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A Multi-Agent System for Cooperative Quadruped Walking Robots

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Abstract: *We are interested in participating in RoboCup (Robot World Cup Initiative) challenge since it is an excellent forum to promote the research in many areas such as artificial intelligence, robotics, and agent technology. This paper introduces our current research efforts to build a multi-agent system for cooperation and learning of multiple legged robots in the RoboCup domain. A behaviour-based hierarchy is proposed for our Essex Rovers robot soccer team to achieve intelligent actions in real time, which includes the neural network based colour detection algorithm and the fuzzy logic based controller. Preliminary results on Sony walking robots were presented.*

Keywords: Mobile Robots, Multi-agent Systems, Robot Control, Cooperative Behaviours

1. INTRODUCTION

Building robotic systems with life-like appearance, behaviours and intelligence has been an ultimate long-time dream in robotics and AI fields [5][13], reflected by many science fiction books and films. It is also an extremely challenging task. Until recently the success of the Honda Humanoid robots P1 & P2 has demonstrated its technical feasibility [3]. At the same time, the advanced-legged robot AIBO, announced by Sony at Japan, resembles the basic behaviour of dogs [12]. These robot pets have been equipped with the brain, sensors and actuators. Their software enables them to have emotions, instincts, learning ability and the capability to mature. Each AIBO turns out differently, as its behavioural patterns continuously change. This is because AIBO acts based upon its feeling and instincts then learns from the results of experience, until maturing.

These exciting new robots not only establish a new dimension for the Robot Entertainment industry, but also provide a complete new testbed for robotics and AI researchers to work on many fundamental research issues such as behaviour adaptation, human-like thinking, evolution, and learning [15]. These will also provide a great potential for successful robotic systems in industry and domestic applications. More specifically, the Sony Legged robot League in RoboCup is an international robot soccer game that has been launched recently based on Sony AIBO robots [12]. This is a very challenging task since the robot posture and its head position constantly change during legged locomotion. Also the planning and control of a team of walking robots in a soccer game is extremely complex.

RoboCup provides a challenging environment for research in systems with multiple robots that need to achieve concrete objectives, particularly in the presence of an adversary team. The methods to handle the complexity within the RoboCup domain include a centralised approach and a decentralised approach [1]. More specifically, in a centralised approach planning and decision-making functions are handled by a single control centre. Each robot contains few simple sensors for control, the actuators for operation, and the communication facilities for data exchange with the control centre. All the robot movements in the system are controlled from the control centre. In contrast, a decentralised control method is to equip each mobile robot with multiple sensors and embedded computers in order to sense its environment, build maps, and plan action [3]. In any unforeseen situation, the robot is able to plan a new path or find a solution without waiting for commands from the control centre. Inter-robot communication becomes necessary since competition for resources should be avoided and sharing experience could improve system performance. This paper is to address how to adopt the decentralised approach to a team of Sony walking robots in the RoboCup domain.

Next section describes the agent architecture of our Essex Rovers team and a number of robot behaviours being defined, including both low-level behaviours for autonomy and high-level behaviours for cooperation. Section 3 addresses the locomotion of quadruped walking robots, with initial experimental results. In section 4, a neural networks based colour detection algorithm and the fuzzy logic based controller are briefly presented. Finally, a brief conclusion and future work are summarised in section 5.

2. AGENT ARCHITECTURE

The main objective for our Essex Rovers team is to build a firm research platform on which future work on multi-agent systems can be done. Currently, a multi-agent framework is proposed based on modular design [7].

2.1 Modular design

The modular architecture is adopted in overall agent implementation as shown in Figure 1. More specifically:

- Perception -- This module includes a multi-sensor system and a local map. The sensors being used are a colour vision system, an infrared range sensor (PSD), 5 touch sensors, 18 optical encoders, 2 microphones, and 3 gyros. Incoming visual, proximity, ranging and auditory information is processed by on-board computer. Neural networks based colour detection algorithm is used to handle uncertain and changing lighting condition. A local map is then built and updated dynamically when new sensory data is available.
- Action -- This module includes one speaker and 18 micro servomotors. Each leg has three joints driven by three servomotors. The synchronisation of quadruped legs for each robot is extremely important for robot actions such as kicking the ball and moving towards the goal. A fuzzy logic controller is used here to deal with uncertainty in sensory data and imperfect actuators. The speaker is used to communicate with teammates for cooperation.
- Cognition -- This module contains a global map, localisation algorithms, object tracking and a planner. The self-localisation is implemented by triangulation based on marker position and angles scanned by each AIBO robot. The ball and other players are tracked by a Kalman predictor in which odometry is modelled as object dynamics and the image is modelled as observation. The global map is in a format of certainty grids with 30*20 cells.

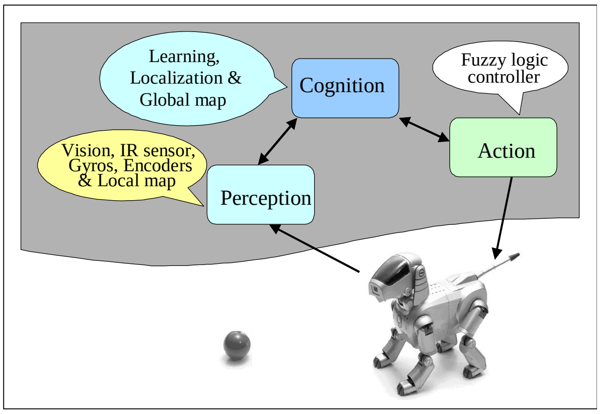

Figure 1 Agent architecture for the Essex Rovers team

2.2 ROBOT BEHAVIOURS

A primary aim in the development of teams of co-operative mobile robots in general, soccer robots in particular, is to synthesis low-level basic behaviours and high-level cooperative behaviours. In general, low-level behaviours enable individual robots to play a role in a specified task or game, and high-level behaviours enable a team of mobile robots to accomplish missions that cannot easily be achieved with an individual mobile robot [9]. Although many different behaviours [2][6] can be synthesised for the co-ordination of multiple robots, several useful behaviours are identified in this application, as shown in Figure 2.

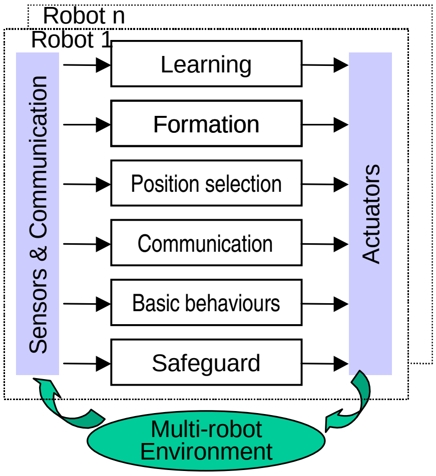

Figure 2 Behaviour hierarchy for multiple robots

These behaviours can be categorised into two levels:

<u>Low-level behaviours for mobility</u>

- Safeguard behaviour – to keep a safe distance among mobile robots during competition, and to protect robots from colliding with other objects.
- Basic behaviours – to enable each robot to play a football game, including kicking the ball, dribbling the ball, passing, intercepting and shooting the gaol.

<u>High-level behaviours for cooperation</u>:

- Communication behaviour – to realise inter-robot communication by either an explicit way using loud speakers and microphones when possible or an implicit way by observing the motion of other robots [4][8].
- Position selection – to find out where each robot is and where is the goal in order to position itself at the optimal position at any moment. This is in fact a reactive planner to generate locally optimal strategies to direct low-level behaviours. It is very important for each robot to play an effective role in the game.
- Formation behaviour – to enable multiple robots to form a team where each robot makes its own contribution towards a common goal.
- Learning behaviour – to learn from its own experience and from other mobile robots. This is a key factor to improve its performance in an uncertain and dynamic environment[14]. Learning here includes both evolving fuzzy rules for low-level behaviours and searching optimal policy for high-level reactive planning.

Additional cooperative behaviours can be synthesised during the next stage of our research, for instance homing behaviour and role switching behaviour. This should be easy to implement in our modular design.

3. SONY ROBOT AND ITS MOTION CONTROL

One of the most important advantages of legged robots is their superior mobility and terrain adaptability to wheeled/tracked mobile robots. Legged robots only require a few discrete footholds to travel around for off-road locomotion where the surfaces are inaccessible to wheeled robots. To make such attractive characteristics more practical, a motion control algorithm should be developed to search and plan an optimum path and the foothold points, and to keep dynamic stability on a rough terrain [16]. Although serious hardware limitations exist, teams with efficient coordination of quadruped leg motion can have major advantages in the RoboCup competition.

3.1 Sony AIBO robot

Each Sony legged robot, AIBO, has a quadruped design, approximately 30cm long and 30cm tall including the head. The merit of the quadruped configuration has two folds: one is that the control of the robot is easier than a biped robot, and another is that two front legs can be used to express emotion and communicate with other robots or human. The neck and four legs of each robot have 3 degree of freedoms (DOFs). The neck can pan almost 90 degree to each side, allowing the robot to scan around the pitch for beacons, ball, and other robots. Figure 3 shows a sketch drawing of one AIBO robot with 15 DOFs.

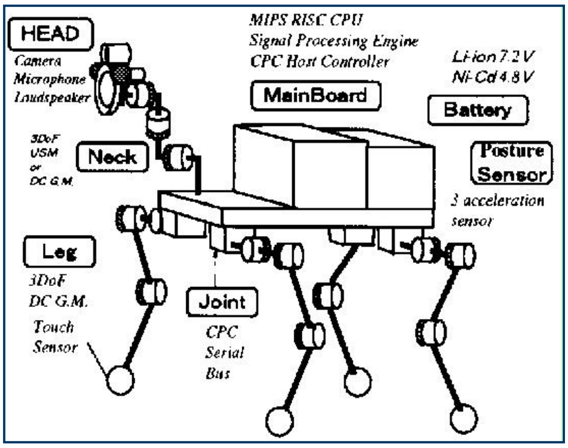

Figure 3 Mechanical configuration [12]

The Sony robots have onboard colour CCD cameras and IR range finders for navigation and localisation, as well as stereo microphones and loud speakers for inter-robot communication. The robots are not controlled remotely in any way. Instead they are controlled by one embedded R4000-series microprocessor with over 100 MIPS performance. The dedicated ASIC modules are used to make the robot small in size and in power consumption [12].

The environment for these robots in the RoboCup competition is a playing field with the dimension of 3m in length and 2m in width. The goals are centred on either ends of the field, with a size of 60cm wide and 30cm high. Six unique coloured landmarks are placed around edges of the field with one at each corner and one on each side of the halfway line. Each landmark is painted with two different colours of which pink colour is either at the top of landmarks on the one-side or at the bottom of landmarks on the other side. These landmarks are used for robots to localise themselves on the field.

3.2 Legged kinematics

As the first step of our implementation, we started from the low-level motion control of the robot. Each leg should be adjusted before their coordination. Assume that the frame (x_0, y_0, z_0) represents the root joint, and the frame (x_2, y_2, z_2) is the knee joint which has the coordinates (0, -a_2, -d_2) in the auxiliary frame (x_1, y_1, z_1). The foot joint is located in the frame (x_3, y_3, z_3). Here we consider a two-joint link with joint angles θ_1 and θ_2, rotated around z_0 and z_2 axis.

The A matrixes for this two-joint link are:

$$^0A_1 = T_{z_0,\theta_1}T_{x_0,a_1} = \begin{bmatrix} c_1 & -s_1 & 0 & 0 \\ s_1 & c_1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}\begin{bmatrix} 1 & 0 & 0 & a_1 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

$$^1A_2 = T_{z_1,-a_2}T_{y_1,-d_2} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & -a_2 \\ 0 & 0 & 1 & -d_2 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

$$^2A_3 = T_{z_2,\theta_2}T_{x_2,a_3} = \begin{bmatrix} c_2 & -s_2 & 0 & 0 \\ s_2 & c_2 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}\begin{bmatrix} 1 & 0 & 0 & a_3 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

where

$$a_1 = 61.00mm, \quad a_2 = 5.50mm, \quad a_3 = 53.62mm, \quad d_2 = 13.00mm.$$

Then the direct kinematics for each leg is:

$$^0A_3 = {^0A_1}{^1A_2}{^2A_3}$$

$$= \begin{bmatrix} c_1c_2 - s_1s_2 & -c_1s_2 - s_1c_2 & 0 & a_1c_1 - a_3c_{12} + a_2s_1 \\ s_1c_2 + c_1s_2 & c_1c_2 - s_1s_2 & 0 & a_1s_1 + a_3s_{12} - a_2c_1 \\ 0 & 0 & 1 & -d \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

where

$$c_1 = \cos\theta_1, s_1 = \sin\theta_1, c_{12} = \cos(\theta_1 + \theta_2), s_{12} = \sin(\theta_1 + \theta_2)$$

3.3 Walking experiments

Here two PID servo controllers are used to drive two motors to rotate from 10° to 80° around θ_1 and θ_2. The corresponding encoders' readings are recorded. The motion trajectory of the robot's feet is shown in figure 4 where the horizontal axis is the cycle time. The motion trajectory of one robot leg is shown in figure 5.

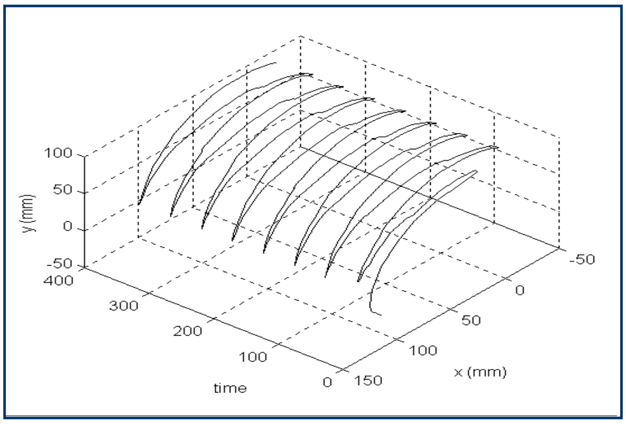

Figure 4 A foot trajectory of one of 4 robot legs

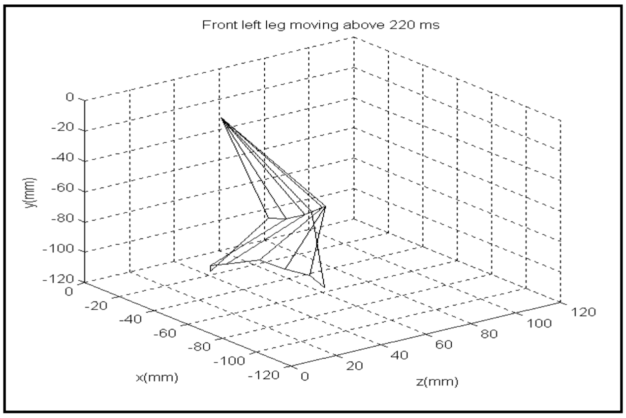

Figure 5 A motion trajectory of one of 4 robot legs

4. OBJECT RECOGNITION & FUZZY CONTROL

4.1 Learn to identify the object

There are two steps in learning to identify the objects. The first step is to train a classified neural network to adjust the colour threshold values off-line. The threshold values are then employed for image processing. For each colour at each Y level, we define a probability that shows the possibility of belonging to this class for a pixel under an adjusting threshold. The developed image tool [8] could be manually used to label this pixel for the colour or background. The probability is defined as a sigmoid function:

$$p(x) = \frac{1}{1 + e^{\mu(T-x)}}$$

where x is a pixel U or V value. T is the adjusting threshold. μ is adaptive parameter for adjusting p(x) to approach 1. For each labelled pixel, the classifying error is $e = (1 - p(x))$. The update for the adjusting threshold is

$$T(k+1) = T(k) - \lambda \frac{\partial e^2}{\partial T(k)}$$

where λ is a learning rate.

The second step for learning to identify the objects is to adjust the threshold on line. For different luminance conditions, 32 sets of U and V thresholds are produced by the first step training. A multilevel back propagation network, as shown in figure 6, is employed to map the relationship between the different luminance conditions and the thresholds. The luminance conditions can be represented by the light energy that is the sum of Y, U and V value of each pixel. Upon training this network, AIBO can measure the luminance conditions in the form of energy and recall the neural network to get the threshold values. These values can be re-setup into the hardware for image thresholding.

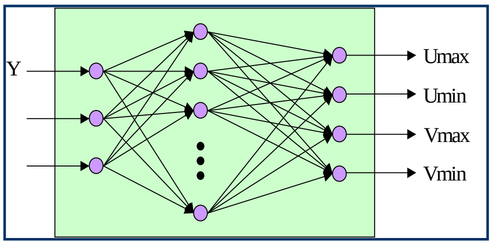

Figure 6 Adaptive threshold for CDT

4.2 Behaviour Fuzzy Controller

A reactive control scheme is employed to each behaviour with sensor data from the local map as inputs and moving command from OPEN-R moving modular as outputs. The sensor data from the local map is corrupted with noise and it forces us to use a fuzzy controller to complete the behaviour commanded from the cognition modular. For example, the ball size measured in pixel from CCD camera and pan angle measured in degree from head motor encoder are used as inputs for ball interception behaviour. The ball size detected in practice is not accurately corresponding to the distance from dog to the ball, but just has fuzzy concept such as small (S), middle (M), or Large (L). The pan angle is accurate to some extent, but it is not the precise direction from dog to the ball since the ball may not stay in the image centre during real time moving. So we have fuzzy concept left (L), zero (Z), or right (R) for the pan angle. The outputs of ball interception are five one-step moving commands available from *OPEN-R* modular, namely, *FORWARD, LEFTFORWARD, RIGHTFORWARD, TURNLEFT,* and *TURNRIGHT* [12].

Figure 7(a) is the membership function for the Pan angle of the robot head and figure 7(b) is the membership function for the ball size. Output command membership is shown in figure 7(c). Figure 7(d) is the rule surface of the ball interception where we take Mamdani's minimum operation as fuzzy implication function and the centre of area method (*COA*) as defuzzification strategy.

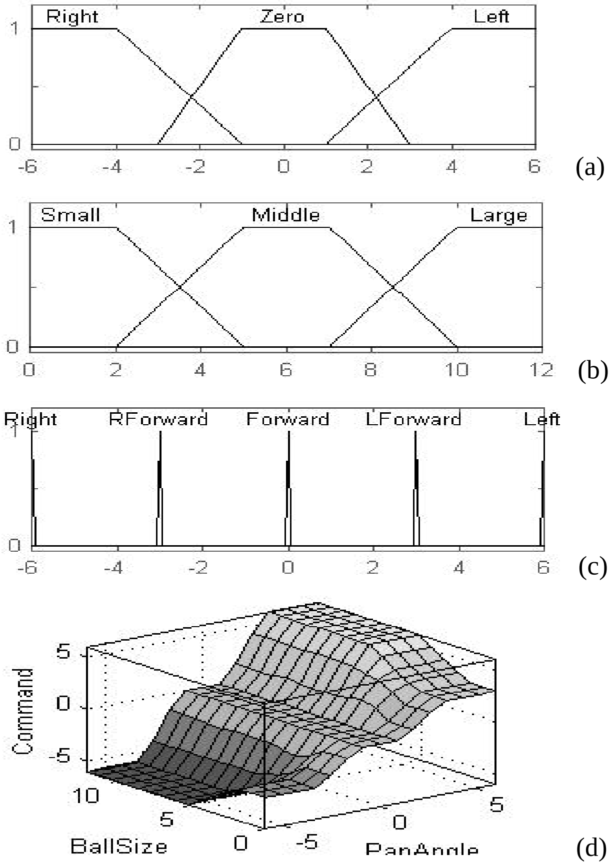

Figure 7 Membership functions and rule surface

5. CONCLUSIONS AND FUTURE WORK

This paper presents a multi-agent system in the robot soccer domain to investigate both behaviour coordination and embodied intelligence. Each soccer robot requires sensor-motor-skills to shoot the ball, to dribble and pass the ball, to avoid serious crashes with other players, and so on. This is very challenging task, as the strategies and behaviours of the opponents are uncertain. This task is significant important for applications-oriented research.

The next stage of our research is to investigate other cooperative behaviours towards real world applications. More specifically, we will address: (i) how adaptation and learning algorithms should be adopted to make robotic systems more flexible in a dynamic environment? (ii) what data fusion algorithms are required to capture environment features effectively and deal with uncertainties? (iii) how low-level behaviours such as kicking, passing are effectively integrated with high-level behaviours, i.e. team formation? More detailed results of the research will be presented in a forthcoming paper because of the page limit for this short paper.

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