the classification problems requires a training dataset. Every instance in any dataset used by machine learning algorithms is represented using the same set of features [14]. In the BELC model, any feature of the dataset is input patterns model. The input pattern is illustrated by vector:

$$X^i = x_1, x_2, \ldots, x_j, \ldots, x_m \quad i = 1,2, \ldots, n \qquad (7)$$

$$T^i = t_1, t_2, \ldots, t_j, \ldots, t_m \quad i = 1,2, \ldots, n \qquad (8)$$

Where n is the instance size and m is the feature size and X^i is an instance and T^i determines the label class of X^i. Also x_{th} is calculate by $x_{th} = [\max(x_i)\ or\ \min(x_i)\ or\ mean(x_i)]$. Where the training dataset are normalized before entering to model between [-1.0, +1.0]. Figure 2 illustrated the proposed method based on BEL for classification problems. Outputs of the model can be obtained from:

$$E = Activation\ Fun(\sum_i A_i - \sum_i O_i (include\ A_{th})) \qquad (9)$$

Where the activation function can be:

$$tansig(x) = \frac{2}{1+exp(-2*n)} - 1 \qquad (10)$$

$$logsig(x) = \frac{2}{1+exp(-\sigma*n)} - 1 \qquad (11)$$

Also, the values of amygdala (A_i) and Orbitofrontal cortex (O_i) are calculated by following equations:

$$A_i = x_i v_i \qquad (12)$$

$$O_i = x_i w_i \qquad (13)$$

Output of amygdala (A_i) that is used for adjusting the plastic connection weights and output of Orbitofrontal cortex (O_i) that is used for inhabiting the amygdala output. Update the weights are calculated by following equations:

$$v_{i+1} = v_i + k_a(x_i \times \max(0, Rw - \sum_j A_j)) + r(v_{best} - v_i) \qquad (14)$$

$$w_{i+1} = w_i + k_o\left(x_i(E' - Rw)\right) + r(w_{best} - w_i) \tag{15}$$

The value v_{best} and w_{best} are the best weight v_i and w_i during training and r is a random number. Find the best values v_{best} and w_{best} simply calculated by following equations:

$$if\ mse(E - T^i) <\ mse(\hat{E} - T^i) \tag{16}$$

$$v_{best} = v_i w_{best} = w_i$$

$$\hat{E} = Activation\ Fun\left(\sum_i \hat{A}_i - \sum_i \hat{O}_i\left(include\ \hat{A}_{th}\right)\right) \tag{17}$$

$$\hat{A}_i = x_i v_{best} \tag{18}$$
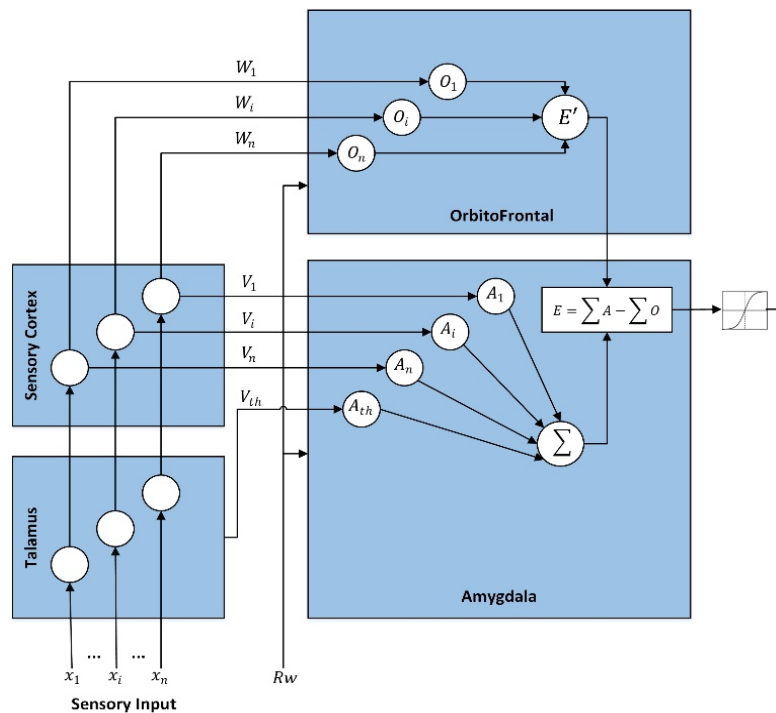
$$\hat{O}_i = x_i w_{best} \tag{19}$$

Figure 2. Graphical model of the BELC

The v_{best} and w_{best} values cause a fast convergence towards the best weight coefficients. The model also needs a target associated to input pattern to adjust the weights. Let Rw be target value (T^i) to pattern (X^i).

$$Rw_i = T^i\quad i = 1,2,\dots,n \tag{20}$$

The value E' are calculated by this equation:

$$E' = Activation\ Fun(\sum_i A_i - \sum_i O_i(without\ A_{th})) \tag{21}$$

The value parameters in proposed method shown in the following table.

Table 1. MethodParameters

Parameters	Value
Number of epoch	100
k_a	2×10^{-2}
k_o	1×10^{-2}
Rw Function	T^i

4. Experimental Result

In this section, we test the BELC method to classify several datasets that have obtained from the University of California, Irvine (UCI) machine learning repository [15]. Every instance in any dataset used by machine learning algorithms is represented using the same set of features. The features may be continuous, categorical or binary. Table 2 shows the main characteristics of the datasets. The developed method was compared with GDBP MLP, KNN, Naive Bayes classifier and BELPR. Also, to evaluate the BELC in the classification problems, mean square error (MSE) and accuracy are performance measures that are generally expressed as follows:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)^2 \tag{22}$$

$$Accuracy = \frac{Correct\ Detection}{All} \tag{23}$$

For all of the learning step, the training set contains 70% of the data and the testing set contains 30%.

Table 2. Datasets

Dataset	Attributecharacteristics	Instances	Attribute	Classes
Iris	Real	150	4	3
Glass	Real	214	9	7
Sonar	Real	208	60	2
Pima	Integer, Real	768	8	2

Table 3. Accuracy of Classification Result for Iris Dataset during 10 Runs

Method	Accuracy (%)	
	Max	Mean
BELC	0.97	0.85
BELPR	0.78	0.70
GDBP MLP	0.97	0.91
KNN	1.00	0.95
Bayesian	0.97	0.02

Table 4. Accuracy of Classification Result for Glass Dataset during 10 Runs

Method	Accuracy (%)	
	Max	Mean
BELC	0.84	0.75
BELPR	0.71	0.68
GDBP MLP	0.76	0.76
KNN	0.84	0.82
Bayesian	0.96	0.86

Table 5. Accuracy of Classification Result for Sonar Dataset during 10 Runs

Method	Accuracy (%)	
	Max	Mean
BELC	0.86	0.73
BELPR	0.74	0.70
GDBP MLP	0.85	0.79
KNN	0.86	0.75
Bayesian	0.79	0.74

Table 6. Accuracy of Classification Result for Pima Dataset during 10 Runs

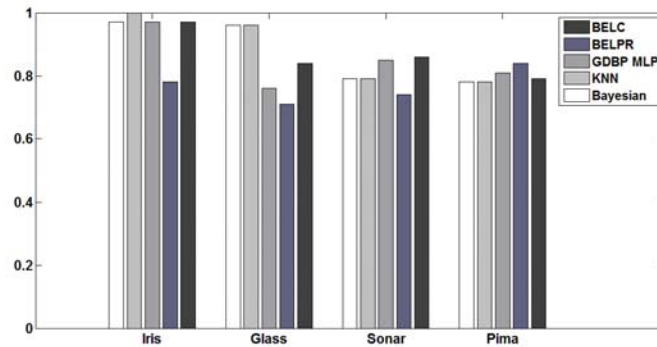| Method	Accuracy (%)	
	Max	Mean
BELC	0.79	0.74
BELPR	0.82	0.75
GDBP MLP	0.81	0.79
KNN	0.78	0.72
Bayesian	0.78	0.72

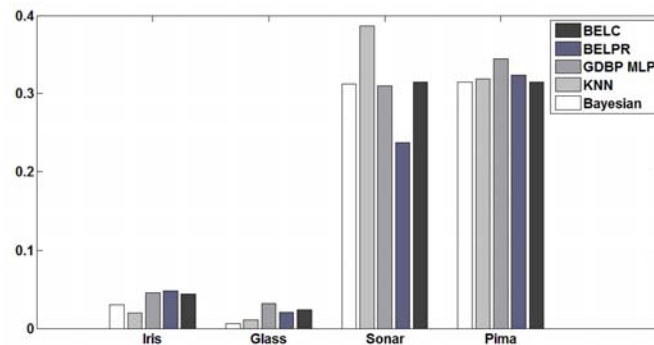Figure 3. Maximum Accuracy Comparison between the BELC, BELPR, GDBP MLP, KNN and Bayesian

Figure 4. Minimum MSE Comparison between the BELC, BELPR, GDBP MLP, KNN and Bayesian

4. Conclusion

This paper presents a new classifier that is inspired by the brain emotional learning (BELC). However, the BELC differs from other methods in the way that the classifiers are fed. The performance of BELC is evaluated by classifying several benchmark data sets and compared with different classifier method. The results indicate a fairly good performance of BELC for classification.

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