Strategies for navigation of robot swarms to be used in landmines detection

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Abstract

This paper presents a novel approach to the detection of anti-personnel landmines that uses teams of cooperating robots. Following hints that originate both from classical robotics and from biology, we aim to defining a set of search strategies suitable for being used in an obstacle-cluttered, two-dimensional space. The paper presents the guidelines of the project, the search strategies that were developed, and the description of a simulator that was designed and implemented to test them.

Brief reviews of the available techniques, of the sensor technologies, and of the current uses of robotic devices in humanitarian demining are also included.

1 Introduction

Landmines constitute a significant barrier to economic and social development for the inhabitants of more than sixty countries. Their capability of remaining active for years after a conflict has come to an end poses a major restraint on post-conflict reconstruction. Despite international efforts to ban the production and use of landmines, the situation continues to deteriorate with landmines being laid about twenty times faster than they are currently being cleared [1].

Demining is an operation filled with risks that currently mainly relies on the skills and patience of courageous individuals. The risks are due to the fact that demining functions are tedious and repetitive, yet demand the application of precise standard actions. Analysis of these actions shows that some of them could be more easily and safely performed by robotic systems. From this perspective, these systems appear to have a role to play in finding and removing millions of landmines from around the world. Obviously, the solution of the problem requires both the construction of autonomous and reliable machines that can operate in rough terrain, and the capability of detecting with good precision and high confidence the location of the mines. In this work, we have defined some search strategies, based on the use of swarms of small robots that have different functions and sensorial capabilities, as it happens in some animals societies such as wasp colonies, fish schools, ants and termites.

2 The problem

The detection of buried landmines for humanitarian-demining purposes is nowadays mainly performed by human operators [2]. Potential mines are located using metal detectors or by hand probing methods. The probe used is generally just a sharp stick or bayonet which is inserted into the ground at an angle not greater than 40° to the horizontal at 2 cm intervals until some resistance is encountered. The effectiveness of metal detectors is often nullified by mines with extremely low metal contents or by soil with high ferrous materials percentage. In fact, there may be up to 1000 metal fragments to be investigated for each discovered mine, resulting in potentially lethal deminer fatigue. 80% of all clearance accidents occur during the investigation of metal signatures. In the probing method, accidents are mainly caused by landmines that for any reason were moved away from their original horizontal position.

Several other methods, such as using dogs that sniff the explosive contents of the mines, are also used, but have significant limitations and cannot be regarded to as general-purpose solutions. In order to reduce risks to human operators some mechanical implements, such as flails, rollers and mine plows have also been developed, although they do not achieve in most situations the standard required for humanitarian demining (guaranteed 99.6% clearance):

1. *Flails* are mechanical devices, which repeatedly beat the ground, typically with lengths of chain. These chains are attached to a rotating drum and their impact on the ground causes the mines to explode. These devices can cause severe damage to cultivable land.
2. *Rollers* generally consist of a number of heavy circular discs, which are rolled along the ground in order to cause the explosion of any mines.
3. *Plows* are generally used for breaching a path through a minefield, as they usually just push the mines to the side. Some plows also attempt to sieve the mines from the displaced soil.

Current technology suggests that robots could be used instead of humans to perform demining, since this application area appears to be perfectly matched to the multi-robot systems concept in the following respects:

1. Minefields are dangerous to humans; a robotic solution allows human operators to be physically removed from the hazardous area;
2. The use of multiple, inexpensive robotized search elements minimizes damage due to unexpected exploding mines, and allows the rest of the mission to be carried on by the remaining elements;
3. Many kinds of mines must be dealt with; the use of many robots allows all targets to be pursued in parallel, rather than one at a time [3];
4. A number of sensors have been developed whose information can be related to the presence or absence of mines [2]. Among these; the most common are ground penetrating radar (GPR), bio-sensors that detect explosive vapors, and sensors that use infrared imaging, thermal neutron analysis, electro-magnetic induction, RF/millimetric radiometry and X-ray backscatter. None of these sensors on their own is however sufficient and hence some combination of these sensors must be used.

It is then quite obvious that best results would be obtained if multiple robots were used. In order to demine effectively, the robots should exhibit a number of attitudes, such as avoiding interference with each other, covering the terrain effectively, sharing the workload, helping each other by providing complementary information via different sensors, and should be capable of dynamic redistribution of the workload in case of robot failures.

Our work investigates the use of teams of variously equipped robots, with different sensors devoted to mines localization. We are not dealing here with any particular kind of sensing device: we only assume that each sensor can detect some sorts of mines located within a given radius. Using a multi-robot approach yields a redundancy that raises the probability of locating mines in at least two different ways. If the robots are all equipped with the same sensors, re-exploring the same area leads to greater chances of locating previously undetected mines.

On the other hand, if they are equipped with different sets of sensors, data fusion techniques can be used to locate mines that are undetectable by a single sensor, without having to deal with complex, heavy and expensive multi-sensor robots. Using multiple, simple robots can also yield other advantages, such as allowing simple configuration of the searching team according to the kind of mines that are likely to be found in each demining campaign.

The problem of controlling robot teams is very important and requires great attention. The drawbacks of traditional centralized control are high computational and communication complexity, lack of flexibility and of robustness. Therefore, a *distributed* control approach is more suitable for the control of systems that include a large number of robots as well as for systems where information about the environment is being collected or sensed by the robots themselves. In such a distributed-control framework, each robot decides its own movements by observing the environment at that moment and applying some pre-defined control laws. The main idea is to design control laws such that the robot system as a whole will achieve the given goals, such as collision-free navigation or forming a spatial structure.

3 Strategies

A collection of robots moving in the same workspace which plan collision-free motions and, at the same time, get from an initial configuration to a goal configuration can be regarded to as a multimover's problem (see e.g. [4] for an excellent in-depth study).

Basically, the robots interact with each other automatically leading towards a consistent growth in terms of computational complexity.

Essentially, the two possible ways to tackle the problem are centralized and decoupled (or distributed) planning.

The former consists of planning the coordinated paths of multiple robots as a path in their composite configuration space as, for instance, the cell decomposition method presented in [5] or the potential field method followed by [6].

One way to reduce the computational load for the multimover's problem is to adopt decoupled planning, i.e. firstly each robot is seen as independent from the others, while interactions among robots are evaluated at a later stage.

A decoupled plan might fail if compared to a plan performed in a centralized manner, the reason being that the former yields sub-optimal yet heuristic solutions.

Some examples of decoupled planning are the prioritized planning [7] and path coordination [8].

The vectorial movement strategy described in the sequel can be regarded to as a decoupled planning. Robots are free to plan their own motions considering local and global information vectorially. The right configuration among them is effectively maintained by adding a swarm control vector.

Strategies for robot swarms navigation require robots capable at least of some basic behaviors such as avoiding obstacles, finding the mines, following a specific path, maintaining a formation [9, 10]. Generating a non-trivial behavior requires effective use of multiple basic behaviors. In this research the problem has been solved with a vectorial movement [11] using a specific vector for each of these basic behaviors. Four vectors have been defined:

1. *V1,* used for avoiding obstacles: it can suppress all other vectors for the time necessary to move past the obstacle;
2. *V2,* used for achieving a goal;
3. *V3,* used for maintaining the position in a specific formation;
4. *V4,* for maintaining the robot direction.

An example of this vectorial combination is shown in Fig. 1, which shows a situation where there are no obstacles along the path of the robots and the team has to maintain a particular formation. When a robot of the team must avoid an obstacle, vectors V2, V3 and V4 are suppressed by V1, that is calculated based on the values read by the onboard sensors. In our simulation each robot has eight sonars, one or more sensors for mines detection and a positioning system such as odometers, GPS or DGPS.

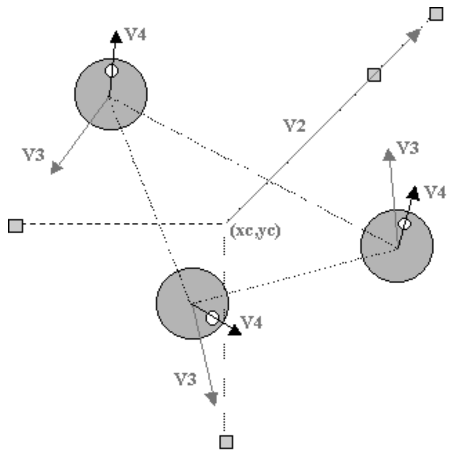

Figure 1. *Vectorial combination:* the three robots move towards a goal position with V2 and tend to maintain a wedge formation with V3, that “pulls” them towards their correct positions, indicated by the small squares.

Using this method, we have so far defined, simulated and compared six strategies:

1. *Random movement;*
2. *Relay clustering;*
3. *Flocking;*
4. *Swarming;*
5. *Formation maintenance;*
6. *Comb movement*.

Random movement: Vectors used in this strategy are simply V1 and V4. V4 is used for the base random movement and V1 for avoiding obstacles and other robots.

Relay clustering: The movement of robots is initially random. When one of them finds a mine, it initiates the relay by transmitting the signal *I found a mine in position (x, y).* Any robot that can find this kind of mine, within communication range of the first robot, heads towards it while transmitting *I see a robot that found a mine in position (x, y).* Any robot within range of the second robot but not of the first one transmits *I see a robot that sees a robot that found a mine in position (x, y)* and heads towards (x, y). In this strategy V1 is used to avoid obstacles, V4 to move around at random until no mines found for a given amount of time, and V2 is used to move towards the mine. This strategy exhibits an emergent behavior that resembles very closely the way some ants behave when one of them discovers a food source.

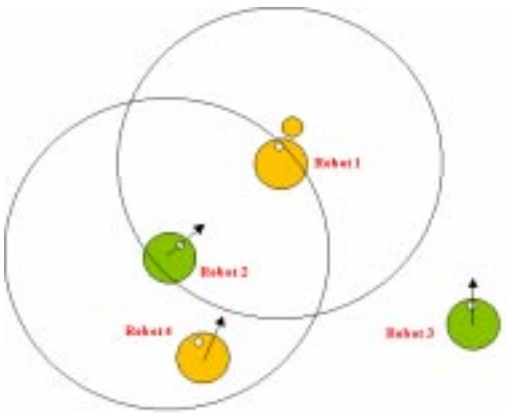

Figure 2. *Relay Clustering:* in the first phase, Robot2 and Robot4 go towards Robot1, that has found a mine. Robot3 still moves at random because it is out of Robot1 range of influence.

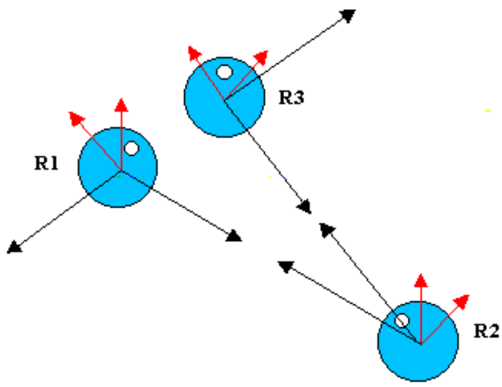

Figure 3. *Flocking:* each robot adds a vector of attraction/repulsion and a component of alignment to the other robots.

Flocking: Flocking occurs in nature and is exhibited by birds, fish and some insects.

This behavior is based on the principle that there is safety in numbers and the whole is more important than the parts. The three rules that implement flocking are:

1. *Cohesion*: each robot shall steer to move toward the average position of local flockmates;
2. *Alignment*: the robots will align to the same direction as their neighbors;
3. *Separation*: all robots in the flock will maintain a separation distance from their fellows.

These three components are added to obtain V3. V2 in flocking is not necessary because the movement of the team is random.

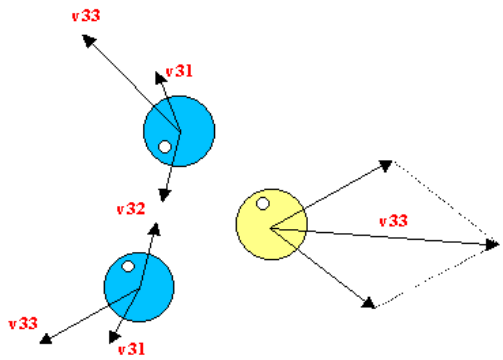

Figure 4. *Swarming:* robots in one team repel robots of another team with v33; v31 is used for attraction/repulsion; v32 for alignment.

Swarming: This strategy works like flocking as far as robots belonging to the same team are concerned, but the flock is split in several teams. Different teams, to avoid each other, must follow these rules:

1. *Attraction*: each robot is attracted to its fellows as the distance between them increases.
2. *Alignment*: the robots will align to the directions of their fellows.
3. *Repulsion*: each robot is repelled by robots belonging to another team.

These three components are added to obtain V3. V2 here is not necessary because the movement of the team is random.

Formation maintenance: This is the first strategy that has a coordinated movement for all the teams. Each team can move using a different formation. Currently, there are three available choices: line, column and wedge. The position of each robot in the formation is fixed relatively to the team centroid, and V3 is used to keep this position. In this strategy, each team follows a specific path defined by an array of points. The movement of each team is obtained with the component V2 oriented from the actual team centroid to the next point in the array. Fig. 1 shows an example: the square points are the positions to be kept in a wedge formation and each robot has V3 pointing towards these points.

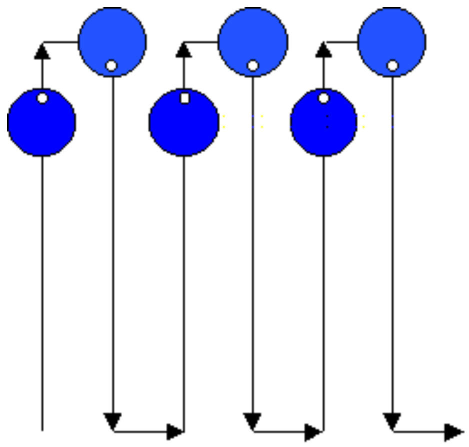

Figure 5. ***Comb*** *Movement:* a team of three robots during comb movement.

Comb movement: This strategy is similar to formation maintenance, but the formation changes from line to column, and vice-versa, passing from a goal to another one. This change realizes a “comb” movement. The robots calculate their next goal point during the movement, operating as in Figure 5.

4 The simulator

The simulation environment should provide an accurate estimate of robot performance in the real world. Simulation is desirable because it offers a means to test many robot system configurations quickly, and, due to the particular nature of the application, this is obviously very important. The test environment for this research, that is based on the Kephera robot simulator, was written in C using the X Windows graphics package. The user interface of the simulator is shown in Fig. 6 and 7. It should be noted that color is an important component of the interface: the authors wish to apologize for the poor legibility resulting from greyscale printing. The robots can sense their location in the environment, and detect obstacles, mines and other robots. The current software configuration allows using three squads of robots, plus a fourth one that simulates removal of detected mines. Each squad can have up to four robots. Mines of different kinds can be laid in the field, along with obstacles such as walls, trees, etc. The capability of each robot of detecting more than one kind of mine allows studying methods for increasing the reliability of the system.

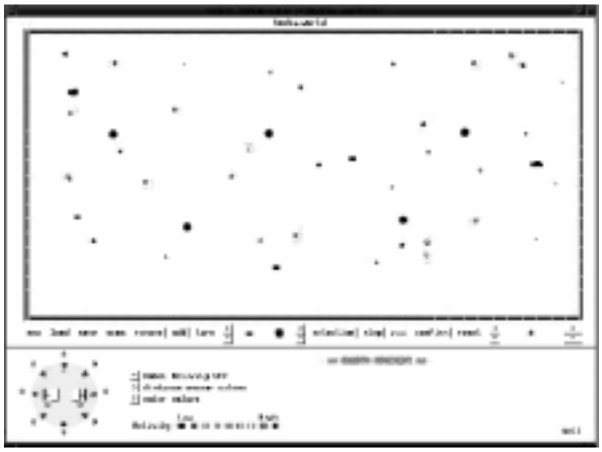

Figure 6. Robot Swarm during a simulation.

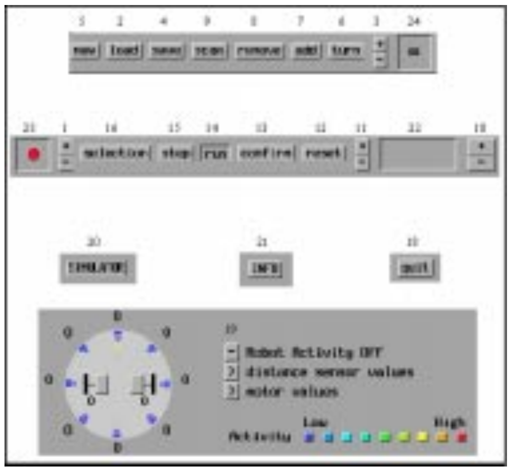

Figure 7. Robot Swarm control panels.

Robot Swarm allows simulating and checking other interesting things, such as robot failures, sensor data values, etc.

In order to make comparisons among different strategies possible, a performance metric had to be established For this research, the time needed to complete the task was chosen as the primary performance index.

Figure 8. *World 1:* Stones (rectangular), a few trees (large circles) and 30 randomly placed mines of three different kinds (small circles).

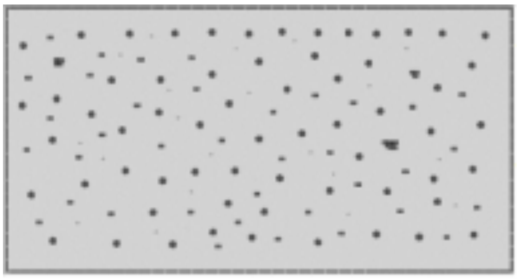

Figure 9. World 2: same as world 1, but cluttered with more obstacles.

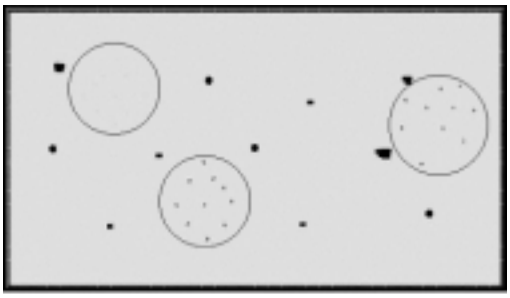

Figure 10. *World 3:* Same as world 1, but the mines of the same kind are gathered together in the field. This situation is very likely to occur in real minefields

Working in the three worlds of Fig. 8, 9, and 10, we have performed five tests:

1. Working in the world of Fig. 8, we compare the performances of all strategies (Fig. 11);
2. Working in the world of Fig. 9, we compare the performance of each strategy against the corresponding strategy in Test 1 (Fig. 12);
3. Working in the world of Fig. 10, we compare the performance of all strategies with the results of Test one and two (Fig. 13);
4. We plot the number of found mines vs. the time that was required to find them for teams of one, two, three and four robots, and for all the strategies
5. We plot the performance while adding a random noise that affects the sensors

Results of Test 1 are shown in Fig. 11, that indicates the number of time units required to clear World 1 with different numbers of robots. Performances of the strategies without a specific formation (1, 2, 3 and 4) are worse than performances of the coordinated strategies (5 and 6). This is because the latter strategies only explore each point with a single robot, and only once during the whole process.

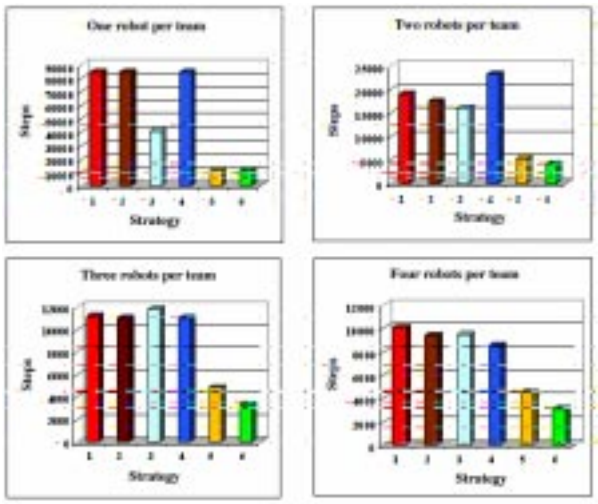

Figure 11. Test one: time required to clear World 1.

The results of Test two, compared with those of Test one, are shown in Fig. 12, where we plot, for teams of one, two, three and four robots, the number of time units required for clearing world 2. Since this environment is heavily cluttered with obstacles, the performance of all strategies is worse than performances in test one: however, coordinated strategies work still better than random ones.

The results of Test three, compared with results of Test one, can be seen in Fig. 13, where we plot, for teams of one, two, three and four robots, the number of time units required to clear world 3. It is interesting to note that Relay Clustering performs much better than in the previous examples. Formation Maintenance and

Comb Movement do not change, because they are independent from the position of mines.

Fig. 14 shows the results of test four. These diagrams show, for various strategies and numbers of robots, the time required to achieve a given number of found mines. Since all worlds contain 30 mines, the last plotted time indicates the total time required to complete the task. Not surprisingly, coordinated strategies find mines at a constant rate, while uncoordinated ones are more efficient when many mines are still undetected. Furthermore, increasing the number of robots per team does not necessarily yield a significant reduction of the required time.

Finally, Fig. 15 plots the performance in function of the sensitivity of mine detection sensors. It can be easily seen that the relation is non-linear. This point is still under investigation.

5 Conclusions

A currently ongoing research that aims at using groups of robots equipped with various kinds of sensors has been illustrated. Emphasis was placed on two main points: clusters of well-organized robots work better than single machines, and strategies to be used when odor sensors are employed need thorough investigation.

Robot Swarms is a part of a much more complex project named "Mine Sniffer", that will use real robots for final testing of the developed methods. Two working prototypes, Speedy and Tobor, have already been already realized, but a simulator is mandatory if the behavior of a large number of cooperating robots has to be studied.

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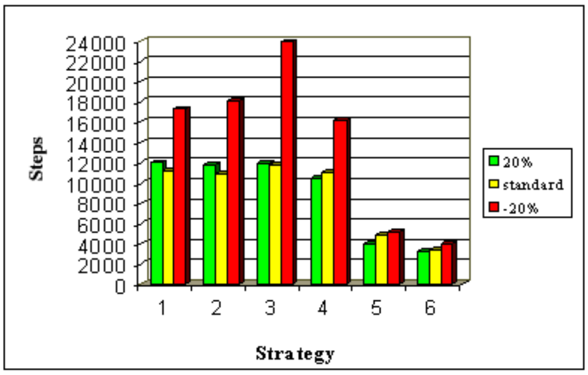

Figure 15. Test five: performances with different sensor sensitivities.

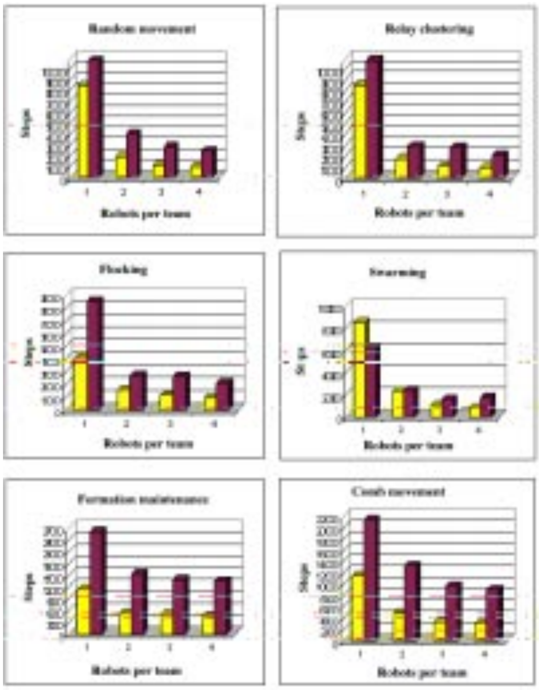

Figure 12. Test two.

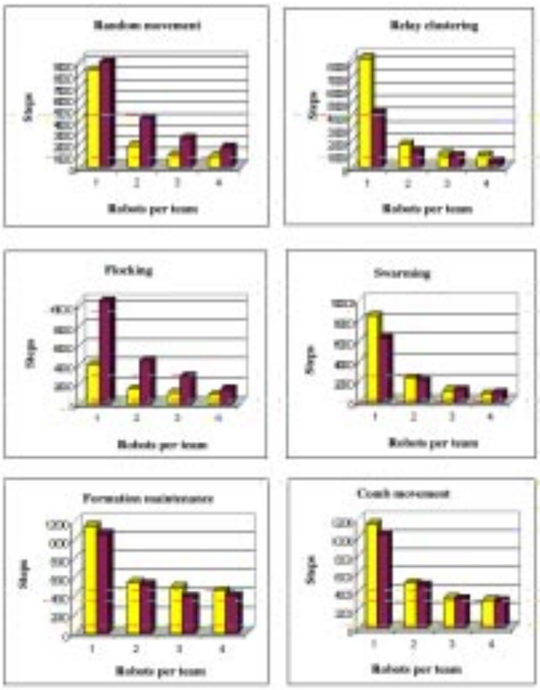

Figure 13. Test three.

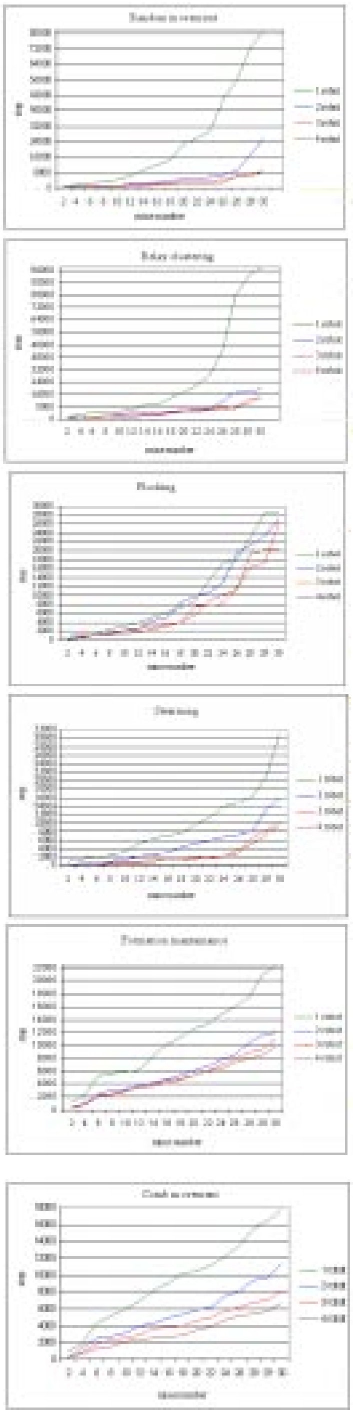

Figure 14. Test four for (from top to bottom): random movement, relay clustering, flocking, swarming, formation maintenance, comb movement.