

Designing a Football Team of Robots from Beginning to End

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Abstract—The Combination of path planning and path following is the main purpose of this paper. This paper describes the developed practical approach to motion control of the *MRL* small size robots. An intelligent controller is applied to control omni-directional robots motion in simulation and real environment respectively. The Brain Emotional Learning Based Intelligent Controller (*BELBIC*), based on *LQR* control is adopted for the omni-directional robots. The contribution of *BELBIC* in improving the control system performance is shown as application of the emotional learning in a real world problem. Optimizing of the control effort can be achieved in this method too. Next the implicit communication method is used to determine the high level strategies and coordination of the robots. Some simple rules besides using the environment as a memory to improve the coordination between agents make the robots' decision making system. With this simple algorithm our team manifests a desirable cooperation.

Keywords—multi-agent systems (*MAS*), Emotional learning, *MIMO* system, *BELBIC*, *LQR*, Communication via environment

I. INTRODUCTION

ROBOTIC soccer is a particularly good domain for studying MAS. It can be used to evaluate different MAS techniques in a direct manner: teams implemented with different techniques can play against each other. Although robotic soccer is a game, most real-world complexities are retained. A key aspect of soccer's complexity is the need for agents not only to control themselves, but also to control the ball which is a passive part of the environment [1].

One problem in robotic soccer (and in robotics in general) is to adapt skills and the overall behavior to a changing environment and to hardware improvements. Motion planning in dynamic environment is a difficult problem, since it requires planning in the state-space, i.e. simultaneously solving the path planning and velocity planning problems [2]. Moving systems are characterized by constraint equations

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involving the time derivatives of the system configuration variables [3].

Due to the limited amount of processing time available to the robot for dynamic strategy planning (a large part of the time slice taken up by the vision system), the collision avoidance and motion code has to be kept as minimal and efficient as possible. Simple strategies have traditionally worked better than more complex and less robust ones [4]. This approach decomposes complex team actions into very simple primitives. We implement and test a learning based method that allow any kind of motions such as direct movement, turning and combinations of these two. The move action beside kick and spin-back¹ make our preliminary actions. These basic actions can be combined to generate all needed skills.

With Development of Artificial Intelligence and Learning methods, its applications spread out increasingly. Some of its most important applications are using them in Control, Robotics and Decision Making. 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 method to control the motion of robots was applying classic controllers like PID, using the mathematical equations of the system and the inverse kinematics. But recently instead of these methods, fuzzy controllers and even neural network are used very frequently [5-8]. In these methods the researchers design some heuristic fuzzy rules. Some more complicated methods are used in this field too [9]. Because of the uncertainty of the robots in real world, these pre-designed controllers may cause many difficulties, such as variation of environment, goal and capabilities of robot. Thus using learning is one way to adapt it to real robots. At first we use BELBIC controller in motion control of the robots and examine our method in the simulation environment with the model identified by LoLiMoT algorithm [10], and its perfect qualification encouraged us to implement it on real robot. In this paper we describe our method in practice and only show the results of simulation, without any explanation about identification and so on.

Although the LQR is a robust optimal controller, in this case because of the difference between the robots, and the uncertainty of the environment and complexity of the exact

¹ - rolling a cylinder to keep the ball in front of the robot. It is shown in Fig.2(a)

dynamic model we can not utilize an exact model for system. For these reasons we propose a direct BELBIC controller which its applications are extended recently [11-15]. Here 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 [16]. So we choose our parameters as an optimal controller and the results demonstrate the desired performance of BELBIC.

Multiagent systems deal with behavior management in collections of several independent entities, or agents. In a multiagent system there is a group of agents cooperating with each other. MAS In particular, if there are different people or organizations with different (possibly conflicting) goals and proprietary information, then a multiagent system is needed to handle their interactions.

In homogeneous, non-communicating multiagent systems, all of the agents have the same internal structure including goals, domain knowledge, and possible actions. They also have the same procedure for selecting among their actions. The only differences among agents are their sensory inputs and the actual actions they take: they are situated differently in the world [1].

In such systems the communication can be more implicit and be done via the environment that the agents are located in. This implicit communication is done via making changes in the environment by one agent and when another agent faces these changes (not necessarily synchronously) selects a behavior which is stimulated by the perceived change in the environment. The act of firing a behavior in another agent is considered as communication, whether happened explicitly or implicitly.

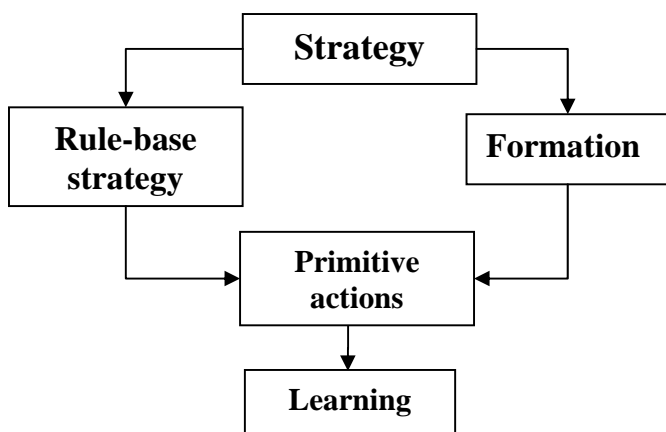


Fig. 1 The model of three-wheel robot

Our General strategy divides into two parts. First one is designing some rules to play reasonable, using primitive actions in critical situations. Another strategy is making good formation via implicit coordination which is useful in many conditions. One of these conditions occurs when one of our players intercept the ball, for his teammates. When the ball is in opponents' Possession and we want to make a desirable

formation to prevent dangerous situation for them, is another such condition. The block diagram is shown in Fig.1.

II. MOTION CONTROL

A. Three-wheel robots motion

Three-wheel robots are one of the common models of robots which are used in RoboCup soccer in the world because they are omni-directional with minimum wheels [17]. The first and most important step for playing football is control the motion of the robots. If the robot can go to every point that we want 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.

Figure 1 shows the schematic of a three-wheel robot and their angles and direction. The relation between velocities of the wheels and differentiation of the position and angle of the robot relative to fixed coordinates is demonstrated in (1).

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

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

In this formula x, y, φ show position and direction of the robot in the fixed coordination, R, L_i, δ are radius of the wheel, distances from the center 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 figure 1) and $\dot{\theta}_i$ is the velocity of the wheel i .

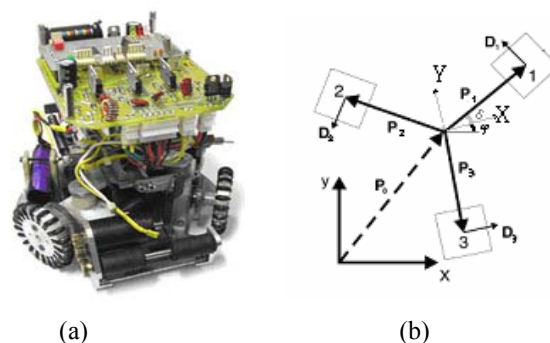


Fig. 2 (a) Figure of our three-wheels robot (b) The model of three-wheel robot

Because of sinusoidal function of φ in matrix M the model is nonlinear. This relation is between the velocities without consideration of the inequality of the motors of the real robot and its geometric characteristics, also the consideration of 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. Our data are images from the two cameras hanged from the roof and three decoders for computing angular velocities of the wheels. Off course with more sensory information, the control can be easier and more accurate.

B. BELBIC

Motivated by the success in functional modeling of emotions in control engineering applications [11-15, 18, 19], 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. We have used BELBIC in several applications [13, 20], where it has performed comparable or even better than functional models of emotional control based on reinforcement learning [21, 22]. A network model has been adopted, developed by Moren and Balkenius [11, 12], 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. In our utilizations of BELBIC the direct approach is taken, in which the intelligent system itself functions as the controller. The most difficult part of using BELBIC in this problem is that our system is MIMO2 and therefore the defining of emotional cue and Sensory Inputs will be very complex. In this section first we describe general aspects of BELBIC and next match it to this problem

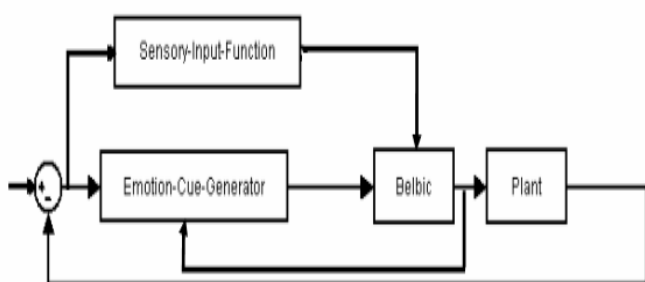


Fig. 3 Control system configuration using BELBIC

The model is illustrated in Fig. 3. 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 (2):

$$\Delta G_a = k_1 \cdot \max(0, EC - A) \times SI \quad (2)$$

Where G_a is the gain in amygdala connection, k_1 is the learning step in amygdala, EC , SI and A are the values of

² The inputs of the controller are the desired position and direction (X, Y, φ) , the velocity of the wheels in this time (3 velocities) and the current angle (7 inputs). the outputs are three voltages to move in correct direction. BELBIC wasn't used in MIMO systems before.

emotional cue, Sensory Inputs and amygdala output at each time. Similarly, the learning rule in orbitofrontal cortex is shown in (3). Inhibition of any inappropriate response is the duty of this block, based on the original biological process.

$$\Delta G_o = k_2 \cdot (MO - EC) \times SI \quad (3)$$

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 (4), in which, O represents the output of orbitofrontal cortex.

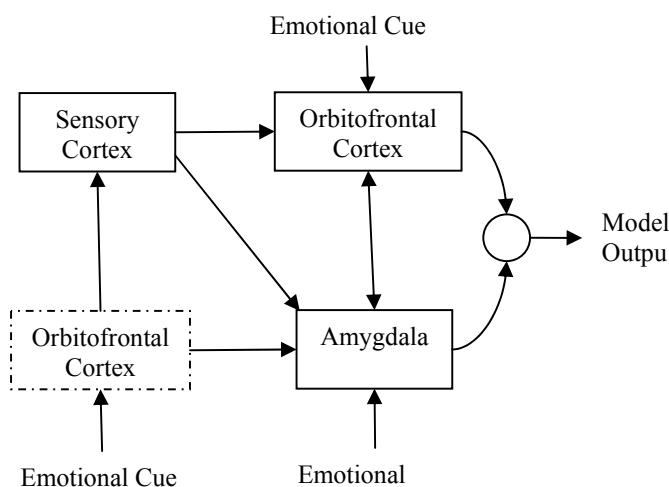


Fig. 4 The abstract structure of the computational model mimicking some parts of mammalian brain

In fact, by receiving the sensory input SI , the model calculates the internal signals of amygdala and orbitofrontal cortex by the relations in (4) and (5) and eventually yields the output MO with (6). Figure 4 shows the structure of emotional system operation introduced in [11, 12]. But as you see in this figure we show the Thalamus with dashed line and it means that we don't use this parameter [16].

$$A = G_a \cdot SI \quad (4)$$

$$O = G_o \cdot SI \quad (5)$$

$$MO = A - O \quad (6)$$

Controllers based on emotional learning have shown very good robustness and uncertainty handling properties [13, 16], 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. The emotional cue and sensory input's

implemented functions are given in (7) and (8),

$$EC = \text{sign}(SI) \cdot \int_0^t (e' Q e + u' R_c u) \lambda^{(t-\tau)} d\tau \quad (7)$$

$$(0 \leq t \leq T)$$

$$SI = M \times e \quad (8)$$

where EC, u, M, T, λ and e are emotional cue, control effort, transfer matrix from section 2, the desired time to reach to goal, forgetting factor and error of the system and the 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 satisfactory 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 errors of the robots don't expose anything about the error of each wheel. If we consider the errors of the input voltages of three wheels, 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 we should determine the kind of our emotion, we consider it as stress, which means its increasing (absolute value of it) shows the system is not work perfectly. Defining EC with (7) has this characteristic and increasing in control effort and error increase our stress in T . The integral considers the earlier errors and assuming $\lambda < 1$ 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 (7) is for tuning the direction of this value³.

C. Simulation Results

We only show the results of the simulation to display the quality of this method that lead us to implement the method in real robot. In this part desired performance of designed BELBIC controller is displayed. 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 30ms. 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.5 shows the robot motion path in 7 seconds. You can see that after the first try the robot can reach the goals before 2

seconds' dead time. Also during the time the accuracy increases.

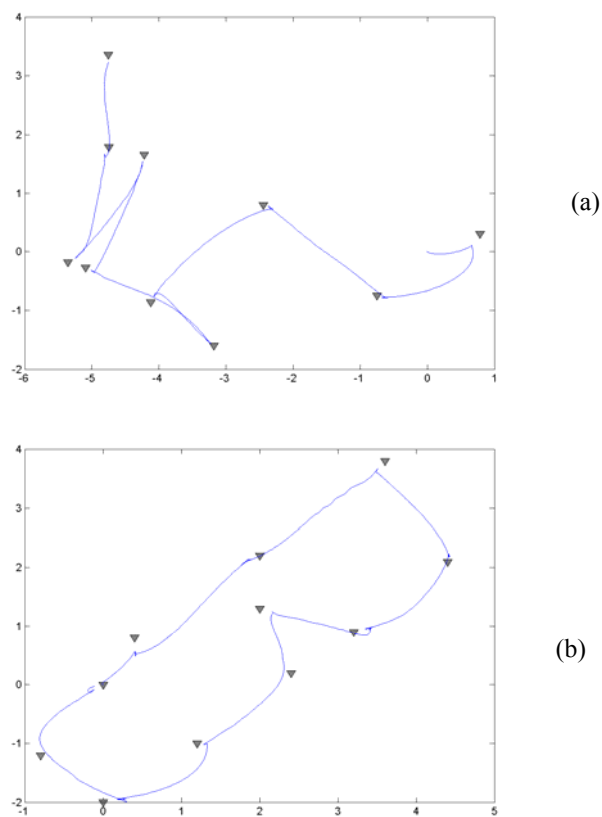


Fig. 5 The motion of the robot a) to reach the random goals, b) in a closed curve. The triangles are the targets of each step and the blue line is the position of the robot. The start point is (0,0)

D. Experimental Results

In this section we summarize the results of our application which display the desired performance of designed BELBIC controller. We used the BELBIC Controller designed in the section 2.2. The outputs of this controller are generated every 30ms.

To evaluate the performance of the BELBIC controller, we specify four points that make a square and the robot should start from one of them go through others and return to the start point. In this test, as we know, the best way is moving on the edges of the square. We have done this test two times: First with a simple algorithm using the relation between direction and wheels' velocities. Fig.6.a shows the results of this method. Secondly we used our BELBIC controller to guide the robot on this path. Fig.6.b depicts the motion of robot with this approach. The numbers in the figures show the sequence of goals. In Fig.6.b you can see that at first the robot moves on wrong way but after a few seconds it learn and improve its

³ Note that we have 3 emotion cues for three BELBIC and we use ith

decision to reach the goal. This figure shows that this method is fast and accurate; the robot amends its parameters very quickly and follows the path with high accuracy. We see that the robot follows the targets mostly in an exact manner. Note that in first method the robot nearly can reach the points but with a lot of perturbations and its accuracy is not satisfying but with BELBIC the paths are nearly direct and the end points are achieved precisely. In addition to this, note that we do not have any sensor and we only use the images received from the camera above the playground and some encoders to measure the velocities of the wheels.

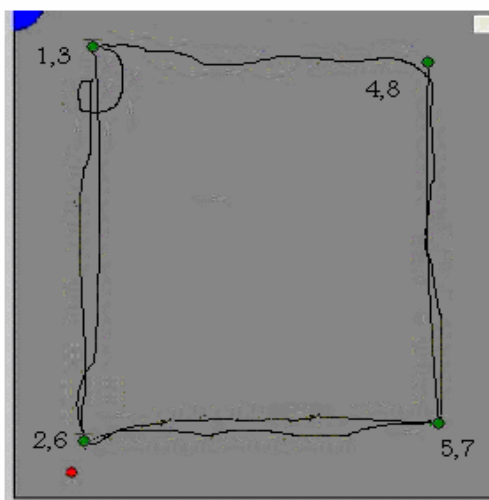
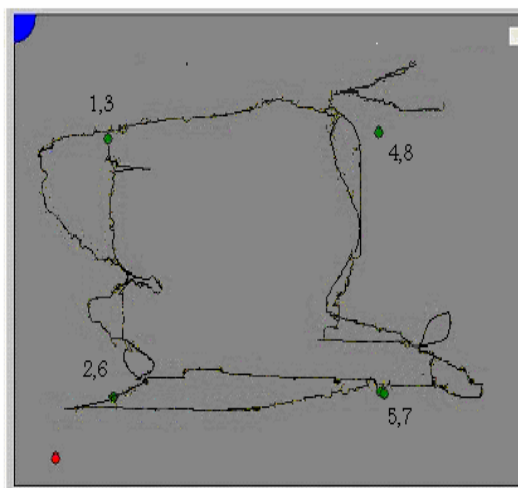


Fig. 6 The motion of the robot in a closed curve a) without BELBIC b) with BELBIC

III. STRATEGY OF FORMATION

sensory input (related to i th wheel) sign for i th emotion cue.

A. Communication via Environment

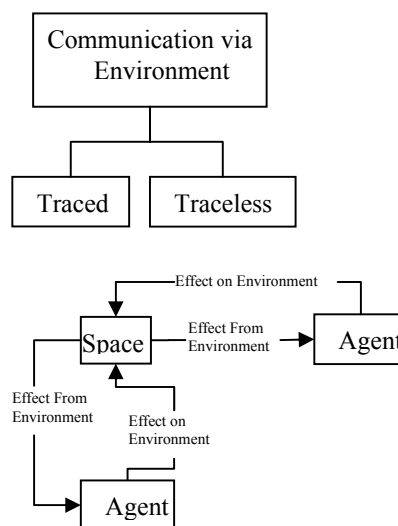
One of the facilities for communication is the environment. This facility is mostly used when there are problems for direct communication between agents. As an example, when the great number of agents makes the direct communication between them difficult or the direct communication is not reliable enough, indirect communication via the environment is an approach.

Communication via environment has two branches named traced and traceless. In traced approach the result of the agents' action remains and changes the environment. Stigmergy is one of the basic concepts in this kind of coordination which is introduced by Pierre-Paul Grasse [23] in the 1950's to describe the indirect communication taking place among individuals in social insect societies.

One of the aspects of a stigmergic system is the environment element which is selected for effects. This element can be selected from a variety of factors. For example in [24] a group of simple robots are in charge of pushing a box while they do not have a sense of their environment. The robots have a few simple rules to follow and a kind of group intelligence is achieved from the whole group. Using artificial emotions is another way of considering the environment as a container. The emotions distributed in the environment affect the individual behaviors of agents and hence the behavior of the whole group is affected [25]. When the communication tools are weak or the communication facilities are not reliable, one of the approaches for compensating such situations is to use environment as a means of communication as shown in Fig. 7. This usage of environment can be appeared as agents with simple actions which affect their surrounding (and hence others). In these systems a group of simple rules form agents' behavior [26, 27].

(a)

(b)



(a)

(b)

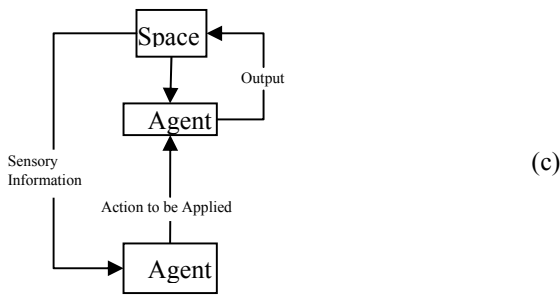


Fig. 7 (a) Environment communication is divided to two groups, (b, c) Agents communicate with their environment instead of themselves and process of affecting environment using actuators and getting effects from environment

In a traceless indirect communication between agents the process of firing behaviors of others exists. In such approaches when an agent makes a change a behavior in another agent is fired. The specific part of this kind of communication is that no trace of the element is remained after the change. Using ideas of birds flocking and fish schooling as a solution is an instance of such systems. As an example for this case we have the spring model that is used for coordination of positions between agents of a group. In these systems the agents look around themselves and make a virtual spring between themselves and their neighbors. They calculate forces of virtual springs and move according to the total forces such that it stops at a balanced position.

B. Architecture of the System

In Robotic Researches There are considerable papers about coordination and strategy in soccer simulation. Finding a way which can adapt the team with different situations and consider all important parameters without too much computation is one of its benchmark. For the coordination between players of the game, we have considered virtual springs between agents. Each agent in the ground has a set of spring connections to some points in the environment. We have considered a group of springs with different characteristics for each of the agents. Table 1. shows the springs which were considered in this paper.

When the springs are used, a group of benefits are gained. These benefits were under investigation using the small size soccer:

- Collapse of players on the ball is controlled: When a group of players collapse on the ball, dangerous occasions for the team are made because some gaps are made in the ground. When spring forces are used, the players of the team do not gather around the ball all together because the spring force between players of the same team are forced to keep a minimum distance with team mates. Hence only one of the members of the team is absorbed to the ball and the others keep formation of the team.

TABLE I
 DIFFERENT ELEMENTS OF THE ENVIRONMENT WHICH AFFECT THE SPRING CONNECTIONS WITH AN AGENT

| ELEMENT | USAGE |
|--------------------------|--|
| Players of the same team | When a player keeps a spring connection with another players of its team, a formation between members of the team is made and hence the distance between members is controlled such that amount of gaps in the team is reduced |
| Opponents | When the players keep a specified range of distance with opponents, they do not get far from opponents such that they find opportunities for making dangerous occasions. |
| Ball | As the ball is one of the main parts of the system. When a group of agents move towards the ball, the whole group and the formation is affected by movements of the ball seeking agent |
| Initial location | When the agents keep spring modeled distances with their initial location, the formation of the team is dependent to the initial formation which is designed for the group. |
| Goals | Both goals (agent's and opponents') are important parts to be considered by the agents. An agent's goal is important for protecting and opponents' goal is an aim for the agents to score. |

- Unlimited distances between players: When the players keep a range of distance with each other, they do not (for any reason) get too much far from each other such that make goal occasions for the opponents.
- Making pressing formations on the opponents: When the members of a team use spring forces for their formations, they keep the formation for surrounding opponent members and hence when attacking the opponents, they keep their formation and pressing situation is made.
- Returning to the own goal when in defense state: When the players are in defense state, they gather around their own goal and this reduces the risk.
- Moving forward when attacking: For attacking situations, the agents are absorbed to the opponents' goal and hence the spring between agents and the opponents' goal is a factor for absorbing agents to the other side of the ground.

IV. RULE-BASE STRATEGY

With concentrating in nature we can find considerable cases of producing more developed action from some preliminary action. There are several works in designing agents like living-beings [28, 29]. In most of the creatures the action are often like these. For example in human only the lowest layers

of brain do optimal. Explaining an instance clarifies the aim. Assume that you want to get something. Do you compute the best angle of motion and tune your arm and fingers in the optimal way? Definitely no. You learned moving your hand to a point and your fingers to grasp something. Hence you utilize your abilities and make the more complex actions. Figure 8 depicts the diagram of producing get from move and grasp. Now we want to extend this simple method to our environment.

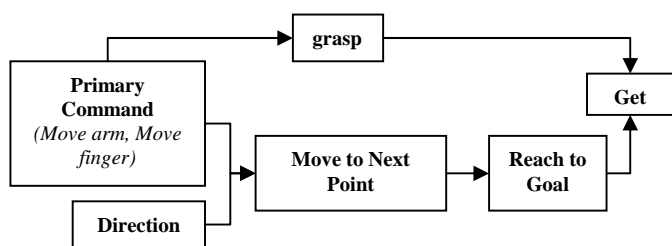


Fig. 8 The block diagram of producing get

We described the strategy of our team when the ball is in our possession or the opponents have the ball but the situation is not critical. In that method we tried to keep good distribution in the field to avoid their attack and to place in free space for our attack. But in some conditions the players should leave their role in formation and do something else. For example when a player move with ball and become close to our goal the most suitable player should attack to him and try to take the ball or when two players come to our goal and one of our players mark the goal-side the other should mark the second player. In states like these some actions must suppress the actions which come from the spring forces. To handle these circumstances we define some primitive actions that are made up of basic actions (move, kick and spin-back). Fig. 9. shows the diagram of producing primitive actions from basic ones.

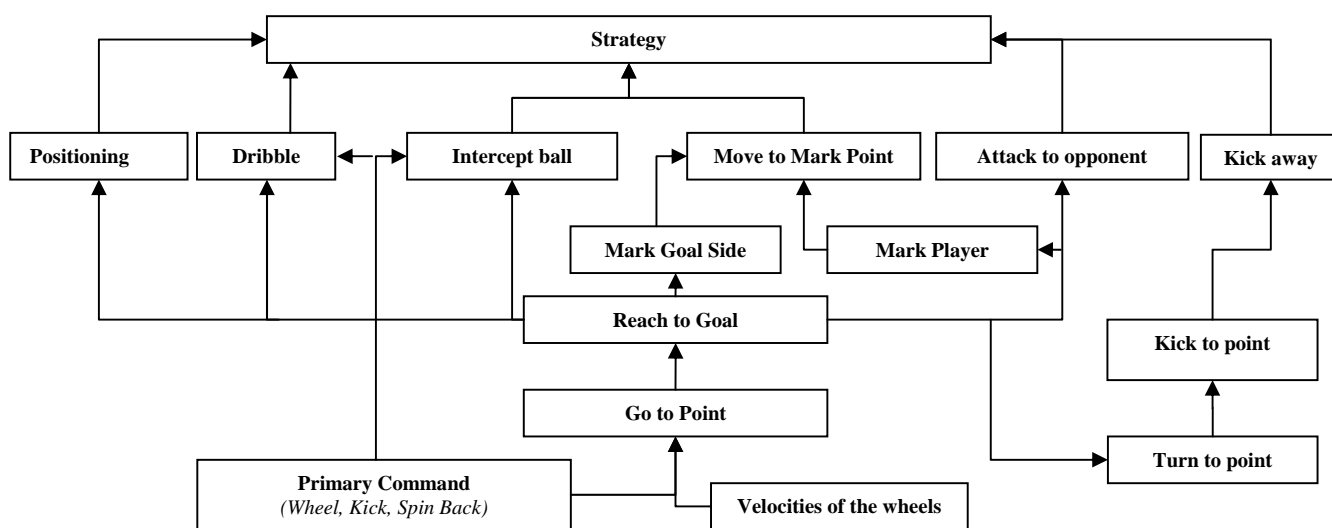


Fig. 9 The block diagram of producing primitive actions from basic ones

V. CONCLUSION

In conclusion the problem of paying football decomposed to two parts; first using primitive actions with some simple rules, when our players intercept the ball and want to attack, second a reasonable and effective formation was achieved via springs. These two high level strategies need some primitive actions which the most important of them, move, was made with BELBIC.

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 good performance too. The importance of this research is in application of emotional machine learning in practical problem. In this work we control the real robot with minimum sensors. This is the first time that BELBIC is used in practical problems. It can increase the confidence of using such emotional learning methods in real world. Another important point of this part was the limited facilities which are used (only the images of camera and encoders for velocities of the wheels).

In second part of this paper we considered an approach for formation in a football team. We proposed approaches like using spring inspired ones to keep the formation of the group. For this approach, the players of a game do not need to have direct communication with each other and instead they make decisions according to their limited observations. Different formations for a team can be achieved by different characteristics and behaviors for the virtual springs assumed for players. We considered the benefits of using spring as a means of communication for better formations in the team of robots. Learning methods can be utilized to obtain the best constants and satisfying distances in different situations.

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