Computational Modeling of Limbic System For Control Applications

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ABSTRACT

This paper deals with modeling the mechanisms of brain limbic system in making emotional decisions. First, the literature on using soft computing and non model-based algorithms in decision support and control problems is given. Then the foundations of brain limbic system in processing emotions are studied and a model capturing minimal characteristics of this system is developed. The model is verified by simulating on acquisition and blocking experiments. After verifying the model, it is adapted to be used in control system applications. The simulation results of controlling underwater depth of a simple model of a submarine, shows the acceptable performance of the model for this application domain.

Keywords: Emotional Decision Making, Brain Limbic System, Associative Learning, Emotional Control

1. INTRODUCTION

Biologically-inspired intelligent systems are increasingly being considered for different application domains [1,2,3]. The limitations of traditional approaches are appreciated when dealing with uncertainties and complexities associated with real-world situations. The intelligent approaches are believed as possibilities for overcoming these problems [4,5].

Bounded rationality and satisficing have been suggested as alternative approaches to fully rational decision making. The so called curse of dimensionality in dynamic programming is an example of the latter problem [6].

In recent years, model-based approaches to decision making are being replaced by data-driven and rule-based approaches [7,11]. The success of fuzzy and neurofuzzy decision making systems also proves that solutions based on approximate reasoning that are less dependent on crisp modeling assumptions are more robust with respect to uncertainties present in the environment [8,9,10,11]. Neural networks, evolutionary strategies and genetic algorithms have also been very popular tools both in decision making and other industrial applications [12,13,14]. New approaches where intelligence is not given to the system from outside, but is acquired by the system through learning, have proven much more successful [15].

The reinforcement learning and a more cognitively based version of that have also been developed in which a critic constantly assesses the consequences of the generated actions in any given state in terms of the overall objectives or performance measures and produces an analog reinforcement cue which in turn directs the learning in the decision making block [15]. This cognitive version of the reinforcement signal is denoted as an emotional cue. It indeed emulates the function of emotions like stress, concern, fear, satisfaction, happiness, etc. to assess the environmental conditions with respect to goals and utilities and to provide cues regulating action selection mechanisms [15,16].

Whether called emotional decision making or merely an analog version of reinforcement learning with critic (evaluative decision making), the method is increasingly being utilized by control engineers, robotic designers and decision support system developers [17,18,19,20].

Although, for a long time, emotion was considered as a negative factor hindering the rational decision making process, the important role of emotions in human cognitive activities is progressively being documented by psychologists [21,22]. It has now become clear that far from being a negative trait in biology, emotions are
important positive forces crucial for intelligent behavior in natural as well as artificial systems [16,23]. In this study, the fundamentals of brain limbic system in making emotional decisions are being studied and simulated for some biologically-verified experiments.

2. Model

In this section, the emotional learning mechanisms in mammalian brain are studied and modeled for decision making experiments. The Brain Emotional Learning module, termed BEL, is initially studied in [18] and justified for applications in control engineering, sensor fusion and signal forecasting tasks [24,25,26].

The algorithm is basically designed to imitate the minimum characteristics of brain emotional processing. As depicted in Fig. 1, the model consists of four components of the limbic system of the brain: Amygdala, Orbitofrontal Cortex, Sensory Cortex and Thalamus. Of them, the first two play key roles in processing of emotions [19].

Fig. 1 Schematic Structure of the BEL system

The idea behind decision-making based on emotional learning is generating the action regarding the emotional cues. The emotional signal can be inherently be positive (e.g. Reward) or negative (e.g. Punishment). The sensory inputs received by the system represent the situation the system is currently experiencing, and the emotional signals reflect the degree of satisfaction with the performance of the system at the time.

The task of the Thalamus is to provide a non-optimal but fast response from the system, where this capability is simply simulated by passing the maximum signal over the sensory inputs, through the Amygdala. This shortcut route improves the speed and fault tolerance properties of the model. The reason is that it bypasses the Sensory Cortex processing and enables the model to generate a non-optimum action, called satisfactory decision, even when the Sensory Cortex gets damaged.

The main goal of the Sensory Cortex in real biological systems is to appropriately distribute the incoming sensory inputs through the Amygdala and the Orbitofrontal Cortex, and in this model, it is represented in terms of a computational delay.

For any sensory input, $s_i$, there is a corresponding Amygdala node, $A_i$, and an Orbitofrontal Cortex node, $OC_i$, which generate the nodal Amygdala and Orbitofrontal Cortex outputs, based on the Eqs. (1) and (2):

$$A_i = G_A S_i ,$$  
$$OC_i = G_{OC} S_i .$$  

The weights $G_A$ and $G_{OC}$ are the nodal weights for the Amygdala and the Orbitofrontal Cortex nodes, respectively. In the above, $i$ is the sensory input (and corresponding Amygdala and Orbitofrontal Cortex nodes) index.

The main learning processes in the system happen in the Amygdala and the Orbitofrontal Cortex, where their weights are updated based on the specific learning rules given by (3) and (4):

$$\Delta G_{A_i} = k_1 S_i \max(0, ES - A_i) ,$$  
$$\Delta G_{OC_i} = k_2 S_i (MO - ES) .$$  

where $k_1, k_2$ are the learning rates, $ES$ is the emotional signal and $MO$ is the model output.

The overall model output, which is actually the action generated by the model, is determined by the following equation:

$$MO = \sum_i A_i - \sum_i OC_i .$$  

From Eq. (5), it is realized that the overall model output is the result of excitatory signals from the Amygdala and the inhibitory signals from the Orbitofrontal Cortex. The Eqs. (3) and (4) also imply that the learning trend in the Amygdala is monotonic, while the Orbitofrontal Cortex can both learn and unlearn (forget). Basically, this is inspired by biology, where based on both good and bad experiences, the Amygdala constantly learns the associations between the sensory input signals and the emotional signal and tends to behave based on the learned associations.

On the other hand, the Orbitofrontal inhibitory signals act to prevent any inappropriate actions to be issued by the Amygdala (and hence, by the total model) when it is found inappropriate.
3. VALIDATION

In this section, two benchmark experiments in biological studies are simulated via the developed model to both verify the accuracy of the model and realize the basics by which the model operates.

**Acquisition:** Acquisition - abbreviated by ACQ - is a basic learning experiment in which the model is expected to associate and dissociate the sensory input signal depending on whether the emotional signal is present to the system or not [18].

Indeed, this is the minimal functionality of any associative learning system to be able to dynamically react based on the given sensory input and emotional signals. The Amygdala-Orbitofrontal Cortex protocol is known to represent these characteristic behaviors. The following are the simulation results of an ACQ experiment. In this simulation, one sensory input and one emotional signal are given to the system as shown in Fig. 2. In the first stage, the sensory input and the emotional signal both have the value of one, where in the second stage, the emotional signal vanishes and then in the third stage, reappears with the value of two.

Then, the next stage starts with a sensory input of value two but no emotional signal is present to the system, where it becomes available then after with the value of one.

Finally, while the emotional signal remains at the value of one, the sensory input signal reappears with the value of 0.6.

The output of the model is given in Fig. 3. As it is observed from the figure, the model does not generate any output value until both the sensory signal and the emotional signal do have some nonzero values.

It is realized that the magnitudes of the output at the steady state track the values of emotional signal. On the other hand, the magnitude of the sensory signal contributes to the rate of learning. This fact is realized at the two final stages where the emotional signal has the value of one but the sensory inputs have values of two and 0.6 respectively. As the Fig. 3 shows, in both stages the output reaches the value of one but much faster at the first time compared to the second time.

![Fig. 4 Amygdala (upper) and Orbitofrontal Cortex (lower) learning through ACQ experiment](image)

The learning trends of the Amygdala and Orbitofrontal Cortex are shown in the upper and lower plots of the Fig. 4, respectively. As it is aforementioned, the Amygdala can not have learning in the reverse direction. In the other words, it can only learn the associations to produce the output signals and whenever the disassociation is required, the Orbitofrontal Cortex increases the inhibition. Fig. 4 shows that in this experiment, the Amygdala reaches the half of its full learning during presence of the emotional signal of magnitude one and reaches the full learning when the emotional signal rises from one to two. Also, whenever the emotional signal disappears and the disassociation is required, the Orbitofrontal Cortex learning is increased.

**Blocking:** Blocking - abbreviated by BLK - is another benchmark experiment for associative learning systems. In BLK experiment, the system is required to avoid establishing unnecessary associations [18]. For example, if the emotional signal is reasonably associated with one sensory input, no other sensory input should be associated. This phenomenon can be described by the principle of parsimony, in the sense that, if one sensory input is enough to capture the behavior of emotional signal, associating it with other sensory inputs is wasting of effort.

To verify this result with the model under consideration, the model is given two sensory inputs and one emotional signal as demonstrated in Fig. 5. At the early times, the emotional signal is merely associated with the first sensory input until the time when the second sensory input appears as well.

Then the emotional signal disappears where some pulses of first and second sensory inputs emerge. In later times, the emotional signals are associated with the second sensory input and then similar pulses of sensory signals emerge again without presence of emotional signal.
The emotional signal is defined as weighted summation of the control error and the plant output. This is given in Eq. (6):

\[ ES = W_1 e + W_2 CO. \]  

(6)

The sensory signal is also defined as the weighted summation of plant output and its rate of change to represent the state of the system. Equation 7 gives the definition for sensory input:

\[ SI = W_3 PO + W_4 \dot{PO}. \]  

(7)

In order to verify the performance of the above controller, the control block diagram of Fig. 8 is simulated on a model of a submarine given in Eq. (8):

\[ G(s) = \frac{0.1(s + 1)^2}{s(s^2 + 0.09)} = \frac{0.1s^2 + 0.2s + 0.1}{s^3 + 0.09s}. \]  

(8)

The learning behaviors of the two Amygdala and two Orbitofrontal Cortex nodes are demonstrated in the Fig. 7. It is realized from the figures that the main Amygdala excitatory learning and Orbitofrontal inhibitory learning happens for the first sensory input. In particular, during the association of the emotional signal with the first sensory input, the second Amygdala and Orbitofrontal Cortex nodes do not react at any level.

**4. Model Adaptation for Control System**

This section describes adapting the model for a control system. To utilize the model as a controller, it should be noted that it essentially converts two sets of inputs into the decision as the output. In fact, depends on the way the emotional signal is defined, different control objectives can be accommodated correspondingly.

Here, the goal of having a low control output is added to the usual goal of minimizing the tracking error. Figure 8 shows block diagram of the closed loop control system including the BEL component as a controller. As given in Eq. 6, the emotional signal is defined as weighted summation of the control error and the control output:

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Figures 9(a) and 9(b) show the closed loop responses of the system when there is no controller and when a BEL controller is used, respectively. The reference is assumed as step of magnitude one. As the figures show, the system by itself is unstable, but when the emotional controller is used, the system shows a stable response with reasonable performance indices.
5. CONCLUSION

In this paper, fundamentals of brain limbic system in emotional decision making are studied. A computational model consisting of main components of brain limbic system is established. Then the model is simulated on two biological benchmark experiments of Acquisition and Blocking.

In the first experiment, the model is found to operate on the basis of dynamic associations or disassociations of sensory inputs and emotional signal. Quantitatively, the response of the model follows the magnitudes of the emotional signal; the higher the sensory input is the faster the response is.

In the blocking experiment, the principle of parsimony is the key fact preventing the system to make associations of emotional signal with unnecessary sensory inputs. The simulation results show that even in the absence of emotional signal, the system shows some transient reactions to previously associated sensory inputs. Furthermore, it is observed that after disassociation of a sensory input, the emotional signal can be re-associated with new sensory inputs.

Then, the learning model is adapted to be used in the control applications domain. To this purpose, the emotional signal and the sensory input are correspondingly defined to fit within a closed loop control block diagram. Due to the fact that these signals can be defined in different ways, various representations of the system and control objectives can be implemented. The emotional signal in this study is assumed to achieve the goal of having low control effort and the usual goal of minimizing tracking error. The simulation of the system with this emotional controller to control a simple submarine model verified its performance for control applications.

6. REFERENCES


