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Co-operating Mobile Robots Approaches

Medhat Awadalla[1], Ayman Al khazraji[2] and Karama Al Delimi[3]

Abstract: This paper surveys the background literature relevant to the work presented on co-operating mobile robots which was examined from different perspectives. First, it was surveyed with a focus on the classification of co-operating mobile robots. Second, the focus shifted to the collective behaviour of social insects and the connection of the functioning principles of social insect colonies with the design principles of artificial systems. Third, the literature was reviewed related to the action selection problem (ASP) and behaviour coordination. Fourth, previous work on robot awareness and its effect on the performance of co-operating mobile robots was examined.

1. INTRODUCTION

During the last few decades, major research efforts have been directed towards improving the performance of individual mobile robots through the use of advanced sensors and actuators as well as the application of intelligent control algorithms. This was mainly driven by the need to perform increasingly complex real time tasks. As a result, individual mobile robots have become very sophisticated. More recently, an alternative approach to achieving complex tasks using multiple co-operative autonomous mobile robots has been investigated [4], [5], [6], [7]. Groups of mobile robots have been constructed, with the aim of studying such issues as group architecture, resource conflict, mobile robots co-operation and learning.

Collaboration increases the performance of a robot team without requiring significant modifications to individual robot capacities. Collaboration may be obtained using communication schemes, implicit communication via the environment or simple explicit communication schemes. By these means, the task accomplished by the team can be more complex and its performance enhanced without losing the autonomy or increasing the complexity of individual robots. In some cases [8], [9], the task may require collaboration for it to be successfully performed at all, where a single robot is not able to carry out the task alone. Such tasks can be defined to be "strictly collaborative".

2. CO-OPERATIVE MOBILE ROBOTICS CLASSIFICATION

Research in the field of co-operative mobile robotics has increased substantially in recent years. Most of this research has concentrated on how to obtain the desired interaction dynamics between agents (robots) to increase the overall team performance. This field can be broadly categorised into two groups: "collective" (swarm type) co-operation and "intentional" co-operation.

Collective robotics is usually behaviour-based and characterised by distributed control of homogeneous robot teams. The desired collective behaviour is obtained as an emergent property of the interaction mechanism designed into each robot. The approaches developed and the problems addressed are for homogeneous robot teams only, in which each robot has the same capabilities and control algorithm. Additionally, issues of efficiency are largely ignored. The types of tasks implemented take inspiration from social insect societies, such as ants and bees.

[1] Electrical and Computer Engineering Department, SQU, Oman, *E-mail: medhatha@squ.edu.om*

[2] Electrical and Computer Engineering Department, CCE, Oman, *E-mail: ayman.alkhazraji@caledonian.edu.om*

[3] Mathematics Department, Nahrain University, Iraq, *E-mail: aldelimika@gmail.com*

A number of researchers have investigated ‘swarm’ robotics such as in [10]. Bayýndýr [11] presented distributed algorithms to bring cooperation between agents, obtained in various forms and often without explicitly programming a cooperative behaviour in the single robot controllers. Offline and online learning approaches were described, and some examples of past works utilizing these approaches were reviewed. Steels [12] presented simulation studies of several dynamic systems to achieve emergent functionality with application to the collection of rock samples on a distant planet. Drogoul and Ferber [13] undertook simulations of foraging and chain-forming robots. Arkin *et al.* [14] implemented research concerned with sensing and communication for tasks such as foraging. Mataric [15] has described the implementation of group behaviours for physical robots such as dispersion, aggregation and flocking. Yan *et al.* [16] and Ferrari *et al.* [17] have detailed an emergent control strategy applied to a group of physical robots performing the task of locating and pushing a brightly-lit box. “Intentional” robotics achieves co-operation among a limited number of typically heterogeneous robots performing several distinct tasks. Such systems normally employ either central control or a mix of central and distributed control Steels *et al.* [18].

In an intentional co-operative system, the robots often have to deal with some kind of efficiency constraint that requires a more directed type of co-operation than is found in collective co-operative systems Murata *et al.* [19]. Furthermore, the robots are usually required to perform several distinct tasks. These missions thus usually require a smaller number of robots involved in more purposeful co-operation, although the individual robots involved are typically able to perform useful tasks on their own. Such systems require a robust allocation of subtasks to robots, to maximise the efficiency of the team, and proper coordination among team members, to allow them to complete their mission successfully. Most existing work on heterogeneous physical robots uses a traditional artificial intelligence approach, whereby the robot controller is divided into modules for sensing, world modelling, planning, and acting. This is the so-called sense-model-plan-act paradigm, in contrast to the functional decomposition method used in behaviour-based approaches.

Many researchers have investigated these intentional co-operative systems. Noreils [20] and Kozma *et al.* [21] addressed one such sense-model-plan-act control architecture, which includes three layers of control. The planner level manages coordinated protocols, decomposes tasks into smaller sub-units, and assigns the sub-tasks to a network of robots. The control level organises and executes the tasks of the robots. The functional level provides controlled reactivity. This architecture was applied to two mobile robots performing box pushing. Cirillo *et al.* [22] addressed the issue of human–robot cohabitation in smart environments. In particular, the presence of humans in a robot’s work space has a profound influence on how the latter should plan its actions. The paper proposed the use of human-aware planning, an approach in which the robot exploits the capabilities of a sensor-rich environment to obtain information about the (current and future) activities of the people in the environment, and plans its tasks accordingly.

Escande *et al.* [23] presented a planner for under actuated hyper-redundant robots, such as humanoid robots, for which the movement can only be initiated by taking contacts with the environment.

Some sense-model-plan-act architecture includes a task planner, a task allocator, a motion planner and an execution monitor. Each robot had goals to achieve, either based on its own current situation or via a request by another team member.

Asama *et al.* [24] described a robot system called ACTRESS, which addressed the issues of communication, task assignment and path planning among heterogeneous robotic agents. Their approach revolves primarily around a negotiation framework, which allows robots to recruit help when needed. They demonstrated their architecture on mobile robots performing a box-pushing task. In general, co-operative (both swarm and intentional) approaches to robotics should include mechanisms within the control software of each robot that allows team members to recover from dynamic changes in their environment or in the robot team. Researchers have recognised that a more promising approach for the development of co-operative control mechanisms is by the inclusion of learning algorithms [25], [26]. Much work in particular has been carried out in the field of multi-agent learning [27], [28]. Applications include predator/prey scenarios [29], [30], multi-robot soccer teams [31] and [32], and box-pushing tasks such as [33] and [34].

3. COLLECTIVE BEHAVIOUR OF SOCIAL INSECTS

Collective behaviour is demonstrated in any type of system where patterns are determined not by some centralised body, but instead by the interactions of a group of decentralised bodies [35], [36]. There is no need for centralised authority at all, nor for explicit communication between interacting bodies. Collective behaviour demonstrates also a fundamentally important principle that has been beneficial to nature and humans alike, namely that some objectives are easier to accomplish in a group rather than by an individual. This interaction does not necessarily require a high level of intelligence, or even communication between the participating bodies, yet objectives may be accomplished that are outside the scope of an individual. Many examples of collective behaviour can be found in nature, e.g. flocking of birds, termites building enormous mounds, and ants collectively carrying a large grasshopper back to the nest to be used as food. A flock of birds manoeuvring through the air is quite impressive. There is no a leader bird telling the other birds which way to move. Each bird simply has an instinctive behaviour to react to the other birds around it, and when they all fly together the result is a collective behaviour called flocking. Another example is ants, which have minimal forms of communication and are considered to have very low intelligence, yet army ants are able to move large objects thousands of times heavier than themselves back to their nest [37]. One ant could not direct the all other surrounding ants to return that object, and could not move the object itself. It is also the case that an ant could not determine the weight of the entire object by simply tugging on it. However, the collective behaviour that results in successful completion of the ants' objective is due to a genetic trait possessed by the ants. As shown by these examples, collective behaviour provides a means for very simple creatures to accomplish complicated objectives.

Social insects can process many sensor inputs, modulate their behaviour according to many stimuli, including interactions with nest-mates, and take decisions on the basis of a large amount of information. The success of social insects lies mainly in their self-organising behaviour (SO), where complex behaviour emerges from the interactions of individuals that exhibit simple behaviour by themselves [38], [39]. They can also solve problems in a changing environment (flexibility) and give the highest level of performance even though some individuals fail to perform their tasks (robustness). More and more researchers are interested in this exciting way of achieving a form of artificial intelligence - swarm intelligence – in which it is attempted to link the functioning principles of insect colonies to the design principles of artificial systems. For example, [40] presented a low-cost active 3D triangulation laser scanner for indoor navigation of miniature mobile robots is presented. It is implemented by moving both a camera and a laser diode together on the robot's movable part. The movable part is actuated by a servo motor through a gear train to achieve a given scanning view angle.

[41] studied distributed coverage of environments with unknown extension using a team of networked miniature robots analytically and experimentally. Algorithms were analysed by incrementally raising the abstraction level starting from physical robots, to realistic and discrete event system (DES) simulation.

[42], [43] stated that social insects such as bees, ants and termites all function collectively as groups, and efficiently accomplish a range of tasks in order to maintain their societies. Kube and Zhang [44] examined the problem of controlling multiple autonomous robots based on observations made from the study of social insects. They proposed mechanisms that allowed populations of behaviour-based robots to perform tasks without centralised control or use of explicit communication. Other researchers presented a collective robotics application whereby a pool of autonomous robots regroup objects that are distributed in their environment [45]. There is no supervisor in the system, the global task is not encoded explicitly

within the robots, the environment is not represented within the robots, and there is no explicit co-operation protocol between the robots. Instead, the global task is achieved by virtue of emergence and self-organisation. Martinoli [46-48], focused on the hardware tools needed to monitor team performances as well as those needed to achieve collective adaptive behaviours. They presented a simple bio-inspired collective experiment, namely the gathering and clustering of randomly distributed passive seeds. Vaughan [49, 50] showed a team of real mobile robots that co-operated based on the ant-trail-following behaviour and the dance behaviour of bees to robustly transport resources between two locations in an unknown environment. Ant-inspired solutions to various search problems have been demonstrated [51], as has chemical trail laying and following in robots [52]. It has been described also an ant-inspired method for exploring a continuous unknown planar region [53]. Such a method might employ robots with limited sensing capabilities but with the ability to leave marks on the ground to cover a closed region for the purposes of cleaning a floor, painting a wall, or demining a mine field. A mark and cover (MAC) rule of motion is proposed using temporary markers ("pheromones") as a means of navigation and indirect communication. Ijspeert [54] investigated collaboration in a group of simple reactive robots through the exploitation of local interactions. A test-bed experiment is proposed in which the task of the robots is to pull sticks out of the ground – an action that requires the collaboration of two robots to be successful. The experiment is implemented in a physical set-up composed of a group of mobile robots, and in Webots, a three dimensional simulator of mobile robots [55].

As mentioned above, through the use of collective behaviour inspired by social insects, simple tasks that require a small number of mobile robots working in uncluttered environments can be accomplished. The question of interest is whether this collective behaviour approach can help complex tasks, such as dynamic target tracking, which require more collaboration, interaction, coordination and awareness among a large number of robots working together in a highly cluttered and dynamic environment.

4. BEHAVIOUR COORDINATION

In behaviour-based robotics, the control of a robot is shared between a set of purposive perception-action units, called behaviours [56, 57]. Based on selective sensor information, each behaviour produces immediate reactions to control the robot with respect to a particular objective, i.e., a narrow aspect of the overall task of the robot such as obstacle avoidance or wall following. Behaviours with different and possibly incommensurate objectives may produce conflicting actions that are seemingly irreconcilable. Thus, a major issue in the design of behaviour-based control systems is the formulation of effective mechanisms for coordination of the behaviours in a robot. This is known as the action selection or behaviour coordination problem [58].

Authors in [59] presented a probabilistic framework for synthesizing control policies for general multi-robot systems that is based on decentralized partially observable Markov decision processes. The latest are a general model of decision-making where a team of agents must cooperate to optimize a shared objective in the presence of uncertainty. Dec-POMDPs also consider communication limitations, so execution is decentralized.

Furthermore, a generative model of affect that attempts to strongly mimic how people emote in order to produce as natural-seeming a system as possible [60]. The model was designed particularly for robots that interact with people over long periods of time. The work focuses on modelling of interaction between emotions, moods, and attitudes for long term. They implemented their affective model on the Roboceptionist, a robot that interacts with people on a daily basis.

Pardo [61] analysed the insights behind the common approach to the assessment of robot motor behaviours in articulated mobile structures with compromised dynamic balance. They presented a new approach to this problem and a methodology that implements it for motor behaviours encapsulated in rest-to-rest motions. The availability of kinematic information about the solution to the task is assumed, but reference is not made to the workspace, allowing the workspace to be free of restrictions.

Behaviour coordination is generally recognised as one of the major open issues in behaviour-based approaches to robotics. It can be split into two conceptually different problems: (1) how to decide which behaviour(s) should be activated at each moment; and (2) how to combine the results from different behaviours into one command to be sent to the effectors of the robot. These are called the behaviour arbitration and the command fusion problems, respectively. Numerous action selection mechanisms (ASMs) have been proposed over the last decade and these can be classified into a number of logical groups that can be classified into state-based and continuous mechanisms [62]. With a state-based ASM, in a given state, only a relevant subset of the behaviour repertoire of the robot needs to be activated. With a continuous ASM, there are no discrete states and the whole behaviour repertoire is available for activation. Saffiotti [63] divided ASMs into arbitration and command fusion mechanisms, corresponding respectively to the state-based and continuous approaches given in [62]. Arbitration is concerned with "how to decide which behaviour to activate at each moment" and command fusion is concerned with "how to combine the results of different behaviours into one command to be sent to the effectors of the robot".

Based on these classifications, it seems that ASMs can be best classified according to one main characteristic, namely whether the ASM can handle only one or multiple behaviours simultaneously.

4.1. Arbitration ASMs

Arbitration mechanisms select one behaviour from a group of competing behaviours, and give it ultimate control of the system (the robot) until the next selection cycle. This approach is suitable for arbitrating between the set of active behaviours in accordance with the changing objectives and requirements of the system under varying environmental conditions. Arbitration mechanisms for action selection can be classified as priority-based, state-based and winner-takes-all. In priority-based mechanisms, an action is selected based on priorities assigned in advance. Thus, behaviours with higher priorities are allowed to take control of the robot. State-based mechanisms select a set of behaviours that is competent to handle the situation corresponding to the given state. Finally, in winner-takes-all mechanisms, action selection results from the interaction of a set of distributed behaviours that compete until one behaviour wins and takes control of the robot.

4.2. Command Fusion ASMs

Command fusion combines recommendations from multiple behaviours to form a control action that represents their consensus. This approach allows all the behaviours to contribute simultaneously to the control of the system in a co-operative rather than a competitive manner. Command fusion mechanisms can be divided into voting techniques, superposition techniques and multiple objective behaviour coordination techniques.

Voting techniques interpret the output of each behaviour as votes, and then select the action that receives the largest number of votes. Superposition techniques combine behaviour recommendations using linear combinations. Finally, multiple objective behaviour coordination techniques provide a formal theoretic approach to making decisions based on multiple objective decision theory.

4.3. Priority-Based Arbitration (Subsumption Architecture)

The subsumption architecture represents a priority-based arbitration mechanism, where behaviours with higher priorities are allowed to subsume the output of behaviours with lower priorities [64].

A "variable priority for robot's movement", beside of the new main priority, was introduced [65]. This variable priority with the new main priority will cause less solving-time. So, it would increase the solving efficiency a lot. One more advantage is that this manner is general and not just for a specific maze. It is important because in today's projects, most of the time, the environment around the robot is not known.

4.4. State-Based Arbitration

4.4.1. Discrete Event Systems (DES)

Behaviour selection is accomplished using state-transition. the multi robot coordination problem of tightly-coupled task execution was addressed using a formal decentralized supervisory control approach [66]. A general architecture for decentralized supervisory control of Fuzzy Discrete Event Systems (FDES) was developed. This architecture is then incorporated for con trolling behaviour-based mobile robots moving in unstructured environments while maintaining a fixed distance between each other, which resembles a tightly-coupled multi robot object manipulation task.

Gamage [67] described a leader-follower based formation control framework to coordinate multiple non-holonomic mobile robots. The proposed strategy deploys a control theoretic bottom-up approach where, continuous controllers were coordinated by a supervisory controlled discrete event system. All the mobile robots were required to navigate in an obstacle populated environment. And the followers were kept a predetermined geometric formation with the leader while being adaptable to the constraints imposed by obstacles on the environment.

Hosking [68] developed a system of systems (SoS) simulation framework using discrete event system specification (DEVS) and data encoded with Extensible Markup Language (XML) tags to support agent-in-the-loop (AIL) simulations for large, complex, and distributed systems. A system of systems approach enables the simulation and analysis of these independent and cooperative systems by concentrating on the data transferred among systems instead of determining global state spaces. A mobile robot is deployed as a real agent working cooperatively with virtual agents to form a robotic swarm in an example threat detection scenario.

4.4.2. Temporal Sequencing

The temporal sequencing approach is also known as perceptual sequencing and is very similar to the discrete-event systems approach [69]. A finite-state automaton is used to sequence between a series of behaviours based on perceptual triggers. At each state, a distinct behaviour is activated and perceptual triggers cause transitions from one state to another. See the same example in figure 1.

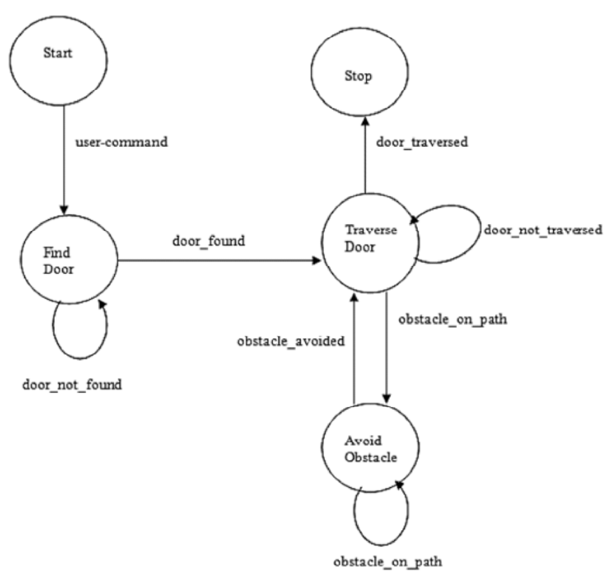

Figure 1: An example FSA encoding a door traversal operation [1, 3]

Fainekos [70] considered the problem of robot motion planning in order to satisfy formulas expressible in temporal logics. Temporal logics naturally express traditional robot specifications such as reaching a goal or avoiding an obstacle, but also more sophisticated specifications such as sequencing, coverage, or temporal ordering of different tasks. In order to provide computational solutions to this problem, they first constructed discrete abstractions of robot motion based on some environmental decomposition. Then they generated discrete plans satisfying the temporal logic formula using model checking tools, and finally translated the discrete plans to continuous trajectories using hybrid control.

Santos [71] addressed the problem of generating timed trajectories and temporally coordinated movements for two wheeled vehicles, when relatively low-level, noisy sensorial information was used to steer action. In coupling of sensory information enabled sensor driven termination of movement. They presented a novel system composed of two coupled dynamical architectures that temporally coordinate the solutions of these dynamical systems. They applied this architecture to generate temporally coordinated trajectories for two vision-guided mobile robots in a non-structured simulated environment, whose goal is to reach a target within a certain time independently of the environment configuration or the distance to the target.

4.4.3. Bayesian Decision Analysis

The approach of sensor planning with Bayesian Decision Analysis is used to address the problem of sensor selection[1]. Sensor selection can be considered a special case of action selection, where the actions are certain sensor operations. It operates according to the purposive paradigm, where the system consists of a set of purposive modules.

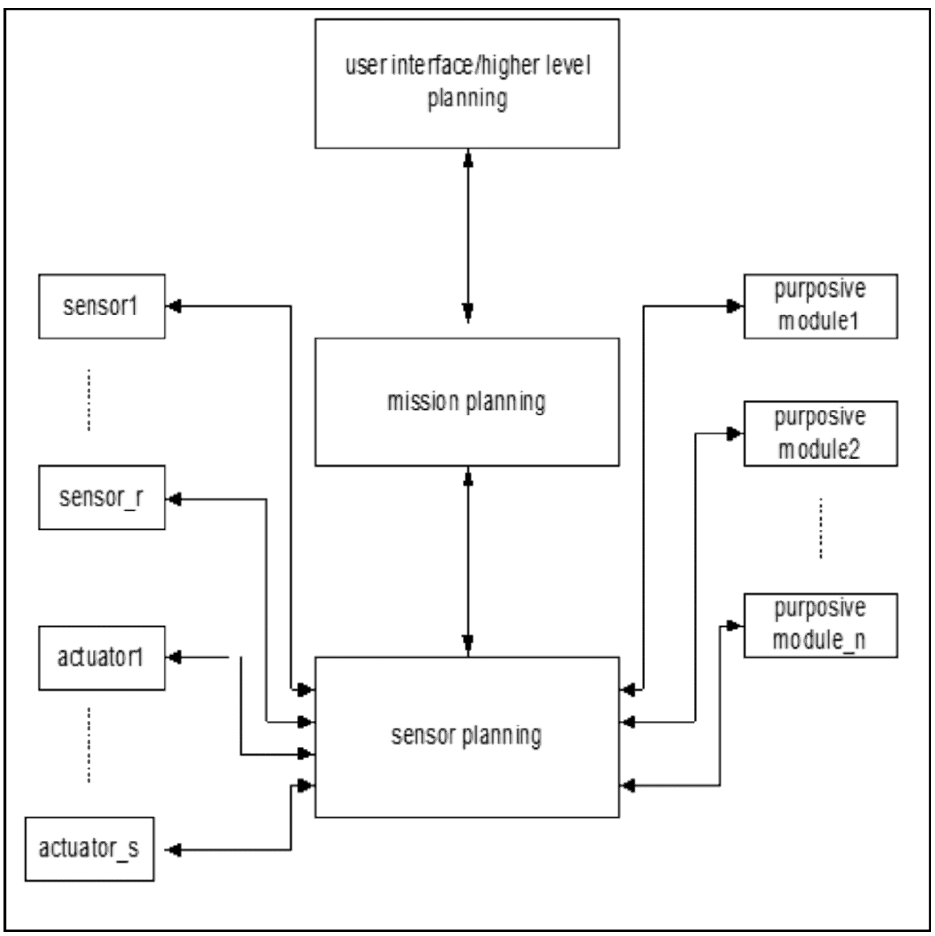

Figure 2: The architecture used in the sensor selection approach [1]

Lazkano [72] presented an attempt to use Bayesian Networks as a learning technique to manage task execution in mobile robotics. To learn the Bayesian Network structure from data, the K2 structural learning algorithm is used, combined with three different net evaluation metrics. The experiment led to a new hybrid multi-classifying system resulting from the combination of 1-NN with the Bayesian Network that allows one to use the power of the Bayesian Network while avoiding the computational burden of the reasoning mechanism. As an application example, a door-crossing behaviour in a mobile robot using only sonar readings in an environment with smooth walls and doors. Both the performance of the learning mechanism and the experiments run in the real robot-environment system showed that Bayesian Networks are valuable learning mechanisms, able to deal with the uncertainty and variability inherent to such systems.

For example, the problem in figure 2 is to decide which sensors to allocate to which purposive modules in order to accomplish a given task, declared by the mission planning-module.

4.4.4. Reinforcement Learning Approaches to Action Selection

A fundamentally different approach to action selection is to learn the action selection mechanism [73]. Of the several learning approaches proposed, the most promising is reinforcement learning. Reinforcement learning in this context operates to induce, based on trial and error, a perception-to-action mapping that maximises some reward. The robot learns the perception-action mapping, known as a policy, by exploring actions that lead to some reward. The reward function is designed so as to encourage desired behaviours and suppress unwanted ones. Thus, the robot will select actions that maximise the expected reward.

Navarro-Guerrero [74] described a novel real-world reinforcement learning method. It uses a supervised reinforcement learning approach combined with Gaussian distributed state activation. They successfully tested this method in two real scenarios of humanoid robot navigation: first, backward movements for docking at a charging station and second, forward movements to prepare grasping. Their approach reduces the required learning steps by more than an order of magnitude, and it is robust and easy to be integrated into conventional RL techniques.

Caroline [75], built a synchrony-based attentional mechanism allowing to initiate and to maintain human robot interactions. Moreover, they raised the question of synchrony detection importance for learning and gaining new competences through the interaction. They previously proposed a synchrony-based neural model capable of giving the robot minimal abilities to select a human partner and to focus its visual attention on this preferred interactant. They extended this model by using synchrony detection as a reinforcement signal for learning (during the interaction) the human partner appearance (shape) in the context of an autonomous mobile robot.

The reinforcement learning control with neural networks (NNs) was recently investigated for a class of pure-feedback systems in discrete time using minimal-learning-parameter (MLP) technique [76]. To make the dynamics feasible for controller design, the nth order system was transformed into the prediction model. The action NN was employed to minimize both the strategic utility function and the tracking error. A radial basis function (RBF) NN was employed to approximate the unknown control with the MLP technique which greatly reduces the number of the online adaptive parameters.

4.5. Winner-takes-All: Activation Networks

In this approach, the system consists of a set of behaviours or competence modules which are connected to form a network. In this network, each behaviour is described by the preconditions under which it is executable, the effects after successful execution in the form of add-lists and delete-lists and the activation level, which is a measure of applicability of the behaviour [77]. When the activation level of an executable behaviour exceeds a specified threshold, it is selected to furnish its action.

A model of analogue K-winners-take-all (KWTA) neural circuit which can identify the K largest from N unknown wide range inputs, where $1 \le K < N$, is presented and analysed in [78]. The model was described by one state equation with discontinuous right-hand side and output equation. An existence and uniqueness, stability and convergence to the KWTA operation of the model states were analysed. A corresponding functional block diagram of the circuit was presented as N feed-forward and one feedback hard-limiting neurons, which was used to determine the dynamic shift of inputs. The model combines such properties as high accuracy and convergence speed, low computational and hardware implementation complexity, and independency on initial states.

4.6. Voting-Based Command Fusion

To manage the ongoing tasks of an agent so that action conflict is minimised and desired levels of compliance with overall goals are achieved, each behaviour votes for one action, which is suitable from its point of view. The votes received from all behaviours are summed for each action and the action with the largest number of votes is then selected. For example, DAMN is a distributed architecture for mobile robot navigation [2, 79]. It consists of a set of behaviours (figure 2.3) that pursue the system goals, based on the current state of the environment. Each behaviour votes for or against each action within the current possible set of actions. The action with the maximum weighted sum of received votes is then selected, where each behaviour is assigned a weight, which reflects the relative importance or priority of the behaviour in a given context.

Sensor fusion method based on vote for robot navigation was developed to distinguish the real sound source from the psudo ones [80].

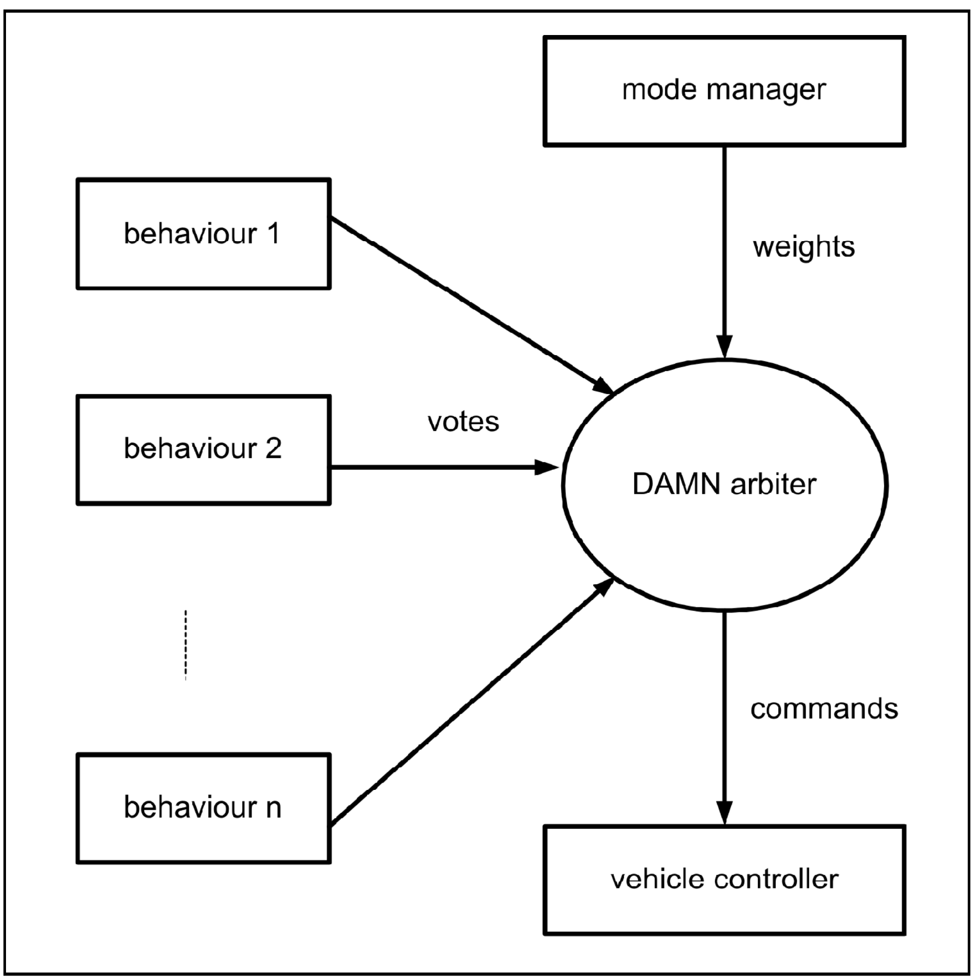

Figure 2.3: A distributed architecture for mobile robot navigation [2]

4.7. Multiple Objective Behaviour Coordination

In this approach, multiple behaviours are blended into a single more complex behaviour that seeks to select the action that simultaneously satisfies all behavioural objectives as far as possible. In [57, 81], mobile robot navigation and co-operative target acquisition examples are given, in which the principles of multiple objective decision-making (MODM) are demonstrated. Simulated as well as real-world experiments show that a smooth blending of behaviours according to the principles of MODM enables coherent robot behaviour.

In [82-84], the authors dealt with multi-objective behaviour coordination of multiple robots interacting with a quasi-ecosystem which was composed of insects and plants. In this ecosystem, there co-exist plants and insects according to specific reproduction rules. In general, the inhabiting area of each species is localized owing to geographical, climatic, and ecological factors. This indicates the population density of each species in one area is different from another according to local environmental conditions. In this study, multiple robots are introduced in order to maintain the ecosystem. Each robot takes actions based on multi-objective behaviour coordination integrating several action outputs.

4.8. Superposition-Based Command Fusion (Potential Field)

The potential-field approach, introduced in [85], is an approach to motion planning where the robot, represented as a point in configuration space, moves under the influence of an artificial potential field produced by an attractive force at the goal configuration position and repulsive forces at the obstacles. Action selection in this case corresponds to a move, at each configuration, in the direction indicated by the negative gradient of the total potential U. The potential function U is constructed as the sum of two potential functions:

$$U = Uatt+Urep \tag{2.1}$$

where Uatt is the attractive potential associated with the goal and Urep is the repulsive potential associated with the obstacles. Much work has been carried out in behaviour coordination and action selection that does not directly relate to the above. Saffiotti [86] espoused desirability functions as an effective way to express and implement complex behaviour coordination strategies within a single robot. The desirability function approach was extended to deal with the behaviours of teams of robots. The authors showed that desirability functions offer a convenient tool to incorporate and blend individual objectives and team objectives. Yamada [87] described an action selection method for multiple mobile robots performing box pushing in a dynamic environment. The robots are designed to need no explicit communication, and to be adaptive to dynamic environments by changing their active set of behaviours. The researchers proposed a mechanism that changed the active behaviour set depending on the situation. Hu [88] presented a feasible solution for a team of autonomous mobile robots to function in a co-operative manner. To realise coordination, a multi-channel infrared communication system was developed to exchange messages among mobile robots. Two examples of flocking and shared experience learning were given to demonstrate the performance of the system. Due to their co-operative nature, command fusion mechanisms promise improved performance over arbitration-based mechanisms. However, there are drawbacks that should be highlighted. Where a linear combination mechanism is employed, the obtained solution might be far from the required one. Command fusion systems are also costly both in computation time and hardware, and unnecessarily so if system accuracy is not critical. Furthermore, in multi-objective mechanisms, it is difficult to control the robots even heuristically to meet all objectives. Fuzzy logic is suitable for a coordination scheme that allows all behaviours to contribute simultaneously to the control of the system in a co-operative rather than a competitive manner. This is therefore the solution proposed in this research for behaviour coordination in the context of dynamic target tracking. When the output of a behaviour is represented by a fuzzy set, the problem of command fusion can be seen as an instance of the problem of combining individual preferences. Fuzzy operators can be used to combine the preferences of different behaviours into a collective preference, and finally to choose a command based on this collective preference. According to this view, command fusion is decomposed into two steps: (1) preference combination and (2) decision. Fuzzy logic offers many different operators to perform a combination and many defuzzification functions to select a decision. It is important to note that the decision taken from the collective preference can be different from the result of combining the decisions taken from the individual preferences. Figure 2.4 graphically illustrates this point in the case of two behaviours B1 and B2 both controlling the steering angle of a mobile robot. This explains why fuzzy command fusion is fundamentally different from vector summation. Several proposals that use fuzzy logic to perform command fusion have appeared in the literature. Curiously enough, the first such proposal was made, in a naive form, by two roboticists who were unaware of fuzzy logic but were frustrated by the pitfalls of existing on-off arbitration schemas [89]. Their suggestion was later restated in terms of fuzzy logic [90]. Other authors have proposed simplified forms of fuzzy command fusion. For instance, Goodridge [91] used weighted singletons as fuzzy outputs and the centre of gravity (COG) method for defuzzification and used symmetric rectangles and COG [92].

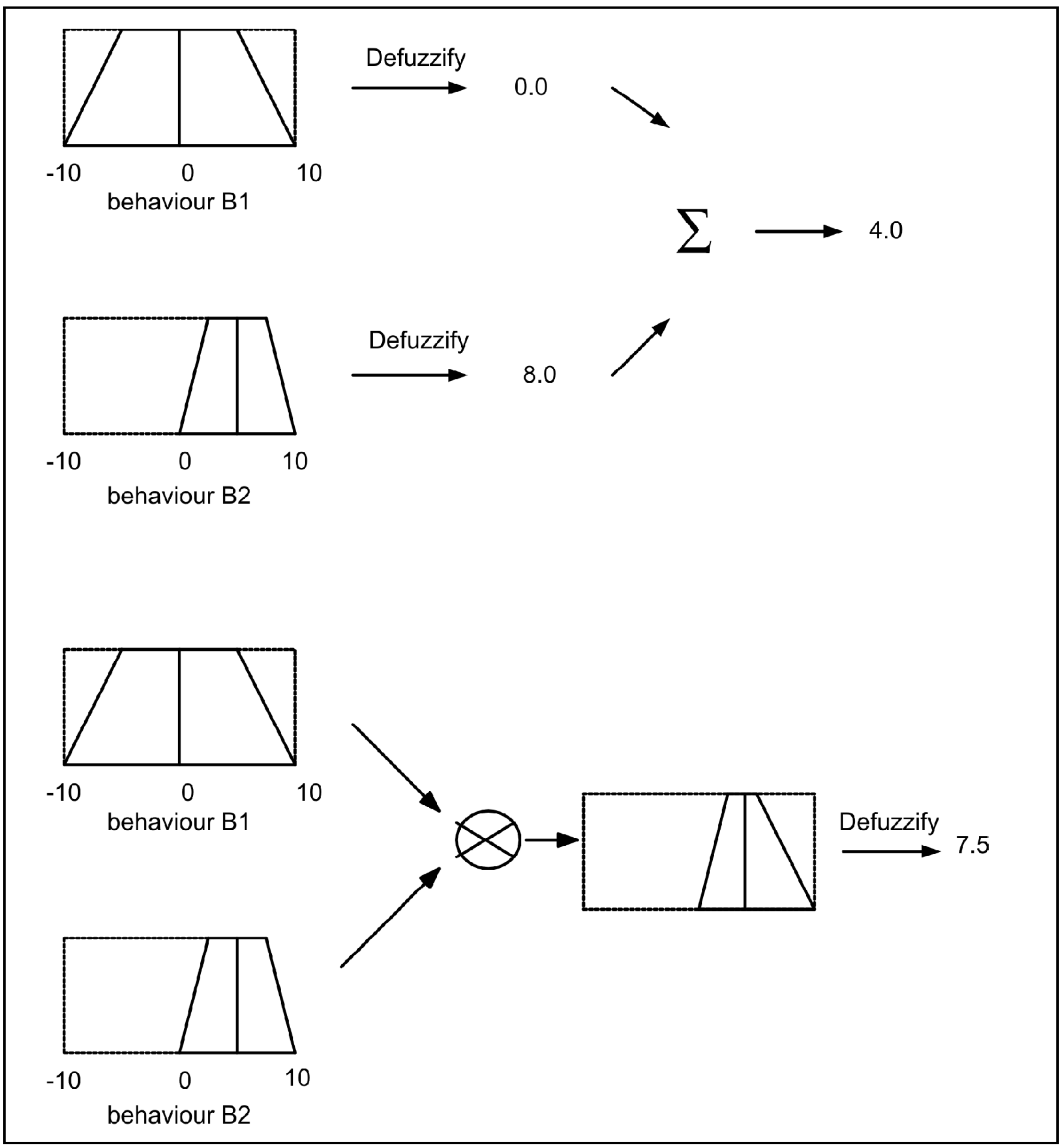

Figure 2.4: Two approaches to command fusion.
Top: combining individual decisions.
Bottom: combining individual preferences.

Even though there is not much work on behaviour coordination based on fuzzy logic, fuzzy logic is widely used in the controlling and learning mechanisms of mobile robots [25], [93].

5. AWARENESS EFFECT ON MOBILE ROBOT CO-OPERATION

Much existing work in the area of robot awareness addresses the problem of global coherence and efficiency by designing robotic teams that use sensor information to glean implicit information on the activities of other robot team members and/or the current state of the world [94]. With these approaches, no explicit communication among robots is utilised. A more difficult approach requires the robots to use passive action recognition to observe the actions of their team-mates and modify their own actions accordingly [95]. A third, quite common, approach involves explicit co-operation among team members by employing direct communication between robots to relay information on robot goals and/or actions to other team members [96]. These three approaches define a continuum in the degree of awareness of a robot of the actions or goals of its team-mates, from implicit awareness through the effect of a team-mate on the world, to passive observation of its actions or goals, to explicit communication of actions and/or goals. These approaches raise interesting questions concerning the impact of the awareness of the robot team members of the actions and/or goals of its team-mates.

MacLennan [97] investigated the evolution of communication in simulated worlds and concludes that the communication of local robot information can result in significant performance improvements. Balch [98] examined the importance of communication in robotic societies performing forage, consumption, and grazing tasks. They found that some communication could significantly improve performance for tasks, and that communication of the current robot state was almost as effective as communication of robot goals. Their research was performed primarily on real robots, rather than simulated robots. For implicit co-operative systems and those using passive action recognition, the question is: What is the impact of a limited ability to sense the effect of robot actions on the world? For explicit communication systems, the question is: ‘What is the impact of communication failure, which leads to the lack of awareness of team member actions/goals?’ or, conversely: ‘What benefits can be gained by using explicit communication to increase robot awareness of team member actions/goals?’ Previous research concerning the effect of robot awareness, or recognition, of team member actions was usually described in terms of the effect of communication in co-operative robot teams. However, Parker [99] has used the phrase “robot awareness, or recognition, of team member actions” to describe precisely the issue of interest (awareness of team-mate actions), rather than the accessing of information that could possibly be communicated between team members. For example, the bid of a robot for an activity in a negotiation system may depend on the current local state of the environment near a given robot, or the sensed location of an intruder, etc. This shows that a robot may become aware of the actions of a team member without the use of explicit communication.

Developing teams of robots that are able to perform their tasks over long periods requires the robots to be aware of and responsive to continual changes in the capabilities of the robot team members and to changes in the state of the environment and mission. Parker [56, 99] described the L-ALLIANCE architecture, which enables teams of robots dynamically to adapt their actions over time. This architecture, which is an extension of earlier work on ALLIANCE [100], is a distributed, behaviour-based architecture aimed at applications consisting of a collection of independent tasks. The key issue addressed in L-ALLIANCE is the determination of which task robots should select to perform during their mission, even where there are multiple robots with heterogeneous, continually changing capabilities present on the team. The L-ALLIANCE architecture is implemented on a team of heterogeneous real robots performing proof-of-concept box pushing experiments. Due to the unreliability of the sensors and actuators employed and uncertainties in the environment, the approach of Parker of using a predefined time for each behaviour resulted in inconsistency, even if the behaviours are repeated and the values are averaged. This is because there is no guarantee that each robot will repeat the same behaviour at the same time. In this respect, it may be preferable to propose an architecture which does not rely on explicit communication or passive recognition and generate automatically the required time for a particular behaviour by accessing an on-line knowledge-base, updated by the use of neuro-fuzzy techniques.

6. CONCLUSION

This paper presented a summary of the main contributions to the state of the art in the field of co-operating mobile robots. The article studied the main results achieved by the researchers during the past three decades. We have considered a hundred past papers as a representative work to illustrate the major progress and innovation for the co-operating mobile robots from different point of view.

Future works can focus on a new paradigm in robotics that combines cloud computing with robotics to get cloud robotics and cloud interaction of robots. Accordingly, standalone robots can use cloud technologies to perform collaborative works. Networked cloud-enabled robots can share computation resources, information and data with each other and can access new knowledge and skills not learned by themselves [101].

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