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A FRAMEWORK AND ARCHITECTURE FOR A COGNITIVE MANAGER BASED ON A COMPUTATIONAL MODEL OF HUMAN EMOTIONAL LEARNING

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ABSTRACT

In this paper we propose an architecture for a cognitive engine that is based on the emotional learning cycle instead of the traditional cognitive cycle. The cognitive cycle that traditionally has been used as reference for cognitive radio is on the basis of the Unified Theories of Cognition (UTC) to model rational decision making in humans. UTC represents a rational goal-oriented decision-action made by an intelligent agent. However, the emotional cycle represents an emotional reaction-oriented cycle instead. These two models differ in function and structure of learning, decision making and optimization. In this work the structure of these two learning cycles are compared and a computational model for artificial emotional learning based engine is suggested.

1. INTRODUCTION

Today, the context of a military operation can span from small special unit operations to large multinational military endowers. To support this large mission spectrum it requires that a force has "tactical agility" [1], i.e. is able to quickly comprehend unfamiliar situations, creatively apply doctrine, and make timely decisions. These requirements demand for a communication infrastructure that is highly mobile and adaptive to the context of operation. Furthermore, the continuously increasing requirement of situation awareness requires more communication bandwidth at the tactical edge. Considering the heterogeneous set of systems of systems that is interacting in forming such infrastructure of networks of networks, the configuration, management and optimization is not a trivial problem. Traditional network management systems often rely on centralized and human-controlled management decisions propagated to network elements, which are clearly not adequate as a centralized entity can never be expected to have and analyze the network state information that is necessary to make informed network management decisions in such a dynamic and agile system that the communication infrastructure of a military operation must be today. The fulfillment of present requirements can only

be achieved by autonomous network management. In the work reported in this paper such a cognitive radio network management system architecture is proposed in the context of next generation military tactical communication system. The emphasis is on the proposed cognitive engine, especially considering features like: capabilities for local processing of goals, monitoring of the local environment, reaction to contextual events by self-configuration and information propagation for interactions with and between components and network elements, objective functions and their interrelations to measuring and control parameters.

2. BACKGROUND

The autonomous management of complex systems is a hard challenge it include different traditional research domains: system theory, artificial intelligence, communication systems signal processing, self-organizing systems and control theory etc. The starting point for creating an autonomous system must be to understand what it should handle and how it is handled manually and in our case these domains are spectrum management and network management of radio communication systems. Traditional spectrum management of military operations follows standardized processes and policies [2], it is handled by the use of spectrum management tools and centralized spectrum databases [3]. In the context of a military operation this coordination is referred to as battle space spectrum management [2]. Important to notice is that the use of electromagnetic spectrum is not limited to communication, many other aspect of a military operation relay on the use of electromagnetic spectrum, some examples are [4]: target acquisition, weapons control and guidance, navigation and terminal control, etc. Experiences from recent operations have indicated that "current operational and tactical radio frequency (RF) spectrum planning and management practice do not keep pace with operations tempo" [5], indicating the lack of automation of managing frequency assignments. Important to notice is that these traditional spectrum management methods lack the ability to dynamically adapt in real-time to dynamic changes in the battle space. Network management refers to

cooperative interaction between application processes in managing and managed systems for the management of telecommunications resources [6]. A more concrete interpretation of the concept can be made through the standardized decomposition of network management into five distinct functional areas:¹

Fault management: is a set of functions that enable the detection, isolation and correction of abnormal operation of the network and its environment.

Configuration management: provides functions to exercise control over, identify, collect data from and provide data to network elements.

Accounting management: enables the measurement of the use of network services and the determination costs to the service provider and charges to the customer for such use

Performance management: provides functions to evaluate and report upon the behaviour and effectiveness of the network or network element, and through monitoring and control actions correct the behaviour and effectiveness of the network.

Security management: simply consists of the functions that are needed for maintain the secure operation of a communications network.

The goal of a joint spectrum/network management system is to achieve coherent and optimal system level behavior through interactions between operators and a large set of low-level control interfaces on network and radio elements. A set of new management challenges, [6]-[10], arise from the increased interconnection of heterogeneous networks, the increasing number of multimodal applications, increasing quality requirements, and the increasing complexity of many mobile networking environments. One such challenge stems from the increased variability reducing the ability of a human actor to perform any form of low-level decision. Next generation tactical radio network includes three main entities: platform, waveform and network. The platform is considered as a hardware that can load and run a set of different waveforms² (and application processes), figure 1. The waveform is the lowest entity representing a software defined transceiver (including relevant protocols) executing on a platform. A network is defined as an autonomous system (AS) of several platforms executing the same waveform forming a joint communication link or a network of communication links to its peer/peers. Each platform also includes routing capability that enabling forwarding between different waveforms, radio networks, and wired physical interfaces,

i.e. Ethernet interface(s). A platform can also instantiate specific application processes except the actual waveforms, e.g. network management agents, cognitive management agents, security management agents platform management

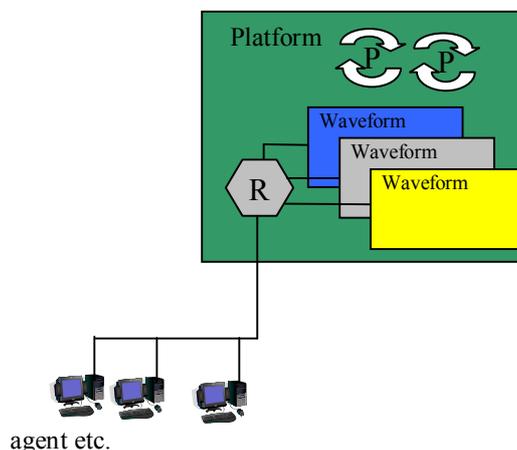


Figure 1. Platform with several waveforms.

2.1 Cognitive Radio and Networks

A cognitive architecture describes the necessary infrastructure for an intelligent system. Such a system should be generic and support different domains and knowledge bases. Cognition is a mental process that includes attention, memory, learning, reasoning, and decision making. A central aspect of a cognitive architecture is the underlying feedback loop for learning in which past interaction guide current and future interaction [11]. The cognitive loop is sometimes referred to as: observe - orient – decide - act (OODA) loop originally derived by John Boyd [12] for fighter pilots to understand the thought process of their adversaries, figure 2.

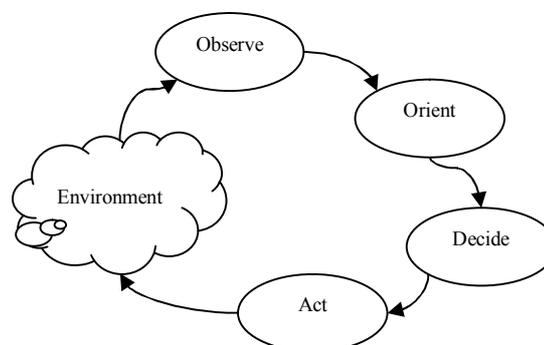


Figure 2. The OODA cycle [12].

¹ The descriptions of the functional areas are adopted from ITU-T M.3400, TMN management functions.

² Important to notice is that can be several instances of one waveform or several different waveforms.

The OODA loop has been adopted in subject areas spanning from business management to artificial Intelligence. The cognitive architecture proposed by Joe Mitola [13] includes a cognitive cycle that is an adoption of the OODA cycle that has ability to perform self-configuration tasks, learn from environment and its pervious action to react on new situation and reconfigure.

3. SYSTEM ARCHITECHTURE

To fulfill the previously mentioned agility requirement of next generation military communication systems, the management system should be based on a multi-tier structure, where individual tiers can operate autonomous without overlaying tiers. These tiers reflects the horizontal structure of a management system, in a networks of networks, including everything from individual parameters of a waveform executing on a platform to higher level policy respiratory for spectrum management and databases for operation plans and geographical information.

The cognitive manager architecture consists of two main parts: low level control/optimization functions and high level reasoning. The low level functions, the blue box in figure 1, is representing all algorithms that control and optimize the operation of the wave form in short term.

The main idea for the high level reasoning module of a cognitive manager, the purple box in figure 1, is to conduct the long term reasoning, learning and decision making, which is the focus of the rest of this paper.

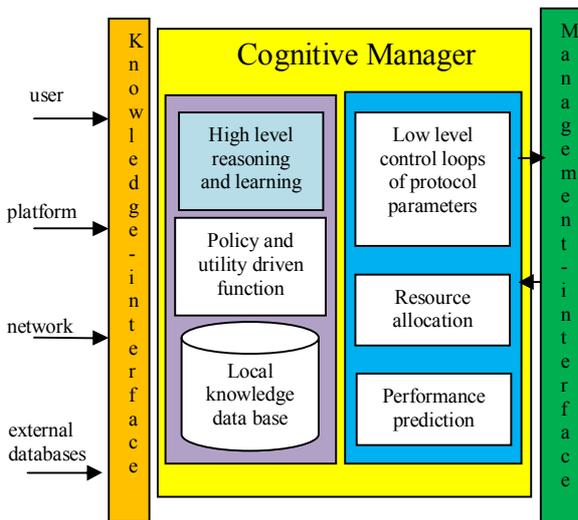


Figure 3. Abstraction of functional modules and interfaces.

4. EMOTION-BASED REASONING AND LEARNING MODUL

As was mentioned earlier, the reasoning and learning module of the cognitive manager is on the basis of brain emotional learning. We illustrate this module using an emotion-based engine that is inspired by human emotional system. Functionally, the emotion-based engine imitates the function of the emotional system in learning and controlling basic instincts in particular fear; structurally, the suggested engine mimics the internal interaction of those regions of brain that are responsible for emotional processing.

4.1. Emotion and Anatomical Aspect of Emotion

For a long time, emotion was not assumed to be related to intelligence in human beings [14]. Hence, the emotional aspect of human behavior has so far received somewhat limited attention in the artificial intelligence research fields. In 1988 emotion was first proposed to be a principle part in human reaction [15]. Neuroscientists and psychologists have made a lot of efforts to analyze emotional behavior and describe emotion on basis of different hypotheses, e.g., psychological, neurobiological, philosophy and learning hypothesis. Studies of the emotional system have not only led to the explanation of emotional reactions by the application of different theories, e.g., central theory and cognitive theory [1]; they have also contributed to the development of computational models of emotional learning that is the basic of emotion-based artificial intelligence (AI) tools, intelligent controller [14], [16], [17] and data driven prediction methodologies [16], [18], [19], [20], [21], [22]. A good example of a computer based model that is relying on the central theory [16] (i.e., which explains how a primary evaluation of emotional stimuli forms emotional experiences) is called a computational model of emotional learning and imitates the associative learning aspect of emotional processing [16], which is based on fear conditioning [23], [24].

MacLean defined a group of the brain regions as the limbic system to describe the anatomical structure of brain emotional learning [25]. The limbic system consists of thalamous, sensory cortex, amygdala, hippocampus and hypothalamus, etc., The roles of the main regions of the limbic system with regard to fear conditioning can be summarized as follows:

- 1) **Thalamus** is the entrance gate of emotional stimuli. It determines the effective values of stimuli [26]-[32] to be pass to the amygdala and the sensory cortex [32].

- 2) **Hypothalamus** consists of several small nuclei and performs a variety of functions. Its main function is to connect the limbic system to the nervous system.
- 3) **Sensory cortex** is a part of the sensory area of the brain and is responsible for analysis and process of received signals [33]-[25], [31].
- 4) **Amygdala** is the central part of the limbic system of mammals and has a principle role in fear conditioning [18]-[26]. The amygdala consists of several parts with different functional roles (see Fig. 1) and it connects through them to other regions of the limbic system (e.g., the insular cortex, orbital cortex and frontal lobe). It has connections to the thalamus, the orbitofrontal cortex and the hypothalamus [34], [35]. During emotional learning, the amygdala participates in many tasks such as: reacting to emotional stimuli, storing emotional responses [36], evaluating positive and negative reinforcement and [37], learning the association between unconditioned and conditioned stimuli [23], [24] and [38], predicting the association between stimuli and future reinforcement [38], forming an association between neutral stimuli and emotionally charged stimuli [37]. The two main parts of the amygdala are the basolateral part (the largest portion of the amygdala) and the centeromedial part. The basolateral part has a main role in mediating of memory consolidation [39], in providing the primary response. The centeromedial part, which is another important part of the basolateral [35], is also divided into several regions [33], [24], [34], [35]. It is responsible for the hormonal aspects of emotional reactions [34] or mediating the expression of the emotional responses [34], [35].
- 5) **Hippocampus** is the main part of the mammals' brain and performs function in the consolidation of information from short-term memory to long-term memory.
- 6) **Orbitofrontal cortex** is located close to the amygdala and has a bidirectional connection to the amygdala. This part is also involved in processing the stimuli, learning the stimulus–reinforcement association. It also evaluates the reinforcement signal to prevent the amygdala from providing an inappropriate response [39].

4.2. Emotion-based methods

We categorize emotion-based methods into three groups: emotion-based decision making model, emotion-based controller, and emotion-based machine learning approach.

1) *Emotion-based decision making model*: Some artificial intelligence (AI) emotional agents such as EMAI (emotionally motivated artificial intelligence) and DARE (Emotion-based Robotic Agent Development) have been developed. EMAI was applied for simulating artificial soccer playing [40] and its results were fairly good. While, DARE was based on the Somatic Marker theory, was examined in modeling social and emotional behavior [43].

2) *Emotion-based Controller*: BELBIC (Brain Emotional Learning-based Intelligent Controller) [7] is an emotion-based controller. The basic of BELBIC was the computational model that was presented by Moren et al [7],[27],[44]. This model has a simple structure (see Figure 4) that has been inherited from the anatomical structure of limbic system, e.g., the amygdala, the thalamus, the sensory cortex. It imitates the interaction between those parts of the limbic systems and formulates the emotional response using mathematical equations [27]. This model that is referred to as amygdala-orbitofrontal subsystem consists of two main subsystems: the amygdala and the orbitofrontal. Each subsystem has several linear neurons and receives a feedback (a reward). BELBIC have been tested for a number of applications: controlling heating and air conditioning [43] aerospace launch vehicles [44], intelligent washing machines [45] and trajectory tracking of stepper motor [46]. BELBIC has shown an excellent performance overcome uncertainty and complexity issues of control applications. Specifically, the BELBIC has been proven to outperform other in terms of simplicity, reliability and stability [16], [41]-[44].

3) *Emotion-based machine learning approach*: Several machine learning approaches have also been developed based on emotional processing of the brain. Some examples are hippocampus-neocortex model and amygdala hippocampus model [47], [48]. These methods combine associative neural network with emotional learning concepts. Moreover, emotion-based prediction models [47]-[48] have been developed to predict the future behavior of complex system. They have been applied for different applications, e.g., solar activity prediction [18]-[20]. Recently, a classification model based on amygdala-orbitofrontal system has also been developed; the obtained results from testing this model on two benchmark data sets has verified its good performance.

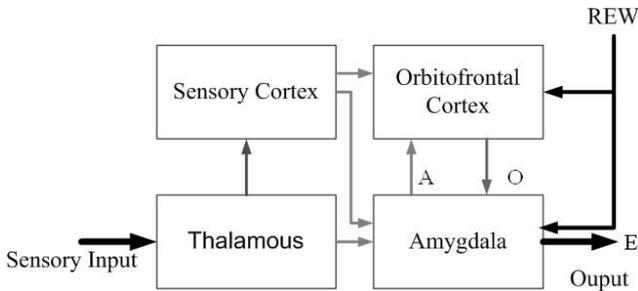


Figure 4. The graphical description of amygdala-orbitofrontal subsystem.

4.3. Emotion-based Engine

Joseph Mitola defined the term cognitive cycle (see Figure 5) to describe the intelligent behavior of radio nodes through five iterative steps: observe, orient, plan, decide and act. Mitola's cognitive cycle has been developed on the basis of the OODA loop that uses Unified Theories of Cognition (UTC) to model rational decision making in human [49]. As a matter of fact, the Mitola's cognitive model is on the basis of logical decision making processes in human considering the all environmental states are fully observable.

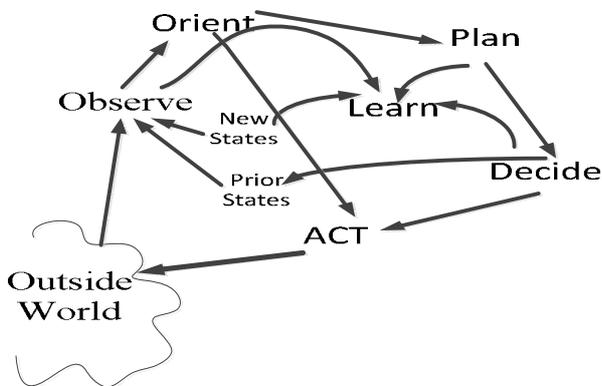


Figure 5. Cognitive radio cycle

4.3.1. Emotional Cycle

We develop an emotional cycle to represent the functions of the reasoning and learning module, assuming environmental changes elicits emotional stimuli that lead to emotional reactions. The emotional cycle imitates the brain's pathway from an emotionally charged stimulus (e.g. fear full stimulus) to an emotionally response (e.g. freezing) and it consists of three steps: sensing, learning and acting (see Figure 6).

In the cognitive radio network context, the emotional stimulus is a vector of environmental changes that can be triggered by different sources, e.g., users, the network policies, radio frequency channels, etc. The emotional

response is a waveform configuration. In the following we explain the cognitive cycle assuming the emotional stimulus that is a vector of environmental information, e.g., channel environment, network interface and user interface is triggered. The sensing step recognizes and interprets the received information. The procedure is led to a low level learning that provides useful information for the following steps. The learning step deals with making an optimal decision. It combines prediction algorithms (regression or classification) with optimization algorithms. The reacting step forms the waveform configuration that is equivalent with the emotional response and sends it to the radio platform.

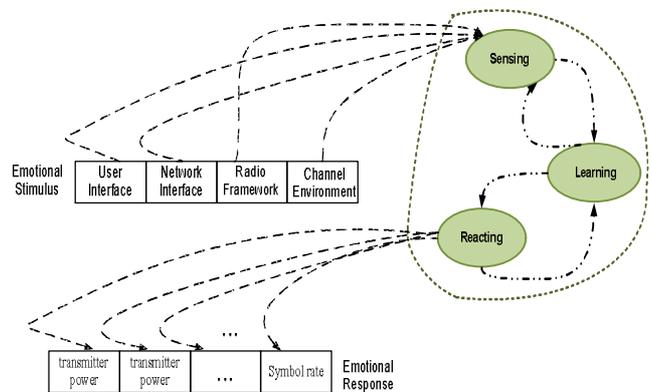


Figure 6. The emotional cycle.

4.3.2. Emotional Cycle and Limbic System

As was discussed earlier, the limbic system is the main responsible of emotional behavior e.g., fear conditioning in mammals. Figure 7 describes the pathways of fear conditioning and shows the connection between the regions of the limbic system. Each step of emotional cycle is equivalent to some regions of limbic system and mimics the functionality of those parts. The sensing step imitates the functionality of the thalamus and sensory cortex i.e., recognition, interpretation, quick perception, accurate representation. This step provides high level information copying the selective and processing procedure in the thalamus and sensory cortex. This information indicates which specific algorithm should be activated in the next step, learning step. The learning step mimics the roles and interactions of the amygdala, hypothalamus and orbitofrontal cortex using prediction, optimization, decision making algorithms. The reacting steps imitate the functions of hippocampus by constantly produce a response (here a waveform) and adjusts it.

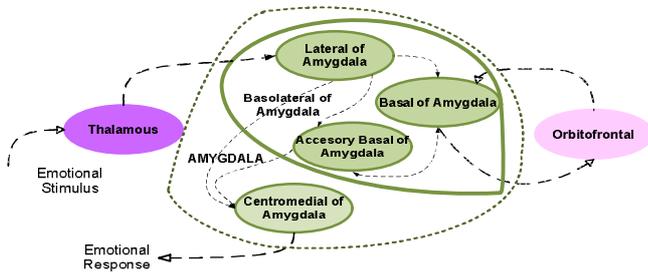


Figure 7. The components of brain emotional system and their connections according to fear conditioning.

4.3.3. Emotional Cycle and Mitola's Cognitive Cycle

As mentioned earlier, Mitola's cognitive cycle and UTC express how a rational goal-oriented decision can be made by an intelligent agent. However, the emotional cycle represents an emotion-oriented action. In addition, the emotional cycle and Mitola's cognitive cycle differs on implementing the learning, decision making and optimization algorithms. Figure 7 depicts Mitola's cognitive cycle and shows how it can be mapped to the emotional cycle. As Figure 8 indicates the sensing is corresponding with: observe, orient and act states of the cognitive cycle. The learning is correspondent with the plan, learn and decide. And the reacting is corresponding with decide and act parts.

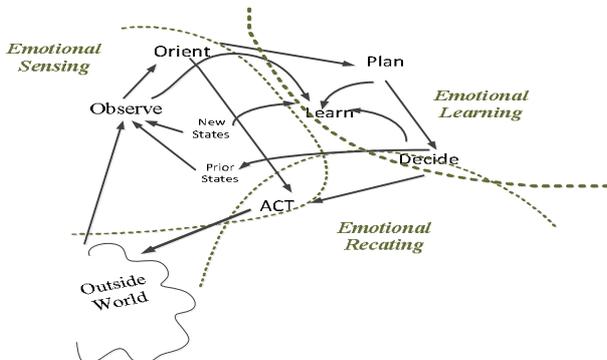


Figure 8. The emotional cycle and Mitola's Cognitive Cycle.

4.3.4. A Simple Structure of the Suggested Engine

A simple structure of the emotion-based engine has been developed and tested for prediction and classification application [18]-[20].

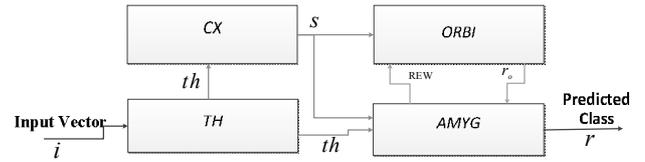


Figure 9. A simple emotion-based engine.

As Figure 9 shows, the structure consists of four parts: THalamous (TH), sensory CorteX (CX), AMYGdala (AMYG) and ORBItofrontal cortex (ORBI). Let us assume i as an input vector of stimulus; the functionality and the connection between the parts can be described as follows:

- 1) TH extracts high level information from the input stimulus, e.g., the maximum value of input vector, i . TH provides th and sends it to AMYG.
- 2) CX also receives th and provides, s that is sent to both AMYG and ORBI.
- 3) AMYG has connections with all other parts. It receives two inputs th and s which are originated from TH and CX, respectively. Using a data-driven method e.g. neural network or neuro-fuzzy method, the AMYG provides a primary response. In addition, a reinforcement signal, REW , is provided by AMYG for this response and is sent it to ORBI.
- 4) ORBI also adapts a learning algorithm and provides a secondary response r_o ; however, the final response, r , is provided by AMYG.

5. PRELIMINARY RESULTS

Applying the suggested emotional learning based engine for predicting time series and classification have indicated excellent results. For example the brain emotional learning-based recurrent fuzzy system (BELRFS) [18] is based on the four previous mentioned modules: TH, CX, AMYG and ORBI. Figure 8 depicts the basic structure of the model and the connection between its sub-modules. BELRFS has been applied for predicting some chaotic time series, e.g. Lorentz time series, and the result was compared with another black box models, local linear neuro fuzzy model with local tree model algorithm (LoLiMoT). Some of the result indications for prediction ability are reproduced in table I below. For comparison of the results, the error index of normalized mean square error (NMSE) is considered as the error measure.

Table I. The NMSEs of BELRFS and LoLiMoT to predict multi-step ahead of Lorenz

Learning Model	NMSE index for multi-step ahead prediction		
	10 step ahead	20 step ahead	30 step ahead
BELRFS	1.463e-4	0.1250	0.6023
LoLiMoT	0.0012	0.1509	0.7086

BELRFS has also been applied benchmarked by predicting sunspot number time series. The obtained results indicate that BELFIS is a reliable, nonlinear predictor model for solar activity forecasting. So as conclusion one can state that it can be applied as a predictor model for the long-term and short-term prediction of chaotic and nonlinear systems which are one important feature for an cognitive manager. Classification ability for a computational model of emotional learning has also been tested by using some benchmark data sets. Table II presents the results of classification of Wine data using the simple emotion-based engine.

Table II. The classification accuracy of BELBEC for the wine data set with 60 samples as training data and 118 samples test data.

Classification Model	Specification of results		
	Structure	The average per class accuracy	The number of training samples
BELBEC without normalized[50]	16 neighbors	%99.02	60
McNN [51]	9 neurons	%98.49	27
PBL-McRBFN [51]	11 neurons	%98.69	29

The Wine data set is a multiclass data set with 13 features and can be categorized into three classes [50]-[51]. The details of the emotion-based engine that is referred to as Brain Emotional Learning Based Ensemble Classifier (BeLBeC) has been explained at [50]. As the table verifies, the emotion-based engine has excellent performance as classification method.

6. CONCLUSION

This paper suggested architecture for a cognitive engine based on brain emotional learning, which differs from previously proposed architectures of cognitive engines. Previous cognitive engines are based on a cognitive cycle that is defined according to the rational reasoning system of the human brain. A rational goal-oriented decision is made by an intelligent agent while the emotional cycle represents an emotional reaction-oriented action. The conducted work indicates that the two systems differs in function and structure of learning, decision making and optimization algorithms. Mitola's cognitive cycle can be mapped to the emotional cycle. As indicated the sensing is corresponding

with: observe, orient and act states of the cognitive cycle.

The learning is correspondent with the plan, learn and decide. And the reacting is corresponding with decide and act parts. Our suggested engine is based on the emotional system. The emotional system is faster and has a more basic structure, from an evolutionary perspective, than the rational system. Preliminary result, for prediction and classification indicate very promising performance and previous work has shown that the computational models of brain emotional learning also can be used for intelligent control. Ongoing work is developing an entity for emotion-based decision making and an emotion-based optimization.

7. REFERENCES

- [1] S. R. Atkinson and J. Moffat, *The Agile Organization – From informal networks to complex effects and agility*, Command and Control Research Program (CCRP) publishing series, 2005.
- [2] *GUIDE TO SPECTRUM MANAGEMENT IN MILITARY OPERATIONS*, ACP 190 (C), a Combined Communications-Electronics Board (CCEB) publication, September 2007.
- [3] W. J. Morgan, *DoD Spectrum Management: A Critical Analysis*, Air Force Institute of Technology, June 2008.
- [4] *POLICY FOR THE COORDINATION OF MILITARY ELECTROMAGNETIC SPECTRUM ALLOCATIONS AND ASSIGNMENTS BETWEEN COOPERATING NATIONS ACP 194*, a Combined Communications-Electronics Board (CCEB) publication, June 2011.
- [5] R. Poe, R. Shaw H. Zebrowitz W. Kline, W. Heisey, F. Loso, and Y. Levy, "Optimal Spectrum Planning and Management with Coalition Joint Spectrum Management Tool (CJSMPPT)," in proceedings of *Military Communications Conference (MILCOM) 2008*, San Diego, U.S. 2008.
- [6] Douglas E. Comer, *Automated Network Management Systems – Current and Future Capabilities*, Pearson Prentice Hall, 2007.
- [7] S. Dobson et al, "A Survey of Autonomic Communications", *ACM Transactions on Autonomous and Adaptive Systems*, Vol. 1 No. 2, December 2006.
- [8] R. Chadha and L. Kant, *Policy-Driven Mobile Ad Hoc Network Management*, Wiley Series in Telecommunications and Signal Processing, 2008.
- [9] M. J. Ryan and M. R. Frater, *Tactical Communications for the Digitized Battlefield*, Artech House, 2002.
- [10] Q. H. Mahmoud, *Cognitive Networks – Towards Self-Aware Networks*, Wiley, 2007.
- [11] R. W. Thomas, L. A. DaSilva, and A. B. MacKenzie, "Cognitive Networks," in proceedings of *First IEEE International Symposium on New Frontiers in Dynamic Spectrum Access Networks 2005*, DySPAN 2005, Baltimore Maryland, U.S. 2005.
- [12] J. Boyd, *A discourse on winning and losing: Patterns of conflict*, 1986.
- [13] J. Mitola, *Cognitive Radio: An Integrated Agent Architecture for Software Defined Radio*, PhD thesis, Royal institute of Technology (KTH), Sweden 2000.
- [14] L. Custodio, R. Ventura, C. Pinto-Ferreira, "Artificial emotions and emotion-based control systems", *Proceedings of 7th IEEE International*

- Conference on Emerging Technologies and Factory Automation*, pp. 1415-1420, 1999.
- [15] J. M. Fellous, J. L. Armony, and J. E. Le Doux, "Emotional Circuits and Computational Neuroscience," in *The Handbook of Brain Theory and Neural Networks*, The MIT Press, Cambridge, MA, 2003.
- [16] C. Lucas, D. Shahmirzadi, and N. Sheikholeslami, (2004) 'Introducing BELBIC: Brain Emotional Learning Based Intelligent Controller', *International Journal of Intelligent Automation and Soft Computing (Autosoft)*, Vol. 10, pp. 11-22.
- [17] S. H. Zadeh, S. B. Shouraki, and R. Halavati, (2006) "Emotional behaviour: A resource management approach", *Adaptive Behaviour Journal*, Vol.14, pp. 357-380.
- [18] M. Parsapoor, M. U. Bilstrup, "Neuro-fuzzy models, BELRFS and LoLiMoT, for prediction of chaotic time series," in *Proc. IEEE Int. Conf. INISTA*, pp.1-5, 2012.
- [19] M. Parsapoor, C. Lucas and S. Setayeshi, "Reinforcement recurrent fuzzy rule based system based on brain emotional learning structure to predict the complexity dynamic system," in *Proc. IEEE Int. Conf. ICDIM*, pp.25-32, 2008.
- [20] M. Parsapoor, U. Bilstrup, "Brain Emotional Learning Based Fuzzy Inference System (BELFIS) for Solar Activity Forecasting," in *Proc. IEEE Int. Conf. ICTAI 2012*, 2012.
- [21] C. Cavada, W. Schultz, "The Mysterious of Orbitofrontal Cortex. Foreword. Cerebr. Cortex," *J. Cerebr. Cortex*, vol. 10, no. 3, pp. 205, 2000.
- [22] C. A. Winstanley, D. E. H. Theobald, R. N. Cardinal, and T. W. Robbins, "Contracting Roles of Basolateral Amygdala and Orbitofrontal Cortex in Impulsive Choice," *J. Neurosci.*, vol. 24, no. 20, pp. 4718-4722, 2004.
- [23] M. L. Kringelbach, and E. T. Rolls, "The functional neuroanatomy of the human orbitofrontal cortex: evidence from neuroimaging and neuropsychology," *J. Prog. Neurobiol.*, vol. 72, pp. 341-372, 2004.
- [24] Damas, B. D. and Custódio, L.: "Emotion-Based Decision and Learning Using Associative Memory and Statistical Estimation," *J. Informatica (Slovenia)*, vol. 27, no. 2, pp. 145-156, 2004.
- [25] J. D. Velásquez, "When Robots Weep: Emotional Memories and Decision-Making," in *Proc. Conf. on Artificial Intelligence*, pp.70-75, 1997.
- [26] S. H. Zadeh, S. B. Shouraki, and R. Halavati, R. "Emotional behaviour: A resource management approach," *J. Adaptive Behaviour*, vol. 14, pp. 357-380, 2006.
- [27] M. Maças and L. Custódio, "Multiple Emotion-Based Agents Using an Extension of DARE Architecture," *J. Informatica (Slovenia)*, vol. 27, no. 2, pp. 185-196, 2004.
- [28] E. Daryabeigi, G. R. A. Markadeh, C. Lucas, "Emotional controller (BELBIC) for electric drives — A review," in *Proc. Annual Conference on IEEE Industrial Electronics*, pp.2901-2907, 2010.
- [29] N. Sheikholeslami, D. Shahmirzadi, E. Semsar, C. Lucas, "Applying Brain Emotional Learning Algorithm for Multivariable Control of HVAC Systems," *J. INTELL. FUZZY. SYST.* vol.16, pp. 1-12, 2005.
- [30] A. R. Mehrabian, C. Lucas, J. Roshanian, "Aerospace Launch Vehicle Control: An Intelligent Adaptive Approach", *J. Aerosp. Sci. Technol.*, vol.10, pp. 149-155, 2006.
- [31] J. L. Armony, and J. E. LeDoux, "How the Brain Processes Emotional Information," *J. Ann. N. Y. Acad.*, no. 821, pp. 259-270, 1997.
- [32] J. M. Jenkins, K. Oatley, N. L. Stein, *Human emotions: A READER*, Blockwell publisher, U.K., 1998.
- [33] D. H. Hubel, M. S. Livingstone, "Color and Contrast Sensitivity in the Lateral Geniculate Body and Primary Visual Cortex of the Macaque Monkey," *J. Neuroscience*, vol. 10, no.7, pp. 2223-2237, 1990.
- [34] J. P. Kelly, "The Neural Basis of Perception and Movement, Principles of Neural Science," London: Prentice Hall. 1991.
- [35] K. Amunts, O. Kedo, M. Kindler, P. Pieperhoff, H. Mohlberg, N. Shah, U. Habel, F. Schneider, K. Zilles, "Cytoarchitectonic mapping of the human amygdala, hippocampal region and entorhinal cortex : intersubject variability and probability maps," *J. Anatomy and Embryology*, vol. 21, no. 5-6, pp. 343-352, 2005.
- [36] C. I. Hooker, L. T. Germine, R. T. Knight, M. D. Esposito, "Amygdala Response to Facial Expressions Reflects Emotional Learning," *Neuroscience. J.*, vol. 26, no.35, pp. 8915-8930, Aug. 2006.
- [37] J. Moren, C. Balkenius, "A computational model of emotional learning in the amygdala," in *From Animals to Animals*, MIT, Cambridge, 2000.
- [38] B. D. Damas, and L. Custódio, "Emotion-Based Decision and Learning Using Associative Memory and Statistical Estimation," *J. Informatica (Slovenia)*, vol. 27, no. 2, pp. 145-156, 2004.
- [39] J. D. Velásquez, "When Robots Weep: Emotional Memories and Decision-Making," in *Proc. Conf. on Artificial Intelligence*, pp.70-75, 1997.
- [40] S. H. Zadeh, S. B. Shouraki, and R. Halavati, R. "Emotional behaviour: A resource management approach," *J. Adaptive Behaviour*, vol. 14, pp. 357-380, 2006.
- [41] M. Maças and L. Custódio, "Multiple Emotion-Based Agents Using an Extension of DARE Architecture," *J. Informatica (Slovenia)*, vol. 27, no. 2, pp. 185-196, 2004.
- [42] E. Daryabeigi, G. R. A. Markadeh, C. Lucas, "Emotional controller (BELBIC) for electric drives — A review," in *Proc. Annual Conference on IEEE Industrial Electronics*, pp.2901-2907, 2010.
- [43] N. Sheikholeslami, D. Shahmirzadi, E. Semsar, C. Lucas, "Applying Brain Emotional Learning Algorithm for Multivariable Control of HVAC Systems," *J. INTELL. FUZZY. SYST.* vol.16, pp. 1-12, 2005.
- [44] A. R. Mehrabian, C. Lucas, J. Roshanian, "Aerospace Launch Vehicle Control: An Intelligent Adaptive Approach", *J. Aerosp. Sci. Technol.*, vol.10, pp. 149-155, 2006
- [45] M. Milasi, C. Lucas, B. N. Araabi, "Intelligent Modeling and Control of Washing Machines Using LLNF Modeling and Modified BELBIC," in *Proc. Int. Conf. Control and Automation*, pp.812-817, 2005.
- [46] A. M. Yazdani1, S. Buyamin1, S. Mahmoudzadeh2, Z. Ibrahim1 and M. F. Rahmat1, "Brain emotional learning based intelligent controller for stepper motor trajectory tracking," *J. LJPS*, vol. 7, no. 15, pp. 2364-2386, 2012.
- [47] T. Kuremoto, T. Ohta, K. Kobayashi, M. Obayashi, "A dynamic associative memory system by adopting amygdala model," *J. AROB*, vol.13, pp.478-482, 2009.
- [48] T. Kuremoto, T. Ohta, K. Kobayashi, K. M. Obayashi, "A functional model of limbic system of brain," in *Proc. Int. Conf. Brain informatics*, pp.135-146, 2009.
- [49] A. Amanna and J.H. Reed, "Survey of cognitive radio architectures," *Proceedings of the IEEE SoutheastCon 2010*, pp.292-297, 18-21 March 2010.
- [50] M. Parsapoor and U. Bilstrup, "Brain Emotional Learning-based Ensemble Classifier (BELBEC)," submitted to *8th International Symposium Advances in Artificial Intelligence and Applications, AIAA 2013*.
- [51] G. S. Babu and S. Suresh, "Sequential Projection-Based Metacognitive Learning in a Radial Basis Function Network for Classification Problems," *Neural Networks and Learning Systems, IEEE Transactions on*, vol.24, no.2, pp.194,206, Feb. 2013.