Fuzzy and Neuro-fuzzy Based Co-operative Mobile robots

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Abstract

This paper focuses on the development of intelligent multi-agent robot teams that are capable of acting autonomously and of collaborating in a dynamic environment to achieve team objectives. A biologically-inspired collective behaviour for a team of co-operating robots is proposed. A modification of the subsumption architecture is proposed for implementing the control of the individual robots. The paper also proposes a fuzzy logic technique to enable the resolution of conflicts between contradictory behaviours within each robot. Furthermore, the paper proposes a neuro-fuzzy based adaptive action selection architecture that enables team of robot agents to achieve adaptive cooperative control to perform two proof-of-concept co-operative tasks: dynamic target tracking and box-pushing. Simulated and real experiments have been conducted to validate the proposed techniques.

Keywords: Multiple Mobile Robots, Behaviour Coordination, Fuzzy Logic technique, Neuro-fuzzy Technique.

1. Introduction

Biological agents, for example social insects, have been manifestly successful in exploiting the natural environment in order to survive and reproduce. Scientists are interested in understanding the strategies and tactics adopted by such natural agents to improve the design and functionality of computer-based artificial agents (robots). They observe how these social insects locally interact and co-operate to achieve common goals. It seems that these creatures are programmed in such a way that the required global behaviour is likely to emerge even though some individuals may fail to carry out their tasks.

In this paper, a biologically-inspired group behaviour for a team of co-operating of mobile robots is proposed. Since co-operation among a group of robots working in an unknown environment poses complex control problems, it is necessary to obtain solutions that achieve a suitable trade-off between the objectives of the robots that can potentially conflict [1]. This highlights the problem of deciding what action to select next as a major issue in the design of systems for control and co-ordination of multiple robots. For this purpose, a new approach of fuzzy logic technique for behaviour coordination in co-operative target tracking is proposed.

Achieving adaptive co-operative robot behaviour is more challenging. Many issues must be addressed in order to develop a working co-operative team; these include action selection, task allocation, coherence, communication, resource conflict resolution, and awareness. Therefore, a neuro-fuzzy based action selection architecture is proposed that enables these robots to achieve adaptive cooperative control despite dynamic changes in the environment and variation in the capabilities of the team members.

The remainder of the paper is organised as follows. Section 2 outlines the background related to the theme of the paper. Section 3 presents collective behaviour of social insects and co-operating mobile robots. Section 4 describes fuzzy-logic-based dynamic target tracking behavioural architecture. Section 5 describes adaptive co-operative action selection architecture. Section 6 shows simulation results. Section 7 describes mobile robots hardware and real experiments. Finally, Section 8 gives the conclusion.

2. Background

The research that closely relates to the topics presented in this paper includes that of [2], they presented a collective robotics application whereby a pool of autonomous robots regroup objects that are distributed in their environment. A team of real mobile robots that co-operated based on the ant-trail-following behaviour and the dance behaviour of bees is presented [3]. An interesting example of decentralised problem - solving by a group of mobile robots is given [4]. A collaboration in a group of simple reactive robots through the exploitation of local interactions is investigated [5]. New methods for tracking ball and players in soccer team and team coordination approaches are proposed [6]. Mobile robot navigation and co-operative target acquisition examples are given, in which the principles of multiple objective decision-making (MODM) are demonstrated [7]. Desirability functions as an effective way to express and implement complex behaviour coordination strategies were espoused [8]. An action selection method for multiple mobile robots performing box pushing in a dynamic environment is described [9]. A multi-channel infrared communication system to exchange messages among mobile robots is developed [10]. A description of L-ALLIANCE architecture that enables teams of heterogeneous robots to dynamically adapt their actions over time is given [11].

3. Collective Behaviour of Social Insects and Cooperating Mobile Robots

The collective dynamic target tracking task investigated here is based on the emergence of collective strategy in prey-predator behaviour, where the predators co-operate to catch the prey or the prey co-operate to defend themselves. The term collective is used in the sense of the collective motion of defence or attack. The dynamics of predator-prey interactions where the predators surround the prey to catch it using local sensor-based interactions among them have been implemented in the task of dynamic target tracking.

In this paper, the subsumption architecture is modified to comprise more than one behaviour module within one layer run in parallel and have the same priority and to allow information exchange between the layers as shown in figure 1. The design of the target-tracking controller begins by specifying the sensing requirements for the task. Collision free movement will require an obstacle sensor; to follow other robots needs a robot sensor; tracking the target will require a target or goal sensor. The lowest priority default behaviours are the "search" and "listen for messages" behaviours. "Search" directs the robot to advance along its current path. Simultaneously, "listen for messages" makes the robot receptive to messages sent by other mobiles. The above default behaviours can be suppressed by the "follow message sender" behaviour if a message has been received from another robot (by means of the robot sensor on the current robot). "Follow message sender" causes the robot to move to its nearest sensed neighbour. The "send message" and "approach goal" behaviours are activated by the goal sensor. "Send a message" makes the robot issue a "target intercepted" message to the other mobiles and "approach goal" directs them towards the target. "Approach goal" causes the robots to turn a number of degrees towards the target while the goal sensor is active. The task is accomplished once several robots collectively have captured the target. The highest priority avoid behaviour becomes active and remains active as long as the obstacle sensor has detected an obstacle. Avoid behaviour turns the robot a fixed number of degrees away from the sensed obstacles at each simulation time step prevents collisions.

4. Fuzzy-Logic-Based Dynamic Target Tracking Behavioural Architecture

Even though the modified subsumption architecture allows more than one behaviour to run simultaneously, however only a behaviour requires to activate the robot actuators modules will get the control of robot actuators at a time. The question arises here is how to control robot actuators when several main behaviours are activated simultaneously. To address this issue, an approach based on fuzzy sets operations

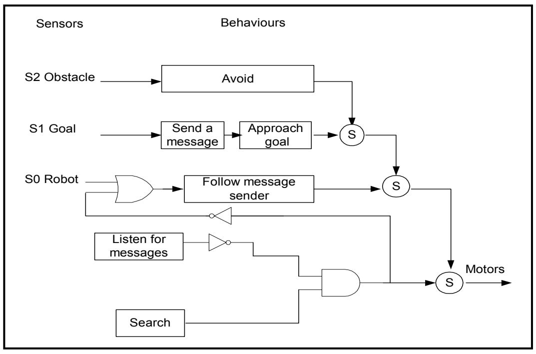

Fig. 1: target - tracking robot architecture

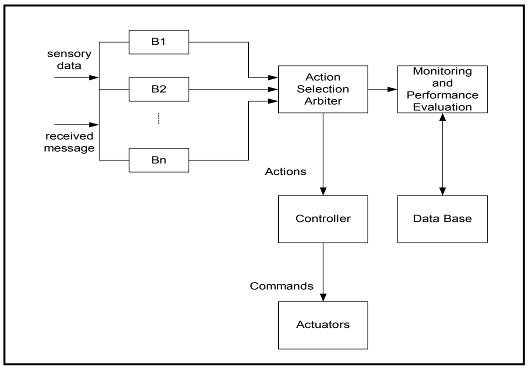

Fig.2: Adaptive action selection architecture

is proposed here that takes into account the recommendations of all applicable behaviour modules. Behaviour coordination is achieved by weighted decision-making and rule-based (behaviour) selection. The weights used for weighted decision-making are the degrees of confidence placed on the different behaviours. They are empirical measures of applicability of particular behaviours. The fuzzy-logic-based architecture for mobile robots, in the context of a dynamic target tracking system, consists of several behaviours, such as target following and obstacle avoidance. Multiple behaviours could share a common fuzzy inference module. Fuzzy control recommendations generated by all behaviours are fused and defuzzified to generate a final crisp control command.

The basic algorithm executed in every control cycle by the architecture consists of the following four steps: (1) the target following behaviour determines the desired turning direction; (2) the obstacle avoidance behaviour determines the disallowed turning directions; (3) the command fusion module combines the desired and disallowed directions and (4) the combined fuzzy command is converted into a crisp command through a defuzzification process.

5. Adaptive Action Selection Architecture

To maintain a purely distributed co-operative control scheme which affords an increased degree of robustness, individual agents must always be fully autonomous, with the ability to perform useful actions even amidst the failure of the other robots. An adaptive action selection architecture based on neuo-fuzzy technique (figure 2) is developed to be fully distributed, and giving all robots the capability to determine their own actions based upon their current situation, the activities of other robots and the current environmental conditions. The monitor function, implemented within each robot, is responsible for observing and evaluating the performance of any robot team member (including itself) whenever it performs a behaviour.

A neuro-fuzzy technique has been used to fine-tune the fuzzy rules and minimise the total error between the desired output and the fuzzy controller output. The structure of the neuro-fuzzy system is shown in Fig.3. The network structure contains six layers. Nodes in layer one are input nodes that represent input linguistic variables. Nodes in layer two are input term nodes that act as membership functions to represent the terms of the respective N input linguistic variables. The nodes in layer three are rule nodes, where each node associates one term node from each term set to form a condition part of one fuzzy rule. The nodes in layer four are output term nodes that act as membership functions to represent the output terms of the respective L linguistic output variables. The number of nodes in layer five is 2L, where L is the number of output variables, i.e. there are two nodes for each output variable. The function of these two nodes is to calculate the denominator and the numerator of a quasi Centre of Area (COA) defuzzification function. The nodes in layer six are defuzzification nodes. The number of nodes in layer six equals the number of output linguistic variables. The structure of the neuro-fuzzy system is created in three steps. The first step is to specify the input and the output variables of the network. The second step is to divide the input-output universes into a suitable number of partitions (fuzzy sets) and to specify a membership function for each partition. The third step is to generate fuzzy rules to perform the input-output mapping of the fuzzy logic system.

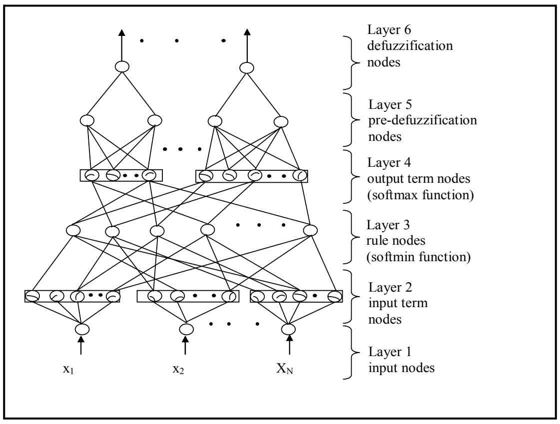

Fig.3: Neuro-fuzzy structure

perform the input-output mapping of the fuzzy logic system. Following this construction phase, the system then enters the parameter learning phase to adjust its free parameters. The adjustable free parameters are the centre (m_{ijs}) and width (σ_{ijs}) of the term nodes in layer four as well as the link weights in layers two and six. A supervised learning technique is employed in conjunction with the back propagation (BP) learning algorithm to tune these parameters.

6. Simulation

The objective of the developed simulation tool is to test the proposed architecture based on the context of the co-operative tasks of dynamic target tracking and box pushing.

6.1. Dynamic target tracking task

For this task, a simulated environment has been designed to model a large population of robots (a few thousand), different obstacles and one target. Two kinds of sensors were simulated: obstacle detection sensors and target detection sensors. Three ultrasonic sensors were modelled to provide information on obstacles to the left and the right, and in front of the robot. The same models were used for the ultrasonic sensors fitted to the moving target. Target detection was simplified by using an infrared source at the centre of the target and infrared target sensors mounted on the robots. Two actuators were modelled, one for each motor (left and right). Experiments were run with different numbers of robots and different obstacle densities. Each experiment on a collection of robots was performed thirty times and the results were averaged. The first experiment analysed how varying the number of robots affected the time required to track (capture) the target. This experiment took place in a limited arena containing one small target and no obstacles. The second experiment differed from the first only by the addition of obstacles in the arena. Figure 4 shows that increasing the number of robots reduced the time required to track the target. However, robot collision and interference tended to degrade the performance. Adding more robots did therefore produce a proportional increase in performance. The first and second experiments were repeated to investigate the application of fuzzy logic technique for behaviour coordination. Fuzzy logic enables to solve conflicts between the contradictory behaviours by selecting an action that represents the consensus among the behaviours as shown in figure 5.

6.2. Box-pushing task

The objective in this task is to find a box, randomly placed in the environment, and push it across a room. The box is so heavy and long that one robot cannot achieve this alone. The Webots simulation tool [12] was used to implement this task. This software operates in three dimensions and enabled the modelling of robots, sensors, actuators, and obstacles, as well as a set of behaviour modules in order to map sensor inputs to actuator outputs. Experiments in [11] are repeated for comparison. In the first experiment, two robots co-operate to find a box and push it across the room, with no obstacles in the environment. In the second experiment, obstacles are added that obstruct one of the two robots to investigate how the other one dynamically reselects its actions in response to changes in the mission situation. The robots are initially situated randomly in the environment and they then start to locate the box (figure 6a). After both of them have reached the, it is assumed that the robot at the left end of the box starts to push first (figure 6b).

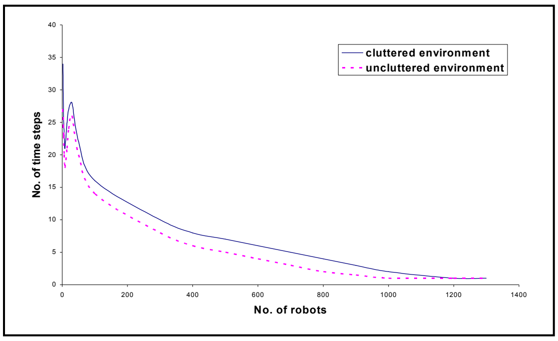

Fig. 4: Target tracking without coordination

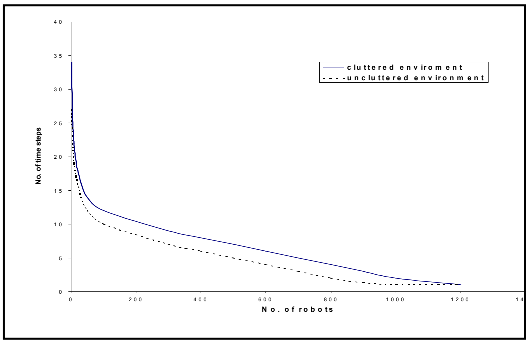

Fig. 5: Target tracking with coordination

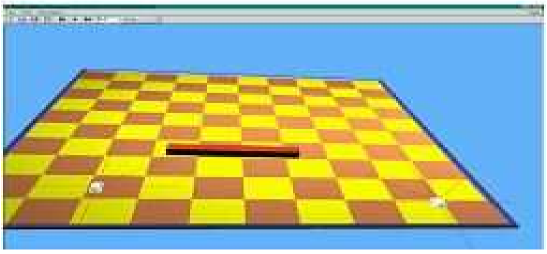

Fig. 6.a: Initial environment

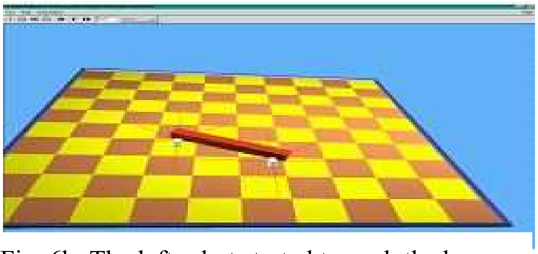

Fig. 6b: The left robot started to push the box

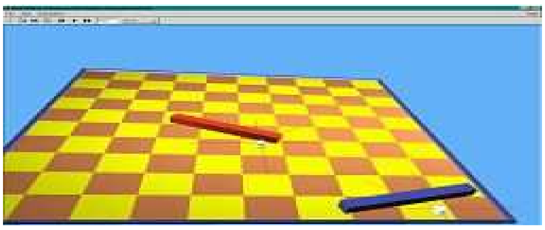

Fig. 6c: The robot moved to the other end to push

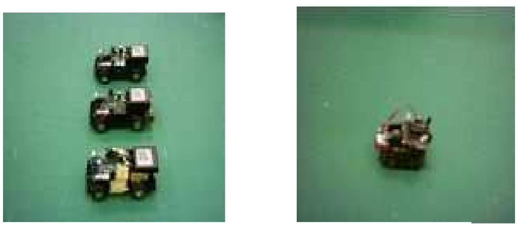

Fig. 7: The robots and target

From sensory feedback and acquired knowledge (learned off line [13]), the box has then to be pushed from the right end. The robot at the right end starts to push and broadcasts that action to the robot at the left end. During the expected time for that action, the robot at the left end monitors the performance of its team mate. In the first experiment, the robots completed the task. In the second experiment, one of them is stuck because of obstacles in the environment while the other has reached the box. Because there is no progress from the other robot, the robot that reached the box starts to push the box from one end. Then it moves to the other end to push (figure 6c). It continues its back and forth pushing executing both pushing tasks as long as it fails to hear that another robot is performing the push at the opposite end of the box.

7. Mobile Robots Hardware and Real experiments

Small radio-controlled toy cars and a small radio-controlled toy tank were adapted to provide the mechanical structures for the mobile robots and moving target, respectively (see figure 7).

The control system for the robots and target was purpose designed for this application as the existing radio-operated controllers in the toy cars and toy tank were not suitable. A robot can detect another robot approaching it from either side of it because one of the side sensors of the first robot will be activated by the signal emitted by the approaching robot. A robot can also distinguish between a target and another robot located on either side of it because of the different signals they emit.

Experiments were run with two or three robots, different obstacles and one target. The first set of experiments analysed how varying the number of robots affected the time required for tracking the target. This experiment took place in a limited arena containing one target and no obstacle. The second set of experiments differed from the first set only by the addition of obstacles in the arena. Figure 8(a) depicts an intermediate stage of three robots are tracking the target. Figure 8(b) shows the final stage when the robots have cooperated and captured the target. It was found that the time required to track and capture the target using three robots was approximately 2 minutes. With only two robots, the required time was about 4 minutes. In the case where three robots and obstacles were included, the time was 7 minutes.

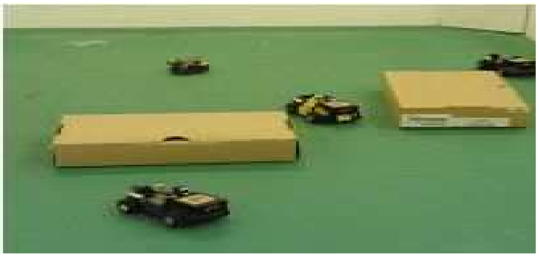

Fig. 8(a): Intermediate stage

Fig. 8(b): the robots captured the target

8. Conclusion

The use of fuzzy logic enabled the resolution of conflicts between contradictory behaviours by selecting an action that represents the consensus among the behaviours and that best satisfies the decision objectives encoded in them. Furthermore, the proposed co-operative robot architecture has been shown to allow robot teams to perform real-world missions over long periods, even while the environment or the robotic team itself changes.

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