A new brain emotional learning Simulink® toolbox for control systems design ⋆

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Abstract: The brain emotional learning (BEL) control paradigm has been gathering increased interest by the control systems design community. However, the lack of a consistent mathematical formulation and computer based tools are factors that have prevented its more widespread use. In this article both features are tackled by providing a coherent mathematical framework for both the continuous and discrete-time formulations and by presenting a SIMULINK® computational tool that can be easily used for fast prototyping BEL based control systems.

Keywords: Brain emotional learning, control systems design, SIMULINK® .

1. INTRODUCTION

The solutions generated by nature, to solve the problems of environmental adaptation of all the living species, have been object of extensive study and analysis. This research was carried out, not only by natural sciences, but also from more technological standpoints. In fact, knowledge gained from studying those natural phenomena has led to an increasing tendency to introduce biomimetics to overcome some engineering problems (Sarpeshkar, 2009). For example, take into consideration the incorporation of nature arising morphologies and locomotion forms as common approaches to many human made machines. Many robots types, in both domestic or industrial applications, are probably the best illustrative examples of an anthropomorphic imitations phenomena. Even if morphological format is fundamental for any species endurance, the greatest achievement of nature was the learning ability inclusion into organisms. Indeed, learning is one of the most important factors for a species survival. The learning process can be viewed in the long term horizon, where genetics is its main driver, or in the short term, where instinct and intelligence takes the main role. Notice that instinct can be considered as long term knowledge: something that is written in the DNA promoted by each non-functional predecessor solution produced by nature. Philosophical questions aside, it is safe to say that learning allows a particular specie, when considering a large time scale, or an individual organism, in a shorter time frame, to adapt to environmental changes and to cope to new operating conditions. This behaviour type is highly desired in engineering applications since the conditions where a system operates are never static. Indeed, the entire field of robust controller design has this particular concern. At the present time, human made machines designed to have reasoning capabilities are synonymous of microprocessor based devices. The digital computers era has open a door for science to incorporate intelligence and adaptability to machines. It is well known that the most ambitious objective in computer science is the creation of a machine with conscience and rational skills. One that is capable of understanding its role in the surrounding environment, to be self aware, to take decisions and to interact with other entities. In short, the development of machines with human-like features designed to tackle specific problems. This machine based conscience abstraction is the "artificial intelligence" paradigm core. Artificial intelligence, or AI for short, involves several and distinct approaches. Some of them are computational methodologies inspired by nature such as artificial neural networks or evolutionary computation. Others, by mimicking reasoning such as Fuzzy logic or Bayesian inference. In essence, the objective is to have a machine equipped with the cognitive functions and the capability to learn and solve problems just like us. Humans address the incoming problematic situations by means of a constant interaction with the world. This

synergy between the environment and the individual is accomplished by constant actions and reactions among them. The individual abilities to deal with the surroundings are not only due to intelligence in the strict sense as AI may suggest. As a matter of fact, frequently, actions are not driven exclusively by logic reasoning but are biased by emotions. Indeed, emotions play an important role in the everyday live and have been a valuable asset in survival and adaptation. A well accepted idea is that emotions were added, by the evolutionary process, as a way to reduce the reaction time. That is, instead of using the reasoning part of the brain to process information and then generate a set of actions, which would take time, the reaction by emotion would be much faster. Emotions can be viewed as a autopilot distilled after millions of years of evolution. They describe a way to react automatically to the world in an unconscious mode. Emotional activity is mainly circumscribed within a set of distinct regions scattered along the brain designated by limbic system. Since emotional feature is a key element in robustness and adaptation capability, it would be important to translate this feature into human made devices. Indeed, emotional response and learning process are nowadays being exploited and used in several control and computational intelligence applications. For example in César et al. (2017) a Brain Emotional Learning (BEL) controller performance was studied when applied to a magnetorheological damper. Khorashadizadeh and Mahdian (2016) have used a Brain Emotional Learning Based Intelligent Controller (BELBIC) to control the voltage tracking in a DC-DC boost converter. In the work of Yi (2015) a robust bio-inspired sliding mode control approach was presented. This strategy is based in a BELBIC and was applied to robotic manipulators with uncertainties in tracking purposes. In Sadeghieh et al. (2012) the position tracking of an electro-hydraulic servo system was addressed. For that, a BELBIC based control system was devised to reach an online intelligent adaptive position tracking system. Within the power systems field, Jafari et al. (2013) used a BELBIC controller with a Proportional-Integer (PI) controller applied to an Interline Power-Flow Controller device. Besides the mentioned works, other areas have been explored having the emotional learning mechanism as the underlying process: from chemistry and mechanics to aerial systems, speech processing, among others (Dorrah et al., 2011; Fard et al., 2010; Huang et al., 2008; Mohammed and Bijoy, 2011). From this point onward, details regarding the limbic system, its mathematical description and its use within the control system applications framework, will be the subject of Section 2. From this work, a SIMULINK® toolbox was developed aiming the translation of this computational paradigm into a user friendly computer format. Its operation mode is described in Section 3. Finally, at Section 4, this work concluding remarks are presented.

2. THE LIMBIC SYSTEM

It is believed that the set of all possible emotions is preprogrammed in the genome. However, these basis emotions can be posteriorly modified based on individual experiences. Anatomically, the brain areas responsible for emotional activity are grouped in the so called limbic system. It should be noticed that it is not a closed question which, and how many, are the elements that constitute the limbic

system. It is generally recognized that the hypothalamus, the amygdala, the thalamus and the hippocampus are the basic structures of this brain activity. Their location, within the human brain, can be found in several books of Neuropsychiatry such as Gloor (1997) and Lautin (2001). Beside emotions, the limbic system supports a variety of other functions such as behaviour, motivation and has a major impact on the memory formation process. It promotes the interconnection between emotional cues and reasoning leading to an internal human state of low emotional stress. This state must be attained even in the presence of distinct external or internal sensory stimuli. That is, the inputs stimuli can put the current state of the limbic system out of balance. The result is the generation of an emotional solution that will, in turn, lead to a higher degree of satisfaction. In general, those stimulus inputs are first delivered to the brain region known as the thalamus. The thalamus behaves as a sensorial switching station that gathers and pre-processes sensory data. With the exception of the olfactory sense, all other sensations are guided, by the nerves network, towards the thalamus. In turn, it forwards those different sensations directly to the amygdala or to appropriate areas of the brain such as the cerebral cortex. The cerebral cortex corresponds to the outermost layer of the brain where the most sophisticated neural processing takes place. The diagram in Figure 1 represents the signal flow within the limbic system departing from the thalamus structure toward the ultimate body response passing through other brain structures such as the amygdala and orbitofrontal cortex. The amygdala
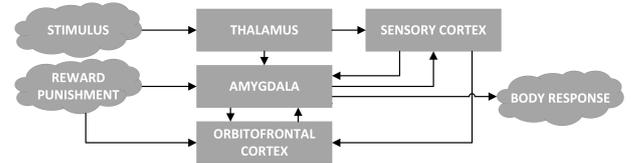

Fig. 1. Amygdala based brain emotional model structure (adapted from Beheshti and Hashim (2010)).

is one of the most important emotion based brain region (Purves et al., 2011). Experimentally, by electric signals, it was observed that its stimulation causes feelings of aggression, fear and anxiety. Notice that the fear sensation is fundamental for the individual survival and self-control, promoting an immediate emotional evaluation of a situation that is even more efficient than complex reasoning and logic. In short, the amygdala is the integrative center for emotions, emotional behaviour and motivation. In Figure 1 it is also possible to observe an additional neural structure designated by orbitofrontal cortex. The orbitofrontal region performs several functions among which is the ability to generate negative reinforcement signals. These signals mitigate any inappropriate responses generated by the amygdala. The orbitofrontal cortex operates based on the difference between expected reward or punishment and the actual ones. The expected motivation is impressed in the brain structures over time as a result of several learning mechanisms and reaches the orbitofrontal cortex via the sensory cortex and the amygdala. The actual reward or punishment comes via the outside world. If the expected and sensed motivation signals are identical, the output is the regular response to that stimulus. Otherwise, the orbitofrontal cortex suppresses the typical emotional re-

sponse and promotes ways for further learning. This learning and adaptation is a key element to organisms robustness when subjected to constantly changing environments. At the same time, robustness to condition changes is also a key feature of any engineering problem. Hence, in the last years, the brain emotional behaviour has been object of attention as a new paradigm in the control systems design field. Hence, the following section will be devoted to dissect and frame the limbic system mathematical model. It is worth to notice that the approach taken here is very different from the ones usually presented in the literature.

2.1 Brain Emotional System Mathematical Description

The robustness and efficiency exhibited by all biological systems are features that drive and inspire humans to learn from nature and try to apply this knowledge into common engineering problems. Of course, biological systems have such a high degree of complexity that, in practice, it is only possible to try to mimic their high level behaviour neglecting many of their functional details. It was in this framework that Balkenius and Morén (2001) presented a simplified mathematical model for the emotional learning carried out in the amygdala. This model formulation will be revisited during this section. Also, an uniform mathematical formulation will be laid on that spans continuous-time and discrete-time models of the limbic system.

The continuous-time version   This section is based on the amygdala-orbitofrontal cortex model initially proposed by Balkenius and Morén (2001). In it, the emotional system have the components interconnected as represented in Figure 2. A total of four main areas can be devised and coupled with the brain limbic section: the thalamus, the sensory cortex, the orbitofrontal cortex and the amygdala.
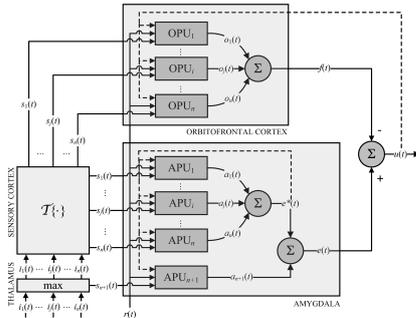

Fig. 2. Overall structure of the limbic model.

In the referred figure, it is assumed a set of n continuous time-varying external stimuli signals denoted by $i_1(t)$ to $i_n(t)$. At this point it is assumed that these input stimuli signals are positive or zero. In addition let's define the vector $\mathbf{i}(t) = [\, i_1(t) \cdots i_n(t) \,]^T$ of those external signals. The thalamus is responsible for the generation of the internal stimulus $s_{n+1}(t)$ which is computed as the maximum value of the input stimuli array $\mathbf{i}(t)$:

$$s_{n+1}(t) = \max\{\mathbf{i}(t)\} \qquad (1)$$

In addition, the thalamus is responsible to forward the input stimuli to the sensory cortex. This neural structure produces the input stimuli array $\mathbf{s}(t) = [\, s_1(t) \cdots s_n(t) \,]^T$

as a function of $\mathbf{i}(t)$ according to an arbitrary transformation function $\mathcal{T}\{\cdot\}$. In Balkenius and Morén (2001) it was considered the identity transform. That is,

$$\mathbf{s}(t) = \mathcal{I}_{(n\times n)} \cdot \mathbf{i}(t) \qquad (2)$$

where $\mathcal{I}_{(n\times n)}$ is the n-dimensional identity matrix. Here, the same transformation will be assumed. However, further research can be done to establish alternative mappings. The amygdala and the orbitofrontal cortex are the two structures where learning takes place. The amygdala incorporates a set of $n+1$ amygdala processing units (APU). It takes the values of the n stimuli signals delivered by the sensory cortex plus the one generated by the thalamus and with a reward signal $r(t)$ associated to the stimuli vector $\mathbf{s}(t)$, produces the internal output $e(t)$. The stimulus and reward signals are tightly interconnected. In fact, a reward without stimulus will not lead to learning. Here, the reward signal $r(t)$ will be assumed greater or equal to zero. The signal $e(t)$ is obtained by the following:

$$e(t) = \sum_{j=1}^{n+1} a_j(t) \qquad (3)$$

where $a_j(t)$ regards the output of the jth APU element at time instant t. This processing element has a structure that can be represented according to the block diagram of Figure 3. The output of each APU is computed as an weighted version of the referred excitation signals. The weighting factor, associated to the amygdala cluster j, is a positive time-varying coefficient, denoted hereby as $v_j(t)$. The APU comprises three inputs and one output. The internal stimulus signal $s_j(t)$, the reward signal $r(t)$ associated to it and $e^*(t)$ which concerns what can be understood as the partial amygdala output. This partial output is computed by neglecting the impact of the thalamus stimulus in the generated signal. That is,

$$e^*(t) = \sum_{j=1}^{n} a_j(t) \qquad (4)$$

where $a_j(t)$ is the output of jth APU at time instant t. In
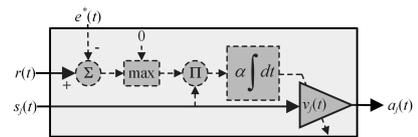

Fig. 3. Diagram of the continuous-time APU element.

the block diagram of Figure 3, the triangle shape element is a gain whose value is, at time instant t and for the input stimulus j, equal to $v_j(t)$. Hence, output signal $a_j(t)$ is equal to the product of $s_j(t)$ by $v_j(t)$. That is,

$$a_j(t) = s_j(t) \cdot v_j(t) \qquad (5)$$

This gain value is time dependent and changes according to a learning rule represented by the dashed lines blocks and signals. One shall define an $n+1$ dimensional vector $\mathbf{v}(k)$ whose elements are, besides the n weighting factors associated to the first n amygdala clusters, the entry $v_{n+1}(t)$ that represents the coefficient associated to signal $s_{n+1}(t)$. Here, $\mathbf{v}(t) = [\, v_1(t) \cdots v_n(t) \, v_{n+1}(t) \,]^T$. Then, the signals generated by the amygdala can be gathered in a vector $\mathbf{a}(t) = [\, a_1(t) \cdots a_n(t) \, a_{n+1}(t) \,]^T$ obtained by,

$$\mathbf{a}(t) = \mathbf{V}(t) \cdot \mathbf{s}^*(t) \qquad (6)$$

where $\mathbf{V}(t)$ is a diagonal matrix whose elements are the ones of vector $\mathbf{v}(t)$. That is,

$$\mathbf{V}(t) = \text{diag}\{\mathbf{v}(t)\} \qquad (7)$$

and $\mathbf{s}^*(t) = \begin{bmatrix} \mathbf{s}^T(t) & s_{n+1}(t) \end{bmatrix}^T$ is the vector obtained by adding the element $s_{n+1}(t)$ to the end of vector $\mathbf{s}(t)$. The model output signal $u(t)$ depends on the difference between the amygdala output signal $e(t)$ and the orbitofrontal cortex output signal $f(t)$. The orbitofrontal cortex output is obtained by summing the contributions of all the orbitofrontal processing units (OPU) whose structure is presented at Figure 4. The inputs to each of
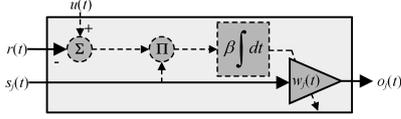

Fig. 4. The continuous-time OPU element.

the n OPU are delivered only by the sensor cortex block. The output of a generic j^{th} OPU is computed by,

$$o_j(t) = s_j(t) \cdot w_j(t) \qquad (8)$$

where $w_i(t)$ is the weight associated to the ith OPU for $i = 1, \cdots, n$. Assuming $\mathbf{o}(t) = \begin{bmatrix} o_1(t) & \cdots & o_n(t) \end{bmatrix}^T$ as the OPU output vector then,

$$\mathbf{o}(t) = \mathbf{W}(t) \cdot \mathbf{s}(t) \qquad (9)$$

where,

$$\mathbf{W}(t) = \text{diag}\{\mathbf{w}(t)\} \qquad (10)$$

with $\mathbf{w}(t) = \begin{bmatrix} w_1(t) & \cdots & w_n(t) \end{bmatrix}^T$. The output signal of the amygdala-orbitofrontal cortex model, at time instant t, will be denoted by $u(t)$ and computed according to:

$$u(t) = \mathbf{1}^* \cdot \mathbf{a}(t) - \mathbf{1} \cdot \mathbf{o}(t) \qquad (11)$$

where $\mathbf{1}^*$ and $\mathbf{1}$ are $1 \times n+1$ and $1 \times n$ unity vectors respectively. The weight update law for the OPU units is derived in the sense that the model output will follow the excitation signal when there is some reward for doing it. Hence, it will seek to minimize the following cost function,

$$J\Big(\mathbf{v}(t), \mathbf{w}(t)\Big) = \left(\sum_{i=1}^{n+1} v_i(t) \cdot s_i(t) - \sum_{i=1}^{n} w_i(t) \cdot s_i(t) - r(t) \right)^2 \qquad (12)$$

The starting point is the conventional gradient descent algorithm whose continuous time version is given by:

$$\frac{\partial w_j(t)}{\partial t} = -\eta \frac{\partial J(\mathbf{v}(t), \mathbf{w}(t))}{\partial w_j(t)} \qquad (13)$$

where $\eta > 0$ is the learning coefficient. Applying this formulation, by considering the cost function expressed by (12), the following weight update rule is obtained:

$$\frac{\partial w_j(t)}{\partial t} = \beta \cdot \Big(u(t) - r(t) \Big) \cdot s_j(t) \qquad (14)$$

where $\beta = 2 \cdot \eta$ is the positive leaning rate coefficient. This weight update rule can be observed in the dashed line of Figure 4. For the APU units, the weights are driven toward a set of values that lead to the minimization between the reward signal $r(t)$ and the partial amygdala signal $e^*(t)$. This can be understood as the amygdala role to seek for

constant reward. In this framework, the cost function to be minimized has the following formulation:

$$J(\mathbf{v}(t), \mathbf{w}(t)) = \left(r(t) - \sum_{i=1}^{n} s_i(t) \cdot v_i(t) \right)^2 \qquad (15)$$

Applying the gradient descent formulation leads to:

$$\frac{\partial v_j(t)}{\partial t} = \alpha \cdot \Big(r(t) - e^*(t) \Big) \cdot s_j(t) \qquad (16)$$

where $\alpha > 0$ is the learning rate. Notice that the weight update law for the APU is more elaborated than the above equation since it is expected that the amygdala learning weights never decrease. Hence the right member of the above expression cannot be negative. This leads to the following non-linear differential equation:

$$\frac{\partial v_j(t)}{\partial t} = \alpha \cdot \max \Big(r(t) - e^*(t), 0 \Big) \cdot s_j(t) \qquad (17)$$

The APU weight update dynamics is also made evident in the dashed line blocks of Figure 3. A final remark regarding the learning rates α and β. Usually their initial choice are positive numbers less than one. Moreover, in the literature, the value of α is assumed to be higher than the one of β (Morén, 2002; Garmsiri and Sepehri, 2014). The reasoning behind this difference can be tracked down to the fact that the former contributes to the excitation and the latter to the output inhibition (Garmsiri and Sepehri, 2014).

The discrete-time version   In this section it will be assumed that the stimuli signals are of discrete-time nature and defined at multiple integer time instants with period T_s. Hence the input vector is now defined as $\mathbf{i}(k) = \begin{bmatrix} i_1(k) & \cdots & i_n(k) \end{bmatrix}^T$ where k represents the integer index of the current sample and the input stimuli array is $\mathbf{s}(k) = \begin{bmatrix} s_1(k) & \cdots & s_n(k) \end{bmatrix}^T$. The model output is described by:

$$u(k) = \sum_{j=1}^{n+1} a_j(k) - \sum_{j=1}^{n} o_j(k) \qquad (18)$$

for,

$$a_j(k) = s_j(k) \cdot v_j(k) \qquad (19)$$

and,

$$o_j(k) = s_j(k) \cdot w_j(k) \qquad (20)$$

The learning law is obtained by assuming a first order approximation to the derivative operation. Using Euler forward approach, equations (14) and (17) are rewritten:

$$\frac{w_j(k+1) - w_j(k)}{T_s} = \beta \cdot s_j(k) \cdot \Big(u(k) - r(k) \Big) \qquad (21)$$

$$\frac{v_j(k+1) - v_j(k)}{T_s} = \alpha \cdot s_j(k) \cdot \max \Big(r(k) - e^*(k), 0 \Big) \qquad (22)$$

leading to the following difference equations:

$$w_j(k+1) = w_j(k) + \bar{\beta} \cdot s_j(k) \cdot \Big(u(k) - r(k) \Big) \qquad (23a)$$

$$v_j(k+1) = v_j(k) + \bar{\alpha} \cdot s_j(k) \cdot \max \Big(r(k) - e^*(k), 0 \Big) \qquad (23b)$$

where the amygdala and orbitofrontal constants are now $\bar{\alpha} = T_s \cdot \alpha$ and $\bar{\beta} = T_s \cdot \beta$ and $\max \Big(r(k) - e^*(k), 0 \Big)$ denotes the piecewise multivariate function:

$$\begin{cases} r(k) - e^*(k) & \text{if } r(k) > e^*(k) \\ 0 & \text{otherwise} \end{cases} \qquad (24)$$

The discrete-time version of both the APU and OPU are illustrated in Figures 5 and 6. As can be seen, the gain
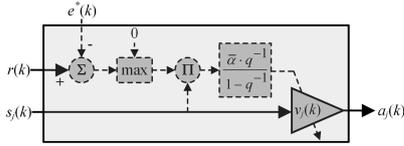
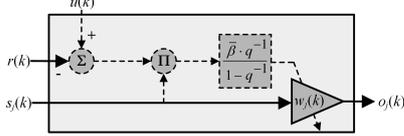Fig. 5. The discrete-time version of the APU.

Fig. 6. The discrete-time version of the OPU.

factor is modified by a discrete-time filter with a pole at $z = 1$. Here, since time-domain signals are present, the backward shift operator q^{-1} is used instead of the filter transfer function in the Z-domain. The filter input is excited by a piecewise linear function whose value is equal to the product of the stimulus signal $s_j(k)$ by $r(k) - e^*(k)$ if $r(k) \geq e^*(k)$ or 0 otherwise. Additional modification to this filter was proposed by Lotfi and Akbarzdeh (2012) where a γ factor was introduced that can modify the pole location. The intuition behind this introduction is to add a decay rate that can be used to model the brain forgetting tendency along time. A more elaborated leaning rule, for the orbitofrontal cortex, was proposed by Morén (2002).

2.2 The BEL based intelligent controller

A control system strategy, based on brain emotional learning, was proposed by Caro Lucas in the early 2000s (Lucas et al., 2004). The limbic model used was based on the neural link, between the amygdala and the orbitofrontal cortex, proposed by Balkenius and Morén (2001) and described in the previous sections. This control paradigm is commonly designated by BELBIC which stands for brain emotional learning based intelligent control. The reasoning behind the integration of the limbic model into a closed loop control system can be tracked down to the seemingly robust way that the brain performs decision making. Actually, control has all to do with decision making: the controller goal is to devise the best input actions based on the incoming information according to the system states. These actions can be taken considering the past, the present or even forecasts on the future system states. Hence the controller produces a mapping between its input signals and the output control signals by means of an arbitrary decision function which can be described by means of differential equations, as in PID controllers, or by an inference mechanism such as in Fuzzy or neuro-Fuzzy control. Alternatively it can be based on the result of the optimization of a cost function such as linear quadratic regulators (LQR) or model predictive control (MPC). In the BELBIC control system architecture this input-to-output transformation is imposed by means of the limbic system model. In this case, both the external stimuli and reward signals are generated in such a way as to produce a closed loop system response according to some target characteristics. In addition, due to the recursive nature of the weights update law, this controller is able to gradually learn how to handle changes in the system dynamics. A key point in BELBIC is the external stimulus and reward

signals definition. Notice that there are not universal rules to carry out this task. This choice is flexible and must be custom defined according to the end application. Different ways to define the emotional signals can be found in the literature (Rouhani et al., 2007; Rahman et al., 2008; Nahian et al., 2014; César et al., 2017). For example in Lucas et al. (2004) the reward signal $r(t)$ is obtained as a weighted sum of the error signal and the control effort and the external stimulus signal $i(t)$ is defined as a linear combination of the system output and its first derivative.

3. THE BEL SIMULINK® TOOLBOX

A more intuitive way to use the BEL paradigm, within a computer environment, is by means of a graphical user interface in the form of block diagram manipulations. In order to do that, a SIMULINK® toolbox was developed and made accessible through the MathWorks™ file exchange website[1]. This section is devoted to describe this toolbox how to use the main BEL blocks in a simple control system application. The idea to develop a brain emotional learning SIMULINK® toolbox is not new and has already been attempted by Mehrabian and Lucas (2006). However, there are two issues with their approach. First, it is not a toolbox but a BELBIC model for a particular problem. This approach do not provide the necessary plasticity for the user to build its own model. Second, and after an exhaustive web search, a copy of the above referred SIMULINK® file was not found.

The BELBIC toolbox file package contains an installation function that the user must execute from within the MATLAB®command line environment. This can be easily done by writing >>installme at the command prompt. The installation operation will require the user to select the BELBICtoolbox.slx and, after that, the MATLAB®program will be automatically restarted. After the installation process, the user can navigate through the SIMULINK® newly installed toolbox. This toolbox is divided into four different axis as can be seen in Figure 7. In the common section the user can find some BEL primitive functions such as the sensory cortex and the thalamus. Those objects are common to both the continuous-time and discrete-time BEL formulation. In the continuous-time
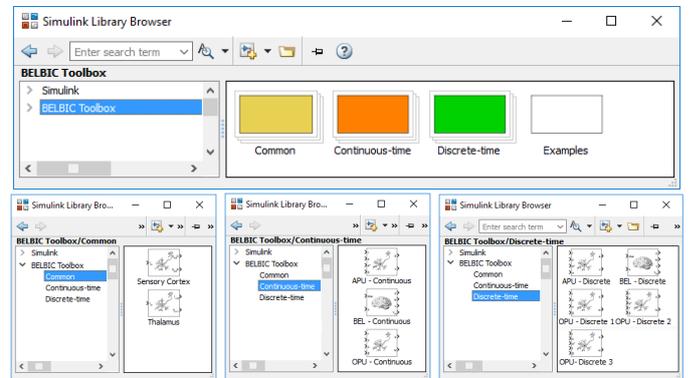

Fig. 7. The BELBIC SIMULINK® toolbox structure.

library the user may find the APU and OPU basic elements

and the BEL system. All these elements have their own mask which is used to tune them by setting appropriate learning coefficients values and initial conditions. The same can be said about the discrete-time version. However, in this case, all the elements require the definition of a sampling period. The fourth sub-library includes a set of explanatory examples on how to fully unleash the power of the presented models. Besides the simplest ones, some more advanced control based cases are provided. Namely the control of a non-linear continuous stirred tank reactor (CSTR) as the one presented in Mehrabian and Lucas (2006) (see Figure 8). Details on both the model and BEL controller parameterization can be found in the toolbox.
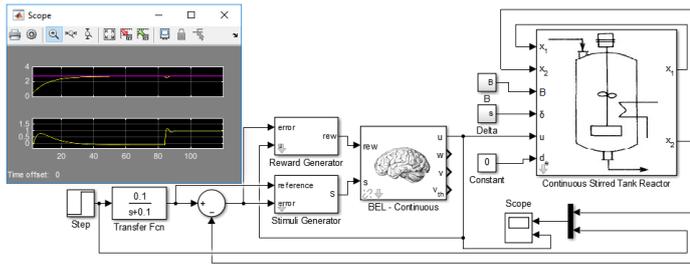

Fig. 8. Non-linear CSTR control using BELBIC.

4. CONCLUSIONS

This work presented a new SIMULINK® toolbox for brain emotional learning. This library is made publicly accessible through the MathWorks™ file repository web site. By providing this set of primitives, the authors believe that the researchers in this field can easily test their control problem using the BELBIC paradigm and thus contribute to disseminate the BELBIC strategy. Moreover this article also describes, in the same framework, both the continuous-time and discrete-time mathematical formulation of BEL model. This can also promote the unification of the model description that, until now, it is fairly scattered along several publications and mathematically inconsistent. Although, this toolbox is by no means closed. Further additions will be provided to extend its capabilities, for example by adding auto-tuning strategies.

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