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Brain Emotional Learning Basic Intelligent Control for Congestion Control of TCP Networks

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ABSTRACT

In this paper, an intelligent controller namely Brain Emotional Learning Basic Intelligent Control (BELBIC) is used to solve the congestion control problem in Transported Control Protocol network (TCP). The performance of the mentioned controller is evaluated in the presence of the systems uncertainties. We also introduce a procedure to design the controller parameters in a simplified manner while meets all the requirements. In the rest of the paper, applying to a real world network model, simulation results are obtained and verify the effectiveness of this method in such networks. The results are compared to those of a previously well designed PI controller.
KEYWORDS: BELBIC, Congestion control, TCP Networks

I. INTRODUCTION

Congestion in a network happens when a link or node is carrying so much data than it can transport. This phenomenon affects on the quality of service in a system and deteriorates it. Typical effects include queuing delay, packet loss or the blocking of new connections. The problem occurs when the buffer of the router is full and consequently some receiving packets are destroyed. Preventing this problem through a suitable method improves the efficiency of a network and ameliorates the quality of service. Studying the traffic control problem resulted in appearing an area called active queue management (AQM).

There has been a growing recognition within the Internet community that the network itself must participate in congestion control. AQM schemes have been proposed to complement the TCP network congestion control. AQM is router-based control mechanism, which aims to reduce packet drops and improve network utilization. So the combination of TCP and AQM is the main approach to solve the problems of current Internet congestion control. Many different researchers have studied this problem and have proposed different methods to solve this problem while each one has several advantages and disadvantages. Some of AQM algorithms can be found in [1-3].

Generally, according to the increasing demand for the internet and other networks, the traffic control problem is still a crucial challenge and there are many attempts to achieve faster and more reliable ones. It seems that network traffic control will not be totally solved at near future. The optimal control of networks including queue cannot be easily obtained even for even in a very simplified case [4].

In this paper we present the design and evaluation of a congestion controller using BELBIC and demonstrate the feasibility of applying this approach TCP networks. Emphasis is placed on development of an on-line direct adaptive output control architecture that employs computational model of emotional learning in amygdale to compensate non-linearities, disturbances and uncertainties in the system. This paper is organized as follows. Section 2 describes what exactly BELBIC is and the needed parameters to design it. In section 3 the model of the TCP is demonstrated. Section 4 explains how to apply BEBLIC in a TCP network and determines the selected parameters. Simulation results are shown in section 5 and finally conclusion reviews the main achievement of this paper.

II. Brain emotional learning basic intelligent control (belbic)

The traditional control methods based on identifying and modeling the system and designing the controller, are proposed according to predetermined goals for the systems under-control. The more these systems are complicated, the harder their identification is by previous methods or in some case it is impossible. On the other hand, according to the dynamic of the system under-control, uncertainty and its change which caused by obsoleteness, it is required to design and recalibrate the controller [5]. The problem of recalibration of controller parameters is intrinsically time consuming. There is a need to recalibrate the parameters automatically or manually even for controllers which are not dependent on the model as fuzzy ones [6]. Therefore, the intelligent and adaptive control is one of the new approaches in control engineering. There is a severe

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tendency in the intelligent control for getting the inspiration from natural systems as fuzzy-neural systems [7], evolutionary, intelligent controllers with reinforcement learning and multi-agent controllers.

There are not enough theories to define the elements of human's mental activities and fewer theories are to find out how to identify the relationships between emotions. Recently, a successful and simple model for emotional education in Amygdala of the brain was proposed by Moren and Balkenius[8] which similarly sensory input cortex obeys Orbital frontal cortex(OFC), Thalamus and generally the parts of brain that are responsible for emotion. As a result, this simple model has been implemented as a feedback to designed control problems as Brain Emotional Learning Basic Intelligent Control (BELBIC).

The general structure of the controller BELBIC is illustrated in figure 1. In the process of emotional learning the elements in brain as Limbic System have essential role. The most important elements formed this system are amygdala and Orbito-frontal cortex (OFC). The cortex provides the data required for these elements among all received data to the brain and thalamus plays the complementary role.

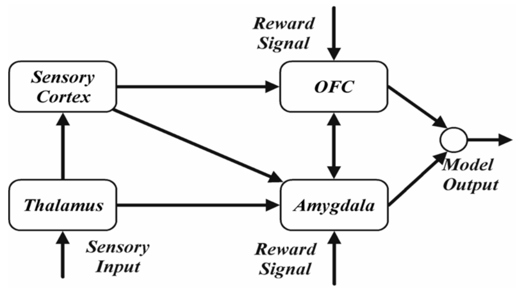


Figure 1. *The outline structure of imitative computational model of some parts in mammals mind*

The emotional learning model in amygdala of the brain and OFC is defined in equation (1). Basically, BELBIC method is a mechanism based on sensory inputs and emotional signs (Reward Signals). Generally, the emotional learning occurs in amygdala. The principle of emotional learning of amygdala of the brain is given in equation (1):

$$\dot{V}_i = \mu_a S_i \max\{0, REW - \sum_i A_i\} \qquad (1)$$

where Vi is the contact gain of amygdala of the brain and μa is the learning step in amygdala, Si is the sensory input per second, and REW and Ai are resistant signal and amygdala output per second respectively. The word max in equation (1) is to smooth the learning changes and avoid decreasing the gain of brain amygdala which it occurs in biological processes in the brain amygdala.

Similarly, the principle of learning in OFC is shown in equation (2):

$$\dot{W}_i = \mu_o S_i (E' - REW) \qquad (2)$$

where wi is the relation weight of OFC. μ0 is the rate of learning in OFC. The node E′ adds all of the outputs of A except Ath(the thalamic contact(4)), then subtracts from the feedback outputs of nodes of O which it can be calculated as

$$E' = \sum_i A_i - \sum_i O_i \quad (\text{ unless } A_{th}) \qquad (3)$$

where O shows the output of OFC. The thalamic contact (Ath) is calculated as

$$A_{th} = \max\{S_i\} \qquad (4)$$

maximum on all over the drivers in Si and other inputs are for the amygdala part of brain. Here there is a shared output node among all outputs of the model which named E. the node E is the sum of all outputs of the node A minus the feedback outputs of the nodes of O. The results of outputs of the model are:

$$E = \sum_i A_i - \sum_i O_i \quad (\text{ including } A_{th}) \qquad (5)$$

Actually, the model calculates the internal signals of amygdala and OFC with receiving the emotional input by equation (6) and finally it generates the output:

$$A_i = S_i V_i \qquad (6)$$
$$O_i = S_i W_i$$

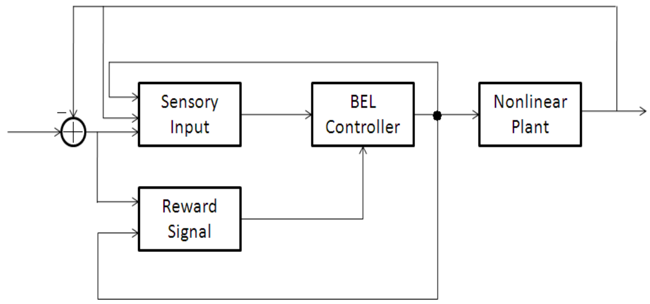


Figure 2. *The structure of control system by using BELBIC*

As amygdala does not have the ability to forget every emotional response which it has learned, it is OFC task to avoid each inappropriate response. The controllers based on emotional learning have suitable stability and present sufficient performance against current uncertainties in the system while they are easy to implement.

To use the model Moren-Balkenius [8] as a controller, it is noticeable that this model basically converts two categories of inputs(sensory inputs and emotional signs) to decision signal as the output.

The structure of control loop discussed is shown in figure 2. The functions used in emotional signs (REW) and sensory input blocks are in equation (7):

$$REW = G(S_i, e, y) \qquad (7)$$

$$S_i = f(u, e, y, y_m)$$

As it is in (7), the sensory input and reward signal can be desirable functions of the output of reference, ym, the output of controller, u and the error of signal as e and the designer is supposed to find a sufficient function for the control.

III. THE MODEL OF TCP SYSTEM

The mentioned system here will be used as a confirmative and conventional model [9].

$$\dot{W}(t) = \frac{1}{R(t)} - \frac{W(t)}{2}\frac{W\big(t-R(t)\big)}{R\big(t-R(t)\big)}p\big(t-R(t)\big) \qquad (8)$$

$$\dot{q}(t) = \begin{cases} -C(t) + \dfrac{N(t)}{R(t)}W(t), & q > 0 \\ max\left\{0, -C(t) + \dfrac{N(t)}{R(t)}W(t)\right\} & q = 0 \end{cases} \qquad (9)$$

IV. DESIGNING THE CONTROLLER BELBIC FOR TCP

A. Selecting the Sensory Inputs

Basically, to design a controller as BELBIC, there is no unique and defined trend in current articles. But a simple method is presented in follow to determine related parameters which that is generally based on different simulations and manual calibration.

Since the action of a control system is based on comparison between the feedback and reference, the sensory inputs for this system are as the reference input which here the size of queue and the error between output and reference are selected as sensory inputs. In order to normalize, some multiples are used:

$$S = [0.1q_c \; 0.01e_q] \qquad (10)$$

where e_q is the error between output and input based on the queue size.

B. Reward Signal

In fact, the reward signal is to minimize the error norm. To do this, a signal as here based on PI is considered:

$$\frac{REW(s)}{e_q(s)} = K_p + \frac{K_I}{s} \tag{11}$$

Determining this multiple is calibrated based on receiving the expected behavior of simulation. K_p= 2.0 * 10^{-4} and KI= 5.0 * 10^{-5} are selected for the simulation.

C. The Learning Multiple of Amygdala and OFC

We can increase this multiple as long as we are not limited. In fact, increasing the learning multiple does make the system more compatible. The limitation is made by increasing the learning multiple which it causes undesirable fluctuations added to system that they will cause instability in the system (we can state this problem by a pole added which it breaks all asymptotes in surface s). Thus it can be said that the learning multiple is supposed to be increased until we have not too much fluctuations in the system. The multiples μ_0=1 and μ_a= 1 are selected for OFC and amygdala to simulate.

V. THE RESULTS

According to mentioned statements so far and considering the notes about the characteristics of a controller [9], a suitable AQM for TCP system was presented. Now we can examine the performance of BELBIC in the traffic control of network. In this simulation, these quantities are selected for TCP system:

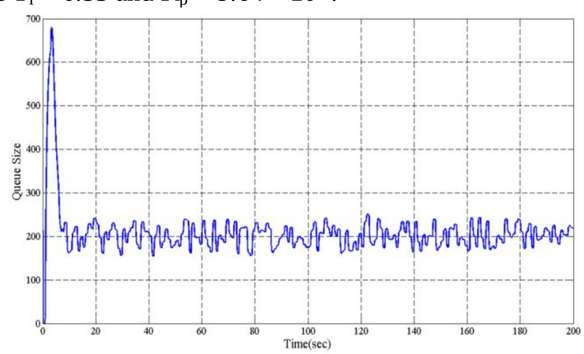
C = 3750;

N = 60;

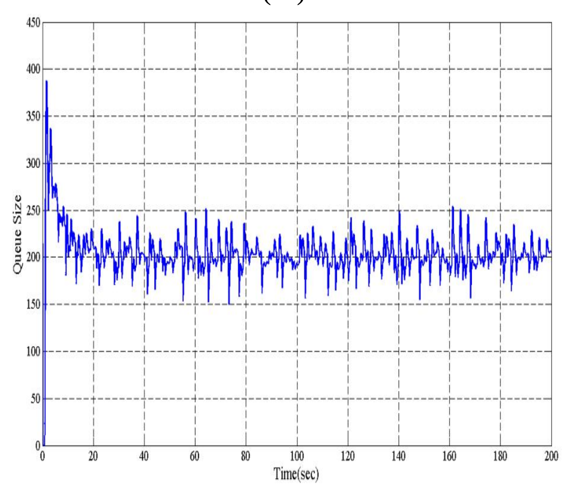
T_p = 0.090;

R = 0.246;

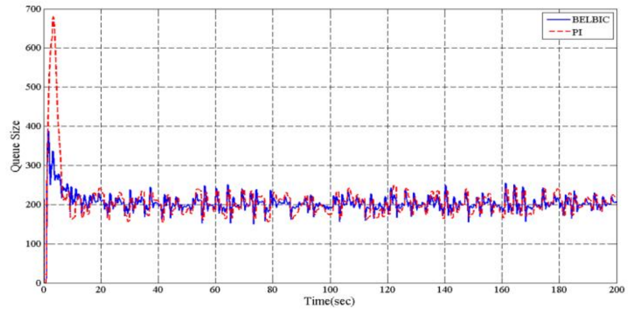
As said in [10], it is supposed to examine the resistance of proposed controller based on the current uncertainties in the system especially the uncertainties in parameters as C, N and T_p. In this regard, 20% uncertainty was considered for each parameter. Figure 3 shows the results of simulating the intelligent controller BELBIC in comparison to the controller PI in [9]. The parameters of this controller are T_i = 0.53 and K_p = 9.64 * 10^{-6}.



(3a)



(3b)



(3c)

Figure 3. *Comparison between size of the controllers PI and BELBIC (separately in 3a and 3b).*

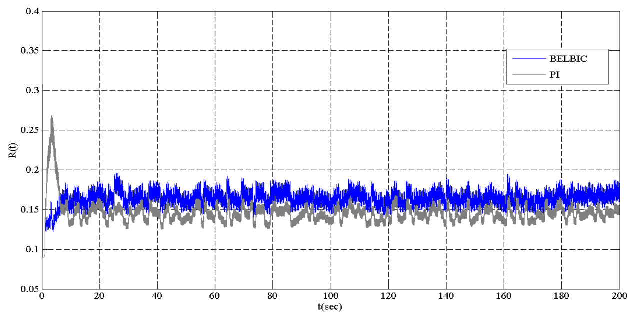


Figure 4. *The comparison of run-trip time for the controllers PI and BELBIC*

One of other characteristics which can be said for suitable controllers [9] is utilizing the queue sufficiently. According to figure 6, it can be perceived that the controller BELBIC has perfectly coped with its tasks in the system. On of other advantages of this controller is that it needs simple forward calculation and as a result, a little time to go to the next step. This problem is considered in simulation as minimization of convergence time total.

VI. Conclusion

In this paper, designing the brain emotional learning based intelligent control was proposed and its performance on TCP system was evaluated. As it was seen, this controller provided very desirable responses against disturbance in the system due to its capability of having online learning. The results showed more suitable performance even in comparison to a resistant controller PI examined in previous well-known articles. Providing higher speed and thus more stable dynamic for the system are two most important factors of advantages of the controller (Figure 4).

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