Emotional Control of a Comprehensive Nonlinear ball and Beam System using SCELIC

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Abstract— **The model of emotional masks is a newly developed AI paradigm based on Minsky's model of emotional mind in his recent book "The emotion machine". The model takes a resource management approach toward modeling the mind and views different processes of mind as resources that need to be managed. In the present work an intelligent controller (SCELIC) is developed based on the model of emotional masks. SCELIC is a model free controller which advantages from several learning tasks. Multiple learnings and adaptive structure make it a powerful adaptive and self-learning tool that performs the tasks of system identification and control in parallel. Furthermore, a comprehensive nonlinear model of a ball and beam system is used as the test-bed. This system is inherently non-linear and unstable, and despite its simple nature, the cascaded dynamics of the system are very similar to planar control of rockets. Although the test-bed considered here is a nonlinear SISO system, this controller can be used for MIMO systems as well.**

Keywords-Attention, Adaptive Control, Emotions, Intelligent Control, Learning

I. INTRODUCTION

There is a lot of time passing from the first usages of machines by humans. The advent of computers was surely a breakthrough in the development of machines as they became much more intelligent. As a result, the more intelligence we put in systems, the more adaptability is required in their control. Therefore, there is a strong relationship between the fields of Control and Artificial Intelligence (AI). AI is defined as "the study and design of intelligent agents" where an intelligent agent is a system that perceives its environment and takes actions that maximize its chances of success [1]. Along with the presence of some sorts of intelligence in machines, there it came the debate over the possibility and need for emotions in machines as well. The truth is that at the first glance, emotions in machines did not seem that sensible but more research in this field have showed that artificial emotions can be an efficient approach if the machine must have the ability of planning or if it faces unknown environments. This is the case of some kind of robots, artifacts, virtual agents, and specially, control algorithms.

There has been a vast research on the topic of emotions among academia, from philosophy to AI. Different theories and models for emotions have been proposed, among which is the very recent model of emotional masks that is based on the theory of an emotional mind. Emotional mind is a theory put forward by the distinguished researcher Marvin Minsky in his recent book "the emotion machine". This theory and model take a resource management approach toward modeling the mind and views different processes of mind as resources that are to be managed.

Resulting from the integration of AI into control theory is the field of intelligent control, a class of control techniques that use various AI computing approaches. Equipped with emotions, this field can produce some efficient methods to deal with various systems. The main idea in this research is to implement emotions in a specifically designed intelligent controller to get the benefits from both paradigms. Such a controller has the potential to present good adaptiveness due to its multiple learning tasks, and the potential to deal with large data and rule bases due to its attention control and emotional masking mechanisms [3]. These ideas are implemented through SCELIC on a Ball & Beam system.

II. CLOUDS OF RESOURCES AND EMOTIONAL MASKS

In the book "The Emotion Machine" [2], Marvin Minsky puts forward a new theory and approach to emotions.

To start the theory he introduces a typical brain as containing many parts that are called "resources." Resources may be defined as any type of mental or physical activity. He believes that resources are any kind of structures or processes, which are from sensory devices to the thinking methods (figure 1).

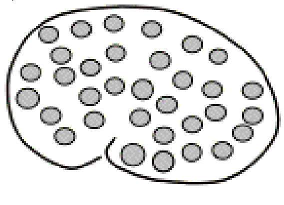

Figure 1. Brain and Resources [2]

Minsky says:

"For example, the state called "Anger" appears to arouse resources that make us react with unusual speed and strength—while suppressing resources that we otherwise use to plan and act more prudently [2]"

He takes a resource-based approach to the definition of emotions and says (figure 2):

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"Each of our major "emotional states" results from turning certain resources on while turning certain others off—and thus changing some ways that our brains behave [2]."

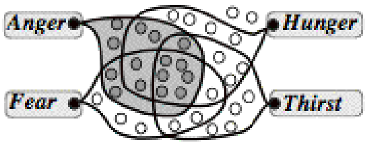

Figure 2. Emotions As Collections of Resources [2]

In [4 and 5], Harati et al. have presented a new computational model of emotions based on Minsky's theory of clouds of resources. To do so they have introduced a model of emotions based on managing mental resources.

They assume the mind as a collection of data and processes and an activation pattern that can perform the role of putting a subset of these resources in the working memory. Therefore, they consider an emotional state, nothing but a state of mind along with a feeling experience.

This model is divided into two parts:

1. An assessment and categorizing mechanism for activation of a proper combination of resources (emotional activation mechanism)
2. A collection of combination of resources among which the proper structure of mind for facing a situation is chosen.

In another work [6] the same authors have argued that in the currently used method of importing a subset of human emotional states into the target artificial system, the major differences between natural and artificial domain is ignored. They have mentioned four main problems existing due to the current method of definition of emotions as:

1. Human's emotional states are modeled based on high level concepts that are not definable in simple systems;
2. Usually the core of emotional system is defined directly by the designer, and usually the system is not able to learn or adjust these hardcode mechanisms;
3. The emotion mechanisms defined in such a way usually play the role of heuristic solutions for specific problems and therefore, are extremely dependent to the knowledge of the designer about the details of the problems that the system may face and their possible solutions;
4. Hardcode emotion definition prevents the systems from forming their own emotional identities and personalities.

In this work, we will try to solve these problems and introduce emotions into the control field without limiting them into these bounds

.

III. SCELIC

The idea of emotional masks provides a system with a resource management mechanism. These masks should be learned by a system itself so that it could form its emotions through time and experience. From an attention control point of view these masks are actually different attentional states of the system.

In such a system, apart from the learning of dynamics, there is also another learning involved, which learns the attention control. So, there are basically two learnings involved. One takes place in one layer that learns to control the plant. The other one should take place in the attention controller that learns which parts of the rule-base should take part in the decision making process. To do that we took several steps:

A. SOANFIC:

SOANFIC [3] stands for self-organizing adaptive network based fuzzy controller. This controller is a developed version of a self-organizing controller which provides a good structure for development of emotions. A Gradient Descent algorithm is used for the learning process in both SOANFIC and attention layer of SCELIC (to be discussed).

B. Step1:

We partitioned the crude rule-based structure into some parts, therefore, partitioning their input spaces as well. The reason for that is to make it easier for the system to define the resources but this also can be a part of the learning process. Actually we used five ANFIS in the lower level of a SOANFIC controller (SOANFIC is separately explained in another upcoming paper), instead of only one.

The rules can be built up based on the learning process. The lower level with this structure can be called the rule-layer or control-layer, because the control rules are learned here. These resources learn in parallel to control the plant.

C. Step2:

Now it is the time for providing the model with an attention controller. These resources have different beliefs about the control signal that should be sent to the plant. The attention controller performs the role of fusion of these beliefs based on situations, i.e. performing the role of emotional masking.

This is done here, by adding another layer to the lower level of the previously explained SOANIFC. This second layer is called the attention layer which provides the model with emotional processing mechanism. The structure is shown in figure 3. This controller is called the Self- Constructing Emotional Learning-based Intelligent Controller or shortly SCELIC.

Figure 5 shows the structure of a SCELC. It consists of three hierarchical levels as opposed to two hierarchical levels in a non-emotional version, including:

1. Performance layer
2. Control layer
3. Attentional or emotional layer

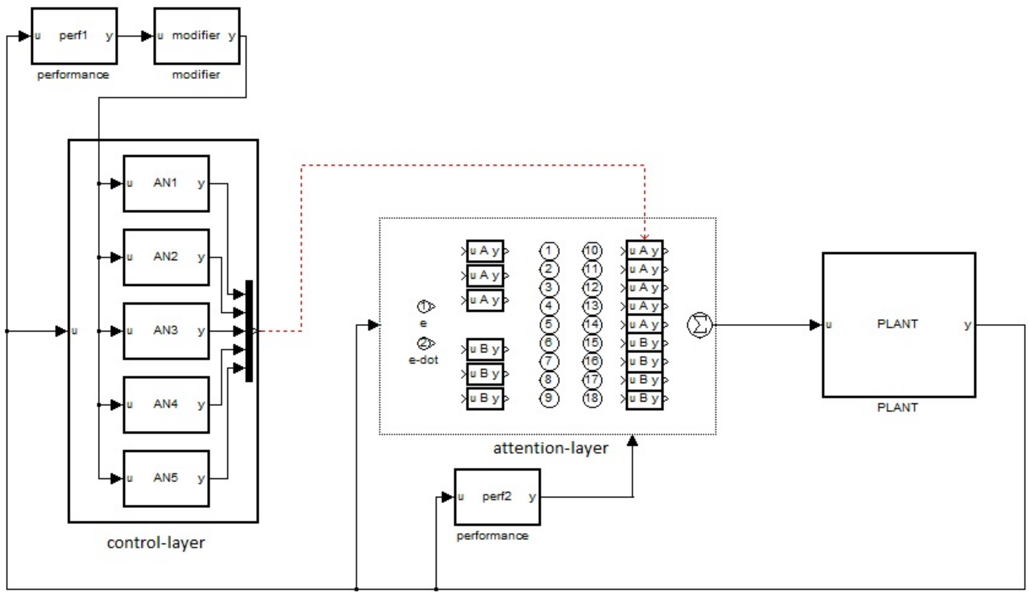

Figure 3. SCELIC Structure

1. *Performance layer:*

A performance layer is a layer responsible for producing the reinforcement signals. In Self-Organizing controllers, it is usually a manually defined table which provides a local performance measure based on the knowledge of the error and change in error. Such a table is shown in figures 4.

		CE												
		−6	−5	−4	−3	−2	−1	0	1	2	3	4	5	6
	−6	−6	−6	−6	−6	−6	−6	−6	0	0	0	0	0	0
	−5	−6	−6	−6	−6	−6	−6	−6	−3	−2	−2	0	0	0
	−4	−6	−6	−6	−6	−6	−6	−6	−5	−4	−2	0	0	0
	−3	−6	−5	−5	−4	−4	−4	−4	−3	−2	0	0	0	0
	−2	−6	−5	−4	−3	−2	−2	−2	0	0	0	0	0	0
	−1	−5	−4	−3	−2	−1	−1	−1	0	0	0	0	0	0
E	0	−4	−3	−2	−1	0	0	0	0	0	1	2	3	4
	1	0	0	0	0	0	0	1	1	1	2	3	4	5
	2	0	0	0	0	0	0	2	2	2	3	4	5	6
	3	0	0	0	0	2	3	4	4	4	4	5	5	6
	4	0	0	0	2	4	5	6	6	6	6	6	6	6
	5	0	0	0	2	2	3	6	6	6	6	6	6	6
	6	0	0	0	0	0	0	6	6	6	6	6	6	6

Figure 4. Procyk and Mamdani's Perf. Table

Instead of a performance table a simple penalty equation can be used (Objective function for Gradient Descent):

$$\Delta P = G_p(e_n + \tau \times ce_n) \times T_s$$

The learning rate G_p affects the convergence rate and T_s is the sample period. This penalty equation is an incremental one because the output is a change to an existing value. In order to keep the update rate independent of the choice of sample period the penalty equation is multiplied by T_s.

2. *Control layer:*

The control layer is responsible for the act of controlling the plant. The input space of this layer is partitioned to 5 parts, to provide the resources of the system, each of which is given to an ANFIS. So basically the 5 parts can be viewed as the resources of the emotional system. The control rules are built up here through ANFIS learning mechanism. These 5 parts learn in parallel how to control or stabilize the dynamics of the system based on the performance signal from pervious layer.

3. *Attention (Emotional) layer:*

This layer is responsible for fusion of the beliefs of the resources from the control layer. It consists of an ANFIS-like mechanism but the output of this layer is a linear combination of the outputs of ANFIS 1 to 5, from the control layer. This layer also uses a performance signal to form its learning.

Layer 1: every node in this layer can be an adaptive one and with the node function:

$$O_i^1 = \mu_{A_i}(x)$$

Layer 2: every node in this layer are fixed ones that multiply the inputs and send the output out or in other words each node output represents the firing strength of a rule:

$$w_i = \mu_{A_i}(x) \times \mu_{B_i}(y), i = 1,2$$

Layer 3: each node in this layer is a fixed node, which calculates the ratio of the firing strength of each rule to all rule's firing strengths:

$$\bar{w}_i = \frac{w_i}{w_1 + w_2}, i = 1,2$$

Layer 4: each node in this layer can be an adaptive node which constructs the consequent part of a fuzzy if-then rule:

$$O_i^4 = AN_i * \bar{w}_i$$

Layer 5: the nodes in this layer are fixed ones that calculate the total outputs of the network as a linear combination of the beliefs of the control-layer:

$$O_i^F = \sum_{i=1}^{n} AN_i * W_i$$

IV. Learning in SCELIC

The learning process takes place in 2 stages:

D. *Stage1:*

In the first stage, there is only an active learning in the control layer and the learning in attention layer is inactive.

1. Input space is partitioned to 5 parts each of which is given to only one ANFIS.
2. The 5 ANFIS learn to stabilize the plant, based on the performance1 signal.
3. The beliefs of AN1 to AN5 is fused using a hard-coded attention mechanism.

E. *Stage 2:*

This stage starts as soon as the control layer learns to stabilize the plant, in this stage the learning mechanism in the control layer is off and the learning in the attention layer is activated.

1. AN1 to AN5 learning have converged and there is no more learning in the control layer.
2. Learning in attention layer starts based on performance2 signal.

V. THE BALL & BEAM SYSTEM

The ball and beam system [11, 12 and 13] is widely used in the field of control, as many important classical and modern design methods can be studied based on it. It is inherently non-linear and unstable, and despite its simple nature, the cascaded dynamics of the system (with 3/4 integrators and an interconnection between rotational and translation subsystems) are very similar to planar control of rockets. The system (shown in Fig. 5) consists of a ball rolling on top of a long beam. This system has a very important property; it is an open loop unstable system, because for a fixed input (beam angle) the system output (the ball position) increases without a limit. The control job is to automatically regulate the position of the ball by changing the position of the motor. This is a difficult control task because the ball does not stay in one place on the beam when $\theta \neq 0$, but moves with an acceleration that is proportional to the tilt of the beam.

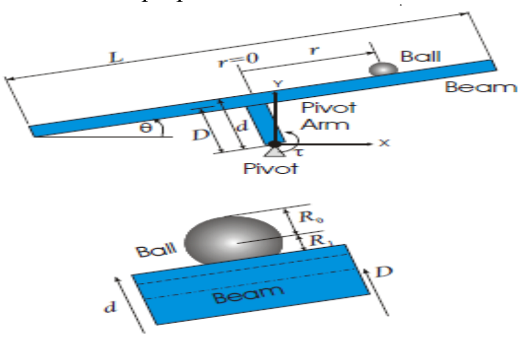

Figure 5. The ball & beam system [13]

Using Lagrange equations, a comprehensive set of equations for the motion of this system can be obtained as follows:

$$m\left[\ddot{r}\left(1+\frac{2}{5}\frac{R_0^2}{R_1^2}\right)+\ddot{\theta}\left(-d-R_1-\frac{2}{5}\frac{R_0^2}{R_1}\right)-\underbrace{r(\dot{\theta})^2}_{Centrifugal}+\underbrace{g\sin(\theta)}_{Gravitational}\right]+\underbrace{C_1\dot{r}}_{\substack{Ball\\Damping}}=0$$

$$\underbrace{-m\ddot{r}\left(d+R_1+\frac{2}{5}\frac{R_0^2}{R_1}\right)}_{Ball\ Translation}+\ddot{\theta}\left(\underbrace{J_{beam}}_{\substack{Beam\\Rotation}}+\underbrace{m\left(R_1^2+\frac{2}{5}R_0^2+r^2+d^2+2R_1d\right)}_{Ball\ Rotation}\right)$$
$$+\underbrace{2mr\dot{r}\dot{\theta}}_{Coriolis}-\underbrace{gMD\sin(\theta)}_{Beam\ Gravitational}-\underbrace{gm(\sin(\theta)(R_1+d)+r\cos(\theta))}_{Ball\ Gravitational}+\underbrace{C_2\dot{\theta}}_{\substack{Beam\\Damping}}=\tau$$

With m being the mass of ball and M the mass of beam; R_0 and R_1 are the radius and the rotation axis of the ball as shown in the figure. D and d are the distance from pivot to the center of mass of the beam and plane of ball contact on the beam respectively. J_{beam} is the moment of inertia of the beam and L is the length of the beam; and finally C_1 and C_2 are the viscous friction coefficient between the ball and the beam and viscous damping constant of the servo-motor. Figure 5 also shows the variables used in the formulation of the problem. The derivation process is explained thoroughly in [13].

VI. SIMULATION RESULTS:

The parameter set used in the simulation are as follows: M=0.5 kg ; m=0.11 kg ; R0=0.015 m ; R1=0.01 m ; d=.035 m ; D=0.03 m ; g=9.81m/s^2 ; L=1 m; J_beam=1/12*M*L^3 kg.m^2 ; C1=0 ; C2=0 ;

And with initial conditions being:

$$r_0 = 0.3,\ \dot{r}_0 = 0,\ \theta_0 = 0,\ \dot{\theta}_0 = 0,$$

In the simulations, SCELIC is starting from scratch without any control rules. The first learning learns the control rules using a hard-coded attention mechanism (figure 8) and the second learning learns how to fuse the beliefs of AN1 to AN5; i.e. learns the attention control process (figure 9).

After 156 epochs in stage 1 of learning process the hard-coded attention mechanism is able to stabilize the plant (figure 6) and the learning is shifted to stage 2. The ball position is shown in figure 9 after 15, 400 and 4000 epochs of learning in stage 2. As it can be seen after a very short time (15 epochs) the attention control mechanism provides a rather satisfactory response from a highly chaotic one but with steady state error. Then the controller learns to make the steady state error as small as possible.

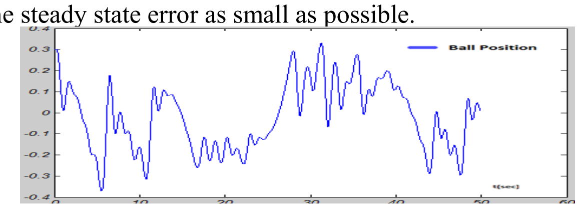

Figure 8. Ball position, Stage 1 of learning- after 156 epochs

As it can be seen from figure 7, AN2, AN3 and AN4 have the greatest effect on the control of the plant and AN1 and AN5 have a very small fusion factors. This means that the system can be controlled using only 3 of its 5 resources with learned fusion factors.

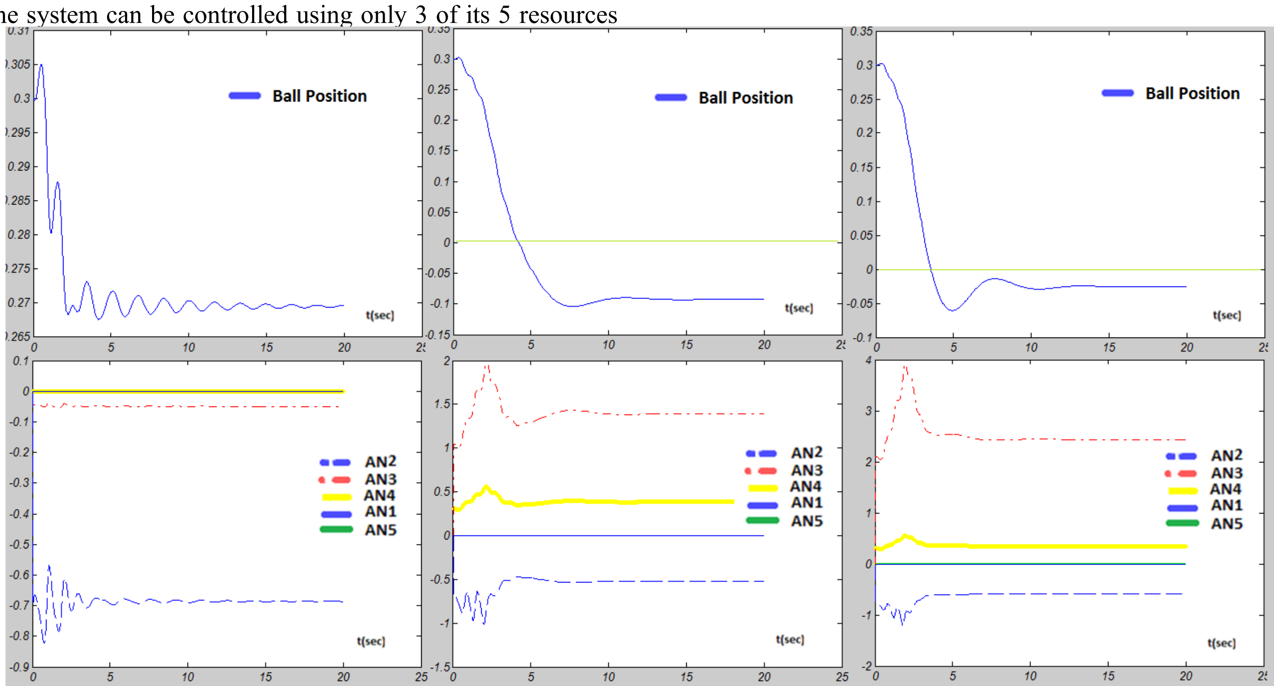

Figure 7. Ball Position (1st row) and fusion factors (2nd row) vs. simulation time after 15, 400 and 4000 epochs respectively

VII. CONCLUSION

In this work we presented the usage of clouds of resources and emotional masks in the field of control. This new approach provides a sensible mapping between what we know as emotions and what is present in machines. The model of emotional masks, models the whole brain structure for emotional thinking as opposed to other methods that model only some parts of the brain.

SCELIC is a model free and self-constructing controller, meaning that it can construct the control rules from the scratch by itself while provided with a very simply developable performance measure by the designer. It should be noted that SCELIC, learns emotions and attention, as opposed to hard-coded emotion definitions that have a little flexibility. Furthermore, to test the applicability of SCELIC, a nonlinear ball and beam system was used as a test-bed. SCELIC showed that it can stabilize the system while starting from scratch and that it can provide a satisfactory response in a rather short time. It can be concluded that the emotional mechanism is most useful when we want to learn to provide a system with a rather satisfactory response in a very short time.

REFERENCES

[1] Russell & Norvig, “Artificial Intelligence: a modern approach”, Prentice Hall; 2nd edition, 2002

[2] Minsky, Marvin, “The emotion machine”, Simon & Schuster Publications (November 7th, 2006)

[3] Saghir H. R. , “Emotional Control”, MS Thesis, Sharif university of technology, 2010.

[4] Harati Zadeh, ” A Model for Generating Emotional Behavior”, PhD Thesis , Sharif University of Technology, 2008.

[5] Harati Zadeh, S., Bagheri Shouraki, S.,Halavati, R ,“Artificial Emotions for Artificial Systems”, Proceedings Of Association For The Advancement Of Artificial Intelligence (AAAI) Conference On Spring/2008

[6] Harati Zadeh, S., Bagheri Shouraki, S.,Halavati, R., “Emotional Behavior: A Resource Management Approach”, International Journal Of Adaptive Behaviour, Vol. 14, No. 4, 357-380 (2006)

[7] Jantzen Jan, “The Self-Organising Fuzzy Controller”, Technical University of Denmark, Department of Automation, Bldg 326, DK-2800 Lyngby, DENMARK. Tech. report no 98-H 869 (soc), 19 Aug 1998.

[8] Procyk T J, Mamdani EH, “a Linguistic Self Organizing Process Controller”, Automatica, Vol.15, No.1, Pp. 15-30, 1979

[9] Jang J S R, “ANFIS: Adaptive Network Based Fuzzy Inference System”, IEEE Transactions, Man & Cybernetics 1991

[10] M. A. Sharbafi, C. Lucas, A. T. Haghighat, O. A. Ghiasvand, and Omid Aghazade “Using Emotional Learning in Rescue Simulation Environment,” in Transactions on Engineering, Computing and Technology, World Enformatika Society, Vol. 13, pp. 333–337, May. 2006.

[11] Wen Yu, “ Nonlinear PD regulation for ball and beam system”, International Journal of Electrical Engineering Education, Jan 2009.

[12] Li. J., Wang H. O., Niemann D. and Bushnell L. “Nonlocal Control of the ball and beam system: Regulation and Tracking”, IEEE world congress on computational intelligence, 1998.

[13] Cazzolato B. S., Wang W., ”Dynamics of The Ball and Beam System”, retrieved on December 2010 from http://sites.mecheng.adelaide.edu.au/robotics/robotics_projects.php