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Target Tracking Control of a Mobile Robot Using a Brain Limbic System Based Control Strategy

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Abstract— **In this paper, a Brain limbic system (BLS) based control algorithm is used to address the problem of target tracking in mobile robotics. The mathematical description of this approach in the form of BELBIC (Brain Emotional Learning Based Intelligent Control; also referred to as BLS) is presented and used to generate appropriate velocity profile for the mobile robot to track its target. The overall performance of the system is enhanced via fuzzy clustering of the error and velocity pairs.**

I. Introduction

In the area of automation, robots or automatic systems are mostly considered to work in known environments. However, complex tasks and special missions such as exploration of unknown environments require further evolution of existing methods. Among possible approaches to be used are method based on emotional signal processing in the brain. In cognitive science, emotional signal processing has been explored for a number of years. Mowrer [1] described a two-process model of learning through amygdalo-orbitofrontal system. Rolls [2] elucidated the mechanism of the emotion and its application to the neural basis of emotion. LeDoux [3] and Rolls [4] explained the function of Amygdala in the emotional process. Balkenius and Moren [7] computationally modeled the algorithm of generating emotions in the human brain and verified this model using basic simulations.

Later on, Lucas, et al. [8] introduced the application of Moren's model, which they termed Brain Emotional Learning, or BEL, as an intelligent controller. Mehrabian and Lucas [9] designed a robust adaptive controller for stable uncertain nonlinear systems with BEL. Chandra and Langari [10] analyzed the BEL based approach, which they referred to as Brain Limbic System, or BLS, by using methods of nonlinear systems theory. Shahmirzadi, et al. [11] compared the BEL/BLS based control with sliding mode control. BEL/BLS has also been evaluated in systems ranging from washing machines (Lucas, et al. [12]), HVAC systems (Sheikholeslami, et al. [13]), to aerospace launch systems (Mehrabian, [14]), micro-heat exchangers (Rouhani, et al. [15]), and path tracking (Jafarzadeh, et al. [20]), etc.

In this paper, we utilize the Brain Limbic System (BLS) based control in a mobile robot target tracking problem. By introducing BLS (also referred to as BEBLIC; Brain Emotional Learning Based Intelligent Control) the mechanism of decision making based on the brain limbic systems will be explained. The BLS/ BELBIC control is applied to a mobile robot with two different approaches, BELBIC along and BELBIC with fuzzy clustering. The performance of BELBIC is demonstrated using simulation results and future work will be discussed.

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II. Brain Emotional Learning

The main components of the human brain involved in processing emotions are shown in Fig. 1. As it is evident, the Amygdala and the Orbitofrontal Cortex (OFC) are mainly involved in generating human emotions. The Amygdala learns appropriate connections between neutral and emotionally charged stimuli while the OFC tries to inhibit inappropriate connections as the goal or the context changes.

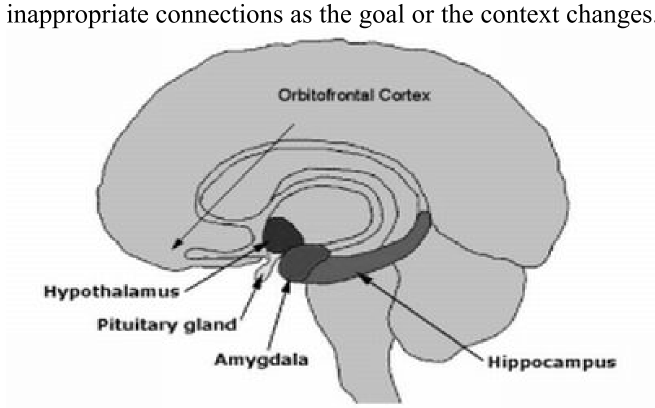


Fig. 1. A generic view of the human brain

Moren and Balkenius [5], [7] developed a computational model of the so called brain emotional learning process as schematically depicted in Fig. 2. Eqns. (1) through (5) capture a simplified model of this process. Here the Amygdala and the OFC are modeled as simple gains G_{A_i} and G_{OC_i}, with the sensory input signals denoted by SI_i and the emotional reward signal by *Rew*. Note that ΔG_{A_i} and ΔG_{OC_i} represent the incremental adjustments of each gain with respect to the sensory inputs and emotional reward. Also note that A_i is the output signal of the Amygdala while OC_i is that of the OFC. The difference between these two signals, i.e., *MO* is the model output:

$$MO = \sum_i A_i - \sum_i OC_i \quad (1)$$

$$A_i = G_{A_i} \cdot SI_i \quad (2)$$

$$OC_i = G_{OC_i} \cdot SI_i \quad (3)$$

$$\Delta G_{A_i} = \alpha \cdot SI_i \cdot \max\left(0, Rew - \sum_i A_i\right) \quad (4)$$

$$\Delta G_{OC_i} = \beta \cdot SI_i \cdot \left(\sum_i A_i - \sum_i OC_i - Rew\right), \quad (5)$$

where α, β are the learning rates. The Reward signal, *Rew* (also called the Emotional que Signal, or simply the Emotional Signal, ES) is internally generated (possibly by the pre-frontal cortex, which is not shown in the reference figure.) Note that in Fig. 2 the Thalamus functions as a communicator between the cortical and the other parts of the loop. The Sensory Cortex manipulates the sensed input to produce SI.

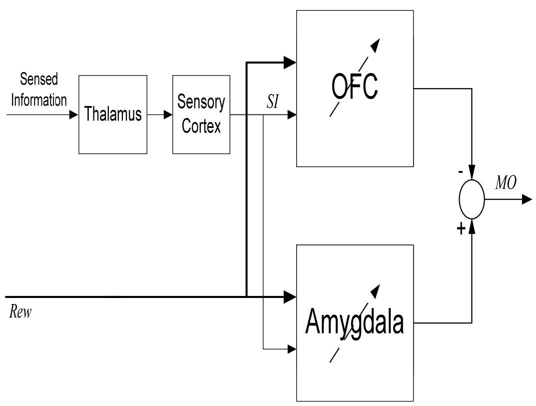


Fig. 2. A computational model of BEL

In reference to (4), the Amygdala output increases up to such time as when it reaches the level of *Rew*. However, in the OFC the gain G_{OC_i} can increase or decrease based on the values of *Rew* and the model output. As a result the OFC inhibits the emotional outputs for inappropriate associations or reinforces the appropriate ones. Note that the once the system reaches its target value, the parameters referenced above no longer vary. In other words, the relevant parameters converge to their final values.

III. APPLICATION TO A MOBILE ROBOT

In this section, the application of the aforementioned approach to a mobile robot is considered. The kinematic model of wheeled mobile robot is described as follows:

$$\dot{x} = v\cos\theta \quad (6)$$

$$\dot{y} = v\sin\theta \quad (7)$$

$$\dot{\theta} = w, \quad (8)$$

where v and ω are the translational and the angular velocities of the robot respectively. A two-wheeled robot is controlled by changing the speed of each of its two motors. These in turn change with translational and angular velocities of the robot. To explain the robot coordinate, ego-centric (robot centric) coordinates are introduced [21].

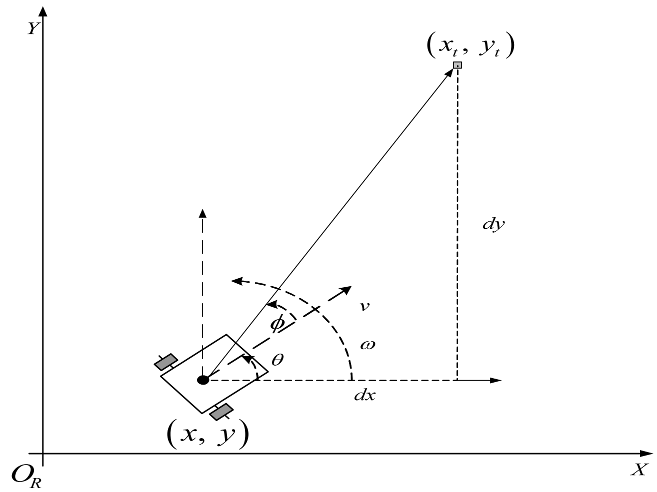


Fig.3. Mobile robot coordination

In ego-centric view, the robot does account for the relative position of the target with respect to itself. Therefore the position of the agent is always the origin O_R when a new target or mission is given. However, the robot keeps the final direction of its previous task as the initial robot direction as it sets to execute a new mission.

We have used the potential field methodology in this problem. The robot is attracted to the goal and this attraction force is represented as a vector form whose magnitude is the distance error between the robot position (x, y) and the target position (x_t, y_t) (defined as sensory input *SI*) while its direction is the direction (defined as $\phi + \theta$) is oriented towards the target. The Rewards function (*Rew*) is chosen as the summation of the weighted *SI* and u_P, the control input to the plant, i.e. robot velocity. As explained in the previous section, the model output converges to a constant as it accomplishes its task. In this specific case of target tracking, robot velocity might not reach zero as the robot reaches the target. As a result, the robot may fail to reach the target. To prevent this problem, we modify the translational velocity by multiplying *SI* and the output *MO*, as follows

$$u_P = SI \times MO. \quad (9)$$

This method guides a rational velocity profile, which is initially accelerating at first period and decelerating as it approaches to the target as shown in Fig. 4. Accordingly, *SI* and *Rew* are given by

$$SI = \sqrt{(x_t - x)^2 + (y_t - y)^2} \quad (10)$$

$$Rew = \gamma SI + \delta u_P, \quad (11)$$

where $\gamma = \frac{v_{\max}}{e_{\max}}$, *MO* is the model output. The positive constant δ is defined by the user.

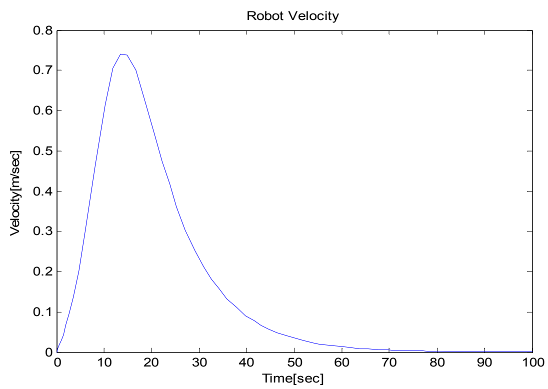


Fig. 4. Translational velocity of the robot

By substituting (10)-(11) into (4) and (5) we have

$$\dot{G}_A = \alpha \max\left\{0, \gamma + \left(\delta SI - 1\right)G_A - \delta G_{OC} SI\right\} SI^2 \qquad (12)$$

$$\dot{G}_{OC} = \beta\left\{ \left(1 - \delta SI\right)G_A + \left(\delta SI - 1\right)G_{OC} - \gamma\right\} SI^2 . \qquad (13)$$

From Fig. 3., we defined ϕ as the difference between the angle to the target from robot position and the robot's direction

$$\phi = \tan^{-1}\left(\frac{dy}{dx}\right) - \theta . \qquad (14)$$

The idea is to generate the angular velocity according to the magnitude of the angel ϕ :

$$\omega = \varepsilon \phi \qquad (15)$$

where ε is a proportional gain. Therefore, the control inputs, translational velocity and angular velocity, of the mobile robot are given by

$$\begin{aligned} v &= \delta u_P \\ \omega &= \varepsilon \phi \end{aligned} \qquad (16)$$

IV. Target Tracking via BELBIC

The schematic model of a mobile robot with the BLS control system is given in Fig. 5. Distance/ Angle error block calculates the errors to produce *SI* and *Rew* as inputs to the BLS controller. The dotted line represents the mission completion signal flow. We defined a reasonably small neighborhood (a ball) centered at the target position for the robot to determine whether the task is accomplished. Once the robot completed its mission, the target generator receives

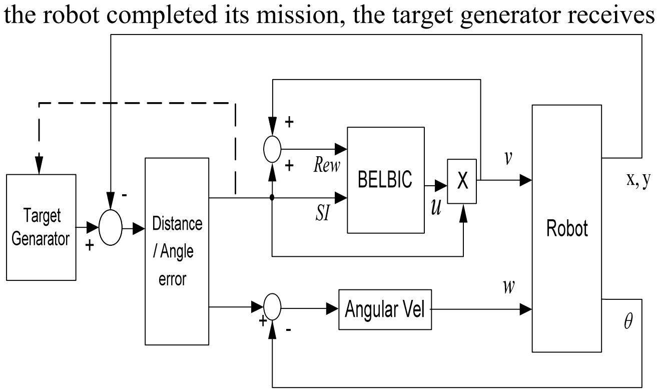
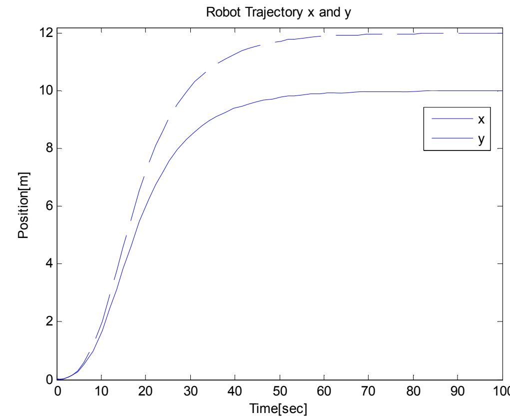
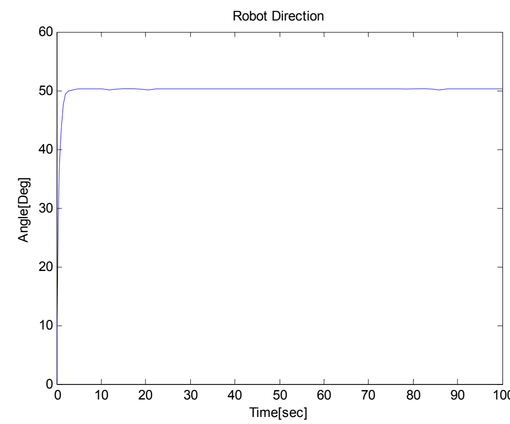


Fig. 5. Schematic model of target tracking mobile robot

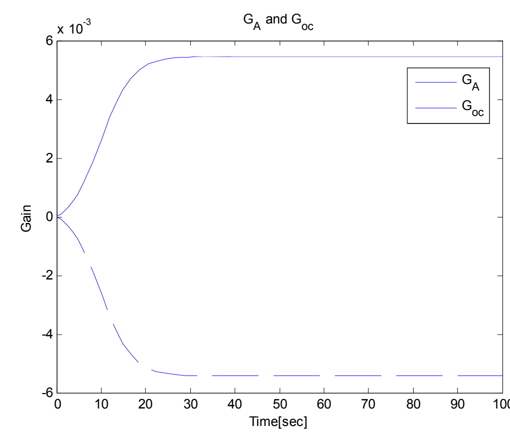
a command to assign a new mission. This process lets the robot execute the multiple missions in sequence. Fig. 6. shows Matlab simulation results to demonstrate the performance of a mobile robot with single and multi targets. The multiple targets missions are accomplished in sequence. In the multi target results figure, A, B, C, and D implies the sequence of the mission accomplished.



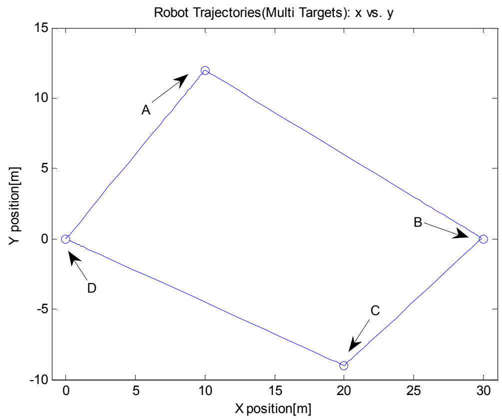
(a) Robot Trajectory x vs. y



(b) Robot direction



(c) Change of Amygdala and OFC gains



(d) Multi target tracking trajectory of a mobile robot
Fig. 6. BELBIC mobile robot target tracking

V. FUZZY CLUSTER USED TARGET TRACKING METHOD

In this section, we utilize BELBIC with fuzzy clustering method by mapping error and velocity pairs on a 2 dimensional plane. As shown the Fig. 7, there are two regions in the error vs. velocity plot. We defined a desired velocity line which is diagonal in the middle of Fig. 7. $Cd1$ and $Cd2$ represent the upside area of the line and downside of the line, respectively. For the robot to track the target, it has to generate the desired translational velocity given the present distance error. If the error is large the robot needs to speed up, however, as the robot comes closer to the target, it must be decelerated to avoid collision. Therefore when the agent locates $Cd1$ the velocity has to be reduced and vise versa.

In reference to Fig. 7, let us define e_a as the distance error at robot location, 'a'. For other locations, i.e. 'b', 'c', and 'd', e_b, e_c, and e_d are defined as well. Let v_H be the robot velocity at locations 'a' and 'b', and v_L be at 'c' and 'd' respectively. When they are compared, the velocity of the robot at location 'a' has to be changed to the desired velocity

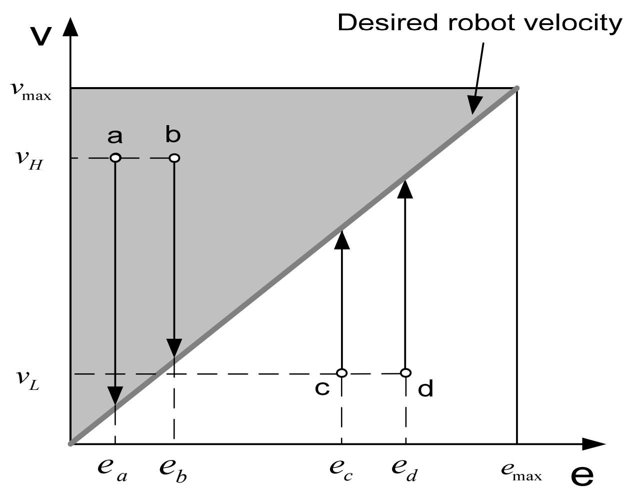


Fig. 7. Error and velocity pair

(marked by the oblique line in Fig. 7) faster than that of 'b' because the distance from the desired location is larger. This concept is implemented through acceleration of v. For example, 'a' and 'd' should have larger absolute value acceleration than 'b' and 'c'. From this notion, we use fuzzy rules to as described below.

To cluster each velocity and error pair, 121 fuzzy rules are defined as shown

R_1 : *If error is 0 and velocity is 0, then* $Cd1$ *is 0 and* $Cd2$ *is 0.*

R_2 : *If error is 0 and velocity is 1, then* $Cd1$ *is 1 and* $Cd2$ *is 0.*

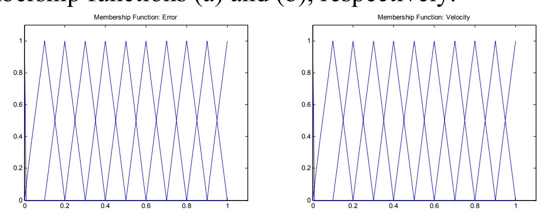
R_3 : *If error is 0 and velocity is 2, then* $Cd1$ *is 2 and* $Cd2$ *is 0.*

$\vdots$

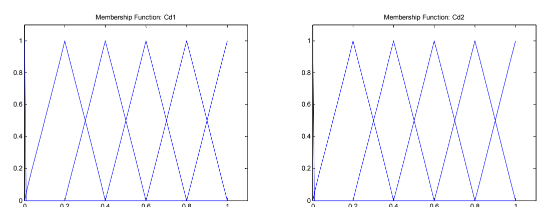
R_{120} : *If error is 10 and velocity is 9, then* $Cd1$ *is 0 and* $Cd2$ *is 1.*

R_{121} : *If error is 10 and velocity is 10, then* $Cd1$ *is 0 and* $Cd2$ *is 0.*

Fig. 8. shows the antecedent and consequent membership functions used to form fuzzy rules. The distance error and translational velocity are normalized to apply fuzzy membership functions (a) and (b), respectively.



(a) Error membership function
(b) Velocity membership function



(c) $Cd1$ membership function
(d) $Cd2$ membership function
Fig. 8. Antecedent and consequent membership functions

Now, the fuzzy output is manipulated to generate Reward

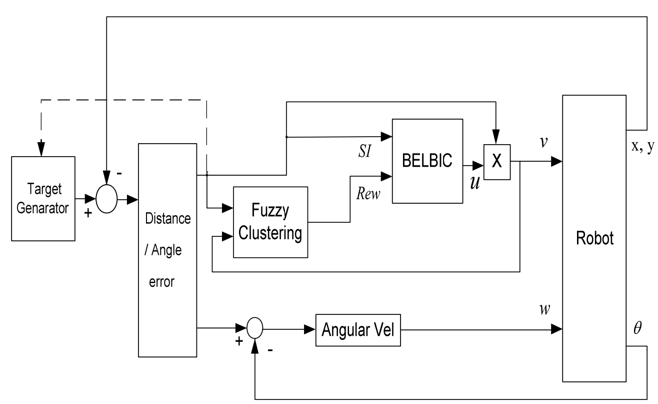


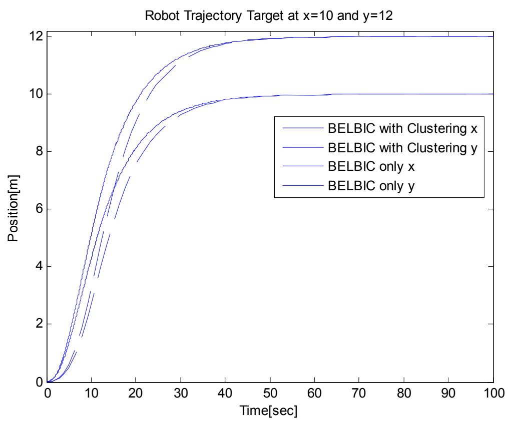
Fig. 9. Schematic model of fuzzy cluster used target tracking method

function as an input to the BELBIC. Fig. 9. shows the flow of signals to implement this concept. Feedback distance error, as well as velocity are used to generate Cd_1 and Cd_2, which are in turn used to create *Rew* by the following rule

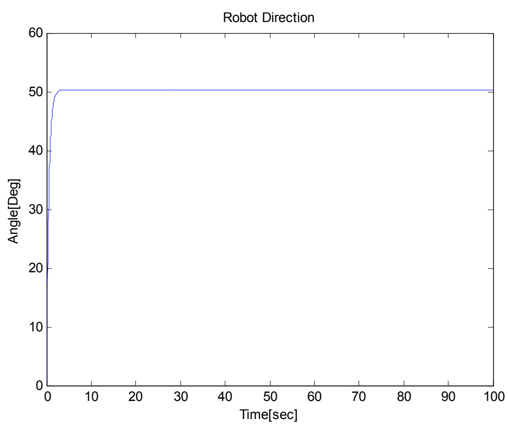
$$Rew = \mu_1 Cd_1 + \mu_2 Cd_2 + v\,, \tag{17}$$

where μ_1 and μ_2 are constants.

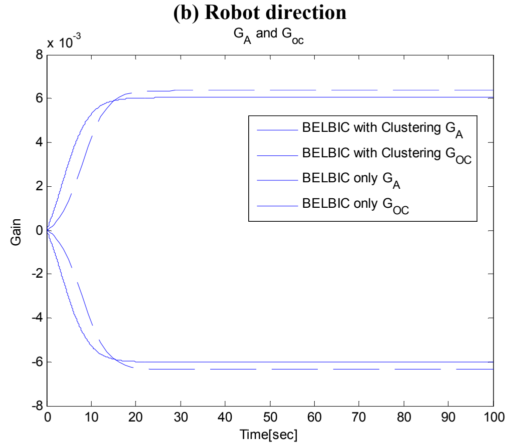
Fig. 10. depicts the comparison of simulation results from BELBIC and fuzzy clustering BELBIC. When they are compared with the results of BELBIC alone, we can observe



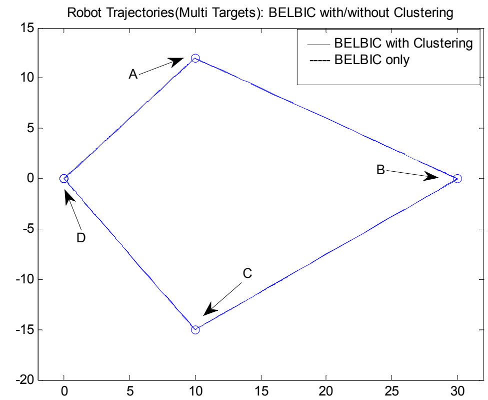
(a) Robot Trajectory x vs. y



(b) Robot direction



(c) Change of Amygdala and OFC gain



(d) Multi target tracking trajectory of a mobile robot

Fig. 10. Fuzzy cluster BELBIC mobile robot target tracking

the task speed of cluster applied method is a little bit faster. Again, the multi target tracking result is given at the last figure and it shows that the trajectory of each method has few differences which occur at the beginning of targeting.

VI. CONCLUSIONS

In this paper, the application of Brain Limbic System (BLS) or alternatively Brain Emotional Learning Based Intelligent Controller(BELBIC) to a mobile robot is considered. The main contribution and what we emphasize is the application of BELBIC to a mobile robot. The simulation results demonstrate the performance of BELBIC. Also when the fuzzy clustering method is combined with BELBIC, the performance is improved. In both methods, the robot could track the assigned target successfully.

The BELBIC consists of the Amygdala as a reactive layer and the OFC as somewhat deliberative layer. By this research, we recognized that the learning that occurs in BEBLIC is not necessarily retained once the mission is changed. In other words, as the target changes the memory in BELBIC is reset.

Therefore we conclude that BELBIC can be used as short-term intelligence model. As shown in the simulation

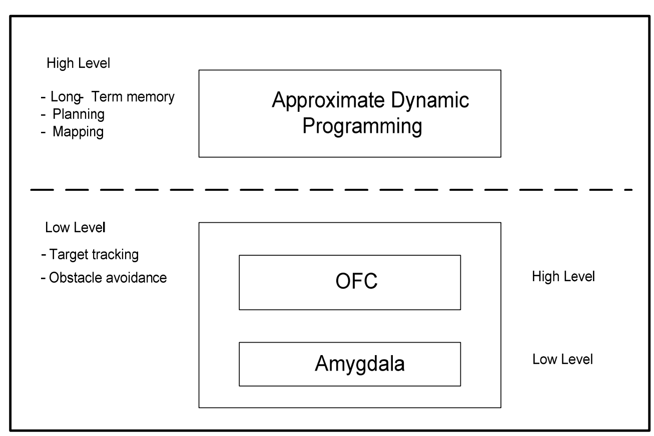


Fig. 11. Schematic of an artificial intelligent mobile robot

results, BELBIC works very well at the lower, or reactive layer. However, to develop more intelligent agents that can plan and navigate under unknown environments autonomously, a long-term deliberative layer is necessary. Figure. 11. is a schematic of an artificial intelligent structure. BELBIC is utilized as a short-term intelligence model to task accomplishment and Approximate Dynamic Programming or equivalent method will be used as task planner and mapping tool. To verify the utility of BELBIC, the experiment with real mobile robot will be conducted. And as the next step of work, the development of the higher level intelligent structure will be planned.

ACKNOWLEDGEMENTS

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REFERENCES

[1] O. H. Mowrer, *Learning theory and behavior*, New York:Wiley, 1960.

[2] E. T. Rolls, A theory of emotion, and its application to understanding the neural basis of emotion, in *Emotions: neural and chemical control,* Y. Oomura, Ed., Tokyo: Japan Scientific Societies Press, pp. 325-344, 1986.

[3] J. E. LeDoux, In search of an emotional system in the brain: leaping from fear to emotion and consciousness, in *The cognitive neurosciences,* M. S. Gazzaniga, Ed., Cambridge, MA: MIT Press, pp. 1049-1061, 1995.

[4] E. T. Rolls, A theory of emotion and consciousness, and its application to understanding the neural basis of emotion, in *The cognitive neurosciences*, M. S. Gazzaniga, Ed., Cambridge, MA: MIT Press, pp. 1091-1106, 1995.

[5] J. Moren and C. Balkenius, "A Computational Model of Emotional Learning in the Amygdala," in *Proc. 6th International Conference on the Simulation of Adaptive* Behavior, Cambridge, Mass., MIT Press, 2000.

[6] J. Moren, "Emotion and Learning-A computational model of the amygdale," Ph.D. Dissertation, Lund Univ., Sweden, 2002.

[7] C. Balkenius and J. Moren, “Emotional Learning: A Computational Model of the Amygdala,” *Cybernetics and Systems: An International Journal*, vol. 32, pp. 611-636, 2001.

[8] C. Lucas, D. Shahmirzadi, and N. Sheikholeslami, “Introducing BELBIC: Brain emotional learning based intelligent controller,” *Intelligent Automation and Soft Computing*, vol. 10, no. 1, pp. 11-21, 2004.

[9] A. R. Mehrabian and C. Lucas, “Emotional Learning based Intelligent Robust Adaptive Controller for Stable Uncertain Nonlinear Systems”, *International Journal of Intelligent Technology*, vol. 1, no. 1, 2005.

[10] M. Chandra and R. Langari, “Analytical Study of a Control Algorithm Based on Emotional Processing,” in *Proceedings of the 2006 American Control Conference*, Minneapolis, Minnesota, USA, June 14-16, pp. 3433-3438, 2006.

[11] D. Shahmirzadi, R. Langari, L. J. Ricalde, and E. N. Sanchez, “Intelligent vs. sliding mode control in rollover prevention of tractor-semitrailers,” *International Journal of Vehicle Autonomous Systems*, vol. 4, no.1, pp. 68 – 87, 2006.

[12] Lucas, R. M. Milasi, and B. N. Araabi, “Intelligent modeling and control of washing machine using locally linear neuro-fuzzy (LLNF) modeling and modified brain emotional learning based intelligent controller (BELBIC),” *Asian Journal of Control*, vol. 8, no. 4, pp. 393-400, 2006.

[13] N. Sheikholeslami, D. Shahmirzadi, E. Semsar, C. Lucas, and M. J. Yazdanpanah, “Applying brain emotional learning algorithm for multivariable control of HVAC systems,” *Journal of Intelligent and Fuzzy Systems*, vol. 17, no. 1, pp. 35-46, 2006.

[14] R. Mehrabian, C. Lucas, and J. Roshanian, “Aerospace launch vehicle control: An intelligent adaptive approach,” *Aerospace Science and Technology*, vol. 10, no. 2, pp. 149–155, 2006.

[15] H. Rouhani, M. Jalili, B. N. Araabi, W. Eppler, and C. Lucas, “Brain emotional learning based intelligent controller applied to neurofuzzy model of micro-heat exchanger,” *Expert Systems with Applications*, vol. 32, no. 3, pp. 911-918, 2007.

[16] H. Rouhani, A. Sadeghzadeh, C. Lucas, and B. N. Araabi, “Emotional learning based intelligent speed and position control applied to neurofuzzy model of switched reluctance motor,” *Control And Cybernetics*, vol. 36, no. 1, pp. 75-95, 2007.

[17] R. Mehrabian, C. Lucas, “Intelligent adaptive control of non-linear systems based on emotional learning approach,” *International Journal on Artificial Intelligence Tools*, vol. 16, no. 1, pp. 69-85, Feb, 2007.

[18] T. Babaie, R. Karimizandi, and C. Lucas, “Learning based brain emotional intelligence as a new aspect for development of an alarm system,” *Soft Computing*, vol. 12, no. 9, pp. 857-873, 2008.

[19] R. Mehrabian, C. Lucas, and J. Roshanian, “Design of an aerospace launch vehicle autopilot based on optimized emotional learning algorithm,” *Cybernetics and Systems*, vol. 39, no. 3, pp. 284-303, Apr. 2008.

[20] S. Jafarzadeh, R. Mirheidari, M. R. J. Motlagh, and M. Barkhordari, “Designing PID and BELBIC controllers in path tracking problem,” *International Journal of Computers Communications & Control*, vol. 3, pp. 343-348, 2008.

[21] R. R. Murphy, *Introduction to AI Robotics*, Cambridge, MA: MIT Press, 2000.

[22] R. Siegwart and I. R. Nourbakhsh, *Introduction to Autonomous Mobile Robots*, Cambridge, MA: MIT Press, 2004.