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Using BELBIC based optimal controller for omni-directional three-wheel robots model identified by LOLIMOT

Maziar Ahmad Sharbafi[a,*], Caro Lucas[a], Aida Mohammadinejad[b]

[a]*Department of Electrical & Computer, University of Tehran, Tehran, Iran*
[b]*Department of Electrical, Khaje Nasir Toosi University of Technology, Tehran, Iran*

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Abstract

In this paper, an intelligent controller is applied to control omni-directional robots motion. First, the dynamics of the three wheel robots, as a nonlinear plant with considerable uncertainties, is identified using an efficient algorithm of training, named LoLiMoT. Then, an intelligent controller based on brain emotional learning algorithm is applied to the identified model. This emotional learning is based on a computational model of limbic system in the mammalian brain. The Brain Emotional Learning Based Intelligent Controller (BELBIC), using the concept of LQR control is adopted for the omni-directional robots. The performance of this multi objective control is illustrated with simulation results based on real world data. This approach can be utilized directly to the robots in the future.

Keywords: Reinforcement Learning; Emotional Learning; Neurofuzzy identification

1. Introduction

Our knowledge about the plant or process that should be controlled is often combined with uncertainty. Mostly, even after identification; some unconsidered events may change its characteristics like aging, friction, and etc. Noises and disturbances may cause some problems in the systems too. In recent years, data-driven and rule-base approaches are utilized more than model-based approaches to decision making.

In omni-directional robots which are used in RoboCup the preliminary methods of control the motion of robots were applying classic controllers like PID using its mathematical equations and the inverse kinematics. Recently instead of these methods, fuzzy controllers are used too much [2, 11-13], in which, the researchers design some heuristic fuzzy rules. Neural network is another common approach to control of the robots' motion [13]. Because of the uncertainties of the robots in real world, these pre-designed controllers may cause many difficulties, and "Reinforcement Learning" is one way to cope with them. In this paper we try to identify and obtain a model of system and then train an emotional controller based on BELBIC.

At the first step we use LoLiMoT, to identify the robot's dynamic because of its special characteristics like accuracy and velocity of operation in control applications [19]. Next, we have added the goal of keeping the control effort as low as possible to the usual goal of tracking the set point to implement control that is not cheap (Control system whose performance measures are of the plant input are called cheap) [1]. So the parameters are chosen according to designing rules of the optimal controller.

Although the LQR is a robust optimal controller, in this case many problems avoid us from utilizing exact model for the system to design the controller. Some of them are the difference between the robots, the uncertainty of the environment and complexity of the exact dynamic model.

[*] Corresponding author. Tel.: +98-21-66937246; fax: +98-21-66937246; e-mail: m.sharbafi@ece.ut.ac.ir.

For these reasons we propose a direct BELBIC controller which its applications extend recently [4-8]. The results demonstrate the desirable performance of this method which is inspired from the mammalians learning.

The rest of this paper is organized as follows: Section 2 formulates the problem of three-wheel robot. In section 3, we describe a summary about LOLIMOT and the identification difficulties of this system. BELBIC is described in section 4. Section 5 illustrates the simulation results obtained with this way and finally, section 6 concludes this paper.

2. Three Wheel Robot Motion

Three-wheel vehicle design is the simplest omni-directional model. One of the common usages of such mobile systems is in RoboCup soccer competitions. The first and most important step for playing football is control of the robots motion accurately and smoothly. If the robot can go to every point precisely, it can catch the ball, can defend against opponent's shoot and carry the ball to a suitable point. In the next step the strategies should be designed.

Fig. 1 shows the schematic of a three-wheel robot and its angles and directions. The relation between velocity of the wheels and differentiation of the position and angle of the robot relative to fixed coordination is demonstrated in (1).

$$M = \frac{1}{R}\begin{bmatrix} -\sin(\delta+\varphi) & \cos(\delta+\varphi) & L_1 \\ -\sin(\delta-\varphi) & -\cos(\delta-\varphi) & L_1 \\ \cos(\varphi) & \sin(\varphi) & L_2 \end{bmatrix}$$

$$\begin{bmatrix} \dot{\theta}_1 \\ \dot{\theta}_2 \\ \dot{\theta}_3 \end{bmatrix} = M \times \begin{bmatrix} \dot{x} \\ \dot{y} \\ \dot{\varphi} \end{bmatrix} \quad (1)$$

In this formula $\dot{x},\dot{y},\dot{\varphi}$ show position and direction of the robot in the fixed coordination, R, L_i, δ are radius of the wheel, distances from the centre of the robot to the wheels and the angle between the orientation of the robot and direction of the first wheel, respectively (they are shown in Fig. 1) and $\dot{\theta}_i$ is the velocity of the wheel i.

Because of sinusoidal function of φ in matrix A the model is nonlinear. This relation is between the velocities without consideration of the inequality of the motors of the real robots and its geometric characteristics. Also the considering the dynamic rules of the real system make it more complex. To control the position and direction of the real robot we give three PWM voltages to the motors and the relation between the produced force of motor and the voltage is important too.

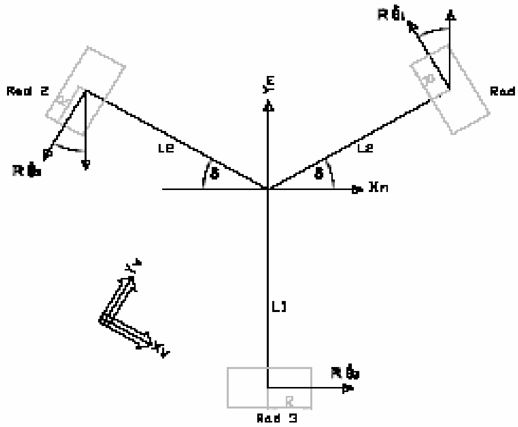

Fig. 1. The model of three-*wheel* robot.

3. Identification with LoLiMoT

Many attitudes in identification can be seen in the literature based on the nonlinear function approximators. An alternative approach is to design a nonlinear model consisting of several linear functions. The major output function is derived from a combination of linear models. Many training algorithms and structures are suggested for the mentioned networks such as TSK, ANFIS, LoLiMoT and PLN neurofuzzy networks [3, 15-17]. Because of the accuracy and convergence speed, LoLiMoT is selected in this research. In the following, the nonlinear dynamic processes modelling, using LoLiMoT algorithm is described.

The network structure of a local linear neurofuzzy model [3] is depicted in Fig. 2. Each neuron realizes a local linear model (LLM) and an associated validity function that determines the region of validity of the LLM. The validity functions form a partition of unity, i.e., they are normalized as shown in (2). For any model input $\underline{u}$, the output of the model is calculated as (3).

$$\sum_{i=1}^{M} \varphi_i(\underline{u}) = 1 \quad (2)$$

$$\hat{y} = \sum_{i=1}^{M} (w_{i,o} + w_{i,1}u_1 + \ldots + w_{i,n_x}u_{n_x})\varphi_i(\underline{u}) \quad (3)$$

Thus, the network output is calculated as a weighted sum of the outputs of the local linear models where φ_i is interpreted as the operating point dependent weighting factors. The network interpolates between different Locally Linear Models (LLMs) with the validity functions. The linear network parameters are w_{ij} s. The validity functions are typically chosen as normalized Gaussians. If these Gaussians are furthermore axis-orthogonal the validity functions are

$$\varphi_i(\underline{u}) = \frac{\mu_i(\underline{u})}{\sum_{j=1}^{M} \mu_j(\underline{u})} \quad (4)$$

With

$$\mu_i(\underline{u}) = e^{\left(-\frac{1}{2}\left(\frac{(u_1-c_{i,1})^2}{\sigma_{i,1}^2}+\ldots+\frac{(u_n-c_{i,n})^2}{\sigma_{i,n}^2}\right)\right)} \quad (5)$$

The centres and standard deviations are nonlinear network parameters. In the fuzzy system interpretation each neuron represents one rule. The validity functions represent the rule premise and the LLMs represent the rule consequents

The LoLiMoT algorithm consists of an outer loop in which the rule premise structure is determined and a nested inner loop in which the rule consequent parameters are optimized by local estimation. In this loop the worst partition is selected in each step and split into two parts in every direction, and then the best new division is chosen to continue till the convergence condition is reached.

The training algorithm LoLiMoT is found out to be rapid, precise, self tuned and more user friendly than other conventional methods for training of neurofuzzy networks which makes it more acceptable in online control applications[3,14]. The model based on this training algorithm is used in the following process control.

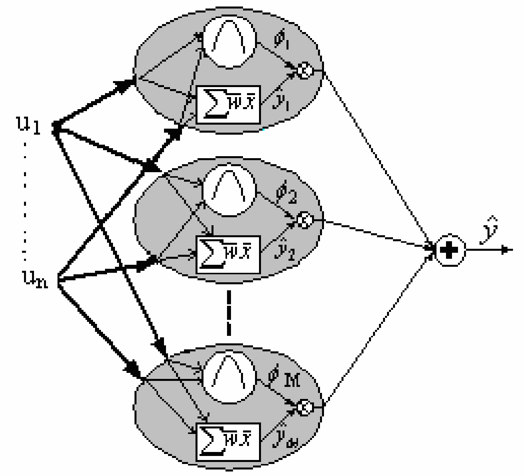

Fig. 2. Network structure of a local linear neurofuzzy model with M

4. BELBIC

At Motivated by the success in functional modelling of emotions in control engineering applications [4-8, 10, 18], the main purpose of this research is to use a structural model based on the limbic system of mammalian brain, for decision making and control engineering applications. A network model have been adopted which is developed by Moren and Balkenius [4, 5], as a computational model that mimics amygdala, orbitofrontal cortex, thalamus, sensory input cortex and generally, those parts of the brain thought responsible for processing emotions. There are two approaches to intelligent and cognitive control. In the indirect approach, the intelligent system is used for tuning the parameters of the controller and in the direct approach; the intelligent system itself functions as the controller. In our utilizations of BELBIC the second approach is taken. The most difficult section of using BELBIC in this problem is that our system is MIMO and it makes a big complexity in defining emotional cue and Sensory Inputs. In this section, firstly, general aspects of BELBIC are described and matching it to this problem is stated in the following.

As the model illustrated in Fig. 3 shows, BELBIC is essentially an action generation mechanism based on sensory inputs and emotional cues. The emotional learning occurs mainly in amygdala. The learning rule of amygdala is given in formula (6):

$$\Delta G_a = k_1.\max(0, EC - A) \times SI \quad (6)$$

Some Where G_a is the gain in amygdala connection, k_1 is the learning step in amygdale, EC, SI and A are the values of emotional cue, Sensory Inputs and amygdala output at each time. Similarly, the learning rule in orbitofrontal cortex is shown in formula (7). Inhibition of any inappropriate response is the duty of orbitofrontal cortex, which is completely based on the original biological process.

$$\Delta G_o = k_2.(MO - EC) \times SI \quad (7)$$

In the above formula, G_o is the gain in orbitofrontal connection, k_2 is the learning step in orbitofrontal cortex and MO is the output of the whole model, where it can be calculated as formula (8). In this formula, O represents the output of orbitofrontal cortex.

In fact, by receiving the sensory input SI, the model calculates the internal signals of amygdala and orbitofrontal cortex by the relations (9) and (10).

$$MO = A - O \quad (8)$$

$$O = G_o.SI \quad (9)$$

Fig. 4 shows the structure of emotional system operation.

$$A = G_a.SI \quad (10)$$

Controllers based on emotional learning have shown very good robustness and uncertainty handling properties [1, 7], while being simple and easily implementable. To utilize our version of the Moren-Balkenius model as a controller, it should be noted that it essentially converts two sets of inputs (sensory input and emotional cue) into the decision signal as its output

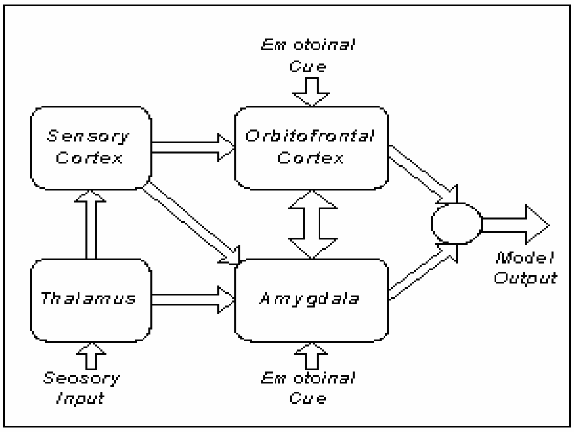

Fig. 3. The abstract structure of the computational model mimicking some parts of mammalian brain

The structure of the control circuit we implemented in this study is illustrated in Fig. 4. The implemented functions in emotional cue and sensory input blocks are given in (11) and (12),

$$EC = \int_0^t (e'Qe + u'R_c u)\lambda^{(t-\tau)} d\tau \times sign(SI) \qquad (0 \le t \le T) \quad (11)$$

$$SI = M \times e \qquad (12)$$

Where EC, u, M, T, λ and e are emotional cue, control effort, transfer matrix from section 2, the desired time to reach the goal, forgetting factor and error of the system. Also Q and R_c are the coefficients which determine the importance of the error against control effort and make the EC similar to cost function in LQR, these parameters must tuned for designing a satisfying controller with reasonable trade of between them. In the choice of these two signals some principles are taken into consideration as following:

1- Sensory input is a kind of control signal which explain the sense of the environment, so it should be chosen as a function of error, but the error of the robots do not expose anything about the error of each wheel. If we consider the error of the real values of the input voltages of three wheels with this sequence, we will have strong sense about SI. So using matrix M to convert the error of the position of the robot to error of each wheel is reasonable.

2- At first, the type of the emotion should be determined. Here it is considered as stress, which its increasing (absolute value of it) shows that the system is not work properly. Defining EC with (11) has this characteristic and increasing in control effort and error increase our stress in time T. Considering $\lambda < 1$ gives more importance to online data than previous ones. Another point in defining EC is that the Emotional cue is compared with the control signal (MO) therefore its value should be about MO so the sign-function in (11) is for tune the direction of this value. Thus The Emotional cue can be defined as (11).

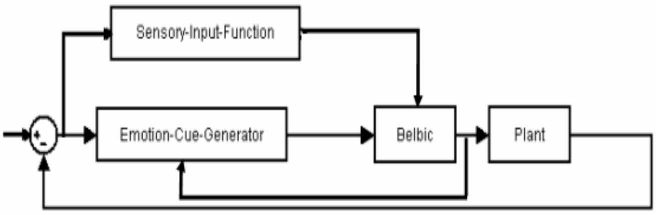

Fig. 4. Control system configuration using BELBIC

Tuning this parameter plays one of the most important roles in designing BELBIC controller.

5. Simulation Resuts

In this section we summarize the results of our simulations which display the desired performance of designed BELBIC controller. At first we tried to extract a model for the system to determine displacement and direction whereas the motors' voltages were used as inputs. We generated 4000 random input voltages in range of -12 to 12 Volt and then obtained the correspondent output displacement and direction data to reach an efficient database for LOLIMOT identification system. Fig. 5 demonstrates that the real output is perfectly matched to the output of the identifier. This quality was gained after reaching to 15 neurons.

After identification of the robot's motion, we design a BELBIC Controller with structure described in the previous section. The outputs of this direct BELBIC controller are generated every 100ms. This time is determined by the constraints of the real system.

To evaluate the performance of the BELBIC controller, we specify a random path for robot to follow which is defined using several target points on the path every two second. Fig. 6, 7 and 8 show the displacements of the robot in x and y directions and the orientation of the robot respectively. We see that the robot follow the targets mostly in an exact manner. Fig. 9 displays generally the robot motion path in 20 second.

In Fig. 10 we determine a closed path starting from the point is (0,0). In this example we want to show the satisfying accuracy of this algorithm. The performance is improving during learning and with more points we will reach to more accurate motion too.

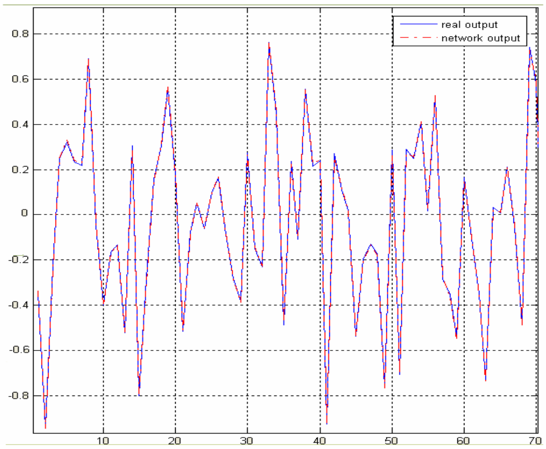

Fig. 5. Result of the identification of the angle of the robot, the horizontal axis is time

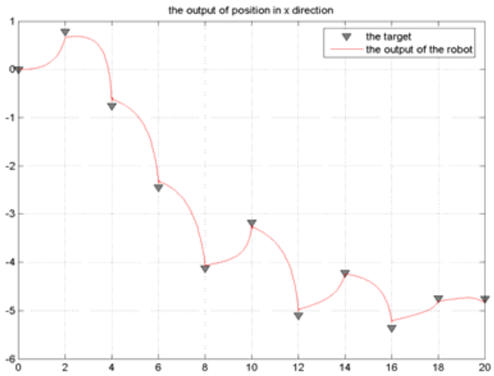

Fig. 6. The position in x direction, the triangles are the targets of each step and the red line is the position of the robot, the horizontal axis is time.

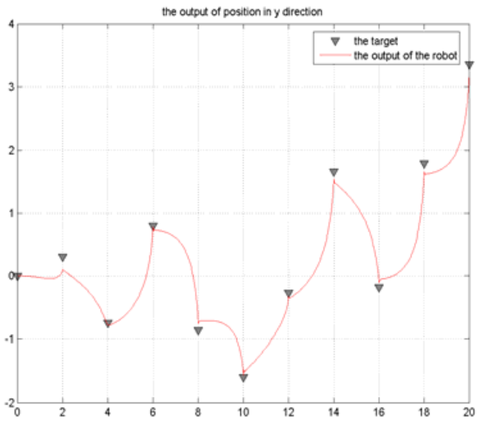

Fig. 7. The position in y direction, the triangles are the targets of each step and the red line is the position of the robot.

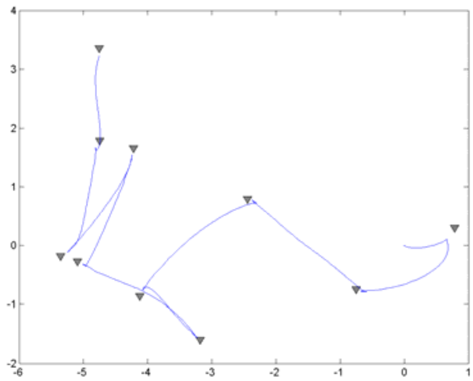

Fig. 8. The direction of the robot, the triangles are the targets of each step and the red line is the direction of the robot, the horizontal axis is time.

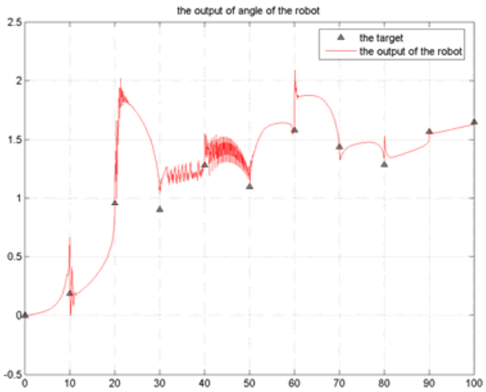

Fig.9. The motion of the robot in 2d plane, the triangles are the targets of each step and the blue line is the position of the robot

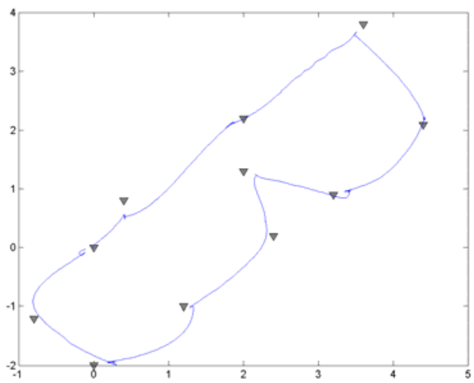

Fig. 10. The motion of the robot in a closed curve, the triangles are the targets of each step and the blue line is the position of the robot.

6. Conclusion

A new emotional controller based on BELBIC model is presented in this paper for control of the motion of the three-wheel robot. We designed controller using direct approach, indirect approach based on optimal controller can be implemented too. But it seems that the direct approach is more effective. Our system was MIMO and this was the most challenging part of this problem. Maybe the BELBIC controller with easier relation for EC and SI can result better performance too. The importance of this research is in applying the emotional machine learning in practical problem. In this work we control the identified model of three-wheel robot, and it can be applied to the real robot too.

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