Foraging in Real and Simulated environments for a Robotic Swarm based on an Adaptive Response Threshold Model

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***Abstract*— Developing a realistic animal-like highly organized swarm system, which is capable to adapt to environmental changes as well as dynamic situations is undoubtedly complex. A good labour division model, which can regulate and achieve an efficient work distribution among swarm agents is a crucial element for this kind of systems. In this paper, we analyze and compare the use of an extended model of the classical Response Threshold Model named Adaptive Response Threshold Model (ARTM) in real-robot and simulation scenarios. Experiments were carried out with the purpose of studying the effects and the performance of this new model under foraging missions. Results presented in this paper verify, that the resultant optimized model can improve adaptation capabilities of previous systems, such as reducing collision duration among robots in foraging missions, therefore making a swarm of robots able to adapt more efficiently to dynamical situations and hence increase its survival rate.**

I. Introduction

Several studies [2], [3] have been paying special attention to simple mathematical models based on Fixed Response Thresholds Models (FRTM). These mathematical models, which are believed to be very close to the mechanisms that regulate the division of labour in insect societies [4], have been extensively used in foraging tasks (regarded as the canonical test domain for collective robotics), with very limited [3] or no communication available [2], making the system extremely scalable.

In previous studies [5] we proposed and outlined an adaptive version of the classical FRTM in which the response threshold (θ) is changed accordingly to the environmental conditions.

Extensive simulation an real-robot experiments have demonstrated that ARTM can perform better under simulation scenarios and remarkably better under real-robot conditions.

One of the main reasons behind the big performance difference between both methods is their behavior against collisions and other disturbances. This paper explains how ARTM is able to adapt more efficiently to dynamic foraging scenarios as well as reducing collision duration within realistic environments.

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II. Methods

A. Adaptive Response Threshold Model (ARTM)

The Adaptive Response Threshold Model (ARTM) described in [5] is an extension of the classical Fixed Response Threshold Model (FRTM), in which the response threshold (θ) is calculated dynamically instead of remaining fixed.

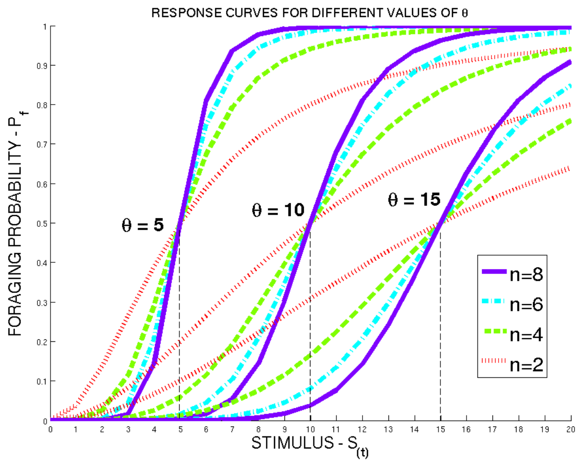


Fig. 1. Response curves for different θ values. Each θ represents the middle point of their associated response curve. Robots with lower θ will be more responsive to smaller stimulus $S_{(t)}$ values. On the contrary, robots with greater θ will become less responsive to small stimulus and will tend to remain idle for longer time.

Fig. 1 depicts different response curves for $\theta = 5, 10, 15$ as well as for several values of n. Fig. 1 shows ARTM's behavior and suggests that robots with a lower θ threshold will become more "sensitive" to smaller stimulus values and therefore have a higher tendency to go foraging. On the contrary robots with a higher θ will become less "sensitive" to small stimulus and will tend to remain idle for longer time.

B. ARTM Foraging Framework

Fig. 2 shows a general overview of ARTM's foraging framework. The major difference in comparison with previous fixed response threshold models such as FRTM, is the rectangular box (outlined with dashed boundaries) representing the Discrete Attractor Selection Model (DASM). DASM

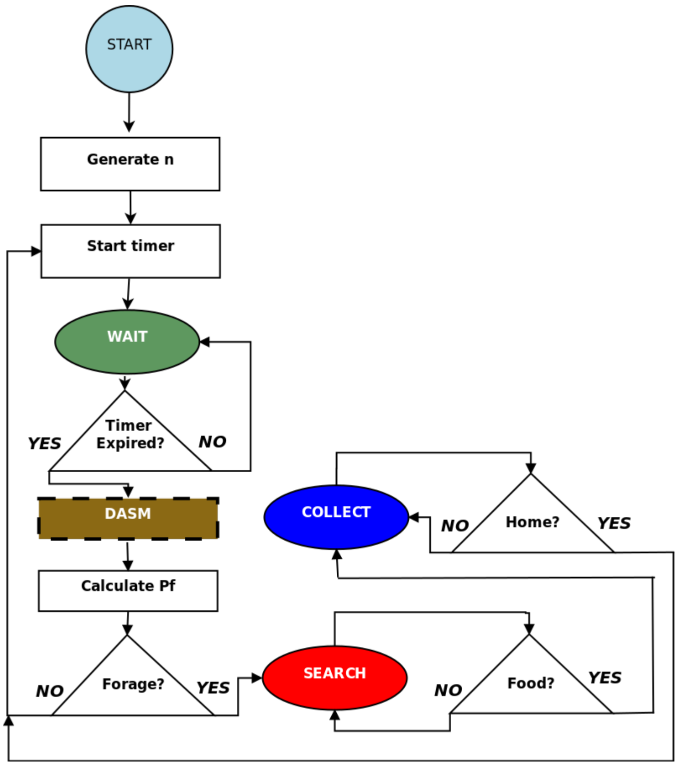


Fig. 2. Task allocation Diagram of ARTM. ARTM's main difference compared to previous methods such as FRTM is the addition of DASM.

is the algorithm in charge of dynamically calculate the θ threshold according to different environmental conditions.

ARTM's basic task allocation cycle is composed of the following 3 basic states :

- **Wait** : At the beginning of the foraging mission all robots are in *Wait* state. The robot initializes a timer, whose length is determined at the beginning of the simulation. When the timer expires, the robot senses the current stimulus ($S_{(t)}$) value and calculates the probability of going foraging (P_f). The transition from the *Wait* state to the *Search* state occurs based on P_f.
- **Search** : The Robot starts a random search for food tokens. If the robot finds a food token, it triggers the *Collect* state. If not, it keeps searching until it finds one.
- **Collect** : Once the robot obtains a food token, it returns home. Once it has placed the food token into the nest, it re-enters the *Wait* state.

1) Discrete Attractor Selection Model (DASM): In this research paper we decided to use a Discrete version of the well-known Attractor Selection Model [1] due to its simplicity in the analysis and the good results obtained through extensive experiments. DASM's general diagram is depicted in Fig. 3.

Fig 3 shows a classical Probabilistic Finite State Machine (PFSM) model based on a discrete probabilistic distribution.

$$\theta_{(t+1)} = \theta_{(t)} + w_{(t)} \tag{1}$$

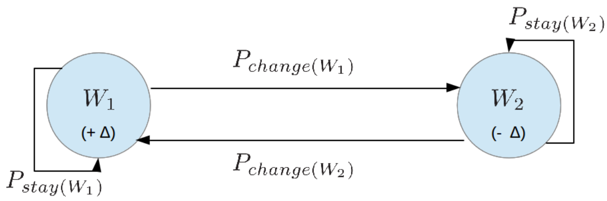


Fig. 3. Overview of DASM graph

TABLE I
SYSTEM'S INPUT MAPPING BASED ON THE STIMULUS GRADIENT ($S_{(t-1)} \geq S_{(t)}$) AND THE CURRENT STATE OF THE SYSTEM ($w_{(t)}$).

Σ	$W_{(t)}$	$S_{(t-1)} \geq S_{(t)}$
1	$+\Delta$	true
0	$-\Delta$	true
0	$+\Delta$	false
1	$-\Delta$	false

$$p(w_{t+1}) = \begin{cases} P_{stay(w_{t+1})} = \begin{cases} P_{stay(w_t)} + \alpha, & \text{if } \Sigma = 1 \\ P_{stay(w_t)} - \alpha & \text{if } \Sigma = 0 \end{cases} \\ P_{change(w_{t+1})} = 1 - P_{stay(w_{t+1})} \end{cases} \tag{2}$$

$$P_{change(w_{t+1})} + P_{stay(w_{t+1})} = 1 \tag{3}$$

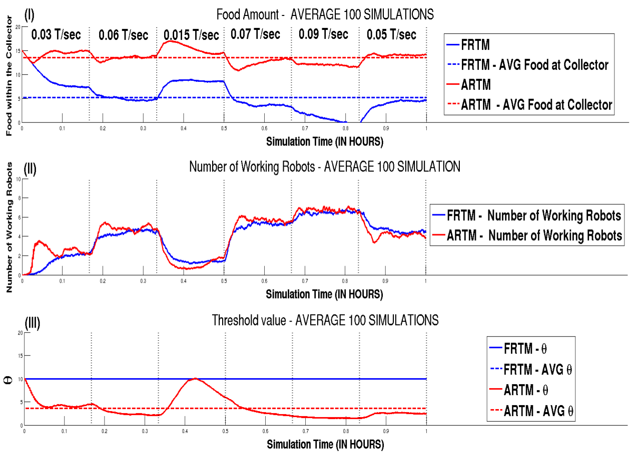
When robots are near the nest, they are able to sense the current level of stimulus $S_{(t)}$ and compare it to the previous measured value $S_{(t-1)}$. Depending if $S_{(t-1)} \geq S_{(t)}$ is true (there was an improvement at food reserves) or not (there was a decrement at the food reserves) and the current state of the system ($W_{(t)}$) (Table I), DASM's transition probability function p described in (2) and (3) will bias the system to remain at the same state or change to the next one. Therefore, increasing or decreasing the Θ threshold.

III. Results

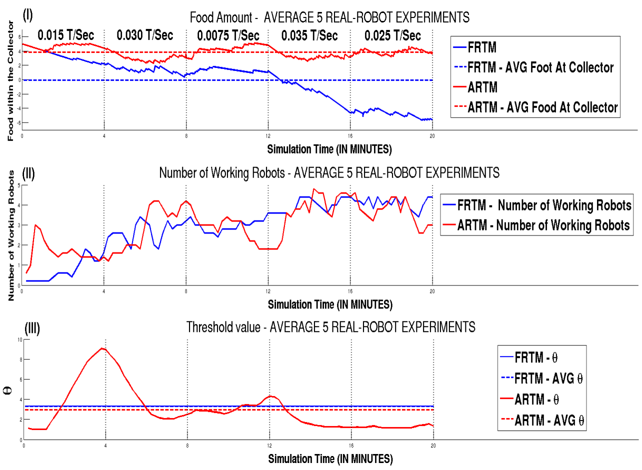
According to simulation (Fig. 4(a) (I)) and real-robot (Fig. 4(b) (I)) experiments, ARTM can maintain a food level really close to its initial value and considerably higher than FRTM's one when different consumption rates C_{rate} are applied against the swarm's nest reserves.

Fig. 4(a) and Fig. 4(b) (II) show the total number of working robots for FRTM and ARTM. Even though both methods show similar patterns, ARTM is able to activate more robots within the sections where C_{rate} is relatively high. Moreover, in sections where the C_{rate} is not as high, ARTM is able to activate less robots than FRTM in response to the lower demands of the system and therefore optimizes the swarm's resources. Fig. 4(a) and Fig. 4(b) (III) show the progression of θ during both set of experiments.

Fig. 5(a) and Fig. 5(b) (I) show the average number of working robots (N_v). The differences in N_v values between the two methods resulted in a very similar averaged N_v value (depicted with dashed lines) for the two sets of experiments, and therefore showed that almost the same amount of robots

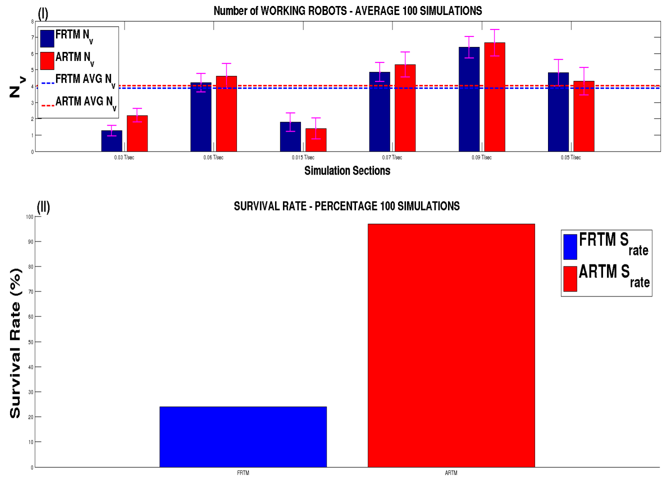


(a) Time Series Simulation Results

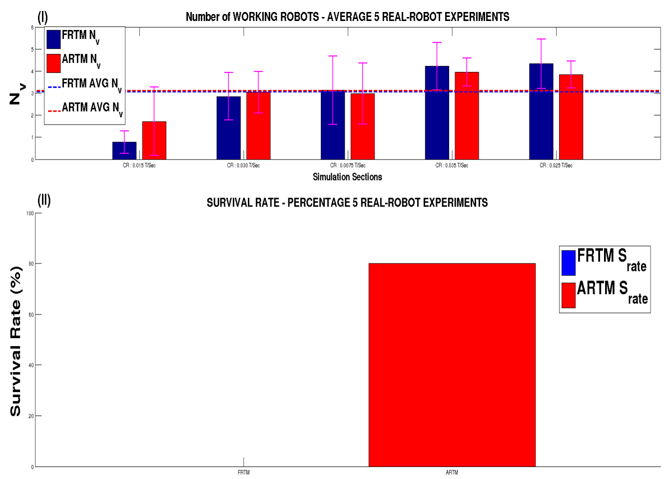


(b) Time Series Real-Robot Results

Fig. 4. Averaged results for 100 simulations (a) and 5 real-robot experiments (b). (I) Shows the effect of different consumption rates against food reserves. (II) Shows the number of working robots within each section of the experiments. (III) Shows the progression of the threshold θ during the simulation.



(a) Bar Series Simulation Results



(b) Bar Series Real-Robot Results

Fig. 5. Averaged simulation results and standard deviations for 100 simulation runs (a) and 5 real-robot experiments (b). (I) Shows the average number of working robots (N_v) during the sections of the experiment process. (II) Shows the survival rate (S_{rate}) of the whole system.

and the same amount of energy was employed by both division of labour methods.

Finally, Fig. 5(a) and Fig. 5(b) (II) shows swarm's survival rate (S_{rate}) for both methods. S_{rate} can be described as the number of times (in percentage) robots are able to maintain a positive amount of food at the nest during the whole foraging mission. It is easy to see that ARTM's survival rate was considerably higher than FRTM's one.

A. *Response to Collision*

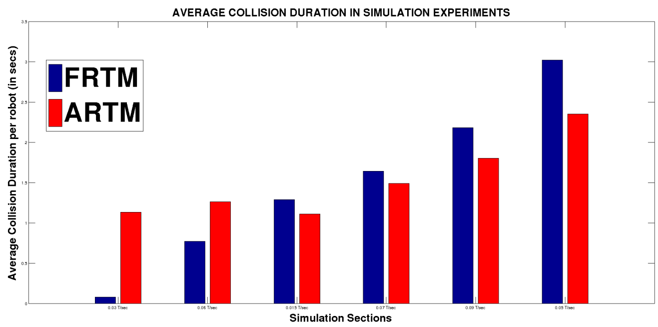
During real-robot experiments, failures and disturbances are highly likely to occur. One of the most common in foraging missions are collisions among robots. These collisions are especially problematic since they might end up hindering the whole foraging process or disturbing the work of productive robots. During our experiments, situations in which robots near the foraging nest unintentionally block the path to incoming robots trying to deliver food tokens, were specially frequent. Since Fig. 5(a) and Fig. 5(b) (I) shows a very similar N_v, we can state that collision time has a great impact in the performance of the system.

It is important to remark, that neither ARTM or FRTM have a clear premise of how to conduct proper collision avoidance. However, our gathered results suggest that ARTM has the ability of resolving this type of collisions in shorter time (Fig III-A) than FRTM.

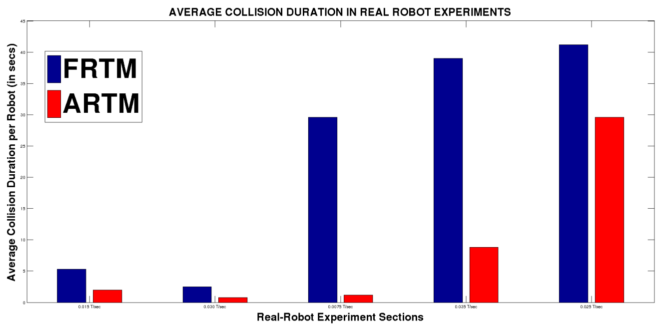
The proper adjustment of θ can bias robots in Waiting state to go foraging in cases of need (low food amounts at the nest) and therefore unblock the path in a faster way. This leads to a great difference in the total time each robot is stuck and unproductive during the foraging process (Fig. 7).

IV. Conclusions

An optimized division of labour algorithm for a simple foraging task has been proven to be efficacious in order to achieve efficient and adaptive workload distribution for



(a) Collision Duration in Simulation Experiments



(b) Collision Duration in Real-Robot Experiments

Fig. 6. Average Collision duration per section (in secs) during simulation (a) and real-robot experiments (b). ARTM has the ability to resolve collisions in shorter time in all experiment sections than FRTM.

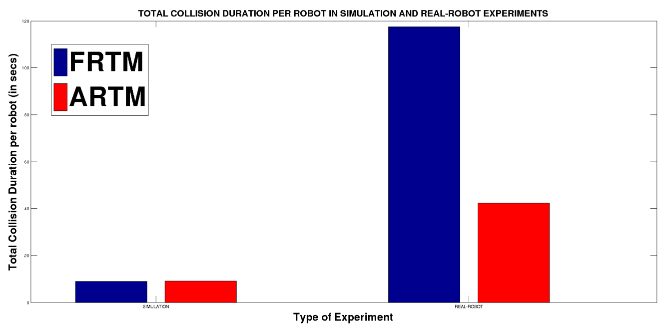


Fig. 7. Total accumulated collision duration for simulation and real-robot experiments.

a small size swarm of robots. ARTM can not only adjust the number of working robots efficiently according to the amount of food left at the home base, but also in a more adaptable way than previous methods, drastically increasing the system's survival rate (S_{rate}) within a foraging mission. We assume that one of reasons behind the big difference in the performance of ARTM compared to FRTM is robot collision behavior. We think the variety of θ can contribute to the adaptability of system especially in real-robot scenarios.

V. Acknowledgements

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