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How Wireless Sensor Networks Can Benefit from Brain Emotional Learning Based Intelligent Controller (BELBIC)

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Abstract

Wireless sensor networks (WSNs) are composed of small sensing and actuating devices that collaboratively monitor a phenomena, process and reason about sensor measurements, and provide adequate feedback or take actions. One of WSNs tasks is event detection, in which occurrence of events of interest is detected in situ whenever and wherever they occur. Some examples of these events include environmental (e.g. fire), personal (e.g. activities), and data-related (e.g. outlier) events. Simply speaking, event detection is a classification process, in which membership of data measurements to each event class is determined. Neural network is one of the classifiers that have often been used for detecting events with known patterns. One of the techniques to maximise the neural network performance during classification process is enabling a learning process. Through this learning process, neural network can learn from errors generated in each round of classification to gradually improve its performance. In this paper we investigate applicability of Brain Emotional Based Intelligent Controller (BELBIC) to improve neural network performance. Empirical results show that incorporating the BELBIC with neural networks improves the accuracy of event detection in many circumstances.

Keywords: Neural Networks, BELBIC, Wireless Sensor Networks, Event Detection

1. Introduction

With the proliferation in Micro-Electro-Mechanical Systems technology, which has facilitated the development of smart sensors, wireless sensor networks (WSNs) have gained worldwide popularity in recent years. WSNs are composed of small sensing and actuating devices that collaboratively monitor a phenomena, process and reason about sensor measurements, and provide adequate feedback or take actions. One of WSNs tasks is event detection, in which occurrence of events of interest is detected in situ whenever and wherever they occur. Some examples of these events include environmental (e.g. fire), personal (e.g. activities), and data-related (e.g. outlier) events. Event detection can be considered as a classification process, which can be performed both supervised and unsupervised. The former refers to identification of event classes with known patterns, while the latter refers to identification of event classes with unknown patterns.

Neural networks are one of the classifiers which have been extensively used for classification purposes. Recently, they have also found application in WSNs [1, 2, 3, 4, 5, 6]. One of the techniques to maximise the neural network performance during classification process is enabling a learning process. This learning process utilises a feedback mechanism through which the neural network learns about its classification performance and gradually improves it.

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One of the computational models, which has the potential to be used for this purpose, is the Brain Emotional Based Intelligent Controller (BELBIC). BELBIC is a computational model based on the limbic system in the mammalian brain developed by Lucas et al. [7]. The model uses the network model developed by Moren and Balkenius [8] to model emotional part of the brain.

The block diagram of the BELBIC is illustrated in Figure 1. BELBIC has been employed as a feedback controller in control design problems [9]. Lucas and his colleagues use the term emotional learning for the emotional control process of the BELBIC model. In emotional learning, emotions are produced by the performance of the output and are used as a reinforcement mechanism to the learning process. The emotional learning algorithm has three distinctive properties in comparison with other learning methodologies [10]. Firstly, one can use very complicated definitions for emotional signal without increasing the computational complexity of algorithm or worrying about differentiability or renderability into recursive formulation problems. Secondly, the parameters can be adjusted in a simple intuitive way to obtain the best performance. Finally, the training is very fast and efficient [10].

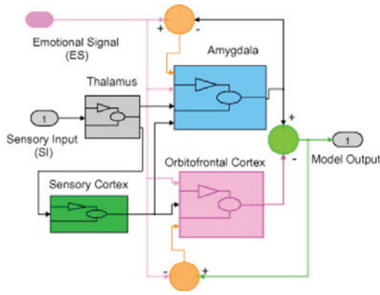


Figure 1: Block diagram of BELBIC [11]

Generally speaking, BELBIC is an error reduction system that can be incorporated to any system to reduce the system error. In this paper, we investigate its applicability for WSNs. Specifically, we aim to investigate impact of combining BELBIC with the neural networks on event detection accuracy. The remainder of this paper is organised as follows: Section 2 presents related work on use of emotional learning as a feedback mechanim, while Section 3 explains our method. Section 4 presents the experiment results followed by a discussion. Finally, Section 5 provides some concluding remarks.

2. Related Work on Emotional Learning

Jalili-Kharaajoo et al. [12] apply intelligent controller to traffic control of ATM networks. First, the dynamics of the network is modeled by a locally linear neuro-fuzzy model. Then, an intelligent controller based on brain emotional learning algorithm is applied to the identified model. Simulation results show that the proposed fuzzy traffic controller can outperform the traditional usage parameter control mechanisms in terms of better selectivity and effectiveness. Mehrabian et al. [13] present a theoretical analysis of online autonomous intelligent adaptive tracking controller based on BELBIC for aerospace launch vehicle. The algorithm is very robust and fast in terms of adapting to dynamic change in the plant, due to its online learning ability. Development and application of this algorithm for an aerospace launch vehicle during atmospheric flight in an experimental setting is presented to illustrate the performance of the control algorithm. Rouhani et al. [14] propose a BELBIC based control to govern the dynamics of electrically heated micro-heat exchanger plant. First, the dynamics of the micro-heat exchanger, which acts as a nonlinear plant, is identified using a neuro-fuzzy network. To build the neuro-fuzzy model, a locally linear learning algorithm, called LoLiMoT, is used. Then, a BELBIC based controller is applied to the identified model. The impact of BELBIC in improving the control system performance is shown by comparing the results obtained from classic PID controller without BELBIC. The results demonstrate excellent improvements of control action without any considerable increase of control effort. Khorramabadi et al. [15] describe the design and evaluation of a reactor core power control based on emotional learning. The controller includes a neuro-fuzzy system with power error and its derivative as inputs. A fuzzy critic evaluates the current situation and provides the emotional signal (stress). The controller modifies its characteristics so that the critical stress is reduced. Simulation results show that the controller has good convergence and performance robustness characteristics over a wide range of operational parameters. Jamali et al. [16] utilise a model driven development approach for implementation of emotional learning as a bio-inspired algorithm. They implement the BELBIC model on FPGA. They then use the obtained embedded emotional controller, called E-BELBIC, for controlling cranes. Dehkordi et al. [11] develop a BELBIC based control mechanism for the switched reluctance motor (SRM) speed. Motor parameter changes, operating point changes, measurement noise, open circuit fault in one phase and asymmetric phases in SRM are also simulated to show the robustness and superior performance of BELBIC. To compare the BELBIC performance with other intelligent controllers, Fuzzy Logic Controller (FLC) is developed and system responses with BELBIC and FLC are compared.

3. Improving Neural Network Performance using BELBIC

Situational awareness and fast and reliable detection of events of interests whenever and wherever they occur require bringing intelligence as close as possible to the point of action. Transmission of huge volume of sensed data is neither feasible not useful as it wastes network limited resources in terms of bandwidth, energy, and processing capability. Artificial intelligence and machine learning techniques have proved to be suitable to be used on wireless sensor nodes to detect events and activities fast and reliably [2, 6]. To this end, one of the often used techniques is the neural network. Main problems of using the neural network for event detection in WSNs are complexity of the training phase and lack of its adaptability to dynamic nature of events.

Due to inherent errors in sensor data, training phase of a neural network always suffers from some degrees of error. This in turn leads to lowering down the event detection and classification accuracy. To compensate this error, we propose to use a feedback mechanism and more specifically to use BELBIC.

As it can be seen from Figure 1, output of BELBIC (E) is the difference between all the excitatory Amygdala and inhibitory Orbitofrontal Cortex nodal outputs [16]. We calculate E by using $\sum_i A_i - \sum_i O_i$ formula.

For each sensory input S_i received by the model, there is one corresponding Amygdala node A_i and one Orbitofrontal Cortex node O_i, which generate the nodal Amygdala and Orbitofrontal Cortex outputs [16]. We use the $A_i = V_i \cdot S_i$ and $O_i = W_i \cdot S_i$ formulas to calculate these outputs. V_i and W_i are the adaptive gains of the Amygdala and Orbitofrontal Cortex, respectively.

Our adaptation rules are $\Delta V_i = \alpha \cdot max[0, SI_i \cdot (S_i - A)]$ and $\Delta W_i = \beta \cdot SI_i \cdot \sum_i (O_i - STRESS)$ where STRESS is the emotional signal or reinforcing signal, α is adjusting term for learning speed in Amygdala, and β is learning rate factor in Orbitofrontal Cortex. It can be seen that Amygdala gain cannot be negative because of the max function [11]. One may notice that Orbitofrontal learning rule is very similar to the Amygdala rule. The only difference is that the orbitofrontal connection weight can increase or decrease as needed to track the required inhibition [16].

3.1. Finding the Correct Configuration for BELBIC

Finding the correct configuration for BELBIC is of utmost importance. The correct configuration is found empirically. We have performed many experiments with different parameters (e.g., sensory input, stress signal, and learning rate constant values) and different combinations of BELBIC and neural network. Figure 2 illustrates the error produced by the best configuration we found.

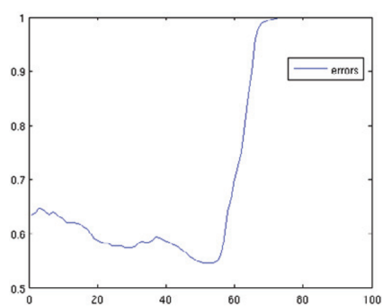


Figure 2: Error results of running BELBIC with suitable parameter configuration

As it can be seen from the figure, error first gradually decreases until around 60^{th} iteration, at which it starts to increase very quickly. After the 70^{th} iteration error reaches 1. This is because BELBIC tends to produce values that approaches to 1. The BELBIC iteration which produced output with the best error rate is used to improve the neural network performance.

In our experiments with different sensory input and stress signals (which is always error-dependent), BELBIC output has been forced to stay between zero and one. Experimental results show that using *error* as sensory input and *errorxerror* as stress signal is the best configuration. Learning rate constant values define the dependency of current BELBIC output to the previous iteration output and adjust the gap between these outputs. As a result, they adjust performance speed of the BELBIC. We empirically found out that 0.001 creates a reasonable performance speed improvement without generating a serious gap between iteration BELBIC outputs. In addition to these parameters, finding an appropriate number of nodes is also important. Using large number of nodes does not change output but increases running time of the error correction loop. Using small number of nodes, on the other hand, does not lead to good results.

3.2. Integrating BELBIC with Neural Network

BELBIC's ouput can be integrated with the neural network in the following ways:

- before the input layer, as illustrated in Figure 3 left. In this case BELBIC's output is summed up with the input of the neural network.
- after the output layer, as illustrated in Figure 3 middle. In this case BELBIC's output is summed up with the output of the neural network.
- before input layer and after the output layer, as illustrated in Figure 3 right. In this case two BELBICs are used. Output of one of them is summed up with the output of the neural network, while output of the other is summed up with input of the neural network.

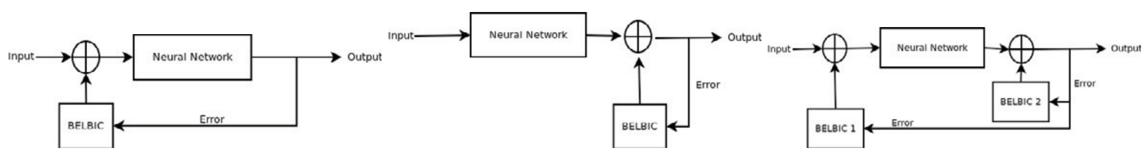


Figure 3: Integration of BELBIC with Neural Network: (left) as input, (middle) as output, and (right) as both input and output of the neural network

4. Experiments

To investigate impact of BELBIC on event detection and classification of neural network, we perform experiments on three datasets. Neural networks used in these experiments have the same properties and parameters. They are feed forward back-propagation neural networks which have been trained for 100 epochs and have five hidden layer neurons. We train them by gradient descent back-propagation training algorithm. We chose this node number and training algorithm for a fast creation and training of the networks. BELBIC parameters are also the same in all our experiments. We use 10 nodes, 100 as iteration limit, and 0.001 as learning rate constant for amygdala and orbitofrontal cortex. Sensory input is equal to error, while stress signal equals to square of the sensory input (*errorxerror*). Error is the difference between neural network classification accuracy and the actual classification.

4.1. Forest Fire Dataset

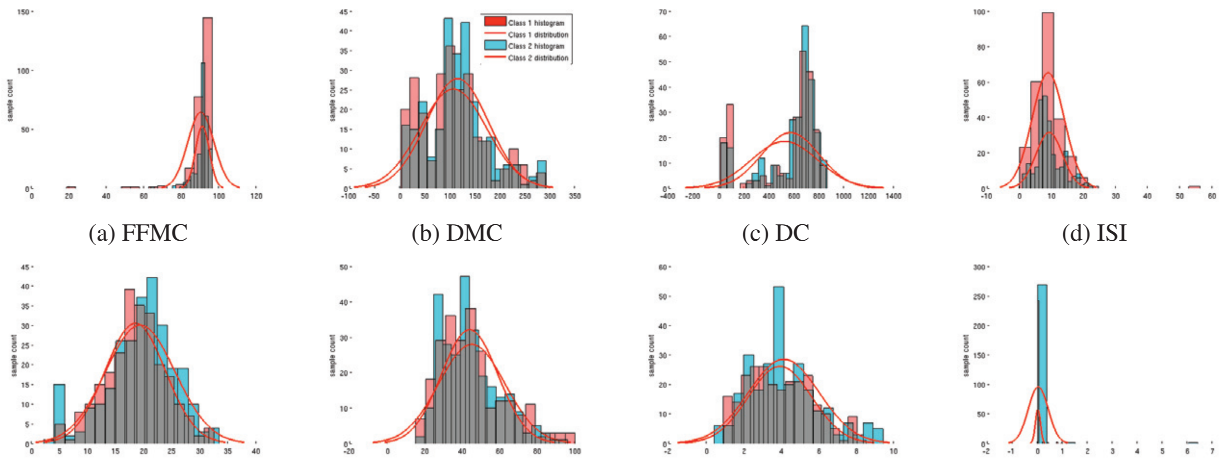
This data set is obtained from UCI machine learning repository (http://archive.ics.uci.edu/ml/). Forest fire dataset [17] is reduced to eight features: FFMC, DMC, DC, ISI indexes from FWI system [1], temperature in Celsius degrees, relative humidity, wind speed, and outside rain. There are two classes, i.e., fire and no-fire, and 517 instances in the

[1]Canadian Forest Fire Weather Index System, http://cwfis.cfs.nrcan.gc.ca/background/summary/fwi

dataset. The dataset suffers from a small number of fire incidents with a large burned area. Statistical information[2] of the dataset is presented in Table 1. Figure 4 illustrates the overlap between different classes. The more classes overlap, the more complicated the classification.

Table 1: Forest fire dataset (517 instances, 2 classes: fire, no-fire)

input	min	max	mean	std
FFMC index from the FWI system	18.7	96.2	90.6447	5.5201
DMC index from the FWI system	1.1	291.3	110.8723	64.0465
DC index from the FWI system	7.9	860.6	547.94	248.0662
ISI index from the FWI system	0	56.1	9.0217	4.5595
temperature in Celcius degrees	2.2	33.3	18.8892	5.8066
relative humidity in %	15	100	44.2882	16.3175
wind speed in km/h	0.4	9.4	4.0176	1.7917
outside rain in mm/m^2	0	6.4	0.0217	0.296



(a) FFMC (b) DMC (c) DC (d) ISI

(e) temperature (f) relative humidity (g) wind speed (h) outside rain

Figure 4: Forest fire data histogram (red: no-fire, blue: fire)

4.2. Residential Fire Dataset

This data set is produced by NIST group (http://www.nist.gov/). Residential fire data set contains temperature, ion, photoelectric, and carbon monoxide (CO) sensor values. There are two classes, i.e., fire and no-fire, and 2506 instances in the dataset. Statistical information of the dataset is presented in Table 2. Figure 5 illustrates the overlap between different classes. The more classes overlap, the more complicated the classification.

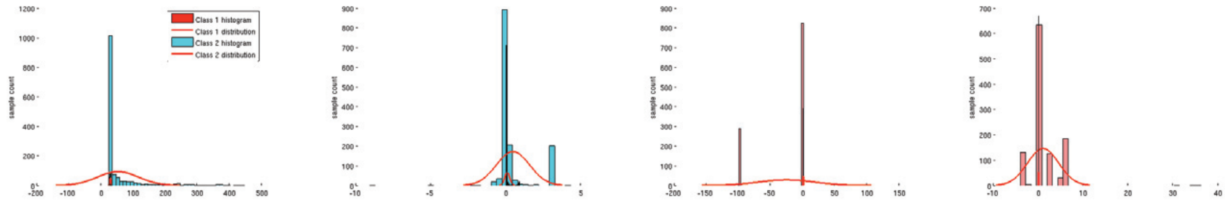
4.3. Activity Dataset

This dataset contains accelerometer and gyroscope data generated by a number of sensor nodes attached to a person performing various activities. The dataset was made available to us by the Medisch Centrum Twente (MST) (http://www.mst.nl/). The dataset contains four features as: Z vector of gyroscope installed on the right foot, Y vector of accelerometer installed on trunk, Z vector of accelerometer installed on trunk, and X vector of accelerometer installed on left foot. There are three classes, i.e., standing still, walking, and sitting, and 8330 instances in the dataset. Statistical information of the dataset is presented in Table 3 and Figure 6 illustrates the overlap between different classes.

[2]For all histograms x axis shows *values* and y-axis shows *sample count*

Table 2: Residential fire dataset (2506 instances, 2 classes: fire, no-fire)

input	min	max	mean	std
temperature	22.88	445	41.05	49.3469
ion	-9.0614	4.2826	0.2841	0.8568
photoelectric	-100	0.471	-11.4929	31.962
CO	-4	36	0.4462	2.3687

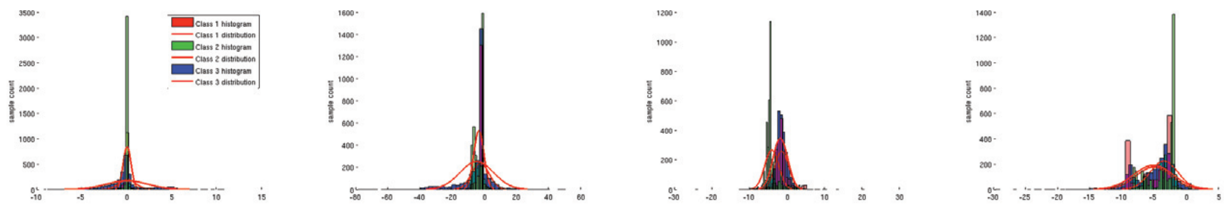


(a) temperature (b) ion (c) photoelectric (d) CO

Figure 5: Residential fire data histogram (red: no-fire, blue: fire)

Table 3: Activity dataset (8360 instances, 3 classes: standing still, walking, sitting)

input	min	max	mean	std
right foot gyroscope Z vector	-9.233	10.7756	-0.040	1.4355
trunk accelerometer Y vector	-78.7644	50.0057	-3.9921	6.942
trunk accelerometer Z vector	-24.5415	20.3732	-2.8579	2.2486
left foot gyroscope X vector	-29.8074	1.8017	-4.4615	2.753



(a) right foot gyroscope Z (b) trunk accelerometer Y (c) trunk accelerometer Z (d) left foot gyroscope X

Figure 6: Activity data histogram (red: standing still, green: walking, blue: sitting)

4.4. Experimental Results

We performed 10 experiments (Specs. of the computer: 2.8 GHz Core 2 Duo CPU, 4 GB memory, Ubuntu GNU/Linux) using MATLAB 7.11 (R2010b) for each dataset and we presented mean of these experiments below.

Neural network creation, training and finding BELBIC timing for forest fire dataset are shown in Table 4. Average detection error of neural network with and without BELBIC on the forest fire dataset is illustrated in Figure 7.

Table 4: Forest fire dataset task timings

Task	Time for plain data (seconds)	Time for normalized data (seconds)
Neural network creation	2.1	2.0329
Finding the best BELBIC	3.4795	3.4436

Timing of the creating neural network and finding the best BELBIC for residential fire dataset is shown in Table 5. Average detection error of neural network with and without BELBIC on the residential fire dataset is illustrated in

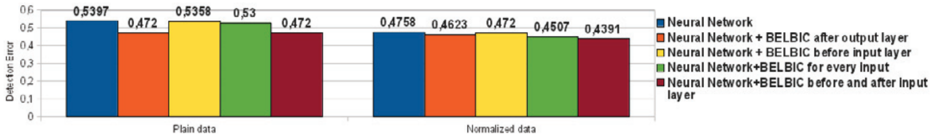


Figure 7: Average detection error of neural network with and without BELBIC on forest fire dataset

Figure 8.

Table 5: Residential fire dataset task timings

Task	Time for plain data (seconds)	Time for normalized data (seconds)
Neural network creation	4.9107	4.8058
Finding the best BELBIC	3.3819	3.3487

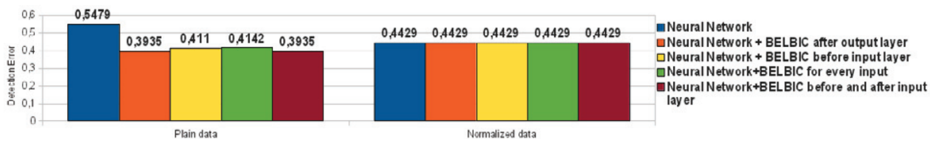


Figure 8: Average detection error of neural network with and without BELBIC on residential fire dataset

Timing of creating neural network and finding the best BELBIC for activity dataset are shown in Table 6. Average detection error of neural network with and without BELBIC on the activity dataset is illustrated in Figure 9.

Table 6: Activity dataset task timings

Task	Time for plain data (seconds)	Time for normalized data (seconds)
Neural network creation	11.3189	10.4885
Finding the best BELBIC	4.2399	4.5216

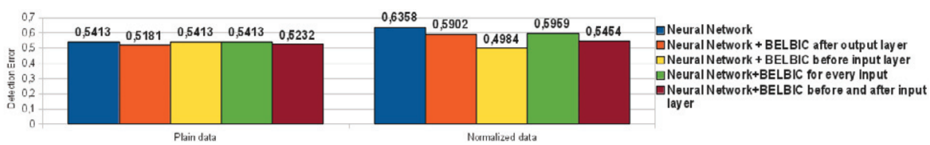


Figure 9: Average detection error of neural network with and without BELBIC on activity dataset

4.5. Discussion

Looking at the experimental results, we can draw the following conclusions:

- BELBIC improvement strongly relies on dataset properties. Some datasets can be easily classified by neural network, as the overlap between features and classes is low. Sine neural network already generates a good detection accuracy for such datasets, using BELBIC with this kind of datasets does not lead to considerable improvement. In our experiments, residential fire dataset is an example of datasets with low overlap between features and classes.
- Execution time of finding the best BELBIC strongly depends on number of iterations and slightly on size of the dataset.

- Neural network creation and training time depends on size of dataset used in these phases and the parameters chosen.
- The most accurate BELBIC parameters are found empirically and are application/problem specific.

5. Conclusion

In this paper we investigate impact of BELBIC, a feedback and reinforcement mechanism, on event detection and classification accuracy of neural networks. BELBIC and neural networks are both computationally light and hence good candidates to be implemented on the wireless sensor node platforms to enable situational awareness at the point of action. Our experimental results show that neural network event detection error can be reduced by using BELBIC.

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References

[1] M. Bahrepour, Y. Zhang, N. Meratnia, P. Havinga, Use of event detection approaches for outlier detection in wireless sensor networks, in: ISSNIP, 2009, pp. 439 –444.
[2] M. Bahrepour, B. J. van der Zwaag, N. Meratnia, P. Havinga, Fire data analysis and feature reduction using computational intelligence methods, in: Advances in Intelligent Decision Technologies, Vol. 4, 2010, pp. 289–298.
[3] M. Bahrepour, N. Meratnia, P. Havinga, Fast and accurate residential fire detection using wireless sensor networks, Environmental Engineering and Management Journal 9 (2) (2010) 215–221.
[4] M. Bahrepour, N. Meratnia, P. Havinga, Use of ai techniques for residential fire detection in wireless sensor networks, in: AIAI 2009 Workshop, Vol. 475, 2009, pp. 311–321.
[5] M. Bahrepour, N. Meratnia, P. Havinga, Sensor fusion-based event detection in wireless sensor networks, in: MobiQuitous, 2009.
[6] M. Marin-Perianu, P. J. M. Havinga, D-fler - a distributed fuzzy logic engine for rule-based wireless sensor networks, in: Ubiquitous Computing Systems, 2007, pp. 86–101.
[7] C. Lucas, D. Shahmirzadi, N. Sheikholeslami, Introducing belbic: Brain emotional learning based intelligent controller, Autosoft 10 (2004) 11–22.
[8] J. Moren, C. Balkenius, A computational model of emotional learning in the amygdala, in: 6th Int. Conf. on the SAB, 2000.
[9] A. R. Mehrabian, C. Lucas, J. Roshanian, Design of an aerospace launch vehicle autopilot based on optimized emotional learning algorithm, Cybernet. Syst. 39 (2008) 284–303.
[10] T. Babaie, R. Karimizandi, C. Lucas, Prediction of solar conditions by emotional learning, Intelligent Data Analysis 10 (2006) 583–597.
[11] B. M. Dehkordi, A. Parsapoor, M. Moallem, C. Lucas, Sensorless speed control of switched reluctance motor using brain emotional learning based intelligent controller, Energy Conversion and Management 52 (1) (2011) 85–96.
[12] M. Jalili-Kharaajoo, M. Sadri, F. H. Roudsari, Emotional learning based intelligent traffic control of atm networks, in: ISNN, 2005.
[13] A. R. Mehrabian, C. Lucas, J. Roshanian, Aerospace launch vehicle control: an intelligent adaptive approach, Aerosp. Sci. Technol. 10 (2) (2006) 149 – 155.
[14] H. Rouhani, M. Jalili, B. N. Araabi, W. Eppler, C. Lucas, Brain emotional learning based intelligent controller applied to neurofuzzy model of micro-heat exchanger, Expert Syst Appl 32 (3) (2007) 911 – 918.
[15] S. S. Khorramabadi, M. Boroushaki, C. Lucas, Emotional learning based intelligent controller for a pwr nuclear reactor core during load following operation, Annals of Nuclear Energy 35 (11) (2008) 2051–2058.
[16] M. Jamali, A. Arami, M. Dehyadegari, C. Lucas, Z. Navabi, Emotion on fpga: Model driven approach, Expert Systems with Applications 36 (4) (2009) 7369–7378.
[17] P. Cortez, A. Morais, A data mining approach to predict forest fires using meteorological data, in: New Trends in Artificial Intelligence, Proc. of the 13th EPIA 2007 - Portuguese Conference on Artificial Intelligence, APPIA, 2007, pp. 512–523.