Collective Task Achieving Group Behaviour by Multiple Robots

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Abstract

In this paper, we explore the idea of using environmental cues as a control for a chain of sequential behaviours which, when taken together, define a task achieving group behaviour. Our approach is to define the collective task, to be performed by multiple robots, as a group behaviour. The group behaviour is a set of behaviours performed in sequence, each of which specify a single step in the collective task. An environmental cue is used to control the transition between each behaviour, thus allowing the progress of the collective task to self-govern its execution. We propose to simplify the recognition of the environmental cue by characterizing the robot's sensor input patterns as a classification problem, solved using an Adaptive Logic Network (ALN) and implemented using simple combinational logic. We provide a description of our Collective Robotic Intelligence Project (CRIP) including our simulation results and our multi-robot system on which these results will be deployed.

1 Introduction

Can collective tasks be accomplished using group behaviours? Interest in accomplishing tasks by using multiple robots has resulted in systems designed using cooperative behaviour [8, 5, 1, 4, 9]. Our previous work [7] demonstrated that computationally simple control mechanisms allowed multiple autonomous robots to perform simple tasks without centralized control or use of explicit communication. In this paper, we explore the idea of using environmental cues as a control for a chain of sequential behaviours which, when taken together, define a task achieving group behaviour.

Collective tasks are defined as a result of a group of task achieving robots all with a common purpose. For example, a group of robots designed to keep a table top free from objects, will collectively locate and push to an edge any object placed on the table. When the object is heavier than a single robot can move, the cooperative efforts of the group is required. Similarly, consider the task of a group of fire fighting robots. A fire that quickly spreads is easier to bring under control if a system of multiple robots can physically distribute itself over the area. Collective tasks of these forms are suitable to the multiple robot approach.

Research projects are now beginning to investigate the cooperative behaviour of multiple robot systems necessary for collective tasks. Such tasks include simple retrieval tasks, flocking, and cooperative pushing [1, 8, 3, 6].

Our own work has examined the problem of controlling multiple autonomous robots. Based on observations made from the study of social insects, we proposed some simple mechanisms used to invoke group behaviour in simple mobile robots. The proposed mechanisms allowed populations of behaviour-based robots to perform tasks without centralized control or use of explicit communication. Some of these mechanisms have been tested on a group of five homogeneous mobile robots [7].

The remainder of this paper is organized as follows. In section 2 we discuss collective tasks which are suitable for multiple robot systems. In section 3 we examine how a group behaviour can be constructed from a sequence of individual task achieving behaviours, and how environmental cues can be used to activate each behaviour in sequence. In section 4 we present an approach we are investigating to simplify the recognition of environmental cues. In section 5 we describe briefly our Collective Robotic Intelligence Project (CRIP) and both the simulation results and implementation of our multiple mobile robot system. Finally, section 6 summarizes our work to date.

2 Collective Tasks

Solving tasks with the use of multiple robot systems has advantages researchers are just beginning to explore. For example, tasks with an inherent parallel nature, such as search, can be accomplished in a shorter time frame using multiple searching robots. The multiple robot approach also serves to increase the redundancy and distribute the risk of single failure; an important feature of any system working in a hazardous environments.

Distributing a task over multiple robots does not simply divide the time necessary for task completion by the number of robots. Issues involving cooperation and task progression must also be addressed when designing a collective task suitable for execution by a multiple robot system.

Cooperation comes into play when the collective tasks involve several robots working together towards some common goal. In these situations some mechanism must exist which both allows for the cooperation to take place and to regulate the progress of the cooperative task. In the next section we discuss one possible approach using group behaviours.

3 Group Behaviour

Collective tasks to be performed by multiple robots can be defined using group behaviours. A group behaviour is a set of behaviours performed in sequence, each specifying a single step in the collective task. An *environmental cue* is used to control the transition between each behaviour. This allows the progress of the collective task to self-govern its execution. We propose to simplify the recognition of the environmental cue by characterizing the robot's sensor input patterns as a classification problem, solved using an Adaptive Logic Network (ALN) and implemented using simple combinational logic.

A group behaviour can be defined as a sequential set of behaviours each of which are activated by a specific sensor pattern. For example, consider the simple task depicted in Figure 1. The objective is to move the box from its initial position at X to a position designated as Y. The task can be specified with the following four behaviours.

- *Find-Box* B_1.
- *Move-to-Box* B_2.
- *Push-Box* B_3.
- *Move-to-Y* B_4.

Given that the box is too heavy for a single robot to move, the task will require the cooperative efforts of at least two robots. The above four behaviours in this example are simply ordered $\{ B_1, B_2, B_3, B_4 \}$ and define the *transport* group behaviour.

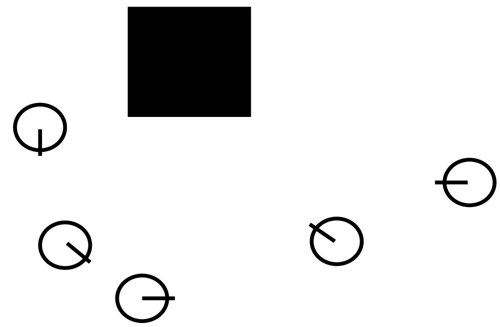

Figure 1: The robots (circles) must locate and collectively push the box from position X to position Y.

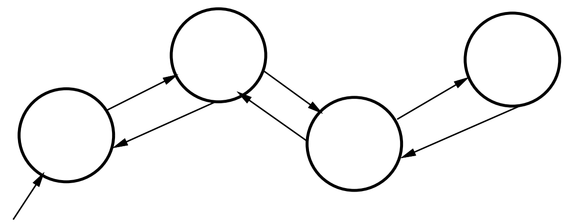

Figure 2: State transition diagram for the *Transport* group behaviour, consisting of the four behaviours labelled $B_1 - B_4$. The environmental cues which cause transition are labelled as e_1, e_2, and e_3.

The transition between behaviours is specified by an environmental cue. In this example, three cues are necessary and are represented by three sensor patterns. This could be implemented with three separate sensors, but this does not have to be the case. The environmental cues are:

- *box-pattern-sensor*, e_1, used to locate the box.
- *box-contact-sensor*, e_2, used to touch the box.
- *location-Y-sensor*, e_3, used to find position Y.

An example of a transition between the *Find-Box* and *Move-to-Box* behaviour is given by: $T_1 : e_1 \& \neg e_2$. Figure 2 is a state diagram of the *transport* behaviour, with the environmental cues labelled as e_i.

Environmental cues allow the progress of the collective task to self-govern its execution. Consider the task of building an archway, illustrated in Figure 3, by a group of construction robots. The archway collective task consists of three steps:

1. Construct a free standing pillar of blocks of type b.

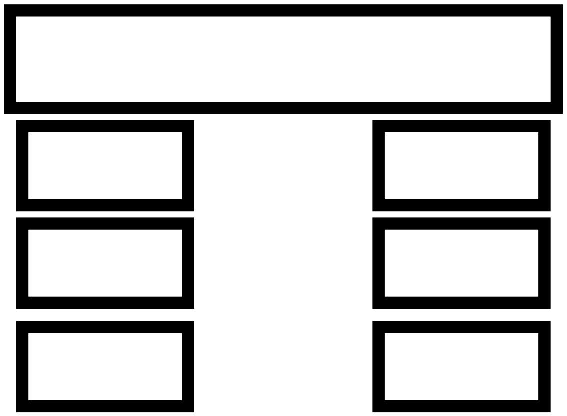

Figure 3: The archway collective task

2. Construct a free standing pillar in close proximity to a pillar.

3. Place a beam of type a on top of the pillars.

The last step will require an environmental cue that recognizes two adjacent pillars, before activating a *place-beam* behaviour. Likewise, in order to construct a pillar an environmental cue will have to recognize a partially complete pillar, allowing a *block-placing* behaviour to continue constructing the pillar. As the construction task proceeds its progress governs the execution of the task, as environmental cues recognize the completion of each step.

In attempting to implement the environmental cues, e_i , we are faced with the pragmatic problem of how to implement this recognition in a computationally simple manner, given that we may not be able to easily characterize the sensor inputs that specify e_i programatically. Our proposed solution is to employ a simple, computationally efficient, pattern recognition mechanism called an Adaptive Logic Network (ALN) [2]. By characterizing the sensor input pattern as a classification problem, which the ALN can be trained to recognize, we hope to simplify the recognition of the environmental cues. Implementation of the ALN is possible in simple combinational logic, making then fast and computationally efficient. In the next section we describe ALNs and our simulation approach.

4 Simulation Approach

Our robot population simulator, *SimbotCity*, described in [6] allows us to model a robot as a collection of sensor systems and actuator resources. Populations can be created which consist of autonomous robots and simple collective tasks specified. Our approach is to train an ALN on the robot's sensor pattern resulting in one ALN tree to recognize each different environmental cue. The single output of the ALN tree will then be used to activate a behaviour in the robot's controller.

4.1 Adaptive Logic Networks

ALNs are a type of neural network constructed using binary trees. Each node in the tree is assigned a boolean function from the set { AND, OR, LEFT or RIGHT } . At the base of the tree are the leaves to which the input vector is presented.

A tree begins with a random node assignment and is trained, resulting in an assignment of the correct boolean function to non-leaf nodes using a simple training algorithm explained in [2]. Once trained, the ALN classify new input vectors into one of the classes established during training.

ALNs offer speed and implementation advantages important in our approach. Both can be attributed to the boolean nature of each node in an ALN binary tree. For example, a node whose assigned boolean function is AND is both quick to evaluate if one input is zero and easy to implement in VLSI circuit technology.

Our main (tentative) conclusion is that, ALNs can be trained to recognize a given sensor input pattern and classify the correct environmental cue, thereby serving as a computationally efficient and fast method to activate behaviour transitions. As our simulation work proceeds, we will see if this approach applys over a wide range of sensor modalities. In the next section we briefly discuss some of the results from our Collective Robotic Intelligence Project (CRIP).

5 Experiments

Our previous work has been looking for suitable control mechanisms with which to control multiple robot systems without using a centralized supervisory approach. As a first step, our research proposed five control mechanisms suitable for controlling populations of behaviour-based robots. Our approach to controlling multiple robots involves the use of group behaviours which may be invoked using several sensory-based mechanisms. The mechanisms proposed have resulted from the study of social insects which exhibit collective task achieving behaviours. To test our control mechanisms we created a simulator, called *SimbotCity*, which allowed us to create configurations of multiple robots designed to achieve simple collective tasks. Once satisfied the control strategies were feasible, we then constructed a system of five physical robots designed for a simple collective task consisting of locating a brightly lit box and pushing it in their environment. The task was such that it could not be accomplished without the cooperative efforts of at least two robots pushing on the same side of the object. [6, 7].

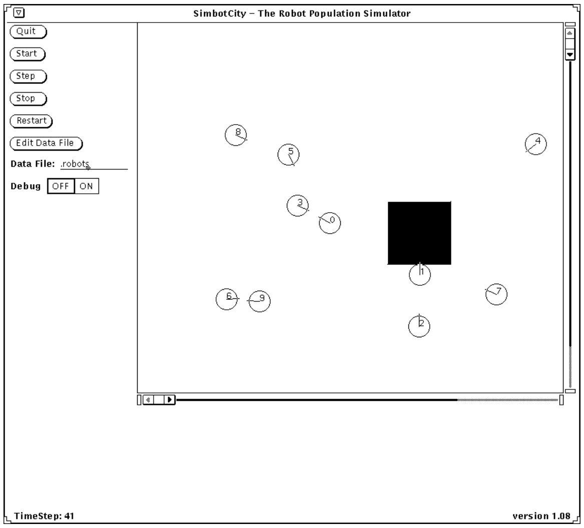

Figure 4: Initial robot configuration. Robots must locate and collectively push the black box.

The approach, employed to control the group of five robots, involved having the robots work toward a common goal (see Figure 4). Using noninterference as a simple form of cooperation, the robots were able to collectively locate and push a brightly lit box in their environment (see Figure 5). The system demonstrated that the common task control mechanism was a feasible approach to controlling a small group of robots using a non-interference cooperation strategy.

An important feature of the system is that simple reflexive behaviours can be used to control the individual robot in a goal directed manner using equally simple binary sensors. The behaviours and their arbitration mechanism are constructed using simple combinational logic. An important implication of this simplicity is that the control architecture could be scaled down to fit on a small silicon chip. This would allow for the creation of a large number of small cost effective robots to be used in areas too small for more traditional robots.

6 Summary

In this paper we have presented our approach towards implementing environmental cues, a mechanism used to control a group of multiple robots and their progress towards executing a collective task. We are exploring the use of Adaptive Logic Networks as a means to implement the environmental cues by characterizing the robot's sensor input patterns as a classification problem. Should the (tentative) simulation results demonstrate the soundness of the approach, we will then implement the results in combinational logic on our system of five physical robots and continue our exploration of cooperative robotic behaviour.

Figure 5: Robot 1 overtakes robot 2 to avoid a collision, while progressing towards the box. Robots 1 and 3 pushing the box forward

References

[1] Ronald C. Arkin. Cooperation without communication: Multiagent schema-based robot navigation. *Journal of Robotic Systems*, 9(3):351–364, 1992.

[2] W. Armstrong, A. Dwelly, J. Liang, D. Lin, and S. Reynolds. Learning and generalization in adaptive logic networks, in artificial neural networks. In *Proceedings of the 1991 International Conference on Artificial Neural Networks*, pages 1173–1176, 1991.

[3] Hajime Asama, Maki K. Habib, Isao Endo, Koichi Ozaki, Akihiro Matsumoto, and Yoshiki Ishida. Functional distribution among multiple mobile robots in an autonomous and decentralized robot system. In *1991 IEEE International Conference on Robotics and Automation*, pages 1921–1926, 1991.

[4] Toshio Fukuda, Tsuyoshi Ueyama, and Fumihito Arai. Control strategy for a network of cellular robots. In *1991 IEEE International Conference on Robotics and Automation*, pages 1616–1621, 1991.

[5] Maki K. Habib, Hajime Asama, Yoshiki Ishida, Akihiro Matsumoto, and Isao Endo. Simulation environment for an autonomous and decentralized multi-agent robotic system. In *1992 IEEE/RSJ International Conference on Intelligent Robots and Systems*, pages 1550–1557, 1992.

[6] C. Ronald Kube. Collective robotic intelligence: A control theory for robot populations. Master's thesis, University of Alberta, Edmonton, Alberta, 1992.

[7] C. Ronald Kube and Hong Zhang. Collective robotic intelligence. In J. A. Meyer, H. Roitblat, and S. Wilson, editors, *Second International Conference on Simulation of Adaptive Behavior*. MIT Press, 1992. to appear.

[8] Maja J. Mataric. Minimizing complexity in controlling a mobile robot robotic population. In *1992 IEEE International Conference on Robotics and Automation*, pages 830–835, 1992.

[9] S. Yuta and S. Premvuti. Consideration on cooperation of multiple autonomous mobile robots. *IEEE/RSJ International Workshop on Intelligent Robots and Systems*, pages 545–549, 1991.