From A Simple Local Vibration Message to The Success of A Global Complex Task

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Abstract

This paper presents the effect of a simple vibration message passed locally between two robots on the success of the whole swarm in implementing a complex best-of-N manipulation task. The task is called the generalized leaf curling task. On an unknown leaf containing edges with multiple levels of stiffness, a group of very simple robots is required to find and collaboratively curl up one of the softest edges. In earlier work, using the "relative-value based randomness" method [Phan and Russell, 2010], our robots have demonstrated the ability to complete this task. However, the success of that algorithm depends strongly on the working environment and requires parameters to be preset. In this work, by incorporating the transfer of a simple message between two robots via local vibrations, the whole robot swarm is able to explore the environment in a particular way that results in finding better and better objects over time. With this trend, it is conjectured that, given enough time, the robots will find the best object in the environment. The success of the new algorithm which is called "local maximum conservation" is demonstrated via high completion rates of the robot swarm in different complex working environments. The algorithm was developed using physical robots and verified by a series of tests using a visualized simulator.

1 Introduction

Swarm robotics, a quite young research area of robotics, focuses on using a group of robots to solve complex collaborative tasks that may be impossible for single robots to complete regardless their intelligence and abilities. Swarm robots are expected to be useful and intelligent systems that can make a large contribution in the areas of robot fundamentals and robot applications. However, there is a contradiction that swarm robot tasks are supposed to be complex and difficult, but each swarm robot must be as simple as possible in terms of both software and hardware. Therefore, there are still many open challenges in swarm robotics waiting for solution from researchers now and in the future.

During more than twenty years of development, a considerable number of swarm robot tasks have been considered and well investigated. Swarm robots may work with no external objects in formation forming or flocking tasks [Sahin et al, 2002] [Turgut et al, 2008], work with only one object as in soccer matches [Kitazumi and Ishii, 2010] or box pushing tasks [Mataric et al, 1995], or with multiple objects as in puck foraging [Liu and Winfield, 2010][Lerman, 2004], sorting [Holland and Melhuish, 1999] [Deneubourg et al. 1991], stick pulling [Ijspeert et al, 2001], or collaborative building [Werfel et al 2004][Steward and Russell, 2006]. Although having different goals, all of these existing tasks share a common point of involving identical objects. All objects are equal for robots in terms of their affordance. This means there is no object that the robots will find harder to manipulate compared to other objects.

Therefore, a type of genuinely difficult tasks for swarm robots, which has not been well considered, is the tasks where the working environment of robots contains objects of different affordance levels. The goal of the robots in these tasks is to collaboratively find and gather at one of the "best" objects to completely manipulate it. Such a task can be called a "best-of-N manipulation task" and it is the focus of our on-going research project. Actually, the term "best-of-N" has been mentioned in some recent literature to name group decision making tasks [Wessnitzer and Melhuish, 2003] [Parker and Zhang 2009, 2011]. However, in those tasks, the robots are only required to make some judgment about different objects, but not to manipulate them.

A particular example of the "best-of-N manipulation task" is our robotic "leaf-curling task" which was initially inspired from the "nest building behaviour" of weaver ants [Wilson, 1982]. On a leaf containing a number of edges with different levels of stiffness, only one or a few edge segments are soft enough for robot ants to curl up if a certain number of robots or more lift the same edge together at the same time. The task of our robots is to not only collaboratively find but also concentrate on one of those softest edges to successfully curl it up. An additional challenge of this task is the affordance level of each edge/object cannot be perceived by the robots without physical contact with it.

To complete such a complex task, it is apparent that the robot swarm must be able to explore the working environment and be aware of the best object. They must then agree with each other via some form of communication to converge on that best object. All of these requirements seem to be clearly achievable for any group of robots equipped with wireless transceiving modules and endowed with sophisticated SLAM abilities. However all of these abilities are not available to our swarm robots – the W-AntBots, which are required to be very simple both in software and hardware. The robots can only sense the states of objects in the environment, which are being manipulated by other robots. And this is the only way they communicate with each other.

In previous work, employing the "basic exploring rule", the W-AntBots have successfully solved the simplified case of the leaf curling task where the leaf had only two levels of stiffness [Phan and Russell, 2010[1], 2011]. Later on, by adding to the "basic exploring rule" the relative-value-based random exploration ability, our robots have achieved high completion rates in some complex environments with objects of multiple levels of affordance [Phan and Russell, 2010[2]]. However, the success of the second method is very sensitive with changes of its most important parameters: K_e – exploration coefficient, and α – convergence coefficient. In addition, optimal values of these two parameters vary strongly in different environments. This means that, in order to achieve a high success rate, the two parameters must be preset for the W-AntBots. Unfortunately, this presetting requirement cannot be a reasonable solution for variable and unknown environments.

In this paper, we introduce a new algorithm, which helps swarms of simple robots to carry out the leaf curling task with high completion rates in unknown complex environments. This algorithm is also developed from the "basic exploring rule", but this time, with the addition of simple bi-directional communication via local vibrations. The algorithm allows our robots to explore the environment in a much more efficient way compared to the "relative-value-based random" method. In particular, the robots are able to collaboratively find and keep track of the object that is currently the best. This is the key factor, improving the performance of our robots in a variable environment. A description of the new algorithm called "local maximum conservation" and its advantageous results are presented in detail later in this paper

This paper is organised as follows: Section 2 summarises previous work including the common working algorithm and the two decision making algorithms: "basic exploring rule" and "relative-value-based randomness". Section 3 is the centre of the paper with a detailed description and explanation about the new method: "local maximum conservation". In Section 4, after a brief overview of the visualized simulator, advantages of the new method are demonstrated and discussed via simulation results. Next, Section 5 demonstrates how vibration communication can be realised on our physical robots, followed by proposals for future experimental scenarios. Finally, Section 6 concludes the paper and proposes future work.

2 Previous work

It is necessary to briefly re-introduce previous algorithms

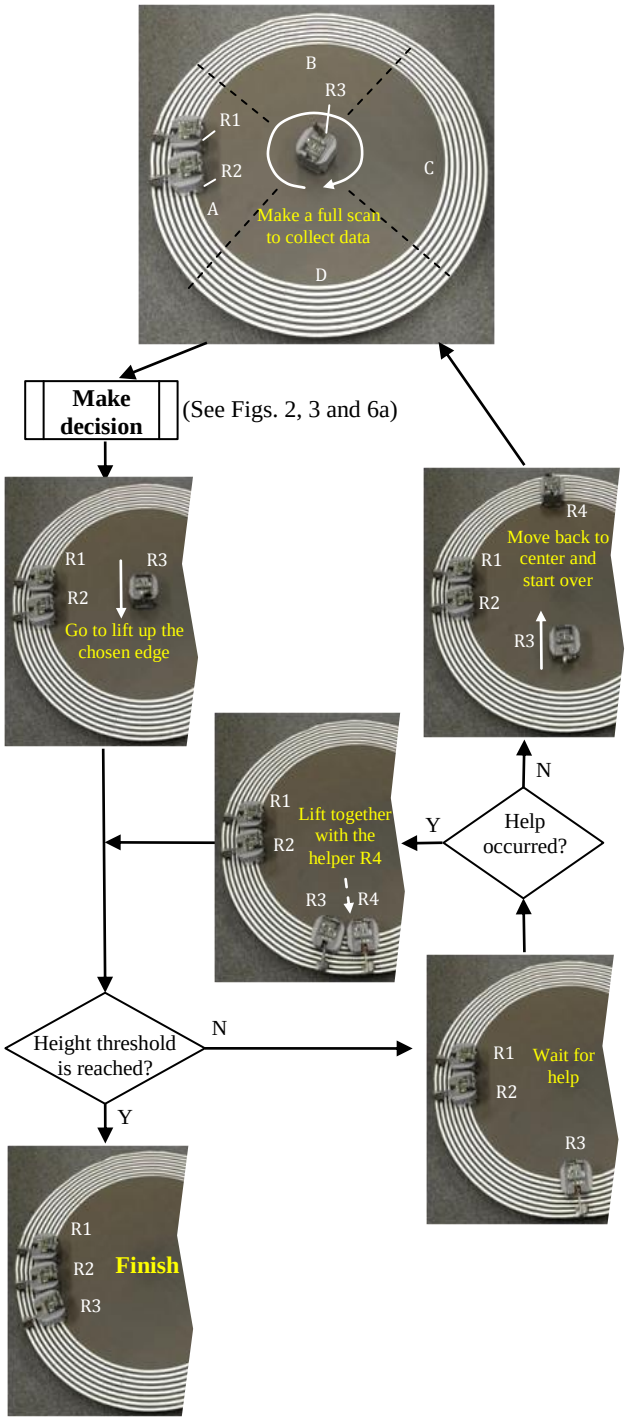


Fig.1. Sematectonic based working algorithm of robot 3. The leaf contains four edges/objects. Object A is the softest one and can be fully curled up by three robots.

developed for our swarm robots as they form the basis that the new algorithm is built on, and they also help highlight the advantages of the new method.

2.1 Sematectonic based working algorithm

Being inspired by the biological world [Wilson, 1982], our swarm robots apply sematectonic stigmergy as their unique communication method. Using this method, a robot receives information from other robots via the changes they make to the objects in the working

environment. In the leaf curling task, each edge is considered an object. The state of each object/edge is the height that it is curled up to by the robots. So the state of an object would be zero if that object/edge is lying flat on the ground. With such a concept, the sematectonic based working algorithm of each robot is built as shown in the Fig. 1. Each robot comes to the working environment in one-by-one order and starts by scanning objects from the center of the leaf. The state of each object is also a datum that each robot receives during the scan process. Based on the set of scanned data, the robot decides which object it should work with. At the chosen object, after trying its best to lift the edge, the robot will wait for assistance from other robots for a certain amount of time called the wait time period. If the wait time expires without any help, the robot will drop the current object and move back to the center to start over.

As the amount of information that each robot can perceive from the environment is limited, the most important part of this working algorithm is the decision that each robot makes based on the current state of the working environment. Effective utilization of this limited information is required to help the robot swarm find and gather at the best object in this complex collaborative task.

2.2 The basic exploring rule

In the first step toward a solution for the generalized case, the leaf curling task was initially considered with a simplified case, where the leaf edges have only two levels of stiffness: soft and hard [Phan and Russell, 2010[1]]. The task of our robots was to find the only soft edge of the leaf. It is necessary to remember that the robots have no awareness of the absolute "stiffness" level of the edges. In other words, lifting an edge, the robot cannot determine that is a hard or a soft edge. With such a condition, to find and gather at the soft edge and to avoid mistakenly gathering at a hard edge, the robots make a decision obeying the following simple rule (Fig. 2): if there are two or more different positive data being read, then choose the object with the best state (datum) to work with, otherwise, choose to work with any zero-state object instead of working with any current positive state object. It can be seen that, this so called "basic exploring rule" advises the robots to extend their search to make sure the object they should work with is the better one, instead of gathering immediately to any object they can see that is being lifted. Indeed, having no absolute scale to individually measure an object, a robot can only tell that an object is lifted high if and only if it sees another object that is being lifted a lesser amount.

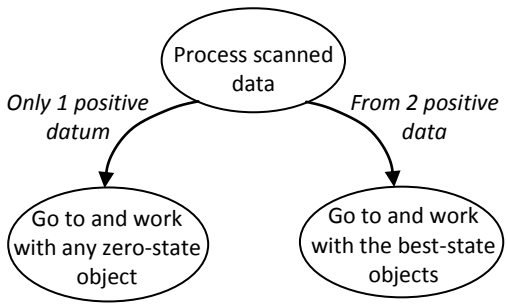


Fig.2. The basic exploring rule

This algorithm is a perfect solution for cases where objects have two level of affordance. However, it demonstrates a big disadvantage when dealing with environments containing objects of more levels of affordance. This problem can be explained via a simple example, where the environment has three affordance levels: 1, 2 or 3 (with 3 being the easiest to lift). In a highly possible case, where objects of level 1 and 2 are found, the basic exploring rule will guide robots to gather at the level 2 object. Therefore, the level 3 object will never be found.

2.3 Relative-value-based noise algorithm

From the above example, it can be seen that, if robots do more exploration of the environment, they will have a chance to find the objects with level 3. To realize this behaviour, another decision making algorithm called "value-based randomness rule" was introduced in our previous work [Phan and Russel, 2010[2]]. The simplified diagram of this decision making algorithm is shown in Fig. 3. Essentially, this algorithm encourages robots to not concentrate too soon on a locally best-level object, but to extend their search to the surrounding area. The main equation (*) specifies that the "distance" of each exploration will be inversely proportional to the ratio of values between highest and lowest data in the scanned data set. According to this equation, the most important components of the algorithm are the two parameters: K_e – exploration coefficient, which decides the exploration range, and α- convergence coefficient, which controls the convergence "speed" of the swarm.

This exploration extending algorithm has demonstrated its ability to help our robots achieve a high success rate in a number of complex environments with objects of multiple levels of affordance. This used to be impossible for the basic exploring rule. However, the success of this algorithm is very sensitive to changes in the two parameters K and α. With values K and α outside of quite narrow optimal ranges, the completion rate of the robot swarm may dramatically decrease, even lower than

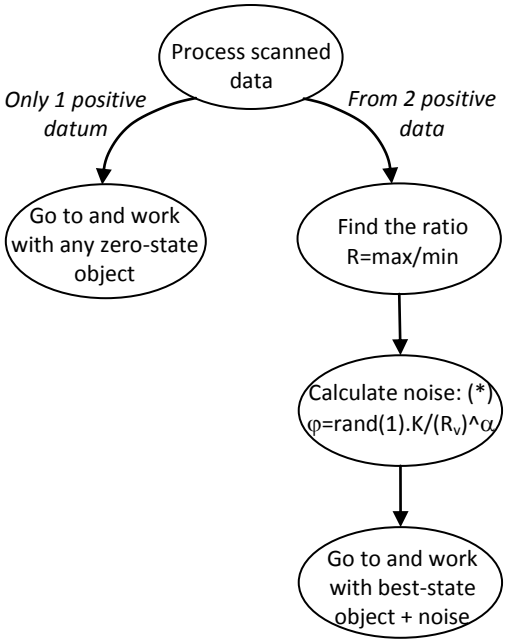


Fig.3. The relative-value-based randomness algorithm

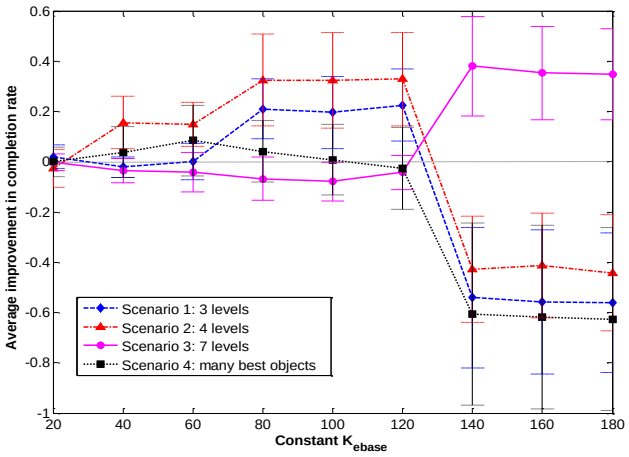


Fig. 4: Difference in completion rate between relative-value-based randomness rule and basic exploring rule.

for the exploring rule. In addition, the optimal ranges of K and α vary for different environments. These two disadvantages can be seen in the Fig. 4, which shows the difference in completion rate between the relative-value-based randomness rule and the basic exploring rule.

Based on the results shown in Fig. 4, it is possible to choose suitable values of K and α for the robots given that the working environments is known before hand. However, our goal is to make the robot swarm to be able to complete the generalized task in a completely unknown environment. Therefore, the relative-value-based randomness rule still cannot be a reliable decision making algorithm. That was the motivation to develop the new algorithm which is described in detail in the following sections.

3 Incorporation of vibration communication

3.1 Local vibration communication

To find a new solution for a problem, it is necessary to analyse the reasons that lead to the disadvantages for the previous solutions. It can be seen that, using the relative-value-based algorithm, although the exploration ability of the robots is really extended, it was not so effective. During simulation runs and physical experiments, there were cases where the whole swarm failed to complete the task even though the best object had been found at least once by the robots. That happened because each robot was not aware of the difference between the object it was manipulating and other objects, being manipulated by other robots. This problem is also the limitation of the pure sematectonic stigmergy method. Indeed, there is only uni-directional information flow that a scanning robot gets from other robots that are manipulating objects. No information of the scan result is transferred from the scanning robot to the manipulating robots.

It is conjectured that if each manipulating robot can receive at least a little information about the performance of other robots in the environment, the collaboration between swarm members and the exploration would be more effective. Being equipped with no wireless, optical or sonic communication devices nor any pheromone releaser and receiver, how can the scanning robot share its scan results with the robots manipulating objects? The answer to this question, which

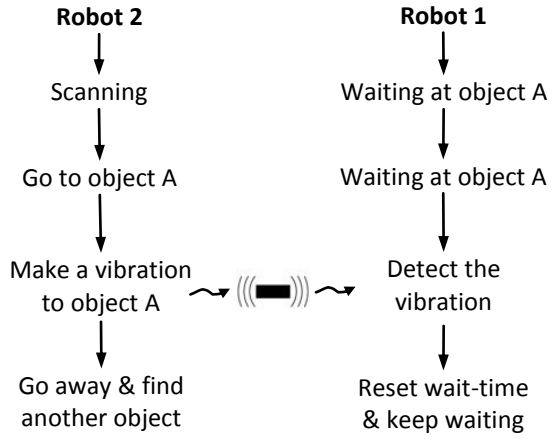


Fig.5. Application of vibration communication between robots in the leaf-curling task

is the key point of the new method, is that: two robots will transfer to each other a message by creating a vibration in the object that they are both simultaneously manipulating.

Utilizing vibration as a mean of communication has been mentioned in a number of other robotics projects. However, in most of the cases, vibrations are made through the ground of the working environment, such as: navigating towards prey via ground vibration [Wallander et al 2001] and transferring information via substrate vibration [Silvola and Russell, 2005]. These works differ from transferring vibration messages between robots via the objects they manipulate, which is discussed in this paper.

An important difference between transferring information via substrate vibration and object vibration is the transfer range. When a vibration is created on the substrate of an environment, it will be propagated to all robots working in that environment. This is a good effect if the transferred information is a common and useful notice for all robots. Nevertheless, if the message is only meaningful for some particular robot but not for other, the omni-directional transferred message might confuse other robots. In the same trend, it also may cause cross-talk errors and error-propagation problems between robots like in wireless communication strategy [Phan and Russell, 2009]. On the contrary, using object vibration, one robot only locally transfers information to another robot which it wants to transfer to. This way helps robots exclude the above listed errors.

Another positive side is that, this way of sending messages fits within the concept of the "communication via the working environment" principle. It even makes the existing concept of sematectonic stigmergy more complete by incorporating bidirectional communication.

The next question is what message can be transferred via a vibration? And how can such a vibration message be applied to increase the performance of a robot swarm in the leaf-curling task?

3.2 The local maximum conservation algorithm

Using signal processing techniques, humans can transfer almost unlimited amounts of information via different forms of vibration. However, for swarm robots, the requirement of simplicity both in hardware and software

does not allow them to transfer sophisticated messages by complicated modulation of the vibration. The information sent using a vibration signal must be very simple. The most important thing is to exploit that limited information in the best way to create useful collaboration between the robots.

To avoid the mistake of losing the "best object" once it has been found as in relative-value-based algorithm, a simple vibration message is applied to modify the "basic exploring rule" algorithm as follows (Fig.5):

- After finishing a whole scan in the center of the leaf, instead of making a decision to immediately work with one object, robot 2 will go to one of the objects with the local-best state. Assume that is object A. It will grasp that object and make a vibration to send a message to the robot already manipulating the object, called robot 1.
- After sending a local vibration message, robot 2 will then move back to the center and try to find a new object (an object which is not currently being manipulated).
- For the waiting robot 1, after getting the vibration message from robot B, it will reset its wait-time. This means that robot 1 will wait longer by one wait-time period.
- Relating this information to everyday life, this message can be abstractly understood as: "you are working well, keep waiting longer".

Compared to the basic exploring rule, the new algorithm adds only one action, which is transferring a simple message locally between two robots. However, in the context of the whole swarm, where the robots alternately repeat their working cycles, this simple local action will create a number of effects as follows:

- The robot working with the best object always waits longer than any other. (As it may get more encouraging messages from other robots).
- Because the best performing robot is notified by not only one robot but also by other robots coming continuously one after another, therefore the it has a high possibility of receiving the correct vibration message at least once even if there are some noises or errors happening in the vibration transfer process.
- The whole robot swarm will find better and better objects over time (if they are available in the environment).
- The swarm will not lose the global best object if it is found although each robot does not know for sure that it is the global best object.

The last two positive effects are the inspirations for the name "local maximum conservation" of this new working algorithm. Another advantage of the new algorithm is that, the exploration range is not limited and absolutely does not depend on the ratio of values between different affordance levels as in the value-based randomness algorithm. This also means that the chance of finding the best object is independent of the affordance values of objects. However, to complete the leaf-curling task, swarm robots not only need to find one of the best objects in the environment, they must also be able to converge on that object to collaboratively manipulate it. The algorithm presented above is only to help the robots to explore the environment and find the best object, but not to guide them to converge. There must be some

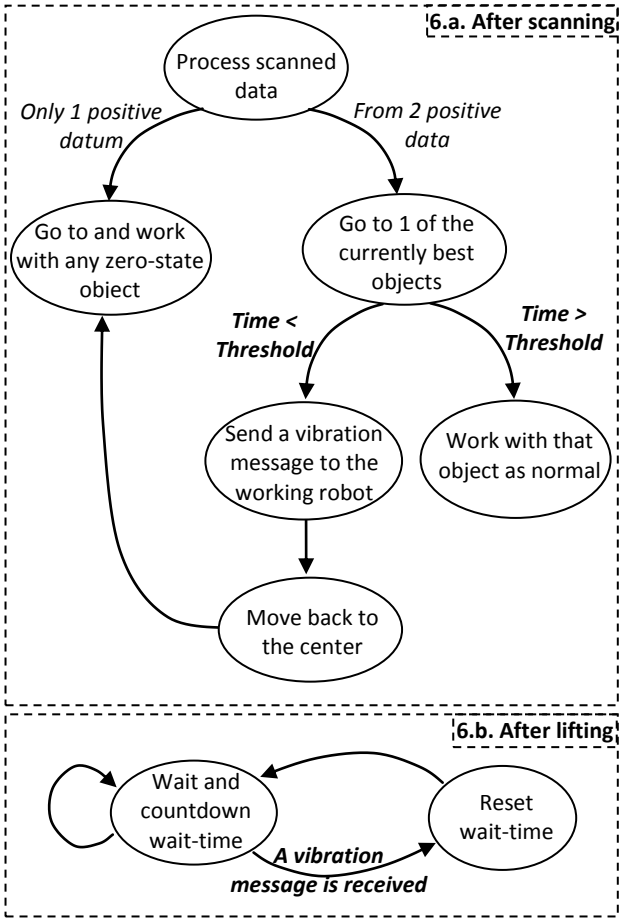


Fig. 6. The local maximum conservation algorithm

threshold, which helps the robots to "switch" from exploring to converging on the best object they have found. Such a threshold can be decided by the value (state) of the objects, or by a time factor. The first option is not feasible because the robots do not have an absolute scale as well as a preset goal to know if the object each one is holding is the best or not. Therefore, using a time threshold to switch between exploration and convergence mode should be a better option. Actually, using time as a threshold to start or finish a job is also a quite normal technique found in the animal world. For example, corals use lunar changes or sunset time to synchronise their spawning [Veron, 2000]; except for owls, most birds return to their nest when the sun sets. In order to realize the use of a time threshold for the whole swarm, all robots will need to have the extra ability of tracking the absolute time flow. As mention above, this would be equivalent to the ability of animals which use natural phenomenon like the sun, and temperature to coordinate their activities. With the introduction of time threshold as a switch between exploration and convergence, the complete "local maximum conservation" algorithm of each robot can be illustrated as in Fig. 6. It should be noted that this algorithm is not only effective for the generalized leaf curling task, it also can form the algorithmic base for other best-of-N-manipulation tasks.

To decide a time threshold to switch between two working modes, two facts should be taken into account. It is obvious that the more time is allocated to exploration, the higher the chance that robots can find the

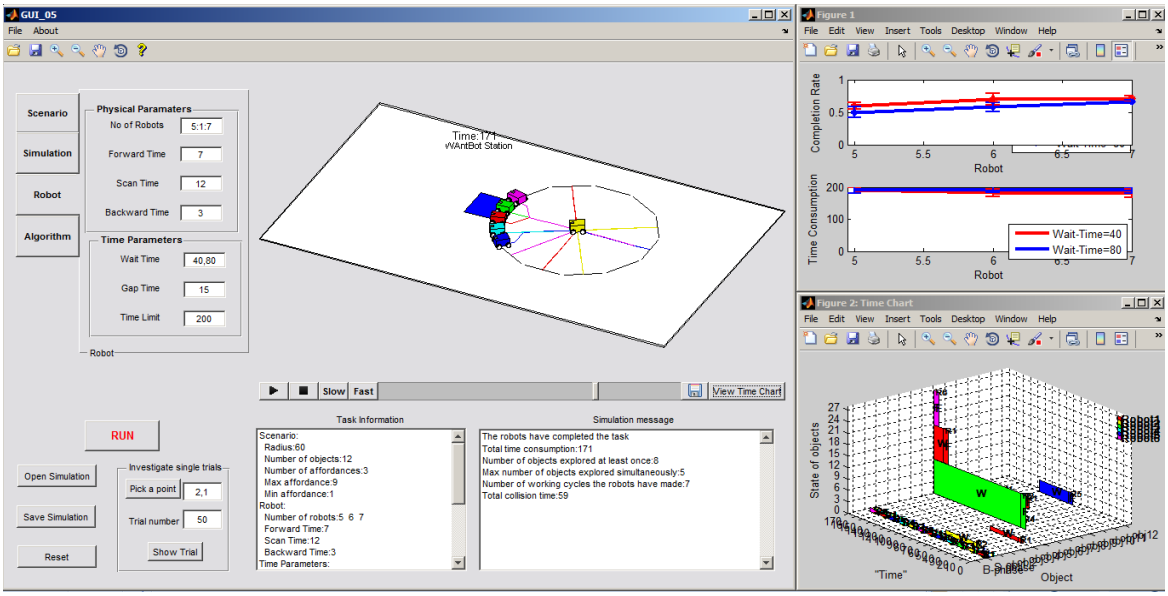


Fig. 7. W-AntBot simulator.

best object. Nevertheless, the time left for convergence must also be enough for the required number of robots to come to the same object and manipulate it. The number of robots required to gather at the same time at the best objects depends the nature of the task, and physical parameters of the robots also are not fixed. For these reasons the time threshold will change from one task to another.

It should be noted that, as robots extend their exploration time, the total time consumption is also lengthened compared to the basic exploring rule and randomness methods. However, this is not a disadvantage as it can guarantee the main goal that is to finish the task with a high completion rate.

It is almost impossible to achieve a completion rate of 100% in all working environments, especially if a small number of robots must work with a large number of objects in a short time frame. However, it can be predicted that this "local maximum conservation" method can substantially improve on the results yielded by the two previous algorithms. This advantage will be demonstrated with a set of simulation results, presented in the next section.

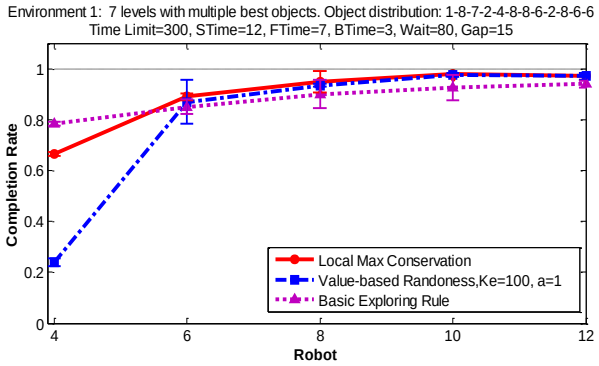
4. Simulation

The new working algorithm was tested using the W-AntBot simulator, whose interface is shown in Fig. 7. This is an upgraded version of a behaviour-based simulation program that was used before to test the two previous algorithms [Phan and Russell, 2010[1,2],2011]. This simulator allows users to customize almost every aspects of a sematectonic stigmergy task from the number of robots, all time parameters of both robots and the task, to the number and distribution of affordance levels of the objects. The simulator can plot different graphs from complete details of each run to comparisons of different results gathered from different simulation runs. Together with a visualized animation window, users can monitor the behviour of each robot as well as examining the effects of each working algorithm.

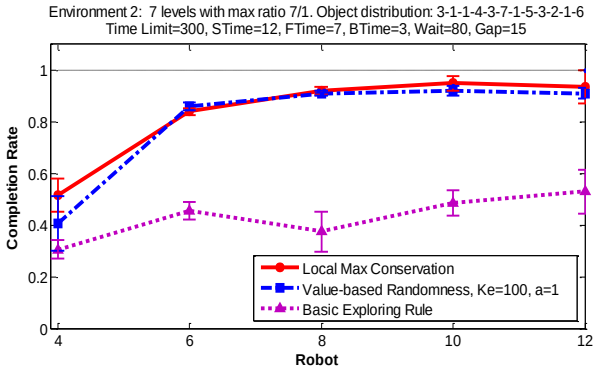
4.1 Simulation results

In this paper, the W-AntBot simulator is used to compare performance of three algorithms: basic exploring rule, relative-value-based randomness and local maximum conservation in different complex environments. All tested environments have 12 objects with multiple affordance levels. The first environment has 6 levels of affordance with multiple objects at the top level. In this type of environment it is relatively easy for the robots to find one of the best objects. The remaining three environments will be harder with only 1 best object and different ratio of values between affordance levels as follows: The environment number 2 has 7 affordance levels starting from 1 to 7. Environment 3 also contains 7 levels but the ratio between the lowest and the highest affordance levels is much larger: 18/1. The last environment has only 3 levels 1, 3 and 5. Time parameters of robots in this simulation are: FTime=7, STime=12, BTime=3, Wait=80, Gap=15. Total time limit =300. To leave enough time for robots to converge as mentioned in previous section, the time threshold of our robots in these simulations will be three quarter of total time limit. The average results of 200 trials for each case are shown in Fig. 8.

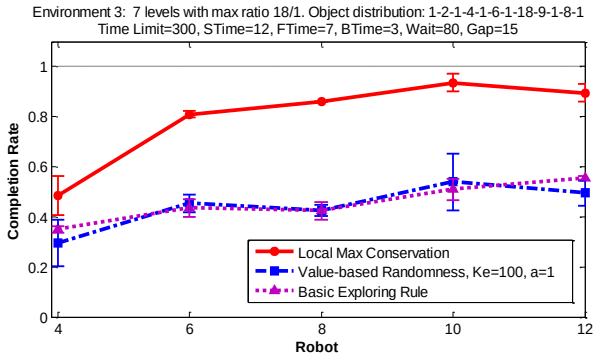
It is can be seen immediately from the graphs of all figures that, the new algorithm obviously improves the completion rate of the robot swarm when working in different complex environments compared to other two algorithms. With a certain number of robots, the new algorithm can reach a nearly perfect completion rate, which is impossible for the other two methods in many cases. In Figs. 8a and 8b, the randomness rule can be a competitor of the new algorithm by achieving almost the same completion rate. But this success of the randomness algorithm only happens for a narrow range of K and α whereas the local maximum conservation method does not depend on any preset parameters. More important, using the same values of K and α, completion rate of the randomness method drastically drops as the environment changes while the performance of the new algorithm still



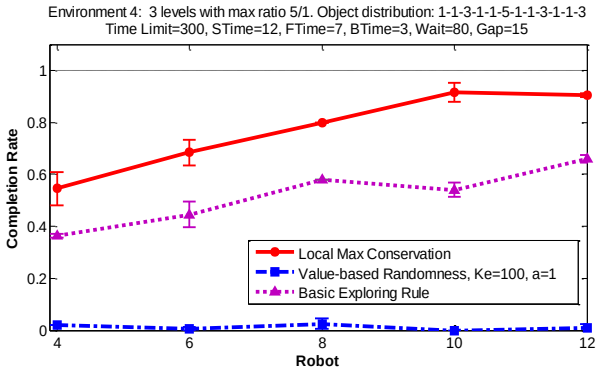
a) Multiple best objects, 6 levels, max ratio = 8/1



b) 1 best object, 7 levels, Max ratio=7/1



c) 1 best object, 7 levels, max ratio=18/1



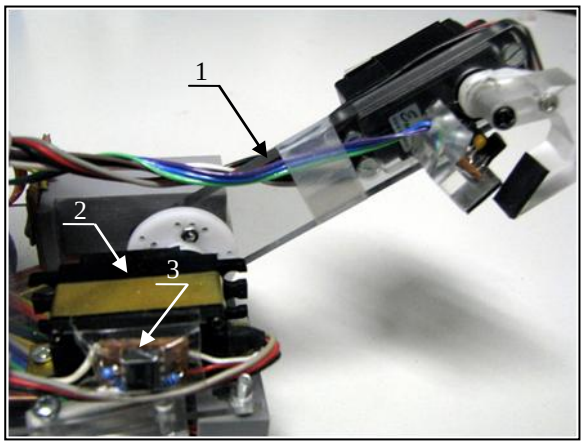
d) 1 best object, 3 levels, max ratio=5/1

Fig. 8. Simulation results in different working environments

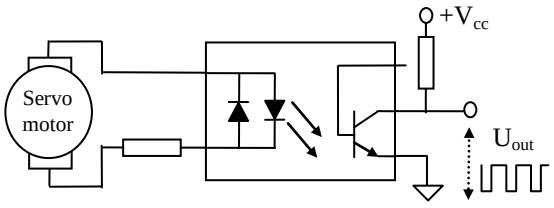
stays stable. Indeed, when the maximum ratio between the easiest and the hardest objects changes from 7/1 in environment 2 (Fig. 8b) to 18/1 in environment 3 (Fig. 8c), completion rate of the randomness algorithm falls from around 92% to the same rate of the basic exploring rule, which is less than 60%. When this easiest-hardest ratio changes in the opposite direction, completion rate of the randomness algorithm becomes much worse with a "straight" plunge to almost zero (Fig. 8d), which means the robot swarm totally fails the task. Whereas, in both of environments 3 and 4, applying the local maximum conservation algorithm, the robot swarm can still achieve success rates of around 92%. This verifies the performance of the new algorithm is independent of the type of environment. This advantage is very important because it will considerably increase the reliability of swarm robots in implementing the generalized leaf curling task in truly unknown environments.

After confirming the advantages of the new working algorithm in simulation, we would like to verify this result using physical robots. The most important aspect in this test is to realize the action of transferring the vibration message between two robots.

5 Vibration communications for W-AntBots



a. Force sensor principle circuit
1. Robot's arm, 2. Servo motor, 3. Force sensor

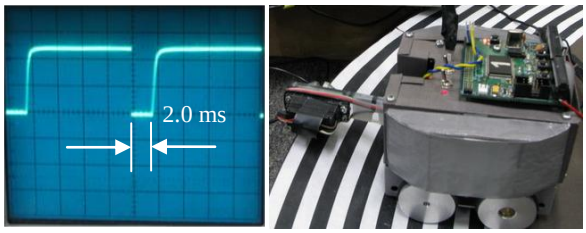


b. Force sensor principle circuit

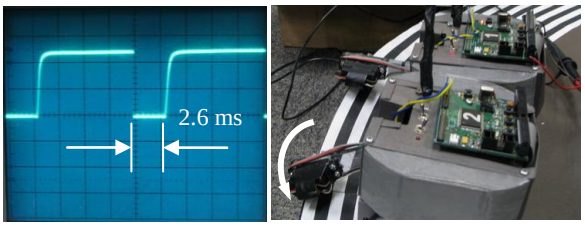
Fig. 9. W-AntBot's arm and its force sensor

5.1 The W-AntBots

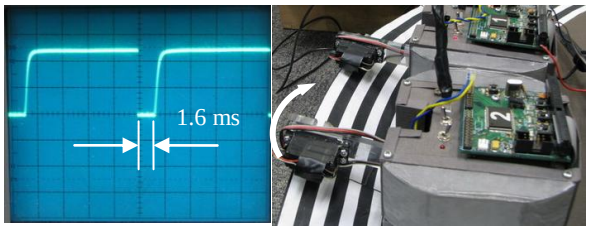
A group of W-AntBots were used for physical experiments, some of which are shown in Fig. 1 in Section 1. The robots can move forward, backward, turn left and right through an unlimited angle about theirs center. They can detect obstacles in front of, behind and below using infra-red proximity sensors. Each W-AntBot is equipped with a line-scan sensor with a 35mm lens to



a. R1 is lifting on its own. Pulse width is 2.0 ms



b. R2 is pushing down. Force applied on R1 is increased. Pulse width = 2.6ms



c. R2 is lifting up. Force applied on R1 is reduced. Pulse width = 1.6ms

Fig. 10. Output signal of the force sensors of R1 when R2 produces a vibration signal.

read the state of each object in the environment which is the height that a leaf edge is lifted in this case. Each robot has an arm with a gripper to grasp and lift the leaf edge (Fig. 9a). The arm of each robot performs a very important function for the new method because its rotation creates vibrations on the leaf edge to send messages to other robots. Furthermore, the arm is also the vibration signal receiver using a force sensor mounted on its joint (Fig.9a). The force sensor of the arm comprises an infra-red opto-coupler connected to the two brushes of the arm's servo motor (Fig. 9b). When a resistance force is applied to the servo, a voltage pulse appears across the two brushes. This voltage has the same period as the PWM control signal, and its pulse width is directly proportional to the servo torque. However, this signal cannot be measured directly from the two brushes. Using this voltage as the input signal, the opto-coupler produces an output signal with the same period and pulse width. Therefore, measuring the pulse width of this signal, the robot can "understand" the force that is applied to its arm.

5.2 Generating and detecting vibration message

Let's consider a typical case, where robot 1 (R1) is lifting one leaf edge, robot 2 (R2) comes to send a vibration message to R1. To generate a vibration, R2 maneuvers beside R1 and grasps the same leaf edge at a point close to the grasped point of R1. When R2 pushes its arm down, it creates an extra force applied to the arm of R1 (Fig 10.b). Vice versa, when the R2's arm is raised, the lifting force required from R1 will decrease (Fig.10c). By alternately lifting and pushing down the leaf edge, R2 produces a low frequency vibration signal. To make sure that R1 can "sense" the peak forces, R2's arm will be held at the lowest and highest position for a short period of time (1second in our test).

There are different ways to detect a periodical signal with pre-known period and amplitudes. In this experiment, W-AntBots detect the vibration signal using a simple method that can be called "consecutive check". During the waiting phase, if R1 detects a significant change of the force on its arm, it will start checking the following sequence of values of the force. If the force matches the anticipated values for two period cycles, R1 will consider that it has just received a vibration message from another robot. The pseudo code for the detecting algorithm is presented in Algorithm 1 below.

Algorithm 1 Vibration signal detecting algorithm

```
while (wait_time > 0)
  digitize sensor signal u(i) to 1 of 3 levels: 1, 0 , -1
  if ( u(i-1) = 1 & u(i) = 1) then
    if ( u(i + period) = 1) then
      if ( u(i + 2*period) =-1) then
        if ( u(i + 3*period) =1) then
          vibration=1;
        else
          vibration=0;
        end if
      else
        vibration=0;
      end if
    else
      vibration=0;
    end if
  end if
end while
```

5.3 Vibration message transfer procedure

The additional action of transferring a vibration message is theoretically quite simple. However, to effectively implement this communication session, or in other words, to make sure that R1 can receive the vibration message from R2 with a high reliability, the robots should carry out the following procedure

Algorithm 2 Vibration message transfer procedure

1. R2 makes a vibration
2. wait for a certain period of time
3. **if** R2 receives a vibration signal from R1 **then**
    R2 drops the leaf edge and goes away.
  else
    repeat from step 1 to maximum of 3 times
  end if
4. **if** receives no respond after 3 times **then**
    adjust position of the grasped point
    repeat from step 1.
  end if

From the above algorithm, it can be seen that one vibration signal can be used to create two different messages for two robots. It can be explained in everyday language that, R2 comes to tell R1: "Hey, you are doing well, keep waiting" and R1 says to R2: "Thanks, I have received your message".

6 Conclusions

This paper has introduced an algorithm called "local maximum conservation" to enable swarms of simple robots to achieve a high completion rate in implementing the generalized leaf-curling task. The key point of the new algorithm is the incorporation of bi-directional vibration communication between a robot scanning the environment and a robot working with an object. By transferring information in this way, the whole swarm is able to extend their exploration in an effective way that always conserves knowledge of the object with the maximum level of affordance. Consequently, the robots are able to complete the generalized task in different unknown complex working environments. The success of the new method was verified using a visualized simulator. In addition, the paper also presented practical experiments demonstrating a method to realize the action of transferring messages via vibration between real robots - W-AntBots.

The next step of our on-going project will focus on implementing a series of physical experiments with W-AntoBots using the local maximum conservation algorithm. To realize that, the test leaf will be made bigger, and it will have a larger number of edges stiffness levels. Performance of the robot swarm will also be investigated in different environment scenarios and with the variation of different parameters such as wait-time, total time limit, number of robots and other. The success of these proposed experiments will provide confirmation for the algorithm and simulations presented in this paper.

To extend the use of this new algorithm to other similar swarm robotics tasks, the effect of transferring vibration signals will be investigated on objects which have different shapes and are made from different materials. The communication mechanism via vibration between robots will also be considered in cases of more than two robots are working with the same object.

The introduction of bi-directional communication via vibration in the context of the leaf curling task makes the concept of "sematectonic stigmergy" to be more effective and increase its range of applications. It is believed that the method presented in this paper will provide a promising basis for the solution of difficult collaborative tasks such as: exploring new planets, finding special objects in hazardous environments or in automation factories.

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