AISIMAM – An Artificial Immune System Based Intelligent Multi Agent Model and its Application to a Mine Detection Problem

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Abstract

Artificial Immune System (AIS) is a novel evolutionary paradigm inspired by the biological aspects of the immune system. The human immune system has motivated scientists and engineers for finding powerful information processing algorithms that has solved complex engineering tasks. This paper discusses two concepts. (a) The behavioral management of artificial intelligence (AI) namely the *intelligent multi agent systems*, (b) The evolutionary computation called the *artificial immune system* that imitates the biological theory called the immune system. The outcome of this research is an **A**rtificial **I**mmune **S**ystem based **I**ntelligent **M**ulti **A**gent **M**odel named ***AISIMAM*** that solves agent-based applications. The model is applied to a mine detection and diffusion problem and the results prove that ***AISIMAM*** has solved the problem successfully.

1 Introduction

The study of biological systems is of interest to scientists and engineers as they turn out to be a source of rich theories. They are useful in constructing novel computer algorithms to solve complex engineering problems. *Genetic algorithms* derived from the principles of genetics, *Neural Networks* derived from brain - nervous systems or neurology (Dasgupta & Attoh-Okine, 1997) and *cellular engineering* based on cell biology are some of the biologically motivated evolutionary algorithms that perform information processing tasks. *Immunology* as a study of the immune system (Elgert, 1996) inspired the evolution of *artificial immune system*, which is an area of vast research over the last few years. Artificial immune system imitates the natural immune system that has sophisticated methodologies and capabilities to build computational algorithms that solves engineering problems efficiently. The main goal of the human immune system is to protect the internal components of the human body by fighting against the foreign elements such as the fungi, virus and bacteria (Timmis et al., 1999). It is interesting to observe that the process of recognition, identification and post processing involve several mechanisms such as the pattern recognition, learning, communication, adaptation, self-organization, memory and distributed control by which the body attains immunity (Dasgupta, 1999).

AIS has made significant contributions to machine intelligence. Applications of AIS are not limited to *optimization, robotics, neural network approaches, data mining* and *image classification* (Hajela & Yoo 1999; Ishiguro et al., 1997; Hoffmann 1986; Hunt & Fellows 1996; Sathyanath & Sahin, 2001).

In this paper, we concentrate on *Multi Agent Systems (MAS)* and their characteristics. Multi agents are population of *agents*, (i.e.), more than one agent reacts to the change in environment to accomplish the task (Huhns & Singh, 1998). Multi agent systems are based on behavior management of several independent agents (M. Wooldridge, 1999).

The objective of the authors was to develop a biological based intelligent multi agent architecture. Multi agent systems have some features in common with the immune system and provide scope for applying immune system methodologies. Therefore, we have applied artificial immune system to multi agent systems for the computational intelligence of agents. The outcome of the research is a generic ***A****rtificial* ***I****mmune* ***S****ystem* based ***I****ntelligent* ***M****ulti* ***A****gent* ***M****odel* named ***AISIMAM***. The model draws an analogy between the immune system and agent methodologies. It applies the immune system principles to the agents to perform a global goal in a distributed manner. *AISIMAM* is applied to mine detection and diffusion problem, a specific application experimented to prove the model. This paper shows that *AISIMAM* solves the mine detection application successfully.

The organization of this paper is as follows. Section 2 presents a brief introduction to the immune system. Section 3 discusses agent definitions, characteristics of multi agents in problem solving. Section 4 focuses on *AISIMAM* with the mathematical derivations and explantions. Section 5 explains the need for the mathematical representation and Section 6 demonstrates the application of *AISIMAM* to a mine detection and diffusion problem. In Section 7 we state the new aspect of this research and in Section 8 we state the scope for future work. Section 9 summarizes the conclusion derived out of this research work.

2 The Human Immune System

The natural immune system is a very complex system with several mechanisms for defense against infectious agents entering our system. The external components to the immune system are *antigens* or called the *non-self cells*, as they are foreign substances to the body. The basic components of the immune system are the white blood cells, called *self-cells* or *lymphocytes* in immunological terms. These specialized cells are classified into two types namely the *B lymphocytes* and *T lymphocytes*.

- *B-lymphocytes* are the cells produced by the bone marrows
- *T* cells develop in bone marrow and mature in *thymus*

The major responsibility of the *B* cells is the secretion of the receptors called the *antibodies* (*Ab*) as a response to the *antigens* that enter the body (*Ag*) (Hajela & Yoo, 1999). The role of these receptors on the surface of the *B* cell is to recognize and bind the antigen. These receptors are called *idiotopes* and *paratopes*. Antigens also have receptors called *epitopes*. The *B* cells generate antibodies of *complementary match* that recognizes and binds the antigen (Castro & Von Zuben, 1999). Complementary match means the generation of an opposite shape or structure that fits well with the antigenic epitope to recognize the antigen. The receptors of the *B* cell change their shape according to the shape of the epitope (Timmis et al., 1999). Figure 1 shows the *B* cell, *B* cell receptors and the epitopes of the antigen.

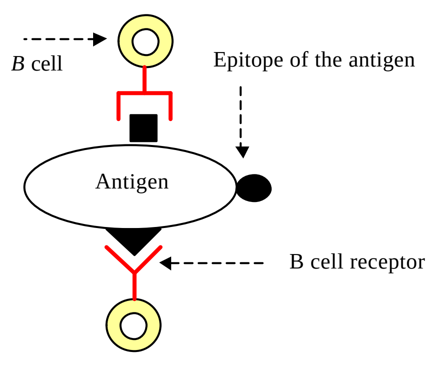

Figure 1: *B* cells, *B* cell receptors, antigen, and epitopes.

2.1 Properties of the Human Immune System

This section briefly discusses some of the properties of the immune system by which the human body attains immunity. The main function of the immune system is to kill the antigen. It is interesting to note that this common goal of the system is handled by the individual components of the immune system in a distributed fashion. At the same time they also have remarkable properties with which they work collectively to perform the task.

The immune system possesses the following properties.

- *Positive and negative selection* is a process of discrimination of self/non-self cells that prevents autoimmuno diseases. This process filters out the cells that would work against the self-cells and only the cells that would not bind the self-cells circulate to fight against the antigens (Dasgupta, 1999).
- *Clonal selection and expansion* is a process of selection of useful cells that recognize the antigen and reproduce those cells. This process of *cloning* multiplies the useful cells that are capable of recognizing the antigens. Therefore, the *B* cells that contain the specific receptor that match a particular antigen are also multiplied. In this process, the clones suffer *hypermutation* that alters the shape of the receptor also called *receptor editing*, thus increasing the affinity between the clone and the specific antigen (Burnet, 1978; Dasgupta, 1999).
- *Immune memory* is a result of clonal expansion. Some of the cloned cells differentiate into *memory cells* and the rest of the clones become *plasma cells*. *B* cells remember the shape of the antigen that they have fought and recollect when they see the same antigen again. This process defined as *secondary response*, is a feedback of the past event for a current input. This process helps the system to learn and is called as *reinforcement learning*. Plasma cells produce cells with higher affinities (Castro & Von Zuben, 1999).
- *Jerne's idiotropic network* deals with the interaction of antibodies. Jerne's network is a network of *B* cells that communicate the shape of the antigenic epitope amongst them through idiotopes and paratopes. This also transforms the receptors according to the antigenic pattern. This shape transformation is an important role of information transfer and communication between the *B* cells (Jerne, 1984).

Figure. 2 show the overall functioning of the immune system. The immune system recognizes the antigens and the antigenic patterns are identified. On identification of an antigenic pattern, the *B* cells communicate the information in parallel to each other by means of paratopes and idiotopes in the network. Paratopes match with the epitopes of the antigen to recognize the antigen. Paratopes also change their shape to strengthen the bond between the epitope and the paratope. However, the binding stays only for a short time called the *tolerization period* (Hofmeyer, 2000) within which a number of receptors should bind the antigen. When this process of binding within a short period happens, the *B* cells gets activated and performs a set of actions to kill the antigen (Hofmeyer, 2000). On activation, every *B* cell responds by changing the shape of the receptor according to the antigenic epitope. *B* cells that have higher affinity towards the antigen are the ones that recognize the antigen. The useful cells undergo multiplication by clonal expansion and produce high affinity cells or clones. Since the antigen has multiple epitopes and the *B* cells are *monospecific* (Castro & Von Zuben, 1999) with a single type of receptor, *B* cells work together to kill the antigen through immune network. Part of the clones differentiate into plasma cells that create higher affinity cells and the rest turn out to be memory cells that remember the antigen that was destroyed. Thus the human system attains immunity against the antigens.

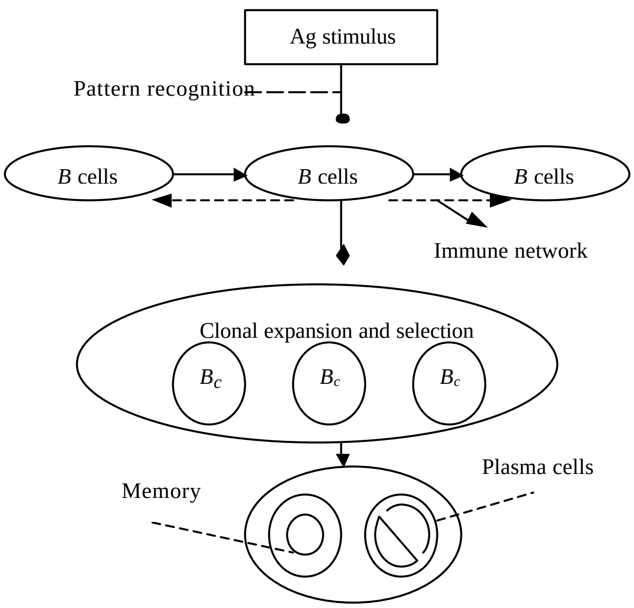

Figure 2: Representation of the human immune system.

3 Multi Agent Systems

Multi agent systems (*MAS*) deal with the behavior management in collection of several independent entities, or *agents* (Wooldridge, 1999). There are several definitions for agents. We have chosen two definitions of agents.

- Nwana and Ndumu defined an agent as "a component of software and/or hardware which is capable of acting in order to accomplish tasks on behalf of its user" (Nwana & Ndumu, 1997).
- Agents that operate robustly in rapidly changing, unpredictable, or open environments, and where there is a significant possibility that actions can fail are known as *intelligent agents* or sometimes called *autonomous agents* (Bond & Gasser, 1998).

Agents can exist alone or in a society of agents called *multi agents* (*MAS*). Multi agents are a population of agents, that is, more than one agent can change the environment to accomplish the task. They are distributed computational systems (Cho & Tae-Lim, 2001) in which each agent in MAS has a list of individual goals or tasks that it will perform. At the same time, MAS has global goals that all the agents will strive to achieve where the individual efforts of each member agent are put together toward reaching the MAS's global goals (Huhns & Singh, 1998). The advantage of the MAS is that the limitations of the individual capabilities of the agents are eliminated (Abul et al., 2000). Agents with a fixed goal learn how to change the environment to achieve the end goal. This process is called *reinforcement learning* in agents. In order to achieve an independent and global problem solving, the agents behave according to its defined characteristics. Some of the characteristics of agents that define their behavior are autonomy, friendliness, reasoning, learning, communication and coordination mechanisms. Similarly, there are different environments according to which the agents perform the goals. The multi agent environment is usually open, decentralized, and contains autonomous agents (Huhns & Stephens, 1999). In summary, agents are entities with well-set goals, actions and knowledge in an environment that senses, communicates, coordinates, learns and makes decisions according to the environment (Cho & Tae-Lim, 2001). The following section briefly describes some of the characteristics of the agents and different kinds of environment (Mohammed, 2000).

3.1 Characteristics of the Agents and the Environment

The characteristics of the agents are as follows.

1. Autonomy in agents is a measure of self-sufficiency. The agents that operate on their own are *independent* agents, and if they are restricted by external influences then they are called *controlled* agents.
2. Sociability is a behavioral measure of an agent to think about itself or about others. An *altruistic* agent acts regardful of others benefits, and is unselfish. In contrast, an *egoistic* agent acts with excessive thoughts of self and is self-loving.
3. Agents could be friendly and be *cooperative* or *compete* with each other.
4. Agents are classified into *reactive* and *deliberative* according to their level of *cognition*. The former ones sense and react in a timely manner for an environmental change and the latter ones reason out before making actions.
5. Mobility determines if the agents are *stationary* or *itinerant*. Stationary agents do not move and itinerant agents are mobile. Other characteristics of the agents that deal with the agent's adaptability, rationality and locality can be referred to the literature (Mohammed, 2000).

An agent may have a problem in deciding which of its actions it should perform in order to best satisfy its design objectives. The complexity of the decision making process can be affected by a number of different environmental properties. The following are various environments stated by Russell and Norvig. (Russell &

Norvig, 1995; Mohammed, 2000).

An *accessible* environment is one in which the agent can obtain complete, accurate, up to date information about the environment's state. The more accessible an environment is, the simpler it is to build agents to operate on it. Complex environments like the physical world are defined as *inaccessible* environments.

There are also other kinds of environments. *Deterministic* environment and *non-deterministic* environment deals with the certainty of agent's action. *Episodic* and *non-episodic* environment deals with the performance of agent's in discrete episodes without any links or linked actions with the past and current data respectively.

4 *AISIMAM* - Artificial Immune System Based Intelligent Multi Agent Model

The backbone of *AISIMAM* involves imitating the human immune system in terms of features and functions in multi agent systems. The motivation for this research comes from the fact that artificial immune system has found solutions for several applications. In the same context agent based solutions have also been developed in different application domains (Cho & Tae-Lim 2001, Abul et al., 2000). The reason for developing the *AISIMAM* is due to the similarities observed between the immune system architecture and the architecture of the agents. The distinct similarities between the agents and the immune system are

- Both are distributed or decentralized systems
- Both have multiple autonomous entities
- Both have individual and global goals
- Both systems learn from their experience
- Both are adaptable
- Both sense the changes in the environment and act accordingly
- Both systems communicate and coordinate
- Both possess knowledge with which they make intelligent decisions.

Therefore, immune system based multi agent architecture is derivable. The following section describes the multi agent systems with necessary comparisons and explanations.

4.1 Comparison of AIS and Multi Agent System Parameters

The model defines the non-self cells (antigens) and self-cells (*B* & *T* cells) as two agents with different characteristics and goals. Therefore, the two types of agents in *AISIMAM* are

- Antigens are modeled as non-self agents (*NAGs*) and
- Lymphocytes or self-cells corresponds to self-agents (*SAGs*)

We define the *environment* to be a matrix in which both the *NAGs* and the *SAGs* operate. The environment can be any one of the types of environment explained in section 3.1 depending on the application. We assume that there is an information vector for each non-self agent. This could represent a disturbance in a process, malfunction or a virus in a computer network depending on the application. The information vectors correspond to the epitopes of the antigen. Similarly, each self-agent has an information vector that defines the self-goals. The information vectors correspond to the receptors of the lymphocytes. The information vector can contain a single datum or multiple data. For example, the information could be a location information, identification number, text information, or all of them depending upon the application. We consider this information to be the idiotopes and the paratopes. However, the model does not distinguish between the paratopes and idiotopes. Instead, the target will be to perform the end goal with the available information by each self-agent. The end goal could be destroying the non-self agent as the antigen is killed in the IS, or it can be to identify the best action sets of each self-agent to react to the non-self agent's action vector. This is however problem dependent.

The information vectors and the characteristics of the self and the non-self agents differ from each other. This is similar to the structures of the epitopes of the antigen and the paratopes of the lymphocytes. In other words, the agents perform individual actions or goals determined by the *action generator* function and the global goal is the coordinated actions of the individual *SAGs.* The individual action of the agent corresponds to the receptor shape change in a *B* cell and the coordinated actions correspond to a group of *B* cells killing the antigen.

The *SAGs* are assumed to have sensory capability to identify the *NAG* within a region called *sensory neighborhood*. They also possess the capability to communicate the *NAG* information to the other *SAGs* within a region called *communication neighborhood*. The model assumes that the communication neighborhood is greater than the sensory neighborhood. This is in comparison with the capability of the *B* cells to recognize the antigenic pattern within a particular neighborhood. In immune system, the communication circle is analogous to communication between *B* cells connected in the immune network (Jerne's Network). In other words, every *B* cell communicates the information to another *B* cell that is within the communication neighborhood in the immune network.

The agent model describes five stages of processing namely *Pattern recognition, Binding process, Activation process, Post activation process and Post processing.*

In pattern recognition, *SAGs* recognize the presence of the antigen by the *stimulation function* and identifies the *NAGs* by an *identifier function*. The model defines an *affinity function* that calculates an affinity value between the actions of the self and the non-self agents. This process is defined as *binding process*. In the immune system, the affinity is proportional to the binding between the *B* cell receptors and the epitopes. The affinity calculation in the agents is similar to the affinity between the epitope of the antigen and the receptor of the antibody. However, the binding is not modeled separately in *AISIMAM*. For instance, the affinity function could be a distance metric such as the Euclidean distance.

In order to imitate the IS, in the activation process we choose the affinity values that are greater then a set *activation threshold*. Activation threshold will help the agents to find out the higher affinity actions called *mature actions* that are closer to the desired goal. Here, we define the *binding period* as the time taken by a number of agents to bind the *NAG*. The model defines this time as a sum of *recognition time* and *grouping time*. Recognition time is the time taken by every agent to recognize the *NAG* and is the same for every agent. The grouping time is the time taken by the other agents to react to the identified *NAG* and this time differs from agent to agent.

The post activation process involves cloning. Here, the agents are reproduced with the mature action. A part of these *cloned agents* differentiate into *memory agents* containing the matured action obtained as a result of a particular *NAG*. The rest of the clones become *plasma agents* that create higher affinity actions through the action generator function. Post processing involves the primary and secondary response of immune memory, which is also included in the model. Hypermutation in agents is the process of generating new actions exists conceptually. Once the end goal is reached, memory agents remember the actions performed to reach the goal.

All the self-agents work in an *agent network* similar to Jerne's network. The process of information transfer and communication between the agents is an analogy of the agent network to the immune network. The nature of the agent network is application dependent. Suppression in the agent network is determined by the *suppression function*. In immune system, even in the absence of the antigenic stimulus, the *B* cells perform suppression. In *AISIMAM*, in the absence of antigenic stimulus suppression is performed. The overall representation of the *AISIMAM* is shown in Figure 3.

4.2 *AISIMAM* - Operational Scheme and the Mathematical Representation

This section deals with the notations used in the model, followed by the definitions of the parameters, and the algorithm.

4.2.1 Parameter Definitions

In the model, we define the agents namely the self agents (*SAGs*) and represent them by S_i, where $i = 1, 2 \ldots N$ and the non-self agents (*NAGs*) as N_j where $j = 1,2 \ldots M$. We define the problem domain or the environment E by $E = S_i \cup N_j \ \ \forall\, i, j$. For all S_i ' E, there exists an information vector of n elements given by $B^i = [b_1, b_2 \ldots b_n]$. For all N_j ' E, there exists an information vector of m elements given by $A^j = [a_1, a_2 \ldots a_m]$. Define T_a to be the activation threshold.

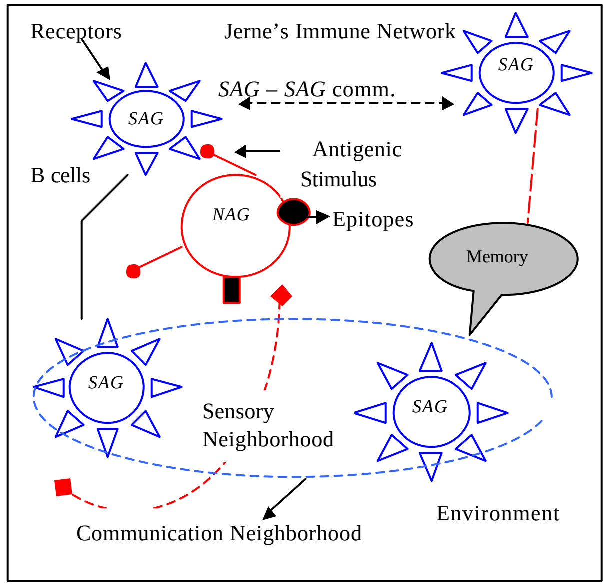

Figure 3: Representation of *AISIMAM* – An AIS based Intelligent Multi Agent Model

4.2.2 *AISIMAM* - Algorithm

Initialize all the parameters defined as above

For each S_i

- Calculate $M_{j,i} = f_1(A^j, B^i)$ where B^i is the information vector of S_i, and A^j is the information vector $\forall\, N_j$ in the sensory neighborhood N_s

$$f_1(A^j, B^i) = \begin{cases} 0 & \text{if no } A^j \\ \neq 0 & \text{if } \exists \text{ an } A^j \end{cases} \text{in } N_s$$

- **If** $(M_{j,i} \neq 0)$
  - o The information about the *NAG* is transmitted to the other *SAGs* through the immune network
  - o **For** each *NAG* N_j, within the N_s, the sensory circle where $j = 1, 2 \ldots e$, and e£ M

1. Pattern Recognition and Identification

Identify the *NAG* using the identifier function I that is given by

$$I_j = f_2(A_j)$$

Generate possible new actions $U_j^i \ldots\ldots U_k^i$ using action generator function that is a function of I_j

$$U_j^i = f_3(I_j) \text{ where } j = 1 \ldots k$$

2. Binding Process

Find the affinity for all possible vectors U_j^i by the affinity function

$$Af_j^i = f_4(U^i{}_j), \forall j = 1...k$$

3. Activation Process

Choose mature actions whose affinity is greater than activation threshold T_a and store in the action set Y

$$Y = \{U_j^i \mid Af_j^i > T_a\} \text{where } j = 1,2......p$$

- The activation of the mature actions within the binding period t_b is given by

$$U_j^i = f_5(Y, t_b) * [u(t) - u(t - t_b)]$$

where $u(t)$ is the unit sep response

$$f_5(Y, t_b) = \begin{cases} 0 & \text{if no activation} \\ \neq 0 & \text{if } \exists \text{ activation} \end{cases}$$

If a best action needs to be chosen, the threshold should be chosen so high that $p = 1$.

4. Post activation processing - Cloning

If $(U_j^i \neq 0)$

In this case, **agents are reproduced** with mature action set Y in *SAGs*. S_i is cloned with mature action set Y to generate q *SAGs*.

S^c where $c = N+1, ..., N+q$

End If

5. Post processing - Memory

Choose s number of memory agents M_z^a from the cloned agents

If $(U_j^i \neq 0)$

$M_z^a = S^c$

where $z = N+1, \cdots, N+s$, where $s < q$

- **Memory Response**

The efficiency of the primary and secondary responses are given by

$$h_p = f_6\,[N_p, T_p]$$

$$h_s = f_7\,[N_s, T_s]$$

where $T_p >> T_s$ and $N_p << N_s$ and N_p and N_s are the number of actions required to kill the *NAG* in the primary response. T_p & T_s are the time taken for the primary and secondary responses respectively. The efficiency of the primary and secondary responses is h_p and h_s respectively.

- **Plasma Response**

Rest of the clones are defined as plasma agents S^z where $z = N+s+1, ..., N+q$. Here q-s agents are added into the system.

End If

End For

Else perform suppression by the suppression function

$P_{i,j} = f_8(B^i, B^j)$ where i, j are of S_i and S_j

End If

End For

5 Need for a Mathematical Representation

The goal of *AISIMAM* is to provide a mathematical representation for the operation of immune system. Several immune modeling such as the immune network model (Castro & Von Zuben, 2001), negative selection algorithm (Dasgupta), mathematical modeling of the clonal selection (Chowdary, 1999) and immune memory (Smith et al., 1996) agent based immune systems (Mori, Tsukiyama and Fukuda 1997, Dasgupta 1998) exist in the literature. *AISIMAM* differs from the other models in the context of mathematical functions defined for the entire process. In order to prove the usefulness of the representation, two applications namely bar code recognition and mine detection are compared.

In the case of barcode recognition, assume that the non-self agents N_j or antigens are the characters to be recognized. The B cells are the software agents S_i whose information vector contains the corresponding *ASCII* characters. Each agent has a defined group of characters. Environment E has the information about the recognized and the unrecognized characters. If the agent can recognize the character, recognition is achieved. Otherwise the agents can communicate through the environment to find if the unrecognized character falls into its category. The stimulus M is defined by the recognition of the start bit pattern of the barcode that defines the start of the recognition process. The identifier function I is a character recognition function. The affinity function Af can be defined as the matching function between the recognized character and the character in the agent's information vector. Affinity threshold T_a can be set to 1 that chooses the best match. In this case cloning is not utilized. Thus the agents are not reproduced. In this application, sensory and communication neighborhood is zero, since the agents are not in a space.

In the case of mine detection application, non-self agents are the mines and the mobile robots are the self-agents. In this case, both are hardware agents. The sensory and communication neighborhoods are defined by the distance metric. The identifier function I becomes finding the mine by the identifier and the location of the mine. The affinity function Af is the Euclidean distance. Affinity threshold T_a can be set to a predefined value. Mine detection application is explained in detail in the following paragraphs.

As can be seen above, the model can be applied to different applications by changing the functions. Therefore, the generalized functions provide a global representation for several agent based applications.

6 Application of *AISIMAM* to a Mine Detection Problem

To experimentally verify the architecture, *AISIMAM* is applied to a specific problem. The problem implemented is mine detection and diffusion. The experiment is simulated in MATLAB. The following section discusses the parameters of *AISIMAM* used for this specific application and the pseudo code for the problem.

6.1 Parameter Definitions

The following section briefly describes the characteristics of *NAGs*, *SAGs* and environment for mine detection.

6.1.1 *NAGs* and its characteristics

The antigen or the Nonself agent (*NAG*) is the mine. Define the area to be explored for detecting the mine. This defines the boundary of the environment for the agents to detect the mine. Mines are deployed in a uniform distribution within the environment. The initial locations correspond to the epitope or the receptor of the antigen. Characteristics of the mines are stationary, unfriendly and competitive. Circling the mine is defined as diffusing the mine.

6.1.2 *SAGs* and its characteristics

Define the *B* cells to be the self-agents (*SAGs*). Deploy all the *SAGs* in a uniform distribution within the environment. The initial locations of the *SAGs* correspond to the receptors of the *B* cells. Characteristics of the *SAGs* are itinerant, independent, cooperative, altruistic and deliberative.

In mine detection application, it is assumed that the environment is accessible and the self-agents get updated information about the environment.

Assume that all the *SAGs* have the capability to sense the mine and communicate between the agents within the sensory and communication circles respectively. We have used Euclidean distance measure for both the cases. Every *SAG* (robot) recognizes the mine and identifies the location of the mine within this sensory circle. On identification of the *NAG* (mine) every *SAG* communicates to the other *SAGs* in a Jerne's network. For this problem, we have assumed Jerne's network as a broadcast network. It is also assumed that the communication between the *SAGs* is larger than the capacity of every *SAG* to sense the *NAG*.

6.1.3 Pseudo Code For The Mine Detection Problem

The pseudo code for the mine detection problem is as follows.

1. Initialize the *SAGs* and *NAGs* in a uniform distribution.
2. diff_use = 0; (Initially there is no diffusion)

2.1 **While (**diff_use $\neq$ number of_mines, N_i**)**

2.2 **For** each *SAG* S_j, do the following

If (there is a mine within the sensory circle)

a) Identify the location of the mine

b) Inform the locations of the mines to the other self-agents within the communication circle. This corresponds to the communication through the immune network.

c) *SAG* generates new actions that are eight different new locations to move

d) Find out the distance (affinity function) between these locations and mine locations. The Affinity is calculated by the Euclidean distance between the generated locations and the robot location.

e) Choose the distance that is lesser than an affinity threshold and move to that location.

f) **If** (this location is the mine location)

If (there are 4 *SAGs* around the mine*)*

Diffuse the mines, update the number of mines diffused, (diff_use = diff_use + 1);

If (diff_use == number of mines),

Break; End If; End While

STOP

Else wait until there are four *SAGs* around the mine; **End If**

Else do step 2.2. c. End If

Else If (there are any self-agents within the Communication circle)

- **If** (non-self information is available) repeat from step 2.2. **End If**

Else Make random movements from the current location, since there is no *NAG* information from other self-agents and no mine detected within the sensory circle

End If; End For; End While; STOP

Memory is not used in this problem since there is no usefulness in remembering the location of the mine once it is detected and diffused.

6.1.4 Simulation Results

We assume that a priori knowledge of the minefield intensity is known in the given environment. In the simulation, this means that the number of mines in the given environment is known. Therefore known number of mines is deployed in a uniformly distributed manner in the given area. This creates the minefield. We also deploy a known number of mobile robots in a uniformly distributed manner in the environment. The simulation differentiates the mobile robot and the mine by using a '+' for a mine and a 'o' for robots for representation while the code identifies a mine by a '0' and the robot by a '1'. The information vector for the mine and the robots contain the initially deployed location information along with the identifier. Table 1 shows an example of the mine and the robot information vector. The simulation also requires setting the sensory circle of the robot and the communication circle. We have assumed that the communication circle is greater than the sensory circle.

Table 1: An Example of Information Vector of Mines and Robots

	X coordinate	Y coordinate	Identifier
Mine	4	5	0
	3	7	0
Robot	2	3	1

The simulation is verified for the following variations.

- By increasing the sensory range from 3 to 9 units of distance measure.
- The communication circle was varied between 5 and 11 units of distance measure.
- Changing the environments area to 10 x10 and 32 x 32 rectangular grids.

Here, the environment is accessible where each *SAG* has the information about the mines and the other *SAGs* in the sensory and communication neighborhood. That is, on identification of the mine, *SAGs* within the communication circle exchange about the number of mines detected and their respective locations through the agent broadcast network. A sample environment vector is shown in Table 2. It can be seen from Table 2 that the robot 1 has the information about mine 1 that is accessible to robot 2 if it is within the communication circle because robot 2 checks for the information available with robot 1 since it has not identified any mines. However, the environment becomes inaccessible on the assumption that the environment is not updated or when the communication circle is zero (c_cir = 0). It is useful to make the environment accessible in practice because, the mobile robots for mine detection can be provided with the capability to communicate.

Table 2: An Example of the Environment Vector

Index	Coordinates (Initial) X	Y	Identifier	No of mines detected	Detected Mine locations
Mines 1	3	7	0	0	--
2	4	5	0	0	--
Robots 1	2	4	1	1	4,5
2	5	2	1	0	--

The experiment is repeated for different populations of mines and robots. The typical range for the mines deployed are varied between 10 and 70 and accordingly and the robots are varied between 40 and 100. Figures 4 and 5 show the simulation with mines and robots with their initial locations and the four agents surrounding the mine. The following results prove that *AISIMAM* is able to solve the mine detection problem successfully.

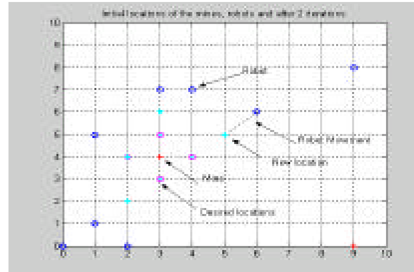

Figure 4: The locations of mines and robots after 2 iterations

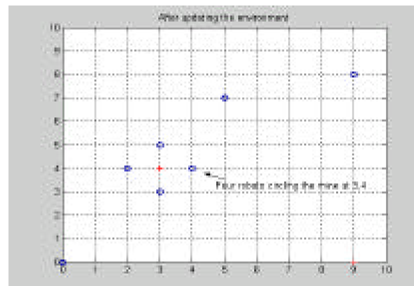

Figure 5: Four robots have circled one mine after three iterations

6.1.5 Observations

The following cases are studied and results are shown below.

a) For an increase in the population of mines and increase in population of robots the computational complexity in terms of rate of convergence (or the number of steps needed for the algorithm to converge) is studied. For an environment size of 32x32 and a constant sensory and communication circles, the individual rates of convergence are shown in Figures 6 and 8 and the average convergence rate can be seen in Figures 7 and 9. In Figures 6 to 9, x-axis is the number of mines, y-axis is the number of agents and z-axis is the number of iterations.

b) For an increase in the sensory region and communication region the computational time in terms of rate of convergence is studied. Increasing the sensory and communication circles reduce the required the number of steps for the algorithm to converge. This is due to the fact that robots senses more area and can communicate with more robots and check if others have mine information if they cannot find any.

The experiment is repeated for the same number of mines and number of robots with a step increase in the sensory and communication circles in the following combinational pairs (3,5), (5,7), (7,9) and (9,11). The number of iterations for a chosen value of robots and mines can be seen in Figures 6 and 8. The Figures 7and 9 shows the average number of iterations for sensory and communication circles to be (5,7) and (7,9). However it was observed that increasing the sensory and communication circle reduces the average number of iterations for the algorithm to converge.

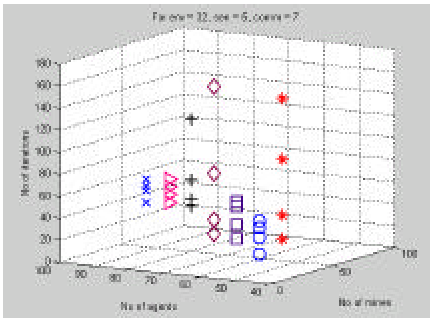

Figure 6: The rate of convergence for variation in mines and agents for 32x32, sen_c = 5, c_cir = 7

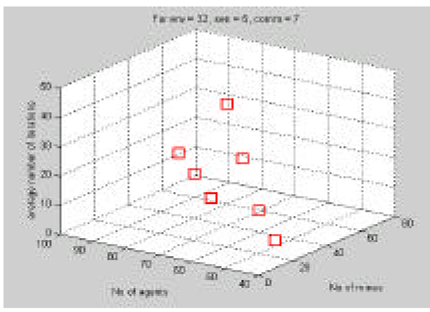

Figure 7: The average rate of convergence for variation in mines and agents for 32 x 32, sen_c =5, c_cir = 7

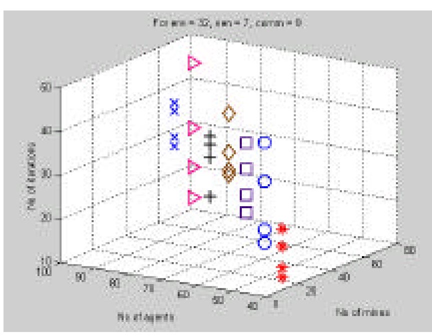

Figure 8: The rate of convergence for variation in mines and agents for 32 x 32, sen_c = 7, c_cir = 9

7 New Aspect of the Work

Literature survey shows that there are several applications on Artificial Immune Systems and Multi Agent Systems independently. Some of the recent work also addresses some of the properties of AIS to agent systems to solve a particular task (K. Mori, M. Tsukiyama and M. Fukuda 1997, D. Dasgupta 1998). *AISIMAM* is a generic model that provides to define the *SAGS* and *NAGS* in terms of functions to be determined by the applications. Individual goals and a global goal for the agents can also be defined by the functions. The model is flexible and unique because the parameters of the model can be changed by the formulated functions depending on the application.

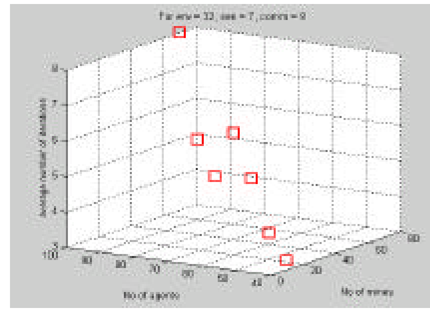

Figure 9: The average rate of convergence for variation in mines and agents for 32x32, sen_c =7, c_cir = 9

8 Future Work

A mathematical representation of the immune network is expected to be added in the future. Further conclusions can be arrived from the following additions. In the mine detection application,

a) We have assumed that the robots themselves do not get destroyed in the detection and diffusion process. But in practice, a robot can fall on the mine during deployment. So in future, the algorithm can be modified to analyze the case of robot falling on the robot while deployment and call that *failure rate analysis*.
b) Another assumption is that the *NAGs* or the mines in this application are static. This is true because in practice all the mines are static. In future applications, the *NAGs* could also be dynamic and hence the experiment can be repeated for the agent behavior.
c) Also, in the mine detection application, the memory is not used. This is because, there is usefulness in remembering either the location information of the mine or the type of mine itself. In future, we can redefine the application more specific by employing different functions for different kinds of mine. In this process, memory will be helpful in remembering the information about the type of mine that could be useful rather than the location information.

9 Conclusion

This research draws a generic model named *AISIMAM* based on artificial immune system applicable to intelligent multi agents. An application for the model is simulated. The mine detection and diffusion problem is experimented and the results show that *AISIMAM* is successful. The motivation for this application is that in future the mine detection can be performed efficiently by deploying mobile robots that have enough intelligence, communication and coordination to detect and diffuse the mines. To verify the generality of the model, more applications will be simulated and verified in the future. This research is conducted with the support of Gleason R&D Funds in Multi-agent Bio-Robotics Lab (MABL) at Rochester Institute of Technology.

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