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IMMUNE INSPIRED COOPERATIVE MECHANISM WITH REFINED LOW-LEVEL BEHAVIORS FOR MULTI-ROBOT SHEPHERDING

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In this paper, immune systems and its relationships with multi-robot shepherding problems are discussed. The proposed algorithm is based on immune network theories that have many similarities with the multi-robot systems domain. The underlying immune inspired cooperative mechanism of the algorithm is simulated and evaluated. The paper also describes a refinement of the memory-based immune network that enhances a robot's action-selection process. A refined model, which is based on the Immune Network T-cell-regulated—with Memory (INT-M) model, is applied to the dog-sheep scenario. The refinements involves the low-level behaviors of the robot dogs, namely shepherds' formation and shepherds' approach. These behaviors would make the shepherds to form a line behind the group of sheep and also obey a safety zone of each flock, thus achieving better control of the flock and minimize flock separation occurrences. Simulation experiments are conducted on the Player/Stage robotics platform.

Keywords: memory-based immune systems; immune network; multi-robot cooperation; shepherding.

1. Introduction

Usually mobile robots need to interact and engage with one another in order to achieve assigned tasks more efficiently. These autonomous multi-robot systems would be highly beneficial in assisting humans to complete suitable tasks. In such systems, distributed intelligence is highly needed in the team whereby decisions are processed in each individual robots.^{1,2} Furthermore, these robots would need to have the mechanism to cooperate so that they would achieve the assigned task.^{3,4}

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Biological systems are examples of distributed information processing that are capable of solving problems in living organisms in a distributed manner. These biological systems include neural networks in the brain that is capable of processing information through impulses at the synapses, genetic systems in constructing the organism genes and immune systems which protect and maintain the homeostatic state of the living organism. Biological immune systems are particularly interesting, not only because they have no central processing but also exhibit cooperative capability among the antibodies in maintaining the internal stable environment of the body.

This leads to the advances in research on Artificial Immune Systems (AIS) and the application of AIS in engineering fields particularly in Multi-Robot Systems (MRS) domain.^{1,3,5} Situations faced by multi-robot systems require real-time processing and response. Furthermore, such situations would also require these systems to be robust to changes in the environment and some unexpected events, such as failure of robots in the team. Thus, mimicking the biological immune system is appropriate.

This paper proposes a refinement upon the memory-enhanced immune system algorithm to achieve better herding behavior in a team of multiple shepherds. Using the algorithm inspired by the immune network theory, the robots have the capability of performing their task in a dynamically changing environment. The proposed refined algorithm is applied to the dog and sheep scenario.^{5,6} Simulation experiments are arranged to investigate the refinements performance using the stated scenario.

2. Inspiration from Immunology

This section explains the principle of the biological immune response and the Idiotypic Network Hypothesis which describe the cooperative behavior achieved by immune systems in vertebrate organisms. This is followed by the generic relation between immune systems and multi-robot systems.

2.1. *Biological immune systems*

Immune system is a system that eliminates foreign substances from an organism's body. These foreign substances such as bacteria, fungi or virus cells that can harm the host are called pathogens. When such substance activates an immune response it is called *antigen*, which stimulates the system's antibody generation. Each type of antigen has a unique set of identification on its surface called *epitope*. These antigenic determinants are where the host's antibodies would attach to by using their paratope, as shown in Fig. 1. *Antibodies* are cells in the immune system that kill antigens in order to maintain the host homeostatic state—i.e. balancing the body's health status.

The immune system can be divided into two general categories, innate immunity

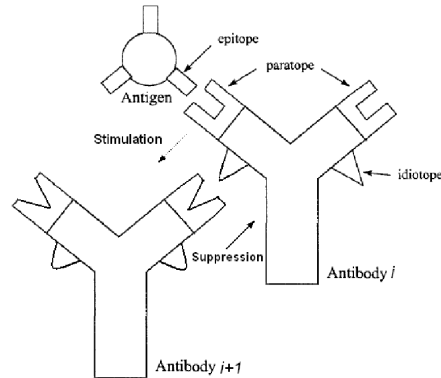


Fig. 1. Antigen-antibody binding and Jerne's Idiotypic Network Theory.

and adaptive immunity. Innate immunity is the first line of defense of the immune system. Generic pathogens that can be recognized and killed by the innate immunity cells would not be able to harm the host further. However, certain disease carrying antigens would bypass this defense mechanism because the innate immunity does not adapt to antigens that originate from various types of illnesses. The adaptive immunity would then play its role through the use of *lymphocytes* which are generally known as white blood cells. Lymphocytes have two main types, *T-cells* that mainly help in recognizing antigen cells and *B-cells* that mainly produce antibodies to fight specific antigens. In humans, T-cells are primarily produced in the thymus while B-cells are produced in bone marrows. These innate and adaptive immune responses make up effective and important defense mechanism for living organisms.

2.2. Biological immune response

The immune response can be described in six general phases of recognition and activation. Pathogen; which are cells from outside of the host organism; is initially digested by Antigen Presenting Cells (APC) where it is broken down into *peptides*.⁷ These peptides will then bind to Major Histocompatibility Complex (MHC) molecules, then presented on the APC surface. T-cells recognize these different APC receptors and thus become activated. They divide and release *lymphokines* that transmit chemical signals to stimulate other immune system components to take action. B-cells would then travel to the affected area and be able to recognize the antigen. This would activate the B-cells which then mature into *plasma cells*. Plasma cells are the ones which release specific antibody molecules that neutralize the particular pathogens.

This immune response cycle results in the host's immunity against the antigen which triggers it, thus having protection in future attacks.⁷ Prominent characteristics of the immune system is that there is no central control of the lymphocytes in

fighting antigens that invade the host and the system's adaptability in responding to various kind of antigens. The B-cells cooperatively merge at the affected area and produce appropriate antibodies for that particular situation. This phase of immune response exhibits cooperative behavior of the related cells.

2.3. *Idiotypic network hypothesis*

Studies in immunology have suggested that antibodies are not isolated but they 'communicate' with each other. Each type of antibody has its specific *idiotope*, an antigen determinant as shown in Fig. 1. Jerne who is an immunologist proposed the Idiotypic Network Hypothesis (also known as Idiotypic Network Theory) which views the immune system as a large-scale closed system consisting of interaction of various lymphocytes (i.e. B-cells).^{8,9} Referring to Fig. 1, idiotope of antibody i stimulates antibody $i+1$ through its paratope. Antibody $i+1$ views that idiotope (belonging to antibody i) simultaneously as an antigen. Thus, antibody i is suppressed by antibody $i+1$. These mutual stimulation and suppression chains between antibodies form a controlling mechanism for the immune response.⁷

Farmer *et al.* proposed differential equations of Jerne's idiotypic network theory.¹⁰ These equations consist of antibodies' stimulus and suppression terms, antigen-antibody affinity, and cell's natural mortality rate. This large-scale closed system interaction is the main mechanism that can be used for cooperation of multi-robot systems.

2.4. *Immune systems and multi-robot systems*

The relationship of the immune systems with multi-robot systems is evident where obstacles, robots and their responses are antigens, B-cells and antibodies respectively. Table 1 lists the parallel terminologies of MRS and immune systems that are being used in this paper.

Table 1. Immune Systems and MRS relationship

Immune Systems	Multi-Robot Systems
B-cell	Robot
Antigen	Robot's Environment
Antibody	Robot's action
T-cell	Control parameter
Plasma cell	Excellent robot
Inactivated cell	Inferior robot
Immune network	Robots interaction
Stimulus	Adequate robot stimulation
Suppression	Inadequate robot stimulation

Immune network theory as previously described is suitable as a basis for emulating cooperative behavior in a multi-robot environment. This is because the

immune network uses affinity measures that are dependent on other cells concentration and location in determining the next action. Other than that, multi-robot systems require recognition ability of obstacles and other robots, which is parallel to the immune system recognition and activation phase of an immune response. Obviously, in immune network the processing of information is done in real-time and in a distributed manner—as what a multi-robot system requires.

3. Immune Inspired Multi-Robot Shepherding

3.1. *Immune-based swarm behaviors*

Sun *et al.* have proposed a model based on Farmer’s immune network equation that involves T-cells as control parameter which provides adaptation ability in group behavior.¹¹ The advantage of adding the T-cell model is that the system adapts quickly to the environment by recovery of antibody concentration to the initial state, when antigens have successfully been removed. Thus, the system is more adaptable to environmental changes.

The group control or coordination phase is done in a distributed manner via local communication between nearby robots. When a robot encounters other robot and both have the same or similar strategy, this strategy is stimulated; if not, the strategy is suppressed. This facilitates the group to self-organize towards a common action which is optimal for the local environment. If a robot is stimulated beyond a certain threshold—which makes it an excellent robot, its behavior is regarded as adequate in the system such that it can transmit its strategy to other inferior robots. This is a metaphor of the plasma cell in the biological immune systems.

3.2. *Multi-robot shepherding problems*

The application domain of multi-robot shepherding is complex, as there are many robot shepherds trying to control a constantly moving flock which comprises of several robots. Some of the approach proposed assumes that the shepherds have a global view of the current environment.^{12,13} However, this assumption makes it not a fully distributed approach. Other than that, usually it is assumed that the shepherds have some *a priori* information regarding the dynamic situation—such as the total number of robots in the flock.

Another problem is regarding the propagation of local group behavior. Other proposed approaches rely on propagation using one-to-one basis (i.e. during two robots encounter).^{5,11} To achieve a more precise description of the local neighborhood environment, local group behaviors should be propagated within the robots’ local neighborhood radius.

3.3. *The INT-M model*

In biological immune response, there is a Clonal Selection process, whereby various B-cells try to identify the antigen. Once the appropriate B-cell is selected, it is

activated and multiplied (i.e. proliferate) so that adequate immune response could be mounted later. The activated B-cells will proliferate and differentiate into *Plasma cells* that will secrete specific antibodies and *Memory cells* which will be in the host body for quite a long time.⁷ These memory cells will act as catalysts in mounting a quick immune response to the same antigen in the future.

In order to improve the approach by Sun *et al.*, a specific memory mechanism is proposed in order to retain the appropriate action for relevant environment condition. This mechanism is introduced when the newly sensed environment is similar to the previous environment. Thus, a quick action-selection process can be executed without the need of re-evaluating the new situation.

The approach is named as Immune Network T-cell-regulated—with Memory (INT-M) which involves modeling the memory part of the biological immune systems.¹⁴ The general algorithm is shown in Algorithm 1 which is an extension of Sun *et al.* approach. The algorithm being displayed is for each robot in the group, and uses Eq. (1), (2) and (3).

$$S_i(t) = S_i(t-1) + \left(\alpha \frac{\sum_{j=0}^{N-1} (m_{ij} - m_{ji}) s_j(t-1)}{N} + \beta g_i - c_i(t-1) - k_i \right) s_i(t-1) \quad (1)$$

$$s_i(t) = \frac{1}{1 + \exp(0.5 - S_i(t))} \quad (2)$$

$$c_i(t) = \eta(1 - g_i(t)) S_i(t) \quad (3)$$

In Eq. (1), (2) and (3), $S_i(t)$ is the stimulus value of antibody i where $i, j = 0 \dots N$, N is the number of antibody types. m_{ij} is the mutual stimulus of antibody i and j , which is detailed in Table 2. g_i is the affinity of antibody i and antigen, which can arbitrarily be assigned using a function. A simple step function is used to assign the antigen to antibody affinity values, i.e. g_i as shown in Table 3. $s_i(t)$ is the concentration of antibody i . The difference with Farmer *et al.* immune network equation is that $s_j(t)$ is not the concentration of self-antibody, but that of other robot's antibody obtained by communication.

Table 2. Mutual stimulus coefficient, m_{ij}

robot $i \setminus$ robot j	Ab_0	Ab_1	Ab_2	Ab_3
Aggregation, Ab_0	1.0	-0.4	-0.2	-0.4
Search, Ab_1	-0.4	1.0	-0.4	-0.2
Dispersion, Ab_2	-0.2	-0.4	1.0	-0.4
Homing, Ab_3	-0.4	-0.2	-0.4	1.0

Algorithm 1 Immune Network T-cell-regulated—with Memory (INT-M)

Require: $t = 0$, $S_i(0) = s_i(0) = 0.5$ for $i = 0 \dots N - 1$, N is number of actions

Ensure: retain previous Ab if robot is excellent and environment is similar

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 $Ab_{max} \leftarrow Ab_1$ , robot  $\leftarrow$  inferior, environment  $\leftarrow$  similar
loop
  Execute  $Ab_{max}$ 
  if robot  $\neq$  inferior then {robot is activated (i.e. excellent)}
    if  $g_i(t) \approx g_i(t - 1)$  then {environment sensed is similar to previous}
       $S_i(t) \leftarrow S_i(t - 1)$ ,  $s_i(t) \leftarrow s_i(t - 1)$ ,  $c_i(t) \leftarrow c_i(t - 1)$ 
    else
      environment  $\leftarrow$  changed
    end if
  end if

  if (robot = inferior) || (environment = changed) then
    for  $i \leftarrow 0$  to  $N - 1$  do
      calculate  $S_i(t)$ ,  $s_i(t)$  and  $c_i(t)$ 
    end for

    if  $S_i(t) > \bar{\tau}$  then
      robot  $\leftarrow$  excellent
    else if  $S_i(t) < \underline{\tau}$  then
      robot  $\leftarrow$  inferior
      if robot encounter  $robot_{excellent}$  then
        for all  $i$  do
          receive  $Ab_i$  and renew  $s_i(t)$ 
        end for
      end if
    end if
  end if

  if  $Ab_i$  has  $max(s_i(t))$  then
     $Ab_{max} \leftarrow Ab_i$ 
  end if
   $t \leftarrow t + 1$ 
end loop

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Eq. (3) is the T-cell model whereby $c_i(t)$ is the concentration of T-cell which controls the concentration of antibody i . k_i is a constant that represents the cell's death rate in biological immune systems. α , β , and η are constants, whereby α

Table 3. Antigen-antibody affinity stimulus function, g_i
 (other index values remain as 0.0)

Task Detected (%)	Task Density	g_i values
(66 – 100]	High	$g_0 = 1.0$
(10 – 66]	Medium	$g_1 = 1.0$
(0 – 10]	Low	$g_2 = 1.0$
0	None	$g_2 = 1.0, g_3 = 0.5$

and β are parameters of response rate of other robot and the environment (antigen) respectively. In biological immune systems, helper T-cells activate B-cells when antigen invades, and suppressor T-cells prevent the activation of B-cells when the antigen has been eliminated thus ensuring that the system adapts quickly to the environment by recovery of antibody concentration to the initial state. The respective values of 0.622 and 0.378 are for the upper ($\bar{\tau}$) and lower ($\underline{\tau}$) thresholds based on Eq. (4) and (5), are used in determining whether a robot becomes an excellent (i.e. plasma cell) or an inferior (i.e. inactivated cell) robot.

$$\bar{\tau} = \frac{1}{1 + e^{-0.5}} = 0.622 \quad (4)$$

$$\underline{\tau} = \frac{1}{1 + e^{0.5}} = 0.378 \quad (5)$$

3.4. *Shepherding test scenario*

In this paper we investigate shepherding behavior of robots. Shepherding behavior is similar to a flocking behavior but having agents/robots outside of the flock guiding or controlling the members.^{12,13} It is similar to multiple combat Unmanned Ground Vehicle (UGV) systems scenario.¹⁵

A distinct part of this study is that we are looking into the refined low-level behavior of the memory-based immune network cooperation approach by the robots (i.e. dogs) in maintaining the herd (i.e. sheep). This utilizes better shepherding control in addition to the advantage of memory in the action-selection phase.

In a dog and sheep problem, a few dogs try to guide a few sheep to the grazing site (also called the safety zone) without going beyond the borders.⁶ Dogs are required to cooperate in shepherding the sheep which are moving away from the dogs or wandering randomly inside the area. The objective is to herd the sheep into the grazing site while having partial information of what is happening in the area. Fig. 2 shows the screen-shot of the dog and sheep scenario.

This problem is highly dynamic and obviously requires the robots to have real-time processing of partial information of the environment. The robot dogs use the proposed immune-inspired approach in cooperating with one another while the robot sheep have basic avoidance and flocking behaviors. Furthermore, the robot

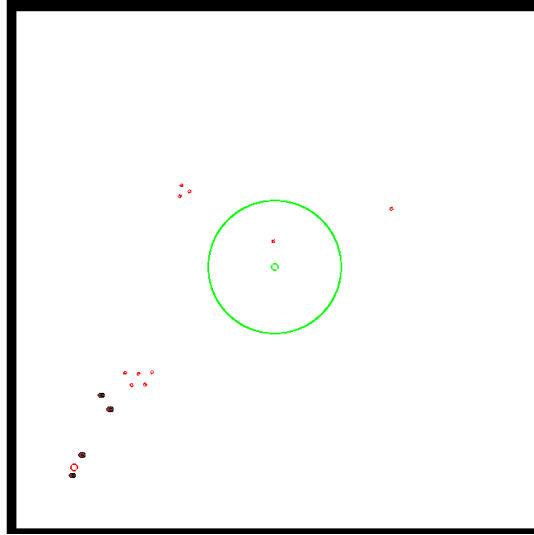


Fig. 2. The Dog-Sheep problem environment with four robot dogs at the bottom-left corner while the smaller robots are the sheep—the grazing site is at the middle of the enclosed field and the bottom-left circle is to mark the robot dogs' start position.

dogs also uses the Vector Field Histogram (VFH+) algorithm provided in the simulation platform for obstacle avoidance and goal-seeking behaviors, i.e searching for the shepherds' positions with respect to the herd.¹⁶

3.5. INT-M refinement

Multiple shepherds pose a few underlying problems regarding the interaction between the shepherds and the flock.¹³ The proposed refinement of the INT-M model is focused only on the Shepherds' Formation and Shepherds' Approach aspects. This refinement is then applied onto the dog and sheep scenario.

The formation involves the robot dogs to line-up behind the group of sheep so that the flock can be better controlled. The approach is also refined as in when a robot dog move towards a sheep it will obey the safe zone of that sheep, so that the sheep would not be influenced by the incoming dog. This will achieve a lower flock separation occurrences, thereby having better shepherding behavior. Fig. 3 is the depiction of the proposed refinement of the model by having the robot dogs forming a line behind the group of sheep.

4. Immune Network Inspired Cooperative Mechanism

This section is to test the underlying immune inspired cooperative mechanism, with regard to the stimulation and suppression of antibodies amongst the group of

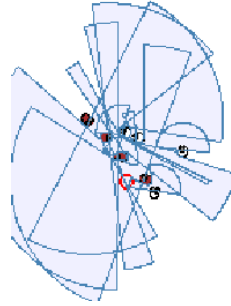


Fig. 3. An example of the refinement of low-level shepherding behavior: robot dogs lining-up (the grazing site is located at the top-right corner).

robots. Simulation experiments were conducted to verify the proposed cooperation mechanism.

The values for the constants are $\alpha = 0.0$, $\beta = 0.05$, $\eta = 0.05$ and $k = 0.002$ which follows Sun *et al.* values, except for η which is our own value.¹¹ At the start of simulations, the values for g_i are set to 0.0 except for g_2 (Dispersion) and g_3 (Homing) are assigned 1.0 and 0.5 respectively.

Robot 4 starts with not seeing any of the tasks (i.e. percentage of tasks detected is 0.0%), although assumption is made that all robots are within each others' communication range. This may happen for instance when robot 4 is facing another direction from the rest of the group. Meanwhile, the other robots are assumed to have already detected 75.0% of the task at start time. Furthermore, it is assumed that all robots remain geographically static over time.

Fig. 4–7 display the average for each antibodies' concentration value (i.e. s_i) over time that was run for several times. The antibody (i.e. strategy) with the highest concentration (i.e. maximum value) of s_i will be selected by the robot to be executed.

4.1. Response to environmental changes

In order to test the response of robot 1–3 towards changes in its environment, all of the robots' tasks detected values are changed to 0.0% at $t = 50$. Fig. 4 shows the effects of this, whereby slower increase of robot 1–3 Ab_2 (Dispersion) value and the gradual decrease of their Ab_0 (Aggregation) value can be seen. This is due to the fact that only robot 4 is influencing this behavior to the other three robots.

For testing the response of robot 4 to environmental changes, the task detected of all robots are assigned to 75.0% at $t = 50$. Fig. 5 displays a steeper and faster increase of Ab_0 (Aggregation) and decrease of Ab_2 (Dispersion) respectively. This signifies a higher level of influence onto robot 4 by the other three robots.

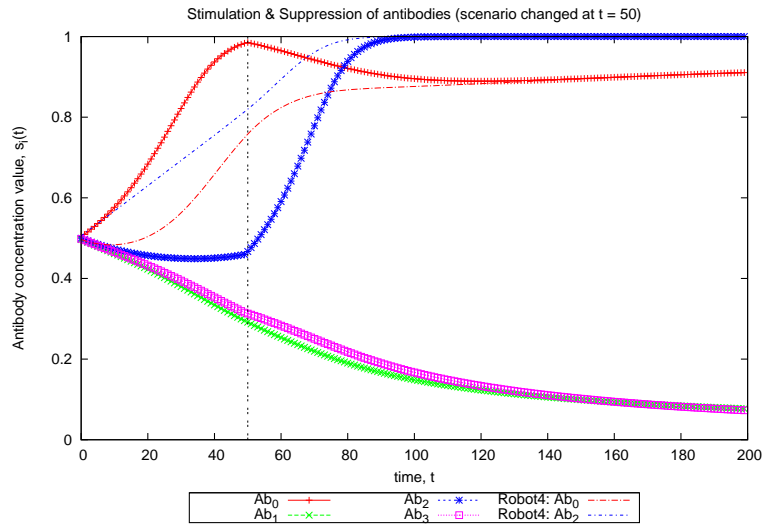


Fig. 4. Ab_0 to Ab_3 are the average of robot 1–3, which start with high task density then changed to 0 density at $t = 50$.

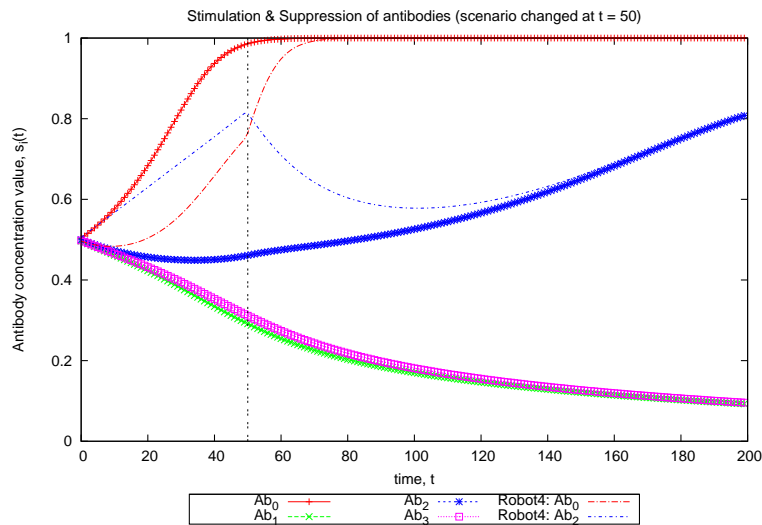


Fig. 5. Ab_0 to Ab_3 are the average of robot 1–3, robot 4 starts with 0 task density then changed to detect 75.0% of the task (like the other robots) at $t = 50$.

4.2. Propagation of stimulation and suppression of antibodies

Simulations are run to evaluate the propagation of stimulation and suppression of various antibodies among the group of robots. These will show that the local group

behavior is propagated within the neighborhood. In Fig. 6 robot 4 gradually becomes Excellent, then at $t = 50$ it is set to be Inferior. The figure shows that in almost instantly robot 4 receives the ‘better’ strategy (Aggregation, Ab_0) from the other robots. However, since its local task detected remains 0.0%, Ab_2 is still stimulated. Robot 4 eventually becomes Excellent again and thus selects Ab_2 (Dispersion) once more—as it would much more ‘believe’ what it can sense. This happens at $t \approx 110$ as shown in Fig. 6.

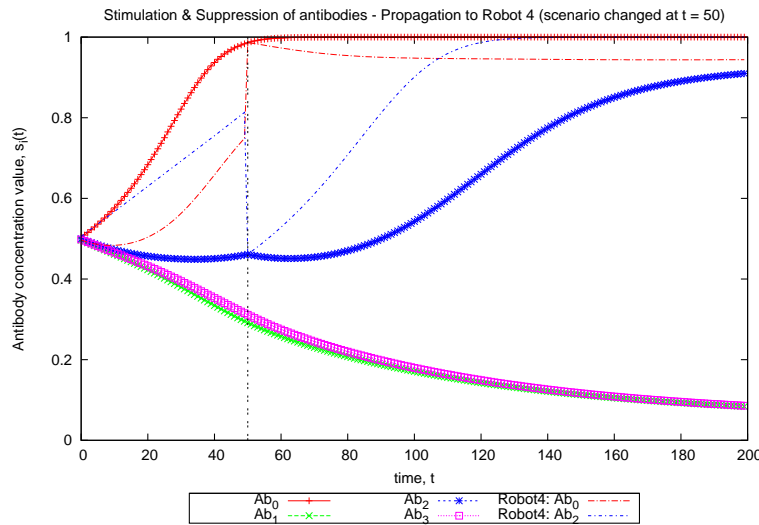


Fig. 6. Robot 4 becomes Excellent over time, then changed to be Inferior at $t = 50$ thus almost instantaneously receives the strategy (i.e. Ab) from the other robots—which in this case is Ab_0 (Aggregation)—but later changed back as it returns to be Excellent once again.

Fig. 7 shows as robot 4 gradually becomes Excellent, it continues to choose (i.e. ‘believe’) Ab_2 (Dispersion) strategy—which is suited to its locally sensed environment (i.e. no task detected). It remains to focus on it’s locally sensed environment, however its Ab_0 (Aggregation) is highly stimulated because of the propagation of this strategy from the other robots. The other robots’ Ab_2 strategy is also stimulated.

5. Simulation Experiments

The proposed approach as described in Algorithm 1 together with the refinements is applied to the dog and sheep problem and adjusted where necessary. The Player/Stage simulation platform on a Fedora 9 Linux operating system is being used to test the refined model.¹⁷ Simulation data had been collected to analyze the behaviors of the simulated robots.

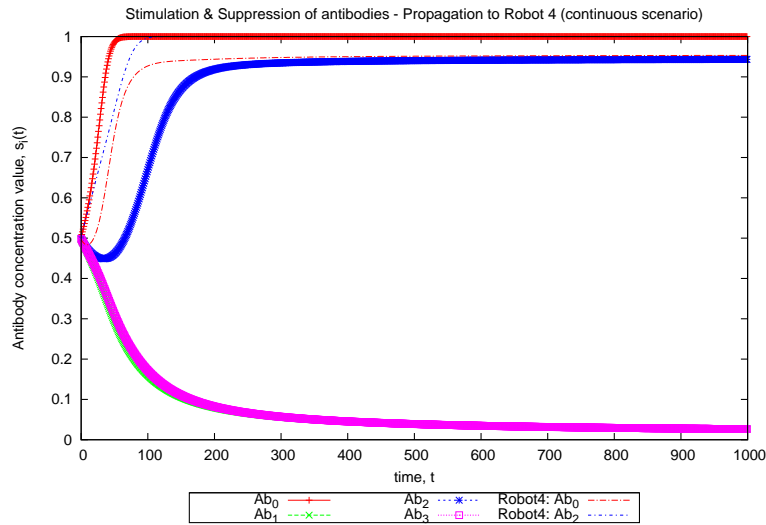


Fig. 7. Over time, robot 4 becomes Excellent and continues to do so as the environment has not changed—thus it maintains its strategy of Ab_2 (Dispersion). At the same time, its Ab_0 strategy is highly stimulated via propagation by other robots.

5.1. Simulation setup

The range for the robot dogs are set to five meters for forward sight (i.e. laser) and 20 meters for emulating sense of hearing. The field is constructed of a walled field with the size of 40 meters each side. The grazing site is situated at the center with a radius of five meters and each sheep that have entered it will stop. Each experiment is limited to a limit of five minutes (i.e. 300 seconds — used in Figs. 8 and 9) and it is done for six times, then the average values are calculated.

5.2. Performance criteria

The performance can mainly be measured on two aspects. The average distance of the flock that is shepherd into the grazing site (which is known as Average Distance to Origin), and also the average percentage of sheep left in the field (which is known as Average Incomplete Tasks) after the maximum time is up. The average percentage of incomplete tasks criterion signifies the ability to maintain the balance of the overall goal of shepherding all the sheep and also completing it within the specified time.

5.3. Simulation results

Fig. 8 shows the average distance of the flock (in relation to the origin) over time. There are three flock sizes in the experiment — from two sheep up until four sheep in a herd. The figure indicates that in average the group of sheep is able to be

contained within the flock. This reflects on the refinements applied to the dogs' shepherding behavior. Furthermore, the average distance of flocks with four sheep is quite stable over time. However, flocks of size two do show a relatively smoother transition over time—indicating that the flock is quite manageable.

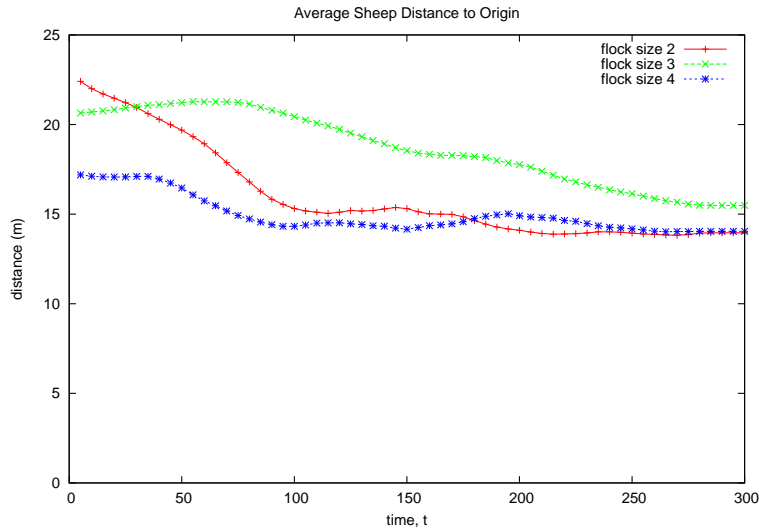


Fig. 8. Average Distance to Origin.

Fig. 9 shows the average percentage of sheep still outside of the grazing site over time. The figure suggests that in average there will at least be some sheep that can be shepherd into the grazing site, because after the time is up all of the flock sizes have less than 80% of incomplete tasks remaining. Nonetheless, the average incomplete tasks percentage for all flock sizes are not less than 60%. In general, flocks of size two can achieve lower incomplete task rate within the time limit. On the other hand, flocks with four sheep display quicker response that might indicate a trend.

6. Conclusions

In this paper a refined memory-based immune system inspired approach for shepherding in multi-robot systems has been proposed. We have described the basic concepts of biological immune systems, and argued that the immune network is a suitable analogy for multi-robot shepherding problem. The underlying immune inspired cooperative mechanism had been described and tested. We have also proposed refinements on the multi-robot cooperation algorithm—the INT-M model, and applied it to the dog-sheep test scenario. Simulation experiments had been

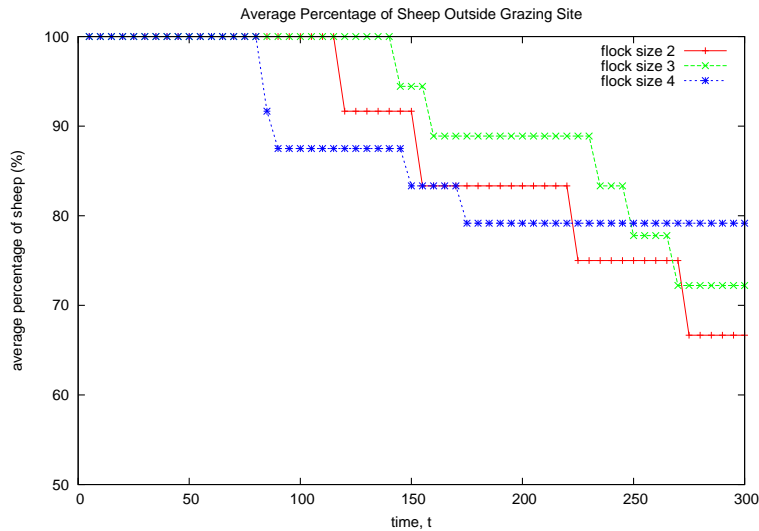


Fig. 9. Average Incomplete Tasks.

carried out to evaluate the cooperative mechanism and the whole approach.

The approach can be extended to other application domains which require several agents (robots) to work cooperatively in a distributed way in a dynamic environment. It can further be implemented on real robots such as the e-pucks to obtain the algorithm performance in real world situation.¹⁸

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