History of Medicine Studies

ISSN:1300-669

Volume 18 Issue 2 July 2022

Pattern Formation and Adaptation in Multi-Robot Systems

Dr G Hemalatha[1,] Dr. M Venkata Narayana[2] Dr V Adinarayana Reddy [3], Dr S Zahiruddin[4]

Abstract

The ability to deploy huge numbers of low-cost robots for duties like surveillance and search has just become viable because to advancements in robotics. It is still difficult to solve the challenge of coordinating several robots to do such duties. Recent research papers on multi-robot systems are summarized in this report. It's divided into two sections.In the first section, we discussed research into the pattern formation challenge, or how to guide a team of robots to and through a coordinated configuration. The second section summarizes the research on multirobot system control that made use of adaptive techniques. We have looked at (1) the use of learning (perpetual adaptation) to make multi-robot systems adjust to environmental and individual robot capability changes, and (2) the use of evolution to develop group behaviors.

Introduction

The ability to deploy huge numbers of low-cost robots for duties like surveillance and search has just become viable because to advancements in robotics. However, coordinating a group of robots to carry out such jobs is still difficult to do. Previous studies on multi-robot systems have taken a more generalized approach (see, for example, the works of Caoet al.[25] and Dudek et al.[7]).In contrast to these, the focus of this article is confined to the most up-to-date research on pattern creation and adaptability in multi-robot systems.The report has two sections. Part one of this series examined research into the pattern formation challenge, or how to command a swarm of robots to build and hold a certain pattern. The second section discusses the research done on multi-robot systems that employed adaption techniques for command. Our research has focused on (1)the use of learning (continuous adaptation) to enable multi-robot systems to react to variations in both the environment and the capabilities of individual robots, and (2)the application of evolution to the generation of collective behaviors.

[1,2,3] Professor, Department of ECE, K. S. R. M College of Engineering(A), Kadapa

[4] Associate Professor, Department of ECE, K. S. R. M College of Engineering(A), Kadapa

ISSN:1300-669

Volume 18 Issue 2 July 2022

Pattern formation in multi-robot systems

Coordinating a collection of robots into and keeping them in a predetermined arrangement (such a wedge or a chain) is the pattern formation challenge.Search-and-rescue operations, landmine disposal, remote terrain and space research, satellite array management, and unmanned aerial vehicles (UAVs) are only few of the current areas of use for pattern creation.Cooperative actions among members of different animal species have also been shown to result in pattern creation. In these cases, animals either maintain a consistent orientation and distance from one another while on the move or cover an area with as much uniformity as feasible.Animals often develop patterns, and bird flocks, fish schools, and ant chains are just a few examples[18].

We divide the research on pattern creation into two categories. The first set of investigations include a centralized unit that manages the team and issues orders to each robot individually. Methods for forming distributed patterns to achieve coordination compose the second category.

Centralized pattern formation

A computational unit monitors the whole group and arranges the members' movements appropriately in centralized pattern creation methods[3, 13, 23, 24]. Each robot's motion is then sent to it through some kind of network.Coordinated movement of many robots along a predetermined route is proposed by Egerstedt and Hu[13]. Separation between route planning and tracking is achieved. It's centralized, and the monitoring of fictitious landmarks is performed independently. The robots are directed by a virtual leader whose course is calculated in advance. They used it to get a group of virtual robots to navigate around a triangle of obstacles. The robots in this case formed a triangle, and its corners navigated around an obstruction that had been placed in their path. The research demonstrates that the provided strategy stabilizes the formation error if the robots' tracking mistakes are constrained ortracking is done precisely.To get a flock of UAVs to fly in formation, Koo and Shahruz [23] suggest using a centralized path-planning technique. One, more competent UAV determines the course for the others to follow. Cameras and sensors are only available to the leader. Through a communication connection, it instructs the other UAVs on the paths they should be following. It is recommended that UAVs launch themselves in the direction of their trajectories and then latch onto them. Experiments investigate both a scenario in which UAVs take off one by one and another in which they all take off at once. The study's primary emphasis is trajectory computation.Belta and Kumar [3] provide a kinetic energy shaping centralized trajectory calculation system. They use a gradually varying kinetic energy meter rather than a constant one. The procedure provides smooth paths for a group of mobile robots to follow. Using a parameter, you may adjust how close the robots are to one another. However, the strategy is not scalable since it does not account for avoiding obstacles.Kowalczyk[24] details a target assignment technique for the formation building issue. In order to achieve the required configuration out of a dispersed collection of robots, the algorithm must first give each robot a targetpoint. Then it creates the priorities and paths the robots need to follow to go where they're going without colliding with each other. There is a buffer zone surrounding each robot's route where bots with lesser priority aren't allowed to go. The robot will wait for the higher priority robot to move out of the way if its path takes it through an area that is off limits to it. Both holonomic and non-holonomic robots are used to validate the approach. The technique presupposes the availability of a centralized processing power and global sensing capability. The method's potential for expansion evades the question. Strategies for centralized pattern creation presume the presence of a communication connection between the central unit and the individual robots, and depend on a single node to manage the whole group. Because of these presumptions, the centralized approach is more difficult to implement, less able to recover from errors, and less competent to manage a large fleet of robots. Decentralized pattern creation techniques provide an option.

Decentralized pattern formation

Communication and completeness of information known by robots impose a trade-offbetween precision and feasibility of forming and maintaining the pattern and the necessityof global information and

History of Medicine Studies
ISSN:1300-669
Volume 18 Issue 2 July 2022

communication. Studies that require global informationor broadcast communication[29, 19, 12] may suffer from lack of scalability or highcosts of the physical setup but allow more accurate forming of a greater range of formations.

On the other hand, studies using only localcommunication and sensor data[21, 22, 10, 5, 17, 15, 9, 11] tend to be more scalable, more robust, and easier to build;but they are also limited in variety andprecision of formationsSugihara and Suzuki[12] achieved pattern formation by providing each robot theglobal positions of all others. In this study, an algorithm is developed for each pattern.The proposed method can uniformly distribute robots creating different patternformations (circles, polygons, line, filled circle, and filled polygon). It can also split a groupof robots into an arbitrary number of nearly equal sized groups. Despite the impressiveresults obtained by this decentralized algorithm, the global communication required toshare information among the whole group, makes it less scalableCarpin and Parker[19] introduced a cooperative leader following strategy for a teamof robots. The robots are able tomaintain a specific formation while simultaneouslymoving in a linear pattern and avoiding dynamicobstacles. The robots use local sensorinformation and explicit broadcast communication among themselves. The frameworkhandles heterogeneous teams, i.e. comprising of robots with different types of sensors, as well as homogeneous ones

Two levels of behaviors were implemented for tasks: team-level and robot-levelbehaviors. Transitions are made when necessary among specific behaviors in these twolevels. For example, when a member of the team faces an obstacle, the whole teamwaits together with that member for it to go away for a certain amount of time. If thistime is exceeded that member circumnavigates the obstacle and the team returns to itsmain task of moving in a formationBalch and Hybinette [21, 22] proposed a different strategy for robot formation thatis inspired from the way molecules form crystals. In this study, each robot has severallocal *attachment sites* that other robots may be attracted to. This concept is similarto molecular covalent bonding. Possible attachment site geometries include shapesresembling where the robot is the center of the shape and the attachmentsites are the ends of the line segments. Various robot formation shapes result fromusage of different attachment site geometries just as different crystal shapes emergefrom various covalent bond geometries. When a teamof robots moving in a formation,they avoid the obstacle by splitting around it and rejoining afterpassing. This approachis scalable to large robot teams since global communication is not used and that local sensing is sufficient to generate effective formation behaviors in large robot teams.

Another method similar to crystal generation which employs a form of probabilisticcontrol is proposed by Fujibayashi et al.[11]. This study makes use of virtual springsto keep two agents in close proximity. Each pair of robots within a certain range ofeach other, are connected via a virtual spring. Each agent is classifiedby the numberof neighboring agents within this range (number of connections). The robots formtriangle lattices that have random outlines. To obtain a desiredoutline, the virtualsprings among some robots are broken with a certain probability. The candidatespringsto be broken are chosen depending on the number of connections the robots it joinshave. This *breaking preference* and the probability of breakingchanges from formationto formation. The algorithm uses only local information and is decentralized. Onedisadvantage of the method is the difficulty ofchoosing custom parameters for eachformation.

A graph-theoretic framework is proposed by Desai[10] for the control of a teamof robots moving in an area with obstacles while maintaining a specific formation.The method uses control graphs to defined behaviors of robots in the formation. Thisframework can handle transitions between formations, i.e. between control graphs.Proofs of the mathematical results required to enumerate and classify control graphsare given. Although the computations for control graphs increase with the number ofrobots,the fact that these computations are decentralized allows the methods describedto be scalable to large groups
Another graph-based approach to *moving in formation* problem is introduced byFierro and Das[17]. They proposed a four-layer modular architecture for formationcontrol. Group control layer is the highest layer generating a desired trajectory forthe whole group to move. Formation control layer implements a physical network, acommunication network, and a computational network (control graph). It maintains theformation by using local communication and relative position information. Kinematicscontrol layer deals with the required linear and angular velocities of robots. Finally, thedynamic control layer handles the task of realizing the necessary speeds given by the kinematics control layer. This four-layer architecture provides an abstraction amongtasks required at different levels. For example, a robot with different mass, inertia,and friction can be used only by

changing the dynamic control layer. Furthermorea modular adaptive controller is described which can manage control of robots withunknown dynamics and learns the robot dynamics on-the field. Hence using a different robot requires no change in the system. The method described is scalable (controlalgorithms scale linearly) and flexible (it allows various formations). Centralized anddecentralized versions of control graph assignment algorithm is also described in the study.

only local communication and sensor information. Obstacle avoidance is also providedin this method. It extends ordinary behavior-based approaches with the application ofsocial roles that represent positions in the formation and with the use of local communication
to improve performance. As new agents join the formation, the shape is *fixed* bylocal communications and role changes where necessary. The locally communicatedinformation reaches the leader, i.e. the front most robot, which knows the whole shapeof the current formation and which decides on the changes necessary. This informationis then propagated to the necessary followers, and the formation is updated. There is noneed to predefine social roles or positions for robots. Everything is done dynamicallyas the formation grows. This method supports various formations and also switchingbetween them, therefore it is flexible as well as being scalable and local.Dudenhoeffer and Jones[5] designed and implemented a tool to model and simulatecollective behavior and interactions of a group of thousands of robots. Usingthis simulationtool, the problem of hazardous materialdetection by thousands of micro-robotsscattered around a region is tackled. Social potential _elds are utilized for coordinatedgroup behavior where robots are desired to stay at a specific distance from others toobtainoptimum coverage of the area. They are also required to wander in this formationto search other parts. The desired behavior is obtained by using a subsumption architecture.This study also validates the proposed method in cases where it is possible foragents to die and where agents have imperfect sensorreadings. The method uses onlylocal information and is scalable to very large groups of robots.Mataric and Fredslund [9] used local information to establish and maintain formationsamong robots. Each robot has a unique ID and a designated friend robot whichit can see through a .friend sensor.. There is also minimal communication betweenrobots: heartbeat signals (robots broadcast their IDs), swerve signals (changing direction),and formation messages. Each robot can learn the number of robots in formationand the type of formation using broadcasted messages. For each formation, each robothas a specified angle which determines the angle it should keep between its front directionand the direction of its friend. This angle is calculated locally. The detailsof this calculation are given in [9]. This study accomplishes the task of establishingand maintaining formations using only local information and minimal communication.
However the possible formations are limited to chain-shaped ones that do not make abackward curve
One of the major reasons why multi-robot systems are preferred over single-robotsystems is their robustness in performance. The robustness of multi-robot systems can
be improved by incorporating adaptation mechanisms that can respond to continuingchanges in the environment as well as in the capabilities of individual robots.

Adaptation in multi-robot systems

In this section we review the studies that used adaptation strategies in controlling multirobotsystems. Specifically we have investigated (1) how learning (life-long adaptation)is used to make multi-robot systems respond to changes in the environment as well inthe capabilities of individual robots, and (2) how evolution is used to generate groupbehaviors.
In multi-robot systems, adaptation can be achieved at two levels: group level andindividual level. We classify the recent studies into these levels and review them in thefollowing subsections

Individual level adaptation

Large state spaces render reinforcement learning models worthless. One solution to this issue is to use many simpler learning modules for various states rather than one complex one. Research by Takayashi [[26]] is one example.A scaled-down version of the robo-soccer challenge serves as the issue examined in his research. It is expected that adversaries would use a variety of strategies, each tailored to its own strengths and weaknesses.Predictors and planners are the two main types of modules. Based on the opponent's past conduct, the predictor can guess what the opponent will do next. The Planner, on the other hand, will create the best possible next step in light of this forecast. Competing prediction algorithms improve accuracy, with only the best prediction module receiving reinforcement. This generates modules tailored to counteract certain enemy strategies.This study applies the concept of ball

History of Medicine Studies

ISSN:1300-669

Volume 18 Issue 2 July 2022

chasing against an unpredictable moving opponent.The outcomes are superior than those of studying a single module on its own. Given enough trials, reinforcement learning converges to the best policy, but in practice, this number of trials is typically too big to be practical. To accelerate the learning process, Piao[20] introduces a new reinforcementlearning algorithm. Rule learning, reinforcement learning, and action level selection come together to form this technique, which may be thought of as a set of behavioral rules for a given condition.Instances, which are states that have traversed a certain time range, make up the rule base.After each epoch, we use the data we've collected to assign labels to these occurrences. The data from these examples is then used to formulate rules. These guidelines serve as a prohibition against pointless or destructive behavior. Hard-coded rules guide the overarching strategy of robots and are used in action level selection. Together, sensor data and action level are supplied into the reinforcement algorithm to produce state information.The reinforcement learning module then learns to produce actions based on the state that has been generated using sensory data and the action level. To solve the robosoccer challenge, Piao uses this strategy. He claims enhanced performance on learning with several robots over conventional Q learning, but only if only one agent is learning at a time.

Since reinforcement learning was designed to work with isolated entities, it lacks tools to facilitate social behaviour. In his work, Tangamchit[16] addresses this issue. The paper discusses the split between systems that are action-based and task-based.Reactive behaviors are generated by action level systems in order to address issues. However, task-level systems create tasks that are made up of smaller tasks that may be delegated to different agents. Cooperation, according to Tangamchit, is defined as "task level activity" in which robots may share resources and obligations.There are two potential incentive systems to think about: global and local. Each unit's reinforcement in a global rewardscheme is shared among all members of the group. under contrast, under a local incentive system, the prize is not shared across the group's individuals. Q-learning and Monte Carlolearning are two of the learning algorithms taken into account. When evaluating the worth of each action over all states, Q-learning utilizes cumulative discounted rewards whereas Monte Carlo learning uses averaging. The episode's reward is the same for every given pair of state actions. This strategy is less efficient because it does not take into account the impact of later acts in an episode that are more likely to result in a positive outcome.

In this research, we focus on a specific subtype of the foraging issue known as puck collecting behavior. Pucks can only be collected and placed in the bin by robots. Except for the action of depositing a puck, all other actions result in a negative reward. There is a puck-free "home" zone, a puck-filled "deposit" zone, and pucks all over the field. This is accomplished with the help of two quite different robots.The first robot has superior mobility and collection capabilities in non-home environments. The second robot can more quickly complete the bin depositaction, but can only travel inside its home territory. For the best results, the robots must work together to transport the pucks back to the home area and then deposit them. Learning at the task level is necessary.

The findings show that local incentives or discounted cumulative rewards, like those used in Q learning, are ineffective for teaching cooperation at the task level. Cooperative strategies for this job emerge instead when global incentives are combined with average rewards.To include domain knowledge, reinforcement learning just needs feedback for the applied sequence of actions. This is often implemented via the selection of reward functions.The role of rewards in a foraging activity is discussed by Mataric[14]. Although mathematically straightforward to examine, single objectives create difficulties in learning and development.

It's challenging to transform actions that are conditional or sequential into a single objective function. Instead, subgoals of the agent are described by many goal functions. Estimators of future advancement are another development. These estimators provide an approximate assessment of progress toward a certain objective. Both of these enhancements (proper subgoal design and subgoal progress estimation) significantly boost the topic's use of domain knowledge. Furthermore, they provide far more reinforcement than conventional approaches by rewarding not just the end result but also smaller, more manageable achievements along the way.Robots performing a real-world foraging activity are used to evaluate the effectiveness of the new strategy. Robots have the job of bringing pucks back and forth from the rink. Robots are also expected to maintain a presence in the house at regular times. To make the robots' state space of the learning issue more comprehensible, we teach them some basic reactive actions. These actions include dropping pucks while at home, avoiding barriers, and retrieving pucks when they are in close proximity to the agent. The ideal strategy is produced by hand and then compared to the experimental results. The results support the usefulness of both intended changes. The study makes a fascinating point about the disruption that agents may produce. The rate of learning and the degree of convergence suffer as the number of learning agents increases.

Cooperation is achieved in Parker's[6] L-ALLIANCE model via the employment of numerous behavior sets and global communications. A observer is assigned to each behavior set. These watchdogs verify the prerequisites for triggering behavior sets and evaluate the agent's and the group's abilities. Parker presents two drives, impatience and acceptance.Both impatience and acceptance reflect a propensity for a robot to take up a duty that was assigned to another robot. The L-ALLIANCE design shifts these intrinsic incentive factors as the learner progresses.Due to the design, robots must constantly update one another on their present status. This design presupposes that a robot is responsible for all potential environmental modifications that emerge from an activity it states. The issue of credit allocation is therefore resolved.The L-ALLIANCE design has the desirable features of dealing with heterogeneous groups and being resilient in the face of failures or shifts in robot capability. In contrast, L-ALLIANCE's assumption-heavy approach to the credit assignment issue necessitates widespread communication.

According to Goldberg et al. [4,] AMM (Augmented Markov Models) are proposed.The added data regarding transitions in AMMmake it a superior Markov model. Instead of producing policy, it is meant to learn from environmental statistics. In contrast to HMMs, which assume that the outcomes of a given set of actions are unknown, AMMs assume that all of the action's details are known.

However, unlike traditional Markov models, AMMs are constructed in stages. They can mimic such higher-order transitions in the system with more accuracy thanks to this incremental buildup. Their research integrates AMMs with BBR [2]. Multiple AMMs, each with a unique time scale, keep an eye on each behavior. This enables the system to react quickly or slowly to changes in its surroundings.

Group level adaptation

By its very nature, reinforcement learning requires a centralized server, making it impractical for use in multi-robot setups. A compromise between centralized and decentralized learning is proposed in Yanli's study[27] on opportunistically cooperative neural learning. When it comes to purely decentralized learning models, each agent maintains its knowledge of the subject to itself. Because of this, the group's performance suffers greatly because of the lack of common experience. By using 'opportunistic' search, Yanli is able to address this issue. The notion of survival of the fittest in genetic algorithms is conceptually comparable to this approach. Low-t networks learn from high-t ones, and vice versa.

Three cases—a centralized one, a distributed one, and an opportunistically dispersed one—are compared in Yanli's study. These hypotheses are tested on a seeking task in which agents are tasked with covering as much ground in a certain area as they can without making too many trips back and forth. Collaboration seems to be the most effective tactic. Each agent plans its next step in advance, and they all take action at once. In addition, agents often discuss future moves with one another. To anticipate the behavior of other agents, each agent uses these plans. These predictions are learning machines. When it is possible to exactly forecast the future activity of other agents, rewards may be determined.

The findings demonstrate that central learning outperforms all other techniques.However, there are a number of issues with fault-tolerance and communication that plague central learning.Both central learning and OCL (opportunistically cooperative learning) perform noticeably better than the distributed-only situation, with OCL coming out on top.

Agah[1] incorporates both personal and social change into his writing. To solve the multi-robot learning challenge, Agah employs a method called Tropism Architecture. As a bridge between perception and behavior, tropismarchitecture facilitates education. Each tropism is characterized by a predisposition to react to certain stimuli. Learned tropisms (i.e. state-action-tendency pairings) are stored in the tropism architecture. Agents make choices by applying tropisms to the present situation. Based on the tropism values, a random process decides what steps to take. This architecture employs both supervised and unsupervised learning methods. Every person's own learningScheme incorporates environmental input into its set of tropisms.Changes include introducing a new legitimate action for the present state, raising the tropism value for a reinforced pair, and switching actions when a negative reinforcement or invalid action is detected.

In population learning, we encode each agent's tropism list as a sequence of bits with varying lengths. A genetic algorithm is used to these sequences of binary digits. Each individual's fitness is determined by adding up all of the positive reinforcement it has received during its own process of learning.Even without reinforcementpropagation as in Q-learning, the results show that this dual approach is effective. Behaviours cannot always be established in advance, and sometimes even behaviours need to be taught. The movement of hexapods is one example. Parker[8] investigated how hexapod robots may learn to do a box-pushing activity together. Since a hexapod robot's movement requires more complex procedures than a wheeled robot's, this is his primary challenge. Parker designed CyclicGenetic Algorithms (CGA), which can manage the complex control needs at hand, for this endeavor.The goal of CGAs is to evolve not only basic stimulus-response pairings, but rather a series of activities. CGA encrypts a sequence of activations that the agent must perform repeatedly.The fitness of each chromosome is determined by running a computer simulation in which the chromosome under evaluation is coupled with the optimal solution to the job at hand. The fitness of the chromosome is evaluated according to the collective's level of success. Using a deliberate approach yields positive results.

For robots to work together, they must be able to coordinate their efforts with one another.The earliest forms of cooperation based their interactions on models of peer communication. This may be necessary for an ideal solution, but it will demand more processing power and data transfer capacity as the number of robots in the system grows.While reducing bottlenecks in communication, local communication does not eliminate them entirely. One approach to breaking through the communication barrier is to use stigmergy. Scalability is achieved by an implicit communication system, which has been seen in social insects. In order to facilitate collaboration between groups of robots, Yamada[28] has developed a functional implementation of an implicit communicationsystem. The difficulty of pushing a box is addressed using this method. An illuminated target indicates success, and it is thought that the robots can sense their own presence, the presence of other robots, and the existence of barriers. In this setup, walls are portrayed as rigid cubes that are ultimately disregarded. In order to address the issue of implicit communication, the writers create fictitious scenarios. Abstrat models of the world's state are calculated based on the data from the sensors and some very rudimentary storage mechanisms (such as counters for certain sensor readings).The robots' behavior is predetermined by a series of rules. Sensor data is used to inform the application of these regulations.

Conclusion

We reviewed the recent studies on the pattern formation and adaptation in multi-robotsystems. The pattern formation studies are classified into two groups. The first groupincludes studies where the coordination is done by a centralized unit that can overseethe whole group and command the individual robots accordingly. The second groupcontains distributed pattern formation methods for achieving the coordination. Thestudies that used adaptation strategies in controlling multi-robot systems were classifiedinto two levels: group level and individual level.

References

[1] Agah A. Phylogenetic and ontogenetic learning in a colony of interacting robots. Autonomous Robots, 4(1)(3):85.100, 1996.

[2] Brooks R. A. Intelligence without representation. Arti_cial Intelligence, 47:139.159, 1991.

[3] Belta C. and Kumar V. Trajectory design for formations of robots by kinetic energy shaping. In Proceedings. ICRA '02. IEEE International Conference on Robotics and Automation, 2002.

[4] Goldberg D. and Mataric M.J. Maximizing reward in a non-stationary mobile robot environment.

invited submission to the Best of Agents-2000, special issue of Autonomous
Agents and Multi-Agent Systems, 6(3):67.83, 2003.
[5] Dudenhoeffer D.D. and Jones M.P. A formation behavior for large-scale micro-robot force
deployment. In Simulation Conference Proceedings, 2000.
[6] Parker L. E. Lifelong adaptation in heterogeneous multi-robot teams: Response to continual
variation in individual robot performance. Autonomous Robots, 3(8):239 . 267, 2000.
[7] Dudek G., Jenkin M., and Milios E. A taxonomy for multi-agent robotics. A K Peters Ltd,
2002. Chapter 1.
[8] Parker G.B. and Blumenthal H.J. Punctuated anytime learning for evolving a team. In
Proceedings of the 5th Biannual World Automation Congress., pages 559.566, 2002.
[9] Fredslund J. and Mataric M.J. A general algorithm for robot formations using local sensing
and minimal communication. IEEE Transactions on Robotics and Automation, 18(5):837.
846, 2002.
[10] Desai J.P. Modeling multiple teams of mobile robots: a graph theoretic approach. In
Proceedings. IEEE/RSJ International Conference on Intelligent Robots and Systems, 2001.
[11] Fujibayashi K., Murata S., Sugawara K., and Yamamura M. Self-organizing formation algorithm
for active elements. In Proceedings. 21st IEEE Symposium on Reliable Distributed
Systems, 2002.
[12] Sugihara K. and Suzuki I. Distributed algorithms for formation of geometric patterns with
many mobile robots. J. Robot. Syst., 13(3):127.139, 1996.
[13] Egerstedt M. and Hu X. Formation constrained multi-agent control. IEEE Transactions on
Robotics and Automation, 17(6):947.951, 2001.
[14] Mataric M.J. Reward functions for accelerated learning. In Machine Learning: Proceedings
of the Eleventh International Conference, pages 181.189, 1994.
[15] Kostelnik P., Samulka M., and Janosik M. Scalable multi-robot formations using local sensing
and communication. In RoMoCo '02. Proceedings of the Third International Workshop
on Robot Motion and Control, 2002.
[16] Tangamchit P., Dolan J.M., and Kosla P.K. The necessity of average rewards in cooperative
multirobot learning. In IEEE International Conference on Robotics and Automation. ICRA
'02., pages (2)1296. 1301, 2002.
[17] Fierro R. and Das A.K. A modular architecture for formation control. In RoMoCo '02.
Proceedings of the Third International Workshop on Robot Motion and Control, 2002.
[18] Camazine S., J.-L. Deneubourg, N.R. Franks, J. Sneyd, G. Theraulaz, and E. Bonabeau.
Self-Organisation in Biological Systems. Princeton University Press, NJ, 2001.
[19] Carpin S. and Parker L.E. Cooperative leader following in a distributed multi-robot system.
In Proceedings. ICRA '02. IEEE International Conference on Robotics and Automation,
2002.
[20] Piao S and Hong B. Fast reinforcement learning approach to cooperative behavior acquisition
in multi-agent system. In IEEE/RSJ International Conference on Intelligent Robots
and System, pages 871. 875, 2002. vol.1.
[21] Balch T. and Hybinette M. Behavior-based coordination of large-scale robot formations.
In Proceedings. Fourth International Conference on MultiAgent Systems, 2000.
[22] Balch T. and Hybinette M. Social potentials for scalable multi-robot formations. In Proceedings.
ICRA '00. IEEE International Conference on Robotics and Automation, 2000.
[23] Koo T.J. and Shahruz S.M. Formation of a group of unmanned aerial vehicles (uavs). In
Proceedings of the American Control Conference, 2001.
[24] Kowalczyk W. Target assignment strategy for scattered robots building formation. In Ro-
MoCo '02. Proceedings of the Third International Workshop on Robot Motion and Control,
2002.
[25] Cao Y., Fukunaga A. S., and Kahng A. B. Cooperative mobile robotics: Antecedents and
directions. Autonomous Robots, 4(1):7.23, 1997.
[26] Takahashi Y., Edazawa K., and M. Asada. Multi-module learning system for behavior acquisition
in multi-agent environment. In IEEE/RSJ International Conference on Intelligent
Robots and System, pages 927. 931, 2002. vol.1.
[27] Yanli Y., Polycarpou M.M., and Minai A.A. Opportunistically cooperative neural learning
in mobile agents. In Proceedings of the 2002 International Joint Conference on Neural
Networks, IJCNN, pages 2638.2643, 2002.
[28] S. Yamada and Saito J. Adaptive action selection without explicit communication for
multirobot box-pushing. In Systems, Man and Cybernetics, Part C, IEEE Transactions
on,Volume: 31, Issue: 3, pages 398.404, 2001.
[29] Cao Z., Tan M., Wang S., Fan Y., and Zhang B. The optimization research of formation
ngs of the 4th World Congress on Intelligent