Simulation of Self-organizing Multi-Robotic System used for Area Coverage and Surround of Found Targets

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Abstract: - Self-organizing robotic systems are able to accomplish complex tasks in a changing environment through local interactions among individual agents and local environment. If a robot views a target or senses the target according to used sensor, it necessitates information whether this target is already guarded on by any other robot. If not, the robot remains to stay (it starts to guard on and raises the attraction of the target cell as well as of its outskirts). If yes, robot continues in walking around the target - one target may cover more cells. One robot can guard on more than one target cells according to its sensors ranges. The robots guarding on found target cells not only need to see the target, they also need to see each other to form a secure surround. In the proposed model, field vector-based area coverage is used in combination with search and surround of some targets distributed in the area.

Key-Words: - Area coverage, Autonomous mobile robots, Self-organizing multi-robot system, Surround of searched targets

1 Introduction

Many of autonomous mobile robots under development nowadays no longer work alone, they work collaboratively. Collaborative robotics can be taken to mean robots collaborating with other robots or with a human; in this context we have taken it to mean collaboration with other robots working towards the same goal.

Collections of locally interacting embodied agents can generate collective performances that are beyond the possibilities of individual agents [1]. Through their interactions they can coordinate and organize their behaviors so that they can achieve goals that are impossible to achieve by individual agents acting alone, e.g. agents can be informed by other agents about portions of the environment that are currently beyond direct sensory access on the part of the individual agent, or collecting information provided by many agents to generate a global knowledge of the environment.

Collaborative robotics is a way to increase the solving performance of a robot team without significantly modifying the robots capacities. When collaboration is obtained with stigmergic mechanisms (i.e. implicit communication via the environment) or with simple explicit communication schemes such as binary signaling, the task accomplished by the team can be more complex and its performance enhanced without losing autonomy or increasing in a relevant way the complexity at the individual level. Collaborating robots must successfully share the task they are assigned. The key to this is the introduction of roles, a type of behavior that the robot must exhibit. Behavior based control of a robot is nothing new, but in the framework of a team of collaborating robots has to be applied as a series of different roles which the robots can use as a means to function more effectively. Control systems in many fields require perfect time accuracy and reliability [2].

Self-organization is one of the most important features observed in social, economic, ecological or biological systems. Self-organizing robotic systems are supposed to be able to accomplish complex tasks in a changing environment through local interactions among individual agents and local environment without an external global control. Self-organizing robotic systems should exhibit life-like features such as self-reconfiguration, self-repair, self-reproduction, self-development, and context awareness. Developing such self-organizing systems, where desired global behaviors can emerge through contextual local interactions among individuals and with the environment is a very challenging task [3].

Team of robots can perceive its environment from multiple disparate viewpoints. Team members may exchange sensor information, help each other to scale obstacles, or collaborate to manipulate heavy objects.

Team of robots which coordinates the actions of individual but centrally controlled robots in the group is called swarm robots. Usage of such robots teams could help to minimize hazardous work for humans, e.g. in fire fighting or similar dangerous tasks. Efficient search and cooperative completion of a task is possible via sophisticated communication methods. A multi-robot system has several advantages, including maximum coverage of the scanned area.

There is a growing variety of autonomous robots inspired by living systems. These robots are intended for inspection of sewage pipes, monitoring of pollution through underwater measurements, space exploration, bio-medical interventions, or nano-engineering. A swarm of small mobile robots is a set of inexpensive robots that explore a dangerous environment with aim to locate enemies or other targets. In non-communicative swarming, the swarm comprises homogeneous and anonymous robots, i.e. robots able to recognize other robots but un-capable to identify them individually.

Communicative swarming is distinctively more efficient than non-communicative one as it increases the swarm control ability. In communicative swarming, the swarm robots interchange information concerning their environment, which enables to arrive to information-aware conclusions. Moreover, the robots make use of the information received from each other, which enables to control cooperative behaviors as e.g. cooperative area coverage or cooperative search/exploration. Multi-robot systems communication can be direct or indirect. Indirect interaction uses passive or active mechanism of indirect coordination between agents or actions (stigmergy).

A swarm is defined as a massive collection that moves with no group organization, much like a swarm of bees or a flock of birds. Similar is a formation, the distinction is made in that it maintains a global structure, much like a flock of geese or a marching band [4]. Robot formations have been applied to applications such as automated traffic cones, while swarm behavior control has been applied to urban search-and-rescue robotics.

The majority of existing multi-robot systems for pattern formation rely on a predefined pattern, which is impractical for dynamic environments where the pattern to be formed should be able to change as the environment changes. In addition, adaptation to environmental changes should be realized based only on local perception of the robots. In [5], a hierarchical gene regulatory network for adaptive multi-robot pattern generation and formation in changing environments is proposed.

The traditional artificial intelligence (AI) approach to robot control is known as deliberative control. In the sense-plan-act paradigm, the robot senses its environment and, taking into account a model of that environment, decides to start the appropriate action. The week point of the deliberative control is possible failure in case of unexpected change of the environment. On the other hand, a reactive system observes the sense-act plan, coupling perception to action without any representation or history stepping in. Reactive control does not need a model of the environment or traditional planning, as it relies on a number of simple behaviors.

In the scope of bio-inspired soft robotics behavior is orchestrated rather than controlled [6]. Different bio-inspired multi-robot coordination systems have been developed [7]: distributed robots for search and rescue, environmental monitoring by highly agile autonomous robots, etc. Agent-based models consist of dynamically interacting, rule-based agents [8].

Area coverage is one of the emerging problems in multi-robot coordination [9]. In this task a team of robots is cooperatively trying to observe or sweep an entire area, possibly containing obstacles, with their sensors or actuators. The goal is to build an efficient path for each robot which jointly ensures that every single point in the environment can be seen or swept by at least one of the robots while performing the task. In barrier coverage robot guards are deployed to prevent intrusion [10].

The foundations of automata theory in swarm systems come predominantly from the cellular robotics systems.

Cellular automata (CA) are abstract models of complex natural systems having large quantities of identical, locally interacting simple components. Modeling based on CA leads to extremely simple models of complex systems. It carries discrete lattice of cells, generally in more dimensions where

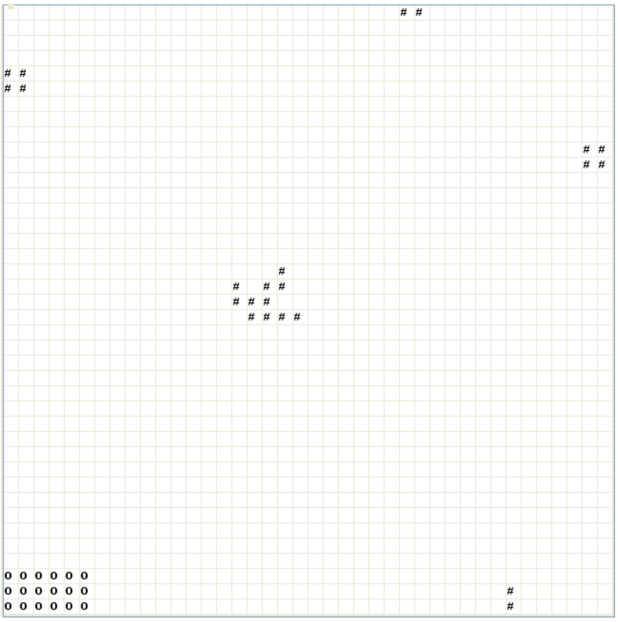

Fig. 1 Start position of robots (circles) and targets (#)

each cell in the lattice contains a number of cells. Each cell can interact with the cells located in its neighborhood. CA modeling represents an accomplished modeling method in biology, but likewise in computer science. Though the CA's construction is simple, its behavior can be very complex.

This paper introduces the multi-robot area coverage problem, wherein a group of robots must inspect every point of a 2-dimensional test environment and surround all contaminations (or enemies) found. Some of the simulation results are presented here. Fig. 1 illustrates start positions of robots and positions of searched targets (contaminations or enemies) in the test area.

A cellular automaton consists of a (1-dimensional) chain or (2-or-3-dimensional) lattice of computational cells, each cell being in one of a given set of states that evolve through discrete time steps. The dynamic behavior of the automaton is determined by a set of rules that govern the change of state of an individual cell with respect to its neighbors. Many practical implications must be considered when a given environment is represented topologically as a cellular automaton referred to as a world-space cellular automaton [4]. One of them is increasing risk of collisions when two robots attempt to move to the same unoccupied grid cell. Other approach is to treat the robots in the formation as cells in a 1-dimensional robot-space cellular automaton. The actual robots that make up the global structure (i.e., not the structure itself) are in this case represented by the cells. This approach overcomes many of the limitations inherent in a world-space automaton.

Similar methods making use of cellular automata do only area coverage or only move on patrol around a given building [11]. Other methods enabling search for target and its encircling, as e.g. morphogenetic swarm robotic systems [3] (dealing with the self-organization of swarm robots using genetic and cellular mechanisms underlying the biological early morphogenesis) use ingenious estimation of shapes and resulting formation of appropriate encircling robots patterns.

2 Collective Emergent Behaviors

Robotic system architectures can be centralized - characterized by a single control agent, or decentralized - no central control agent. The behavior of decentralized systems is often described using such terms as “emergence” and “self-organization.” It is not clear whether the scaling properties of decentralization offset the coordinative advantage of centralized systems. Many systems do not conform to a strict centralized/decentralized dichotomy, e.g. many largely decentralized architectures that utilize “leader” agents. The centralized knowledge store or source of control can be a bottleneck that severely constrains the abilities of the robot team.

Emergence and its accompanying phenomena are a widespread process in nature [12]. Despite of its prominence, there is no agreement in the sciences about the concept and how to define or measure emergence. One of the most contentious issues discussed is that of top-down causation as a defining characteristic of systems with emergence.

The behavior-based approach [13] has become very popular to cope with several robotic applications, also including service robotics (also termed reactive control). It refers to the direct coupling of perception to action as a specific technique which provides time-bound responses to robots moving in dynamic, unstructured and partially unknown environments.

A behavior is defined to be a control law for achieving and/or maintaining a particular goal. Usually, robot agents have multiple goals, including at least one achievement goal and one or more maintenance goals. This requires robot agents to be equipped with a number of behaviors, whose activation or inhibition must be triggered by a specialized module - the arbiter. Depending on its sensor data and/or information coming from an external supervisor, it provides either spatial or temporal ordering of behaviors. The former causes the concurrent activation of a set of primitive reflexive behaviors, also referred to as static arbitration; the latter brings about a sequential activation of different sets of primitive reflexive behaviors, also referred to as dynamic arbitration.

Roles can be defined statically in advance, but they may not necessarily be given to a robot and maintained statically. Instead, robots will often switch roles dynamically, for example when a robot soccer player finds itself in a role that is not suited to its current position as well as another role might be.

A behavior-based approach assumes a robot to be situated in, and surrounded by, its environment. This means that a robot interacts with the world on its own, without any human intervention, i.e. its perspective is different from that of the observer.

The distinction between collective and cooperative behavior is made on the basis of communication. If cooperative behaviors require negotiation between agents, then direct communication is also required. Cooperation is a form of interaction based on some form of communication.

The first, essential step enabling the emergence of a collective behavior is a careful design of the behaviors that any individual robot agent will contain. Further, one has to specify which tasks a group of individual robots can accomplish. Last but not least, a mechanism to initialize the cooperative behavior, eventually considering the level of cooperative strategies the robots must follow to collectively solve given tasks, is necessary. The result of the actions provided by the individual agents will be emergence of a collective behavior.

Rescue robots are useful for rescuing jobs in situations that are hazardous for human rescuers [14]. They can enter into gaps and move through small holes, which is impossible for humans and even trained dogs. Robots should explore in collapsed structure, extract the map, search for victims and report the location of victims in map. The main task of rescue robots is to acquire information about damaged area and victims [15]. The most important work in rescue activity for disaster mitigation is to get the reliable information. One of the goals of the rescue robots is to develop maps of disaster scenes for the human rescue members who go into the scenes for actual rescue works. Integration of multiple, distributed, multimodal and heterogeneous sources of data (sensor data, maps, …) is very important [16], [17].

An additional potential application of the proposed model is for cordoning off hazardous materials. When the distribution of the hazardous materials is detected, model can encircle detected hazardous materials and prevent people from moving into the dangerous area. A deficit at natural disaster management from the viewpoint of safe community concept, promoted by the EU since 2004, has been identified [18].

In order to traverse through a complex environment, swarm robotic systems need to self-organize themselves to form different yet suitable shapes dynamically to adapt to unknown environments [19]. Insects are particularly good at cooperatively solving multiple complex tasks. For example, foraging for food far away from the nest can be solved through relatively simple behaviors in combination with communication through pheromones. As task complexity increases, however, it may become difficult to determine the proper simple rules which yield the desired emergent cooperative behavior, or to know if any such rules exist at all. For such tasks, machine learning techniques like evolutionary computation may prove a valuable approach to searching the space of possible rule combinations.

3 Problem Formulation

Multi-robot shape construction and pattern formation, a typical task for MRSs, has been widely studied. Algorithms in this research field can be roughly divided into three groups: leader/neighbor-following algorithms, potential field algorithms, and nature-inspired algorithms.

Leader/neighbor-following algorithms require that individual robots follow neighbors or leader that knows the aim or target to which the team needs to go. These following robots should get behind a leader's root in a specific geometric relationship with the ones they follow. The second group of multi-robot shape construction algorithms is based on potential field method. The basic idea of this group of algorithms is that each robot moves under the governance of the gradients of potential fields, which are the sum of virtual attractive and repulsive forces. The third group is nature-inspired algorithms.

In field vector-based collision avoidance both target (the attractor) and obstacles (the repulsors) generate their own specific vectors. The target generates a purely attractive field, proportional to the distance, while the obstacles generate a rotational field.

The problem addressed in the paper is to entrap stationary (in future also mobile) targets (e.g. contamination or enemy), using a group of mobile robots. In the proposed model, field vector-based area coverage is used in combination with search and surround of some targets distributed in the area (similar to boundary coverage). Communication via environment (similar to pheromones) is used to share local knowledge on area gained by individual robots. Basic simple behaviors of the robots are:

- area coverage
- collision avoidance
- search for a target
- walk around the target found
- standing on guard at the found targets.

Cognitive and behavioral capabilities in animals are closely coupled and dependent on one another. However, in artificial systems the distinction can be made much more explicit, since models which are focusing on cognitive capabilities are often neglecting or strongly simplifying agent-environment dynamics e.g. assuming complete or global information of the world and other agents.

A better way to design the system is to view the global information as providing general guidance for the longer-term actions of a robot, whereas the local information indicates the more short-term, reactive actions the robot should take within the scope of the longer-term goals. This can often be achieved by combining the use of local and global information into a composite control law that more intelligently interprets the local information in the context of the global knowledge.

This, however, requires a mutual knowledge system [1] for symbolic knowledge (facts) as well as perceptual knowledge. The symbolic knowledge must contain data descriptions of fixed and dynamic objects, their attributes and the relations between the objects. As the system (a robots team) covers a dynamically changing environment, it must be able to learn and forget symbolic knowledge as well as perceptions. The system must be able to ground perceptions to symbols, i.e. label it and relate it to facts. As an example, a vague black blob, perceived by some robots, can be labeled as “door” by a human, after that the robots can use this fact in their world model.

Robotic actions are of two main classes: Ordinary actions effect changes in the world: positioning, displacement, rotation of objects in the workspace, random walk, move forward or backward, turn left or right, effector’s movements, obstacle avoidance, docking, following, … Sensing actions effect changes in robot’s knowledge.

3.1 Assumptions

In proposed model, the following assumptions have been made:

1) All the robots move with equal speed.
2) There is a base station containing a sufficient number of robots.
3) All robots have a limited sensing range, and therefore, they can detect targets and other robots that are within their sensing range only.
4) The communication range between robots is limited. Robots can interchange such information as targets’ location with their immediate neighbors (distance between the two robots is within the communication range). The communication between the robots and the base station is assumed not to be limited.
5) The robot can distinguish between obstacle and boundary.

3.2 Model

One way to simulate a 2D cellular automaton ($k = 2$) is with an infinite sheet of graph paper along with a set of rules for the cells to follow. Each square is called a cell and each cell has several possible states. Several possible lattices and neighborhood structures for 2D cellular automata are possible. This paper considers square lattices.

At start, the robots are arranged in one of the corners of the area (left down on Fig.1). Number of robots and number of rows in which the robots are ordered are selectable. All robots are oriented to Nord at start, and speeds of robots equal. From two most common 2D CA neighborhood templates (Moore neighborhood and von Neumann neighborhood - can be extended) Moore neighborhood (eight surrounding cells, $n = 8$) is used in the model. State of a cell is from a set: empty, robot is in it, target is in it.

Neighborhood size in the model as well as sensors range (for example for contamination detection) is one cell distance ($r = 1$). The model can be further generalized by increasing the possible neighborhood size to more than one cells distance and by enabling different sensors ranges for different kinds of sensors.

For all cells, attractions at start are equal and changes are computed according to robots moves and targets found.

Extra states are used to code the robot's current direction, as well as for remembering cells where some robot already appeared, which is then used for slow forgetting of the robots position history. All cells remember whether and when any of the robots visited the cell. State transition is fired by a set of rules.

3.3 Basic Rules

Each robot looks at the attractions of the nearby cells and its own actual direction and then applies the transition rule, specified in advance, to decide its move in the next clock-tick.

All the cells change at the same time.

Each robot moves to empty neighbor cell with maximal attraction. It tries to move in direction in which it is facing. If it is not possible, the robot direction is rotated clockwise.

Some delicate configuration requiring good decision may on certain occasions happen, e.g. the robot must decide if it is more convenient, or even possible (e.g. by sliding along a wall), to turn around the obstacle, instead of passing through, and which direction to select for this turnaround. Walls have been considered as particular kinds of obstacles, too. A serious problem may arise if both of two opposite directions are blocked due to some difficult configuration. In this case the robot does not move for a while, waiting the other robots' moves.

Basic rule for robots moves is specified as

$$a_r^t \times l_r^t \rightarrow c_r^t$$

where a is attraction, l is location of robot, c is cell to which the robot will move, t is time, and r is sensor range of robots.

All used data are specified and/or evaluated in subsequent simulation steps in multidimensional cells representing the area (area width × area length × number of data types, in our case 40 × 40 × 8):

- Attraction field: at start, attractions of cells are equal (specified maximal attraction value).
- Contamination positions (targets) are input data of a simulation tool.
- Robot identifiers at positions (start and actual positions) and their directions; number of robots and their starting positions are input data. Robot speed is 1 cell per 1 simulation step. Robot range may be different according to carried sensors ranges, e.g. robot may view the target in 2 - 3 cells distance.
- Cell occupied by any of robots is an obstacle prohibiting other robots to take that place.
- Just released cell will set zero attraction.
- Forgetting a visit of a robot: in subsequent simulation steps cell forgets the visit (in each step a small value, and after many steps cell forgets the visit completely). Using these values, the attraction of the cell again raises.
- Obstacles in area (now only area boundaries are considered)
- Positions of found obstacles (e.g. deep ditch - robots can't path through)
- Found targets as well as positions and IDs of robots guarding on them.
- If the robot views the target (or senses the target according to used sensor), it needs information whether this target is already guarded on by any other robot: If not, the robot remains to stay (it starts to guard on and raises the attraction of the target cell as well as of its outskirts). If yes, robot continues in walking around the target (one target may cover more cells). One robot can guard on more than one target cells according to its sensors ranges. The robots guarding on found target cells not only need to see the target, they also need to see each other to form a secure surround.
- Repulsion: the robot starting to guard on the target increases the repulsion of its position's cell with surroundings within sensors distances. In future version, the obstacles will also increase repulsion.

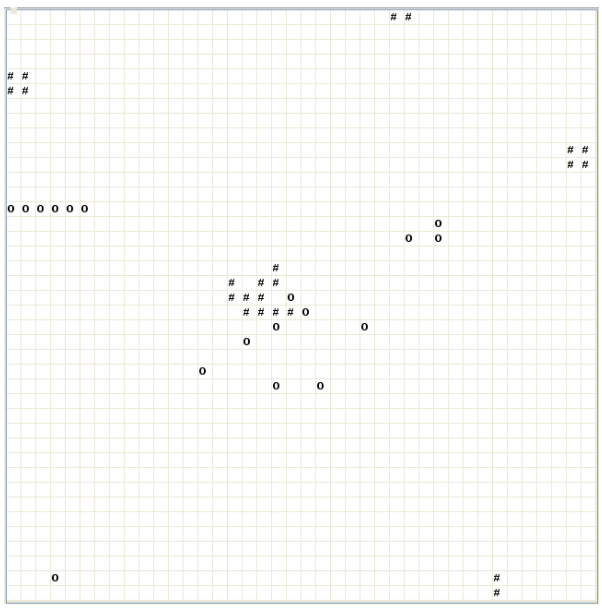

Fig. 2 Position of robots after some steps

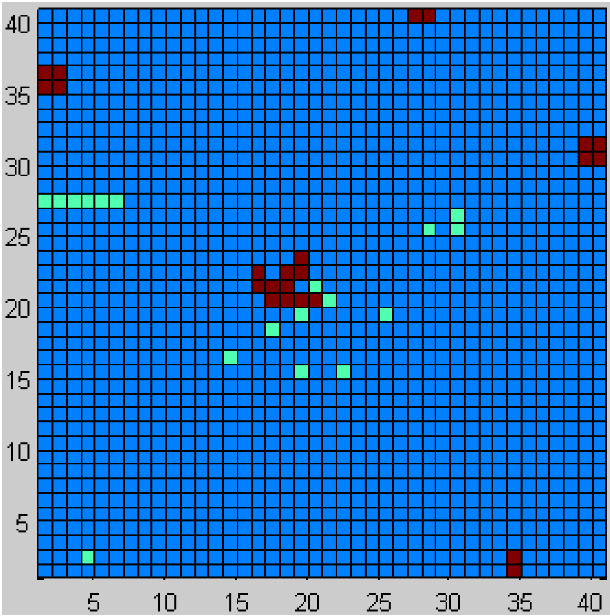

Fig. 3 Position of robots after some steps (same as in Fig. 2) using pseudo-color plot

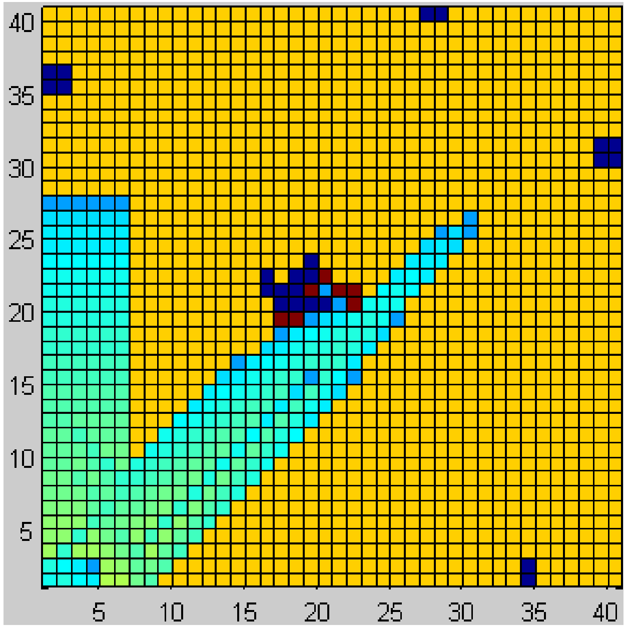

Fig. 4 Same situation as in figures 2 and 3 illustrating changes in attraction field

4 Simulation Results

The proposed model is simulated in Matlab [20]. Fig. 2 depicts positions of robots after several simulation steps (start positions of robots is depicted in Fig. 1 - see section I.). Fig. 3 illustrates the same situation, using pseudo-color plot.

Changes of attraction field in the same situation can be seen on Fig. 4.

In Fig. 5, attraction field changes illustrate that attractions around contamination found have highly increased after several simulation steps (with respect to situation on Fig. 4). If a target is some kind of contamination, the kind of detected contamination is given by the type of sensors carried by the robots. As the target obviously covers more than one cell, probability to find more cells with not guarded target increases in case a robot starts to walk around target. Each robot can guard more targets in its neighborhood range.

Positions of robots standing on guard around found contaminations are illustrated in Fig. 6. From the group of 18 robots in the simulated example, 13 robots were enough to guard on all targets in the area, 5 robots continued in area coverage.

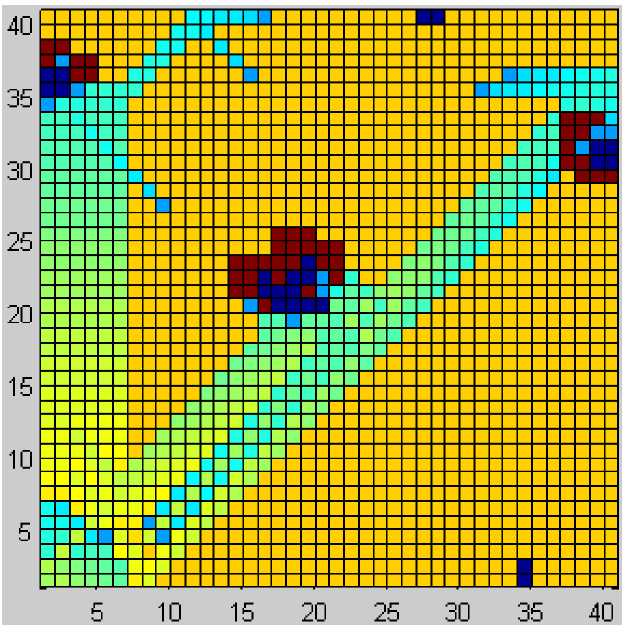

Fig. 5 Attraction field after some more steps (attractions around contamination found are highly increased)

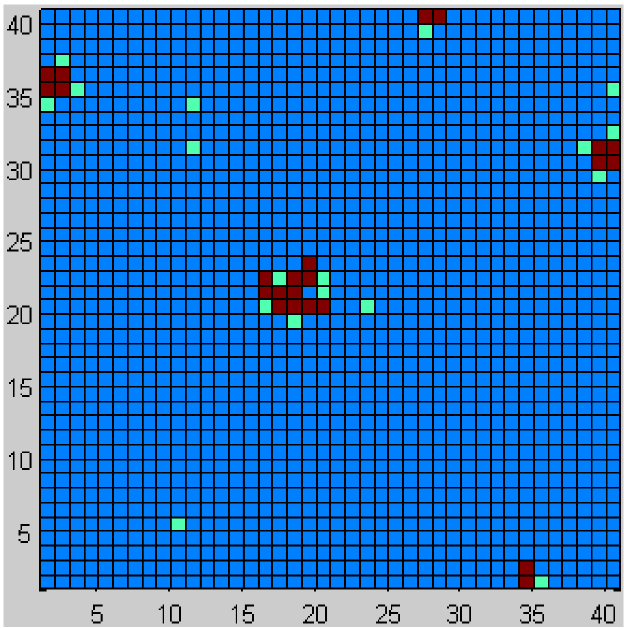

Fig. 6 Positions of robots standing on guard around found contaminations (5 robots continue in area coverage)

Targets are static objects in the environment that need to be encircled by robots. Robot standing on guard refers to the robot that detects at least one target in the environment. Searching robot refers to the robot not having detected any target in the environment, therefore doing area coverage. Searching robot can become robot standing on guard if it detects a target not yet guarded by any other robot.

At first simulation steps, robot group moves together and the robots always try to move in direction they are looking in. As some of the cells are engaged by other robots, or some of the cells have decreased attraction, the group diverged. The isolated robot starts to increase the attraction in its surroundings with the aim to form a robot formation, in order to do area coverage more effectively [21, 22].

The movement behavior of robots not having detected any target is governed by the area coverage, avoid collision, and search for a target behaviors.

Compared to other published multi-robot pattern formation algorithms, one major advantage of approach presented here is that it provides an adaptive mechanism that can dynamically generate an appropriate surround pattern adapted to environmental changes. Most existing MRSs for pattern formation rely on a predefined pattern, which is not applicable to changing environments.

5 Conclusion

Multi-robot boundary coverage requires the robots to cover a given boundary at a given location defined in the global coordinate system. Applications of multi-robot boundary coverage include perimeter defense and area protection, whereas algorithms for multi-robot pattern formation can also be employed to simulate self-organizing properties found in nature.

This paper introduces the multi-robot area coverage problem, wherein a task of a group of robots is to inspect every point of a 2-dimensional test environment and surround all contaminations (or enemies) found. Some of the simulation results are presented. Similar methods making use of cellular automata provide only area coverage or only move on patrol around a given building, etc. Other methods enabling search for target and its encircling as e.g. morphogenetic swarm robotic systems use ingenious estimation of shapes and resulting formation of appropriate encircling robots patterns.

The main new feature of the proposed model compared to existing published solutions is that the target search and round pattern generated by the robots need not be predefined and is adaptable to environmental changes, e.g., the number and location of the targets to be entrapped.

In future work, the presented model will be modified so as to be able to work with mobile targets. It should be pointed out that successful entrapping of the mobile targets is conditioned on the assumption that the movement speed of the robots is faster than that of the targets.

Acknowledgements

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