# Relative-Value-Based Randomness Algorithm for Swarm Robots Working in Heterogeneous Environments

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## Abstract

This paper presents an algorithm, which improves the probability of success for simple swarm robots implementing an extended version of the leaf curling task – one part of the nest building activity of weaver ants [Phan and Russell, 2009, 2010]. The robots are required to have only very basic sensing abilities, and are allowed to transfer information using sematectonic stigmergy – a cue-based indirect communication method. The task of such simple swarm robots is to find and collaborate to manipulate successfully one of the most suitable (easiest) objects in environments where objects have multiple levels of difficulty of some physical property. In earlier work, the original leaf folding task with 2 levels of difficulty of objects was successfully solved using the "exploring rule" [Phan and Russell, 2009]. However, in environments with greater heterogeneity of objects, the exploring rule demonstrated its disadvantages, by achieving very low task completion rates. To address this defect without adding complexity to the hardware of the robots, in this paper we describe in detail an algorithm called relative-value-based randomness (noise). Essentially, this algorithm increases the completion rate of simple swarm robot tasks by encouraging the robots to make a more effective exploration of their complex working environment and to concentrate at a suitable location. The algorithm was developed using physical robots and verified by a series of tests using a simulation model.

## 1 Introduction

Over the last two decades, swarm robotics has been attracting the attention of robotics researchers by its most important advantage – collaboration. Collaboration is the key factor enabling relatively simple robots to implement communal tasks, which are impossible or very difficult for one robot or many independent robots, even if they are endowed with sophisticated sensing abilities.

So far, a number of collaborative robot tasks have been reported in the literature. There is a common feature found in many of these tasks and this is that the objects that the robots work with are identical, such as in foraging [Jones and Mataric, 2003], [Liu and Winfield 2010], stick pulling [Ijspeert et al, 2001], [Lerman, 2004], box pushing [Mataric et al 1995], collaborative building tasks[Stewart and Russell, 2006] [Werfel, 2004]. In some other experiments, particularly the sorting tasks, although there are a few different types of objects differentiated by colour [Holland and Melhuish, 1999] or size [Doneuberg, 1991], [Wilson and Melhuish, 2004], each robot is able to individually recognize them and make use of that information. Because of that, the robots are not required to collaborate to locate one or a number of special objects from a set of unknown heterogeneous objects.

To address this aspect of swarm robotics, we plan to research and develop collaboration techniques to allow simple robots to accomplish value judging tasks in such heterogeneous environments. Since simplicity is one of the main requirements for swarm robots, to make them collaborate to implement this form of relatively complex task is definitely not an easy challenge.

The first step in addressing this problem was suggested by a biological inspiration – the leaf curling task of the weaver ant [Phan and Russell, 2009, 2010]. In this task, the weaver ants have to bend and roll up some natural leaves and stick them together to make a rugby-ball-shaped nest. It is obvious that the elasticity of natural leaves is too strong for one or even two ants to overcome. So the ants need cooperation to complete this task. However, on a regular leaf, not all edges have the same elasticity or stiffness. Due to the vein distribution, the tip of the leaf is usually more pliable than the sides. Therefore, an important aspect of the nest building activity of weaver ants is their collaboration strategy to always find and gather together at the tip of the leaf – the best object in their working environment to work with.

Although there is no clear explanation about the sensing and communication mechanisms the weaver ants use in completing this task, our proposed communication method, called sematectonic stigmergy has demonstrated its usefulness for very simple robots in replicating aspects of the leaf curling task [Phan and Russell, 2009]. An algorithm has been developed which boosts the completion probability of the robots to a near-perfect rate and so edge selection in the leaf curling task could be considered successfully solved for extremely simple swarm robots.

Initial experiments with a 2-difficulty-level working environment formed a good base for extending this leaf curling task to a more general task for swarm robots [Phan and Russell, 2010]. In this generalized task, the working environment of swarm robots will not include two levels of difficulty (the “hard edge” and “soft edge” in the leaf curling task), but it will be extended to contain an unknown but finite number of difficulty levels of objects. The goal of the robots is to collaborate to find and gather at an object with the best or at least near-best feature (flexibility) and successfully manipulate it. In general, the feature could be some other physical property of the objects (not just their flexibility). This could be stiffness, weight, length or heat for example.

This generalized task can be considered as a special case of a problem called “the best-of-N problem”. To our knowledge, there are only two research works mentioning this problem for swarm robots. Those are the bee-inspired nest-site selection task [Parker and Zhang 2009] and prey pursuing activity [Wessnitzer and Melhuish, 2003]. In both of these experiments, the robots collaborate to find the best object using a so-called quorum-based algorithm. In order to implement this algorithm, the robots must have quite sophisticated abilities such as: team mate recognition, team mate counting, pathway remembering and direct wireless communication or pheromone trail communication. However, these additional abilities considerably increase the complexity for robots both in terms of hardware and software. This is against the desire for simplicity for the swarm robots used in this project.

The first “exploring rule” developed in this project was unable to help our robot swarm succeed in environments containing objects with more than 2 levels of difficulty. Therefore, to develop a solution that would allow swarm robots, endowed with very minimal sensing abilities and communicating via sematectonic stigmergy to reliably complete the generalized task is the challenge addressed in this paper.

This paper presents a new algorithm that can improve the completion rate of swarm robots in implementing the generalized task, described above. It is assumed that if the robots are able to make a more complete exploration of their working environment, the possibility that they can find the best object (most pliable part of the leaf in this case) would be increased. However, the robots must also be able to gather together at some object they consider the best. In order to realize this idea, the basic “exploring rule” was extended by adding an algorithm called “relative-value-based randomness”, which is described and discussed in detail later in this paper.

This paper is organized as follows. Section 2 briefly reviews the main parts of the previous work and particularly concentrates on the “exploring rule” method. In Section 3, the relative-value-based randomness method is described including the main idea, algorithmic schema, and governing equations of the new method. Next, the first part of Section 4 provides an overview of the simulation model. Then, the second part of this section presents the simulation results that confirm the benefits of the relative-value-based algorithm on the performance of the swarm robots manipulating objects with a range of different levels of difficulty. In this subsection, some points where the algorithm needs improvement are also discussed. Section 5 briefly describes the experimental robots and scenario, which will be used to verify the proposed algorithm in the next step of the project. Finally, the conclusion and proposals for future work are outlined in Section 6.

## 2 Previous work

### 2.1 Working algorithm of the robots

In previous work [Phan and Russell, 2010], to replicate the leaf curling task of weaver ants, a series of physical experiments was implemented with a group of W-AntBots on an artificial leaf (Fig. 1). Based on the proposed hypothesis about the methods that weaver ants might use in the leaf curling task [Phan and Russell, 2009, 2010], the working algorithm of each robot in this experiment, also throughout our project is illustrated in Fig. 2 below:

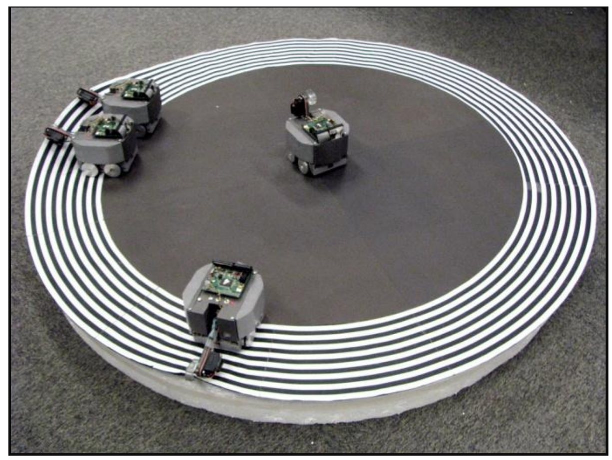

Fig. 1: The leaf curling experiment

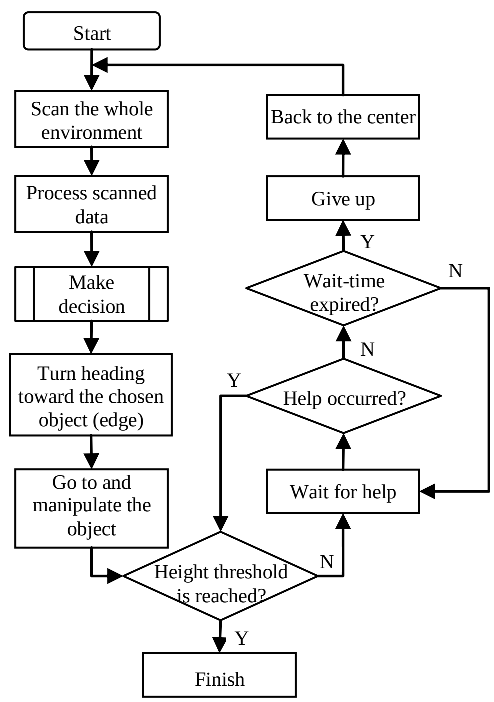


Fig. 2: Working algorithm of each robot

In this algorithm, the two most important parts are: the wait-time limitation and the decision making algorithm. The wait-time parameter allows a robot to provide a source of useful information for other robots (this is particularly important in the sematectonic stigmergy method). Moreover, the wait-time limit is also useful because it gives the robots a chance to make a new trial if their current effort is not effective. Adjustment of this time parameter is able to refine the performance of the swarm to some limited extent. With the second factor, different decision making algorithms can result in different emergent behaviours for the whole swarm. So if the wait-time parameter is designated the quantitative regulator, then the decision making algorithm can be called the qualitative controller for the performance of the robot swarm. Therefore, a smart decision making algorithm is always the most important factor contributing to the success of a robot swarm.

### 2.2 The exploring rule

In the early work of this on-going project, when sematectonic stigmergy was first applied to replicate the weaver ant task, a very simple decision making algorithm was introduced [Phan and Russell, 2009]. It was called the "local rule", which successfully directed the group of robots to the tip of the test leaf if at least one robot discovered the pliable tip. However, that rule demonstrated a significant disadvantage by misleading the group to gather at an undesirable object in situations when the first robot unfortunately chose a "bad" object ("hard" edge of the leaf). The task completion rate rapidly decreases when the ratio between "bad" and "good" objects is raised. The term "objects" in this leaf curling task are understood to represent edge sectors along the whole leaf edge. From this point, the word edge will be used for "edge sector" and considered as a discrete object.

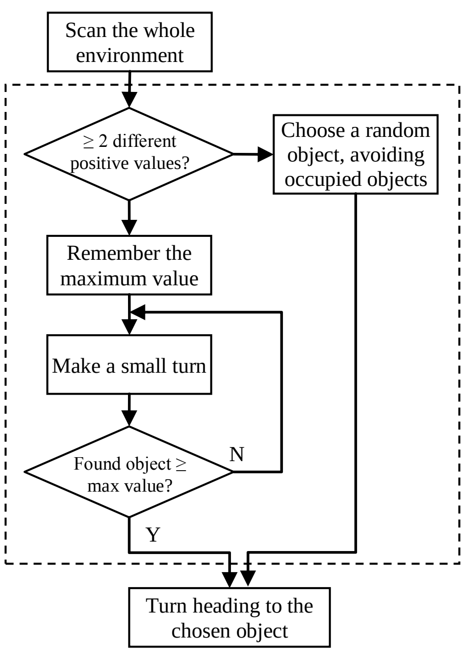


Fig. 3: The exploring rule based decision making algorithm

Later on, to solve this problem, another decision making algorithm was investigated, which is called the "exploring rule" [Phan and Russell, 2010]. This algorithm was built on the main idea that, an object can be recognized as the better one only if there is at least another detectable object having a lower value. Particularly for the leaf curling task, this rule means that, a new robot will go to apply its effort at a lifted edge only if it is the highest among edges with at least two different (non-zero) heights. Otherwise, the new robot will try a random sector of the whole leaf edge that is not currently being lifted (having zero value). This "exploring rule" is illustrated in Fig. 3. More details of this decision making algorithm can be found in [Phan and Russell, 2010].

With the help of a simulation model and physical experiments, the exploring rule has been successfully verified. It demonstrated the ability to improve the completion rate of a robot group implementing the leaf curling task to a near-perfect value of 100% (Fig. 4). In this graph, the completion rate of the robots employing the "exploring rule" is compared with that of the "local rule" and "absolutely random" cases. Another advantage of that algorithm is that it reduces the minimum required number of robots, which are enough to achieve the maximum completion rate [Phan and Russell, 2010].

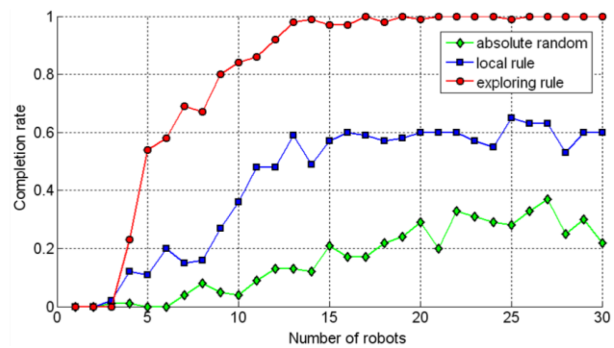


Fig. 4: Effects of the exploring rule for swarm robots implementing the leaf-curling task with the finish criterion that at least 3 robots simultaneously work at the "soft" edge. Parameters used: 14 "hard" edges" and 1 "soft" edge.

## 3 Relative-value-based noise algorithm

### 3.1 Main idea

The exploring-rule-based decision making algorithm successfully enables the robots to accomplish the leaf curling task with good completion rates in relatively simple situations. However, it is unable to help the robot group to reach the same level of achievement in more complex environments. A typical example is a scenario, where the robots have to work with an artificial leaf, which has different edges with 3 separate levels of softness, here given the values 1(stiffest), 2(medium) and 3(softest). In such an environment, if the first two robots I, II chose to lift 2 edges A, B with softness of 1 and 2 relatively, then based on the exploring rule, robot number III should come to work together with robot II at edge B. And edge B would also be the destination for the following robots. This situation will obviously result a failure of the robots to find the softest edge. Although there are cases where one of the first 2 robots will choose one softest edge, the overall completion rate of the robot swarm will definitely reduce. It is sensible to predict that the higher the number of difficulty levels of objects, the lower the completion rate will be.

This problem would not happen if the following robots do not immediately concentrate on the local maximum-value object chosen from the set of its scanned data. To avoid being trapped in this local maximum, the robots should make a further exploration to increase the chance of finding a better object.

Since the swarm robots do not have localizing and pathway remembering abilities, one of the most suitable methods to increase the exploration activity is to add random variations to their decisions. However, for the generalized task, if the exploration activities of the robots are modified by simply adding random variations to the location of their chosen targets, then it seems likely that the robots will ignore the best objects. More importantly there will be chance that they will join to work together with any object. This raises the question of how random variation should be added to the algorithm. A "reasonable" variation should be able to change to accommodate different contexts. The most important changes in the working environment would be changes to the states (values) of the objects, made by robots working with them. These states (values) are inversely proportional to the difficulty (lack of pliability) of the corresponding objects. However, because the number of difficulty levels of objects in the working environment of robots is supposed to be unknown beforehand, the states of objects, scanned by each robot are actually relative values. From this point of view 3 comments can be made:

- State (value) of 1 object cannot be determined to be high or low by one robot if all other objects it can "see" at that moment have the same state.
- State (value) of 1 object is considered high if there is one object that has a lower value.
- In a fixed working environment, the higher the ratio of state between two objects, the higher the possibility that the better-state object can be the best object.

Based on these thoughts, an algorithm called "relative-value-based randomness" is proposed with the purpose of increasing the ability of robots to find and gather at the best object (the easiest object) in a heterogeneous environment. This algorithm will be applicable for other tasks as well as for the extended leaf-curling task, where the "objects" (edges) are continuously distributed. For more general situations, it can also be applied for environments containing discrete objects, distributed along the border of a circular working zone. Details of this algorithm are presented in the next subsection.

### 3.2 The algorithm

The algorithmic schema of the "relative-value-based randomness" is illustrated in the Fig. 5. This algorithm contains 2 steps: In the first step, a robot will work with the original exploring rule algorithm. The most important difference lies in step 2 when there are equal or more than 2 positive values scanned. After turning its heading to the object which has the best value (state) from the set of scanned data, instead of going to work with that object, the robot adds a random variation to the heading of its selected goal. The random variation is denoted $\varphi_e$. The symbol $\varphi$ represents an angular heading and the subscript $e$ indicates "exploration". This random variation is taken from a uniform distribution, which can be readily realized on very simple robots. And more important, the amplitude of the random variation is decided by a coefficient, which is considered the most important part of this algorithm – the exploration coefficient $\boldsymbol{K_e}$:

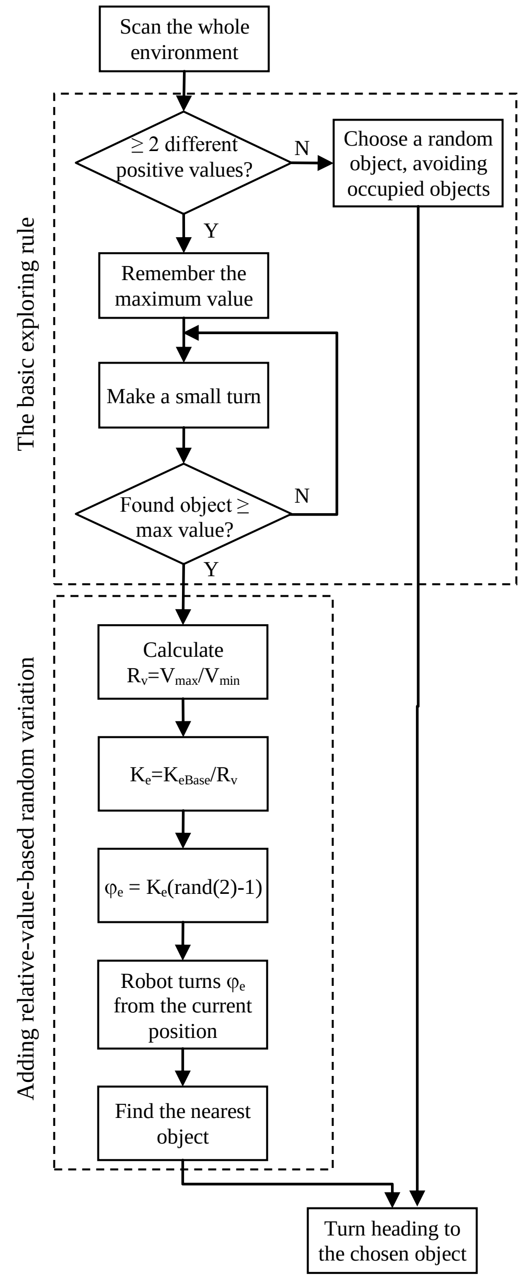


Fig. 5: Relative-value-based decision making algorithm

$$\varphi_e = \pm K_e \cdot Rand(1) \quad (1)$$

The coefficient $K_e$ indicates the maximum possible exploration range of robots in different situations. For larger $K_e$, the greater the range that the robots will explore. The smaller this coefficient, the more tightly grouped will be the positions that the robots will explore centered on the location of the maximum-value object. Before presenting the main equation of $K_e$, it is necessary to explain supporting parameters and variables of the algorithm.

$U_i$ - the state unit (value unit) of *i-th* object which means the state when that object is manipulated by one robot (for the leaf curling task, this is the height of the *i-th* sector of the leaf edge when it is lifted by one robot);

$U_i$ also can be called the flexibility (easiness) of the *i-th* object. Then the "best" object would be the one that has the highest state unit: $U_{max}$. The completion criterion of the task is to have at least $N_0$ robots working together at the object (section of leaf edge), which has $U_{max}$.

$N_i$ – number of robots working with *i-th* object at the moment that this object is scanned;

Then $V_i$ – the value (state) of the object *i* will be:

$$V_i = N_i \cdot U_i \tag{2}$$

If $V_{max} = max\{V_i\}$ – the set of data, received after 1 full scan by1 robot, and $V_{min} = min\{V_i\}$

Then the ratio denoted $R_v$ of 1 set of scanned data by 1 robot will be:

$$R_v = \frac{V_{max}}{V_{min}} \tag{3}$$

And based on these parameters, the change of the exploration coefficient $K_e$ is:

$$K_e = \frac{K_{eBase}}{(R_v)^{\alpha}} \tag{4}$$

The inverse proportionality between $K_e$ and $R_v$ means that: the lower the ratio between maximum and minimum values of the data that the robot scanned, the more the robot needs to explore the working environment to increase the possibility of finding the best object. The higher this ratio, the higher the probability should be that the robot concentrates its exploration close to the maximum-value object. This relation can be explained in by an example illustrated in Fig. 6.

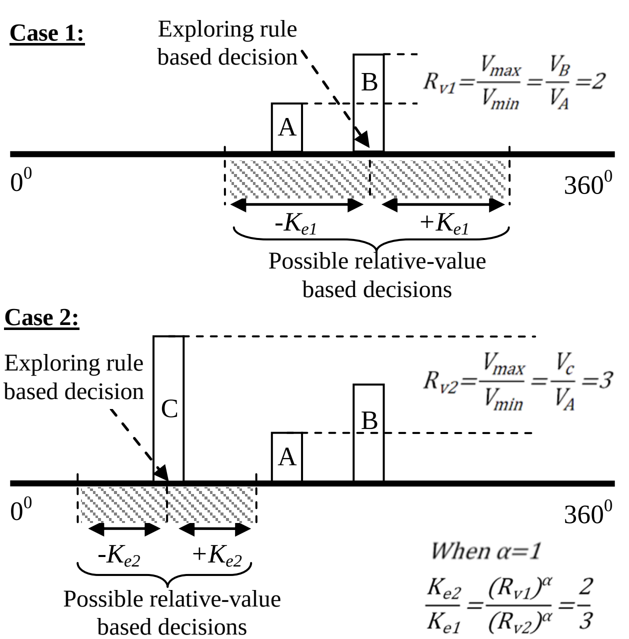


Fig. 6: An example of adding random variation to decisions made by robots. It is assumed that each object A, B, C is being manipulated by 1 robot. "State/Value" of the objects are represented by heights of the corresponding bars. The ranges of relative-value based variations added to the choice of the next robot are within the diagonal hatch zones. Amplitudes of 2 zones are inversely proportional to the ratio $R_v$ in the 2 cases.

In the main equation (4), the exponent $\alpha$ and the constant $K_{eBase}$ at this stage of the project are empirically determined. The exponent $\alpha$ decides the "concentration speed" of robots related to the maximum-value object. Robots will "quickly" concentrate on the local maximum-value object if $\alpha$ is increased; or they will explore the environment "further" if $\alpha$ is set smaller. The other parameter, $K_{eBase}$ is a constant that limits the maximum value of $K_e$. As robots are supposed to work with objects distributed around a circle, the maximum possible exploration range of 1 robot should be $\pm K_e = \pm 180^o$. This means $K_{emax}$=180 with $R_{vmin}$=1. Therefore, $K_{eBase}$ will take 1 value in the range from 0 to $180^o$. It is desired that the robots can concentrate on the best object ($K_e$ is very small) in the case of maximum $R_v$. Therefore the optimal value of $K_{eBase}$ should be proportionally depend on the ratio between state units of the "best" and the "hardest" objects.

To realize this algorithm for swarm robots working in real environments, equation (1) is modified as follows:

$$\varphi_e = \pm K_e \cdot [Rand(2)\text{-}1] \tag{5}$$

This modified equation guarantees the distribution of the random variation to lie in the range from -1 to 1. On the robots random numbers will be generated by sampling an internal timer of the robot's based microcontroller based on external events. This form of timer is available in even the simplest microcontroller. Another concern is that, $\varphi_e$ directs the robot to turn through a certain angle. But in the case of discrete objects, that turn may direct the robot to a place without an object. In this situation the robot needs to add an extra task that is to find and work with the object, nearest to this calculated destination.

Employing this algorithm, it is believed that robots will be able to avoid being attracted by local maximum values. Another advantage is the development of emergent behaviour where the robots can gather together at the best object or at least a near-best object. Therefore, it is proposed that the completion rate of robots working with the generalized task will be improved. This prediction will be examined based on the results of a simulation model.

# 4 Simulation

## 4.1 Simulation model

Since the algorithm described above is most suitable for large sized robot swarms, building a simulation model would be a reasonable and economical way to investigate its effects. Simulation also can save time wear-and-tear on hardware resulting from experiments with large numbers of robots.

The simulation model presented in this paper was built using a discrete time approach, and its elements are states of the robots and states of the objects at every time step. In this model, at each time step, each robot can work in 1 of the 4 following states: (S)earch, (F)orward, (W)ait, (B)ackward. Each state of the robots lasts a certain number of time steps. These numbers can be adjusted so that they are directly proportional to the corresponding time parameters of the physical robots. Besides that, each robot can make 2 decisions: Choose or Give up. A robot transits from one state to another state either by time factor or by its own decision. The state transition process of each robot is illustrated by the finite state machine shown in Fig. 7.

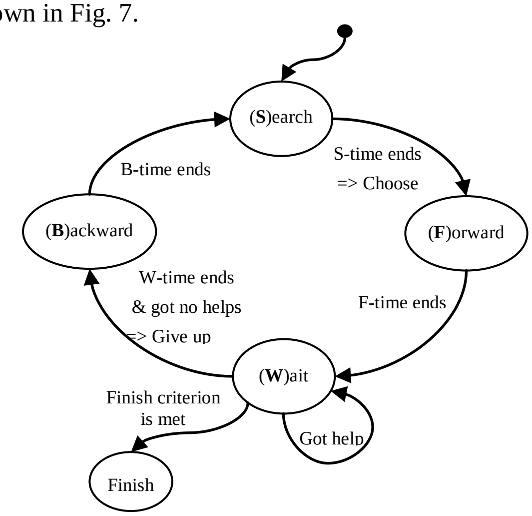


Fig. 7: FSM model of each robot

The state of each object is determined in a simpler way. At each moment, this state of each object is the product of the state unit of that object and the number of robots currently working with it.

However, the state transition process of the whole robot-object system from moment k to moment k+1 is a complicated interaction. This interaction is depicted by the schema shown in Fig. 8.

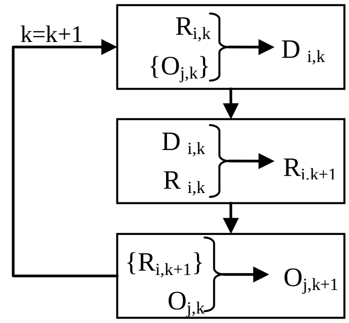


Fig. 8: Interactive state transition process of the whole robot-object system from moment k to k+1.

$R_{i,k}$: State of robot i at moment k

$D_{i,k}$: Decision of robot i at moment k

$O_{j,k}$: State of object j at moment k

{} means a set of all objects or robots

With such a structure, this simulation model can track the states of robots and objects as they evolve in time. An example of the robots' behaviours during a successful simulation trial is shown in Fig. 9. The simulation also allows investigators to test any decision making algorithm and flexibly customize every parameters of the simulation run from wait-time, time-limit, number of robots, number of objects, the lengths of all robots' state: F-time, S-time, W-time, and B-time.

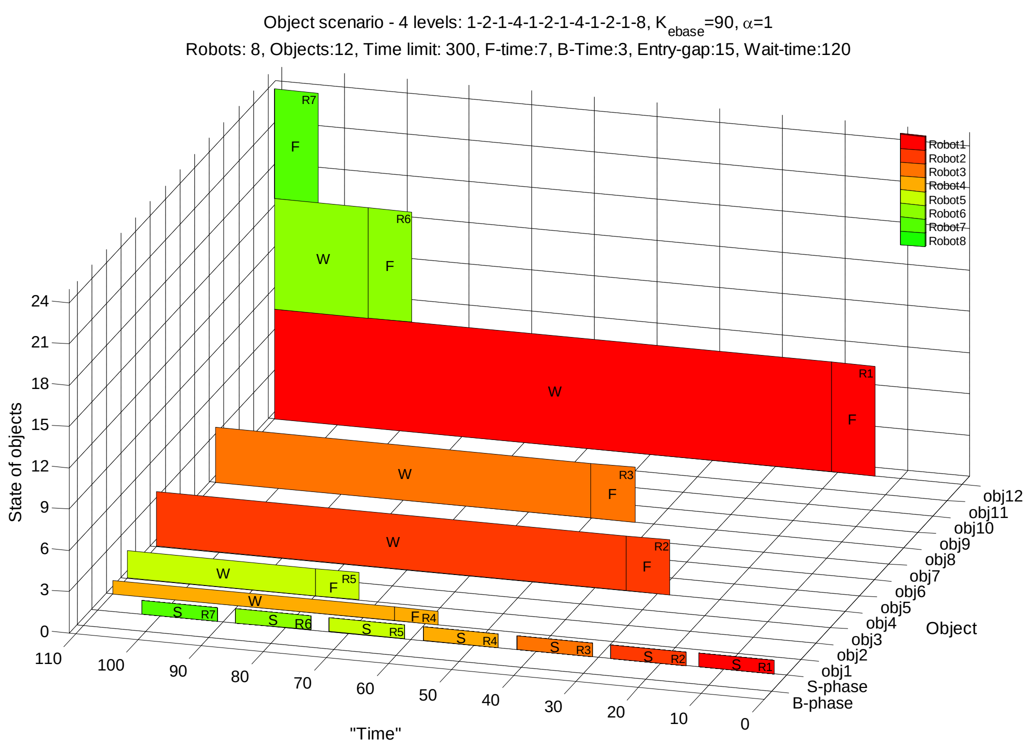


Fig. 9: Behaviours of the robots during one simulation run.

Each vertical rectangle represents the working state of one robot: S: Scan, F: Forward action or W: Wait for help. The robots are distinguished by different colors. The height of each rectangle represents how much one robot manipulates the corresponding object. In the S-phase (Scan) and B-phase (Backward), robots are occupied towards the center of the leaf, which means that they currently are not working with any object. Robots in B-phase are not shown as they make the graphs unnecessarily complicated. In this simulation, object 12 is the "best" one, which has an "easiness" level (state unit) of 8. After 110 time steps, 3 robots number 1, 6 and 7 successfully found and manipulated that "best" object.

## 4.2 Simulation results and discussion

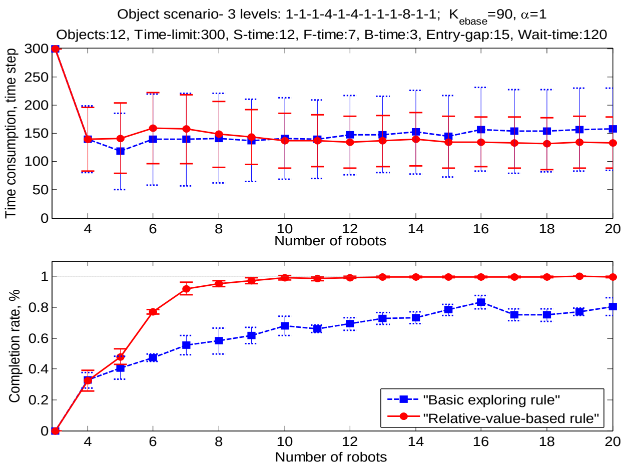


Fig. 10: Performance of the robot swarm's using 2 algorithms. Scenario 1: The objects have 3 different levels of difficulties.

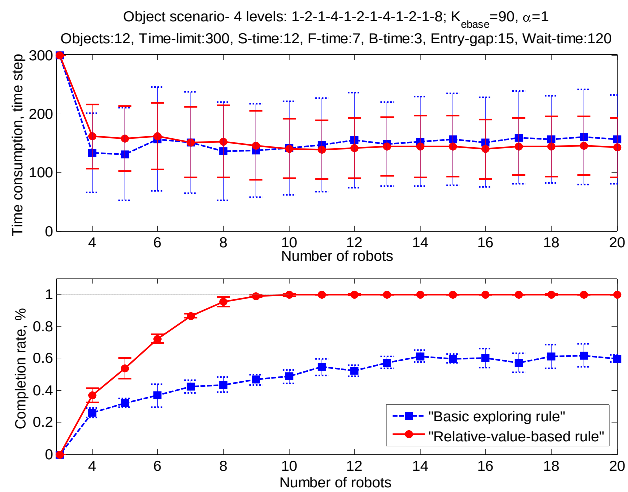


Fig. 11: Performance of the robot swarm's using 2 algorithms. Scenario 2: The objects have 4 different levels of difficulties.

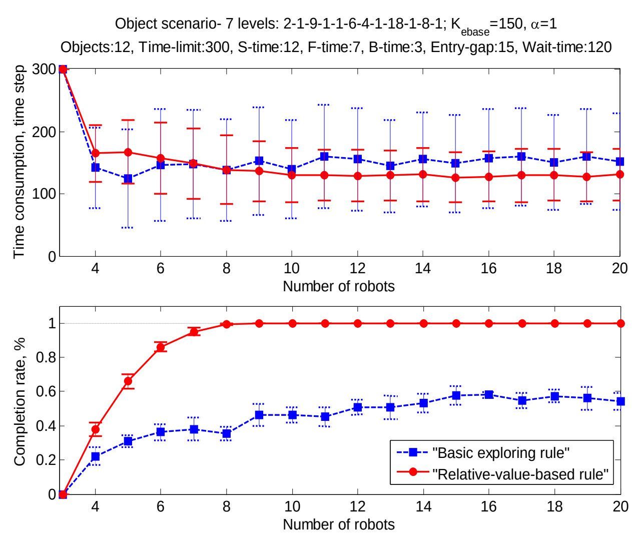


Fig. 12: Performance of the robot swarm's using 2 algorithms. Scenario 3: The objects have 7 different levels of difficulties.

The completion rates and time consumption of the robot swarm in implementing the generalized tasks with different scenarios of heterogeneous objects are shown in the Fig. 10, 11 and 12. The value of each point on the graphs is the averaged value out of 500 trials with the same set of parameters.

In each figure, the completion rate of the swarm is shown on the lower graph, whereas the top graph presents the time consumption of the swarm for the corresponding case. The distribution of objects with different difficulty levels in each simulation scenario is noted in the title of each figure. For each object the lower the value of it state unit then the more difficult it is for the robots to manipulate it. The "best" object is the object with the maximum numerical value of state unit ("easiness"). All other simulation parameters are also shown on the title of each figure. The simulation compares the performance of the relative-value-based algorithm over the basic exploring rule in different working environments. To investigate if the new rule can be applied for a wide range of unknown environments, the differences of the robots' working scenarios are considered not only in terms of the number of objects' difficulty levels: from 3, 4 to 7 levels, but also in terms of the maximum ratio between the "easiest" and the "hardest" objects: 8:1 in the first 2 cases, and 18:1 in the 3rd case. And the orders that objects are distributed around the circular border of the working environments were randomly chosen.

The most obvious results can be seen in Scenarios 1, 2, and 3 (Fig. 10, 11, and 12) where there are significant improvement of completion rates achieved by robots employing the new algorithm over the basic exploring rule. It can be seen that, with the increase in the of number of objects' difficulty levels from 3 to 7, the maximum completion rate of the swarm using the exploring rule decreases from above 80% to below 60%. On the contrary, the robots employing the relative-value-based algorithm still achieve almost the highest rate of success in all cases. It also can be seen from these results that the minimum number of robots which can achieve the maximum completion rate is reduced. While the exploring rule often requires from 15 to 18 robots to reach the maximum rate, the new algorithm only needs 12 robots in the first case and just 10 robots in the next 2 cases to guarantee completion of the task. Moreover, as the standard of the relative-value-based graphs is generally smaller than that of the exploring rule, it can be said that the new rule produces a more stable performance for the robot swarm. While not only improving the completion rate, the new rule also slightly reduces the time which the robot swarm needs to complete the tasks, especially when the swarm has enough robots to reach the highest completion rate.

The common feature of the above 3 working scenarios is that they contain only one "best" object. This case is conjectured to be met more often in the natural leaf-curling situation. However, it would also be useful to test the new rule in a different situation when the number of the "best" objects is larger than objects of other levels. The results of robots working in one of such environments are shown in Fig.13. It can be seen that the relative-value algorithm is also able to improve the completion rate of the swarm in this case. However, a number of disadvantages can be found here: it requires the robots to spend longer time on average to finish the task, especially

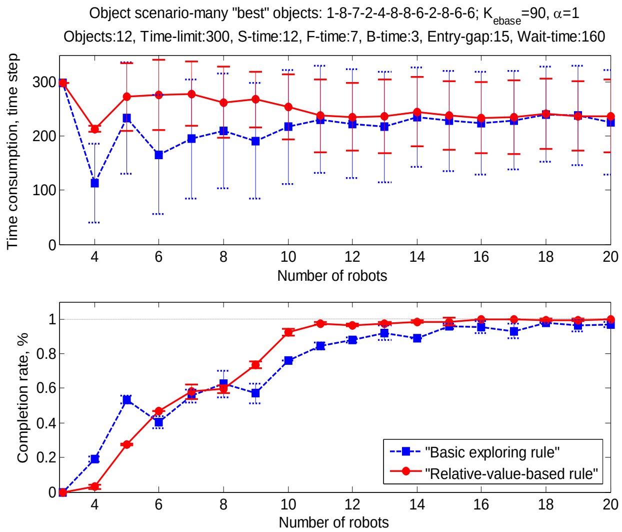


Fig. 13: Performance of the robot swarm's using 2 algorithms.

Scenario 4: The objects have 6 different levels of difficulties and number of "best" objects is many compared to objects of other levels.

with small sized groups of robots; and it needs quite a large number of robots to guarantee a stable high completion rate (from 16 robots). These disadvantages can be explained by the essence of the new algorithm that: if all currently working robots are located at the best objects, this means the ratio $R_v$ = 1, then the next robot to search for an object to work on will explore widely instead of joining at one of the desirable objects. This means the robots will waste time when they could easily complete the task. Unfortunately, such situations will often happen as there are many "best" objects. Therefore, it is obvious that the swarm would require more time, and more robots to finish the task.

All graphs shown above are simulation results with some particular values of $\alpha$ and $K_{eBase}$. It would also be useful to investigate the influence of these 2 parameters on the performance of the relative-value-based algorithm. As mentioned earlier in Section 3, if $\alpha$ decreases, the robots will do more exploration and vice versa. Increased value of $\alpha$ will make the robots gather more "quickly" on the locally best object. As the robots are required to implement both of these 2 activities to be able finish their task, there should be a value of $\alpha$, lying in the middle which balances these two requirements. Indeed, in Fig. 14, it can be seen that with small values (<1), $\alpha$ reduces strongly the completion rate of the robot swarm as the robots pay more attention to exploring the environment and seem to neglect the task of gathering at one of the best objects.

On the other hand, if $\alpha$ is large, the performance of the robots is also negatively affected. In the first 3 scenarios, $\alpha$=1 is the optimal value and 1.5 for scenario 4. This difference correctly reflects the fact that in scenario 4, the robots need to perform more exploration to find the best objects, which was explained in the previous paragraph. Fig. 15 shows the dependence of the swarm performance on $K_{ebase}$. The most obvious result is the difference between the graph of scenario 3 and all the graphs of the other scenarios. This difference is caused by the fact that, in scenario 3, the maximum ratio between difficulties of object is 18:1 which is much larger then 8:1 in all other tested environments.

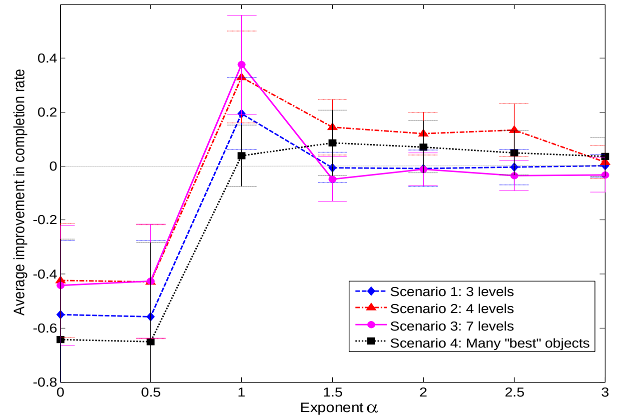


Fig. 14: Impact of the exponent $\alpha$ to the effect of the new algorithm. The graphs show the completion rate difference between 2 algorithms in different scenarios.

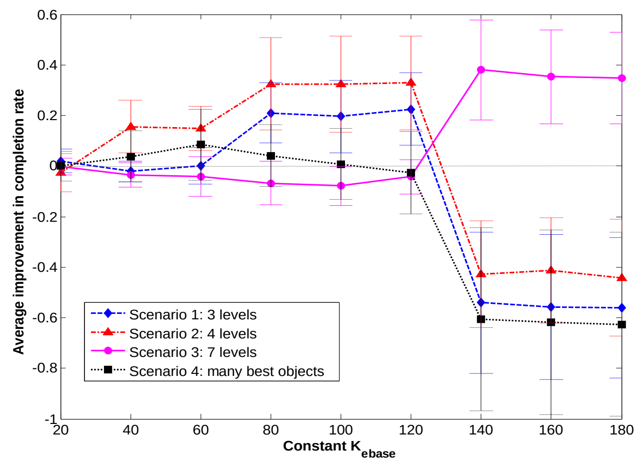


Fig. 15: Impact of the constant $K_{ebass}$ to the effect of the new algorithm

This is a predictable result (see section 3.2). Indeed, if in scenario 3, the robots employed the same value of $K_{ebase}$, used in the other scenarios; they will have a high probability of gathering at a "middle" object which has a ratio of 8:1, instead of gathering at the real best one (which has the state unit of 18). Therefore, the optimal value of $K_{ebase}$ in the scenario 3 should be larger, relatively to other cases so that the robots can gather at the "right" object.

In the first 2 scenarios, the optimal range of $K_{ebase}$ is similar and clearly distinguished. The optimal value of this coefficient in scenario 4 (with many "best" objects) is slightly shifted to the left side. This happens because in such a situation, it is not necessary to have the ratio $R_v = \max\{R_v\}$ =8:1 to make sure that one robot is working with one "best" object. Even with $R_v < \max\{R_v\}$, for example 8:2, 8:6, even 8:7, in this scenario, there is still a good chance of finding a best object. Hence, the robot swarm can still reliably complete the task with smaller values of $K_{ebase}$, which guides them to concentrate more "quickly" on the locally best objects.

## 5 Future experiments

The positive effects of the new algorithm will also be verified by testing a group of W-AntBots on the same experimental leaf as shown in Fig. 1. However, this time that rubber leaf will be reinforced on the bottom side so that it has up to 12 different sectors with a number of different stiffness's. The task of the W-AntBots is to collaboratively find the "softest" sector and successfully lift this edge to a certain height.

The W-AntBots are designed to be very simple mobile robots to comply with the requirement of the task described in this paper. Each W-AntBot can move forward, backward, turn about its centre using its 4 wheels with only 2 driven wheels. With support of a 2 DoF gripper, it can grasp and curl up leaf edges. The sensing system contains only 3 types of simple infra-red based sensors to detect surrounding obstacles, to detect the leaf edges and to "see" the height of lifted edges from a short distance away. In particular, the robots are not equipped with any communication modules or any other sensors which can help them to directly communicate with other team mates.

A series of experiments will be run to investigate variation of different parameters including the number and stiffness of the leaf edge sectors, number of robots, different time-limit, different values of $K_{ebase}$ and different values of $\alpha$. The success of these proposed experiments will provide confirmation for the algorithm and simulations presented in this paper.

## 6 Conclusions and future work

This paper has investigated a new decision making algorithm called relative-value-based randomness for controlling swarm robots. The task of the robots is to cooperatively find and gather at one of the "best" objects to successfully manipulate it in the environment. In this initially unknown environment containing objects with different levels of difficulty they are to find and successfully manipulate this best object. The robots have very simple sensing and vision abilities, no direct communication method and are allowed to transfer information to each other only via the change of objects they work with. Applying the relative-value-based algorithm, the swarm robots are encouraged to explore widely in their working environment to increase the chance of finding the best object and are also guided to concentrate to an object at a suitable location when appropriate. This new algorithm has proved its success by the significant improvement to the completion rate of the robots, compare to the earlier algorithm – the exploring-rule-based algorithm, which succeeded with the special case of 2 levels of object difficulty. With the aid of a simulation model, the new algorithm has shown its ability to help very simple robot swarms to reliably complete the weaver ant task in different working environment scenarios.

The positive performance depends upon the value of the parameters used in the algorithm. At this stage, the 2 parameters $\alpha$ and $K_{ebase}$ are empirically chosen for the robots. However, analysis of the impact of the 2 parameter on the performance of the robot swarm done will form a good basis for further research on the adaptive behaviours of the robots, so that they can automatically adjust these parameters to suit their environment. This is one of the main goals in our future work.

The immediate next step of this on-going project is to verify this relative-value-based algorithm by physical experiment with W-AntBots and the experimental set up shown in the previous section.

Other algorithms also will be investigated for solving the generalized task described in this paper. Those algorithms could incorporate the time dimension into the exploration activity of robots, which is hoped to improve not only completion rate, but also time consumption for robotic swarms. A combination of the relative-value-based algorithm presented in this paper together with a new time-dependent algorithm will also be considered. It is believed that, a complete and adaptive solution for very simple robots to reliably implement a generalization of the weaver ant task will open a number of useful applications for simple robot swarms.

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