Learning in Immune Network Algorithm for Multi-Robot Cooperation

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***Abstract*— The multi-robot system frequently associated with the problem of robot coordination and cooperation as it requires real-time and distributed control. This paper describes biological immune system, immune response, and immune learning through somatic hypermutation. The relationship between immune system and multi-robot system is presented to show the connection between both systems. To improve the cooperative behavior in multi-robot systems, an immune network algorithm is proposed with the extension of learning ability. Jerne and Farmer models of immune network are referred as the foundation of our approach. The proposed algorithm is based on our previous conceptual model and designed particularly for multi-robots foraging task with five different action strategies. The learning concept in the antibody is applied to the robot action. Therefore, the robot swarm is expected to complete the task faster since robots adapt to the environment. For future work, the proposed algorithm will be implemented in a robot simulation environment called ARGoS.**

***Index Terms*— Immune network; Multi-robot cooperation; Immune learning; Somatic hypermutation; Foraging task.**

I. INTRODUCTION

Over the past few years, multi-robot systems have become a vast interest topic in robotics research. It is significant that multiple robots can increase the efficiency and the robustness of the system compared with single robot system. For instance, using multiple shepherds for herding large flock works more efficiently than using single shepherd [1]. Thus, a higher number of robots can produce a self-organized system that is consequently robust to environmental changes [2]. However, it cannot be ascertained that multiple robots always work effectively. The problem in multi-robot system emphasizes the cooperative behavior as it requires real-time and distributed control. Besides that, the probability of complication to occur in the multi-robot system is higher than single robot system as there are many robots to control. Therefore, a cooperative multi-robot is essential to achieve these system goals.

There are various swarm intelligence algorithms applied in multi-robot cooperation [3] such as artificial fish swarm, artificial bee colony [4], ant colony and particle swarm optimization [5]. Other approaches also have been implemented in the multi-robot system, for example, genetic algorithm [6], fuzzy-based algorithm [7], immune-based and market-based [8]. Hoff et al. work differ from other research where the virtual pheromone is applied rather than implementing the physical pheromones [9]. Years later, Hoff et al. focused their work for swarm foraging on two distributed foraging algorithms [10]. However, their work did not emphasize the cooperation behavior amongst the swarm robots.

In the literature, there exist many works inspired by the biological immune system. Umut and Canberk proved that an antigen inspired structure is reconstructed to state the over-energy consuming small base station [11]. Compared with traditional Artificial Immune System (AIS), antibody recognition is initiated only when the type of antigen has changed, which improves the efficiency of the algorithm [12]. Razali et al. has conducted the multi-robot research for shepherding task by applying immune network theory with memory [13]. Khan and de Silva proposed the capability chain concept that exhibits the dependency of multi-robot to work in a cooperative manner [14]. Previous research presents various approach yet the learning aspect has not taken into account. In this study, we focused on the immune inspired approach based on immune network theory. Then, the learning aspect taken from somatic hypermutation concept will be integrated into the multi-robot cooperation. Logically, when the robots learn to adapt to the environmental changes, the system will function effectively as there are lesser complication and the robots work in a cooperative manner.

II. BIOLOGICAL IMMUNE SYSTEM

The immune system protect bodies from being invaded by pathogens and hence prevent diseases. Pathogens could be proteins, viruses, bacteria, parasites or even fungi. Antigens are often found on the surface of the pathogen and react to the immune system. Antibodies will act like the killer of these antigens to prevent the harm to the body. The top part of the antibody is the antigen-binding site called paratope where the antigen-antibody binding occurs. It will attach to the specific part of an antigen called the epitope. Figure 1 illustrates the immune response and antibodies generation phases.

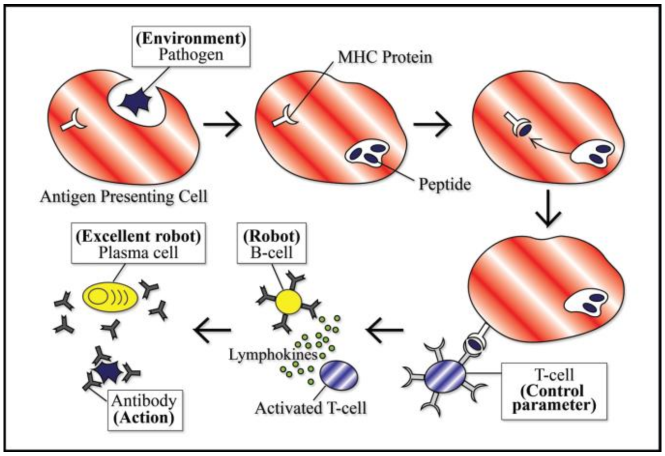


Figure 1: Biological immune response and antibodies generation

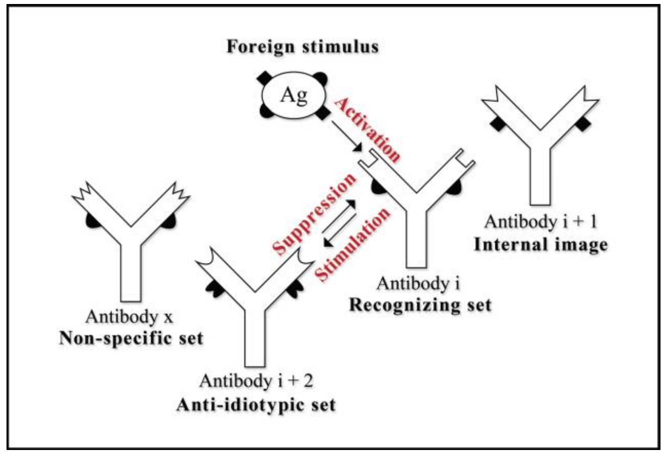


Figure 2: The interactions in the immune system according to the idiotypic network theory

A. Immune Response

The immune response can be categorized into two, namely humoral response and cell-mediated response. Based on Figure 1, when the foreign substance or pathogen encounter the Antigen Presenting Cell (APC), the APC will engulf the pathogen and decompose it into peptides. Other proteins, namely Major Histocompatibility Complex (MHC) molecules attached to these peptides chain and present themselves on the top surface of the APC. T-cell that recognize these presenting receptor then become activated. Activated T cell releases a chemical signal transmitter called Lymphokines. The B cell that received the signal and recognized the antigen will then become activated. These activated B cells known as Plasma cells generates specific antibodies to fight against particular pathogens.

B. Immune Network Theory

Immune network theory known as idiotypic network theory is proposed by Jerne in late 1980's ([22] and [15]). Figure 2 shows the behavior of the immune system and the interaction of the molecules as proposed by Jerne. When the foreign stimulus, antigen (Ag), encounter the antibody and the epitope of the antigen recognized by the paratopes of Antibody *i*, it responds positively to this recognition signal. When the paratopes of Antibody $i + 2$ recognized the idiotopes of Antibody *i*, a negative response occur. This negative response would result in tolerance and suppression [15]. In contrast, stimulation occurs when these Antibody *i* idiotopes are recognized by Antibody $i + 2$ paratopes, thus, its concentration is increased [16].

Other than idiotopes of recognizing set Antibody *i*, a parallel set that matches the binding sites of the Antibody $i + 2$ paratopes are the idiotopes of Antibody x, which the foreign epitope do not fit this Antibody x paratopes. There could be a possibility for the paratopes of Antibody *i* to recognize another matching variable which is the idiotope of Antibody $i + 1$. These sets of idiotopes are called the internal image of the antigen as it is recognized by the same Antibody *i*.

Based on this scheme, the sets become broader within the network as the sets that recognize or recognized by previously defined set continually adapt itself to the environment. Jerne's theory stated that the antibodies are not isolated, but they continue communicating even without the presence of antigens [13]. The binding exhibited by the antibodies is considered as the networking and communication by the cells. In respect of this networking concept, the cooperation among robots can be improved by enhancing this mechanism with the integration of immune learning.

C. Immune Learning by Somatic Hypermutation

In the immune system, the cells need to learn to fight invaders and keep them in memory so that they can respond faster to the second attempt of the same antigen. The immune system learns by the repetition of selection and mutation process to produce better B cells with higher affinity [17]. The learning of antibodies can be seen through the changes in isotype, the changes in avidity and the immunologic learning [18]. In this paper, immune learning through somatic hypermutation is applied to produce an improved multi-robot system.

In general, somatic hypermutation takes place in the variable region of an antibody. There are three segments that represent the germ line in immunoglobulin (Ig) variable region namely variable (V), diversity (D) and joining (J). The primary repertoire of the antibody specificities diversification is due to the integration of these segments [19]. In details, the mutation occurs at the DNA gene base namely adenine (A), cytosine (C), guanine (G), thymine (T) and uracil (U), such as A-T and C-G base pairs. Figure 3 depicts the somatic hypermutation that occurs in immunoglobulin diversification event. There are many V, D, and J in each segment. However, the rearrangement only involves one V segment, one D segment, and one J segment. The variety in each segment led to the diversification of isotypes [19].

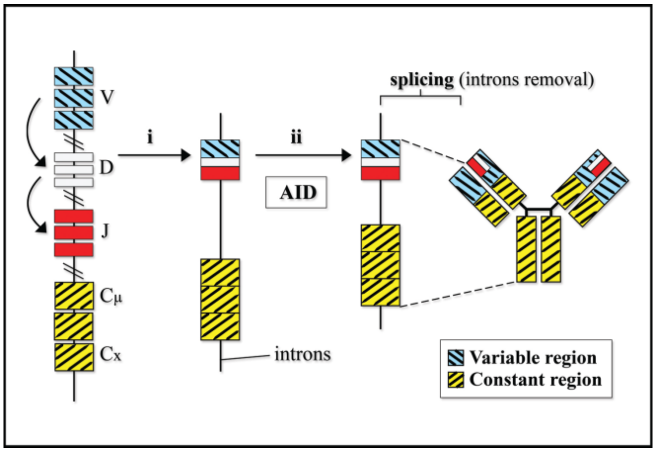


Figure 3: Somatic hypermutation and class switch recombination

The arc arrows show the DJ recombination and VDJ recombination. The VDJ bind brings constant (C) region in close proximity to them. Thus, process (i) in Figure 3 is V(D)J recombination. Activation-induced deaminase (AID) enzyme act as the catalyst to trigger the hypermutation [19]. As AID introduced mutation on the DNA variable region, the antibody produces variants with higher antigen affinity [20]. This somatic hypermutation takes place at process (ii). The antibody affinity is inversely proportional to the mutation. Hence, the greater the antibody affinity the smaller its mutation rate. Plasma cells keep produce antibodies even without the presence of antigen, thus, the probability of mutation to occur is inevitable. Through the repetition of this somatic hypermutation, the antibodies learn to produce improved affinity antibodies. This kind of mechanism brings the idea of learning in multi-robot cooperation system. The presence of the AID can be considered as the other factors that lead to the diversification of robot action.

III. Immune System And Multi-Robot System

A. Relationship Between Immune System and Multi-Robot System

Unlike neural network system, immune system works as a decentralized system which is suitable for dynamic and autonomous robots in the multi-robot system. The inspiration for immune system theory is due to its real-time and distributed manner as required for the multi-robot system [13]. The relationship between immune system and multi-robot system is described as in Table 1. Based on this relationship, a conceptual model based on immune network incorporated with learning in somatic hypermutation had been presented and the details of the conceptual model can be found in our previous paper [21]. Based on the conceptual model, a proposed algorithm for multi-robot cooperation is discussed in Section 4.

B. Foraging Task

The proposed approach is designed to improve robots cooperation for foraging task by applying learning concept in somatic hypermutation with immune network approach. In the multi-robot system, antibody is regarded as robot action strategies. There are five action strategies featured for this task. Table 2 describes the action strategies used by the robots.

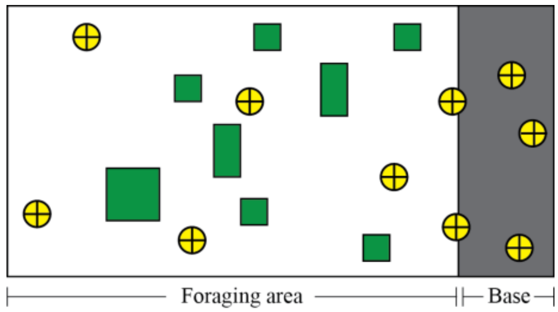
Table 1: Relationship between immune system and multi robot-system

Immune System	Multi-robot System
Antigen	Environment
Antibody	Action strategy
B cell	Robot
Immune network	Robots communication
Stimulus	Adequate stimulation
Suppression	Inadequate stimulation
Plasma cell	Excellent robot
Inactivated cell	Inferior robot
AID enzyme	Time limit

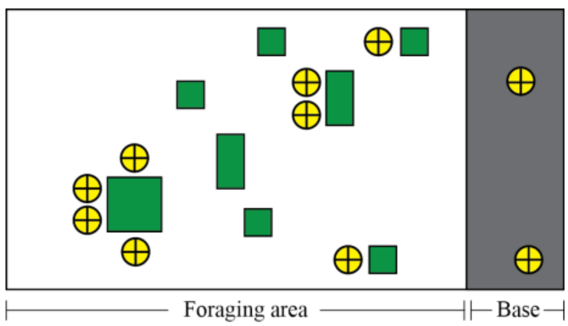
Table 2: Action strategies of each robot

Antibody	Robot Actions
Ab_0	Grouping
Ab_1	Searching
Ab_2	Collecting
Ab_3	Homing
Ab_4	Dispersion

Grouping action, Ab_0, means robot stay and wait for other robots to complete the task cooperatively. For searching action, Ab_1, robot moves randomly to find the task. When object is found, robot needs to collect and bring the object to the base. This action refers to Ab_2. Homing, Ab_3, denotes the robot that returns to the base, and when the robots are close by each other, they will disperse, Ab_4. Supposed that there are ten robots in the environment with five different actions. The different object requires a different number of robots to move to the base. Green rectangular shapes constitute the objects while yellow circle represent the robots. For smaller, medium and bigger object, robot needed are one, two and four respectively. Figure 4 shows an example illustration of the multi-robot foraging task. Robots should collect the green rectangular objects to the base. Since single robot cannot perform a difficult task, robots need to work cooperatively to collect the object. The next section of this paper will present the cooperative and learning algorithm for a foraging task. The robots are expected to complete the tasks successfully as they learn and adapt to the environmental changes.



a) Robots move randomly to search the object



b) Larger object requires more robots

Figure 4: Robot should work cooperatively to complete the task

IV. IMMUNE NETWORK APPROACHES

A. *General Immune Network Algorithm*

Jerne has formally proposed idiotypic network theory [22]. Based on Jerne's hypothesis, Farmer and collaborators presented an immune network model of B-cell as bit string models [23]. Their proposed differential equation integrating the mathematical theoretical immunology and computational intelligence [24]. The differential equation can be summarized as in Equations (1) and (2).

In equation (1), $S_i(t)$ define the stimulus value of antibody type i. N refers to the total number of antibody of type i and i represents the number of antibody type where i=1...N. m_{ij} represent the mutual stimulus of antibody i and j. $g_i(t)$ is the affinity of antibody i and antigen while parameter α and β are response rate of other antibody and antigen respectively [25]. Unlike Jerne's model, the first and second term in this equation represent the stimulation and suppression among antibodies respectively while k_i represents natural extinction coefficient.

Referring to the differential equations, previous researchers had come up with an idea for immune network algorithm. Algorithm 1 shows the general immune network algorithm adapted from [25]. To improve the cooperative behavior in swarm robots shepherding, Razali et al. proposed a refined algorithm with the extension of memory mechanism [13]. In the subsection 4.2, we proposed the algorithm for learning in multi-robot cooperation.

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

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

Algorithm 1 General Immune Network Algorithm adapted from [25]

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

Ensure: Ab with highest concentration is executed

$Ab_{max} = Ab_1$
loop
  Execute Ab_{max}
  for i=0 to N-1 do
    Calculate $S_i(t)$
    Calculate $s_i(t)$
  end for
  if $S_i(t) > threshold_{upper}$ then
    robot = excellent
  else if $S_i(t) < threshold_{lower}$ then
    robot = inferior
    if robot encounters $robot_{excellent}$ then
      for all i do
        receive Ab_i
        renew $s_i(t)$
      end for
    end if
  end if
  if Ab_i has max $s_i(t)$ then
    $Ab_{max} = Ab_i$
  end if
  t=t+1
end loop

B. *Proposed Algorithm*

In this paper, proposed approach is based on Farmer et al. model [23] as in Equation (1) and (2) with the combination of learning concept. Therefore, robots can perform faster secondary response and hence, lead the system to an efficient distributed multi-robot system. An improved immune network algorithm, particularly for multi-robots foraging task is shown in Algorithm 2.

$$threshold_{upper} = \frac{1}{1 + \exp^{-0.5}} \quad (3)$$

$$threshold_{lower} = \frac{1}{1 + \exp^{0.5}} \quad (4)$$

Equation (3) and (4) are from [26] for both $threshold_{upper}$ and $threshold_{lower}$ values. These equations are used for determining the condition of the robot whether it is in excellent state or inferior state. When the robot is excellent, task should be successfully completed. Otherwise, robot is in inferior state and task cannot be completed. The inferior robot will wait for other robots to help it move the object until the time limit is reached. If the *timer* reaches the limit, robot will mutate its action. This mutation of action will occur to prevent system failure. Learning in the system took place from line 22 to 28 in Algorithm 2. Compared with the general immune algorithm, our proposed approach focused on the learning ability by applying learning from the somatic hypermutation concept in our approach. The overall system is expected to complete the foraging task faster since the robots learn to work cooperatively.

Algorithm 2 Immune Network with Learning

Require : t=0, $S_i(0) = s_i(0)$ = 0.5 for i=0...N-1, N is the number of actions, $timer$=0, $timer_{limit}$ = 5
Ensure: Ab with the highest concentration is executed
1: $Ab_{max} = Ab_1$
2: loop
3: Execute Ab_{max}
4: for i=0 to N-1 do
5: Calculate $S_i(t)$
6: Calculate $s_i(t)$
7: end for
8: if $S_i(t) > threshold_{upper}$ then
9: robot = excellent
10: else if $S_i(t) < threshold_{lower}$ then
11: robot = inferior
12: if robot encounters $robot_{excellent}$ then
13: for all i do
14: receive Ab_i
15: renew $s_i(t)$
16: end for
17: end if
18: end if
19: if Ab_i has max $s_i(t)$ then
20: $Ab_{max} = Ab_i$
21: end if
22: if (robot == inferior) then
23: if $timer > timer_{limit}$ then // mutate action
24: Ab_{max}=Ab_i that has second max $s_i(t)$
25: $timer$ = 0 // reset *timer*
26: end if
27: end if
28: $timer = timer$+1
29: t=t+1
30: end loop

V. Conclusion

This paper have explained the biological immune system, immune response and immune learning of somatic hypermutation. The connection of multi-robot system and immune system is shown in a table. In this paper, an immune inspired algorithm is presented based on Jerne and Farmer model. The extension of learning concept is integrated into the proposed algorithm for a foraging task. There are five actions involved in this task namely grouping, searching, collecting, homing and dispersion. The multi-robot system is expected to work faster as the proposed approach provided the learning ability into it. For future work, the proposed algorithm will be implemented in the multi-robot simulation platform known as ARGoS ([27] and [28]).

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References

[1] J.-M. Lien, S. Rodriguez, J.-P. Malric, and N. M. Amato. 2005. Shepherding behaviors with multiple shepherds. *Proceedings of the 2005 IEEE International Conference on Robotics and Automation, ICRA 2005*. April 18-22, 2005. 3402–3407.

[2] M. Dorigo. 2005. SWARM-BOT: An experiment in swarm robotics. *Proceedings of 2005 IEEE Swarm Intelligence Symposium, SIS 2005*. June 8-10, 2005. 192–200.

[3] B. Khaldi and F. Cherif. 2015. An Overview of Swarm Robotics: Swarm Intelligence Applied to Multi-robotics. *International Journal of Computer Applications,IJCA 2015*. 126(2):31-37.

[4] Z. Wang, M. Li, L. Dou, Y. Li, Q. Zhao, and J. Li. 2015. A novel multi-objective artificial bee colony algorithm for multi-robot path planning. *Proceedings of 2015 IEEE International Conference on Information and Automation, ICIA 2015*. August 8-10, 2015. 481-486.

[5] Y. Cai and S. X. Yang. 2013. A PSO-based approach with fuzzy obstacle avoidance for cooperative multi-robots in unknown environments. *Proceedings of 2013 IEEE International Conference on Information and Automation, ICIA 2013*. August 26-28, 2013. 1386–1391.

[6] H. Y. Liu and J. F. Chen. 2006. Multi-robot cooperation coalition formation based on genetic algorithm. *Proceedings of 2006 International Conference on Machine Learning and Cybernetics*. August 13-16, 2006. 85–88.

[7] J. Lin, B. Liu, and Z. Jie. 2009. Research on double omni-directional mobile robot cooperation transport. *Proceedings of Sixth International Conference on Fuzzy Systems and Knowledge Discovery, FSKD '09*. August 14-16, 2009. 145–150.

[8] C. S. Lim, R. Mamat, and T. Brunl. 2009. Market-based approach for multi-team robot cooperation. *Proceedings of 4th International Conference on Autonomous Robots and Agents, ICARA 2009.* February 10-12, 2009. 62–67.

[9] N. R. Hoff III, A. Sagoff, R. J. Wood and R. Nagpal. 2010. Two foraging algorithms for robot swarms using only local communication. *Proceedings of 2010 IEEE International Conference on Robotics and Biomimetics, ROBIO*. December 14-18, 2010. 123-130.

[10] N. Hoff, R. Wood, and R. Nagpal. 2013. Distributed colony-level algorithm switching for robot swarm foraging. *Distributed Autonomous Robotic Systems*. Springer Berlin Heidelberg. 83:417-430.

[11] A. O. Umut and B. Canberk. 2014. Immune inspired green auto-configuration model for self-organizing networks. *Proceedings of 2014 IEEE International Black Sea Conference on Communications and Networking, BlackSeaCom*. May 27-30, 2014. 38–42.

[12] Y. Tao and M. Hu. 2014. A fast immune recognition model based on immune response. *International Journal of Multimedia & Ubiquitous Engineering*, 9(11):85–89.

[13] S. Razali, Q. Meng, and S. H. Yang. 2009. Multi-robot cooperation using immune network with memory. *Proceedings of 2009 IEEE International Conference on Control and Automation, ICCA 2009*. December 9-11, 2009. 145–150.

[14] M. T. Khan and C. W. de Silva. 2008. Autonomous fault tolerant multi-robot cooperation using artificial immune system. *Proceedings of 2008 IEEE International Conference on Automation and Logistics, ICAL 2008.* September 1-3, 2008. 623–628.

[15] A. M. Whitbrook, U. Aickelin, and J. M. Garibaldi. 2007. Idiotypic immune networks in mobile-robot control. *IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics)*, 37(6):1581–1589.

[16] R. Hightower, S. Forrest, and A. S. Perelson. 1996. The Baldwin effect in the immune system: Learning by somatic hypermutation. *Adaptive*

Individuals in Evolving Populations: Models and Algorithms. Addison-Wesley. 159–167.
[17] H. N. Eisen. 1966. Learning and memory in the immune response. *Cancer research,* 26. (9):2005–2011.
[18] J. M. D. Noia and M. S. Neuberger. 2007. Molecular mechanisms of antibody somatic hypermutation. *Annual Review of Biochemistry*. 76:1–22.
[19] G. Teng and F. N. Papavasiliou. 2007. Immunoglobulin somatic hypermutation. *Annual Review of Genetics*. 41:107–120.
[20] A. Raza and B. R. Fernandez. 2015. Immuno-inspired robotic applications: a review. *Applied Soft Computing*. 37:490–505.
[21] N. R. Ramli, S. Razali and M. Osman. 2015. A conceptual model for multi-robot cooperation inspired by immune network theory and somatic hypermutation. *Proceedings of the 2015 IEEE Student Conference on Research and Development, SCOReD.* 13-14 Dec, 2015. 535-539.
[22] N. K. Jerne. 1985. The generative grammar of the immune system. *Bioscience Reports*, 5(6):439-451.
[23] J.D. Farmer, N. H. Packard, and A. S. Perelson. 1986. The immune system, adaptation, and machine learning. *Physica D: Nonlinear Phenomena*, 22(1):187-204.
[24] L. N. de Castro and J. Timmis. 2002. *Artificial Immune Systems: A New Computational Intelligence Approach*. Springer Science & Business Media. 53-108.
[25] S. Razali. 2014. *Immune systems inspired multi-robot cooperative shepherding*. PhD thesis, Loughborough University. Retrieved from https://dspace.lboro.ac.uk/2134/16361
[26] S. S. Joon, L. D. Wook and S. K. Bo. 2001. Artificial immune-based swarm behaviors of distributed autonomous robotic systems. *Proceedings of 2001 IEEE International Conference on Robotics and Automation, ICRA 2001.* May 21-26, 2001. 4:3993-3998.
[27] The ARGoS Website retrieved January, 30, 2016 from http://www.argos-sim.info/.
[28] C. Pinciroli, V. Trianni, R. O'Grady, G. Pini, A. Brutschy, M. Brambilla, N. Mathews, E. Ferrante, G. D. Caro, F. Ducatelle, M. Birattari, L. M. Gambardella and M. Dorigo. 2012. ARGoS: a modular, parallel, multi-engine simulator for multi-robot systems. *Swarm Intelligence*. Springer US. 6(4):271-295.