Similarities and Sensitivity: Immune and Ant Algorithms Applied towards Robotics

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***Abstract*—Over the last five and a half decades, the focus of mainstream artificial intelligence was on creating computers and algorithms that display some human cognitive abilities. Over time, bio-inspired artificial intelligence has shown great success. The ideas of bio-inspired artificial intelligence are taken from biological systems and applied to solve artificial intelligence problems. The future robots and computational devices will have diverse artificial systems including immune systems. The current paper studies the similarities between Ant-based algorithms and Artificial Immune Systems and their further steps in the development of robots. We study the sensitive approaches and several related robotic applications solved by means of both presented algorithms.**

I. Introduction

For the past 55 years, mainstream artificial intelligence focused on creating computers and algorithms that display some human cognitive abilities. Over the time, bio-inspired artificial intelligence (where ideas are taken from biological systems and applied to solve artificial intelligence problems) has somewhat departed from its original source of inspiration (biological intelligence) and has become more concerned with specific tasks such as efficient signal processing, data mining, and optimal control.

Mainstream artificial intelligence has been successfully designing algorithms and devices that solve problems that most humans are not very good at. Examples are games such as Chess, Jeopardy, Go; in the robotics area tasks such as controlling aircraft dynamics; in domains such as bioinformatics where the interest is on finding 3-dimensional structures of proteins. Solving such specialized tasks took away time to focus on the fundamental aspects of biological intelligence such as evolution and learning, behavioral autonomy, and physical embodiment that make biological systems prone to errors, and thus, makes it difficult to make predictions in particular in unknown and changing environments.

During the mid 1980s, a renaissance was witnessed with diverse approaches in order to understand and engineer intelligent systems. Many new fields emerged such as neuromorphic engineering, embodied cognitive science, artificial life, evolutionary robotics, and swarm intelligence. All these new fields have in common that they questioned the validity of the assumptions made and methods applied by mainstream artificial intelligence for creating artifacts that could approximate the operational characteristics and performance of biological intelligence.

Research in artificial intelligence changed around the turn of the millennium where we saw an expansion of the focus of attention from human brains and cognitive reasoning to a wider range of organisms, processes, and phenomena that occur at spatial and temporal scales. This change in focus was not only based on the ‘philosophical’ revolution, but also the technological revolution that we have seen over the recent past. The technological revolution in terms of computational speed as well as memory allows for bigger problems to be solved. Now artificial intelligence systems [18] can embed intelligence into devices, for example, cell phones, mobile robots and intelligent prostheses [9].

Artificial Immune Systems (AIS) is an adaptive system inspired by *Biological Immune System (BIS)* introduced by Dasgupta & Nino [5]. It exhibits intelligence in terms of self-organization, learning, adaptation, recognition, robustness, scalability, theoretical immunology, and observed immune models, which are applied to problem solving; see more details [3], [15]. Immune algorithms are applied in the robotics domain, see [34], [35], [36].

Ant Colony Optimization (ACO) is a bio-inspired metaheuristic described by Dorigo & Stützle [6]. Recently, ant colony algorithms were used to solve the traveling salesman problem with the human-in-the-loop approach [17]. *ACO* has many applications in combinatorial optimization both in theoretical and real complex problems. Robotics is using features of *AIS* and *ACO* in order to make the robots more sensitive to the environment and to learn to adapt their behavior. Robotics applications are inspired by the way *immune systems* and *ants* learn to adapt to pathogens and respectively to the environment by indirect communication. The robots could use signals inspired from ant algorithms where the “signal” is the pheromone trail, and from artificial immune systems where it is used as an antigen signal or a co-stimulatory signal to finally output evolved antibodies or mature dendritic cells as actuation signals. The current paper uses a particular ACO, the *Ant Colony System (ACS)*. Nowadays, ant algorithms are used in robotics [11], [31], [16], especially in route planning and spatial coverage.

Our paper is organized as follows. Section II describes a hybrid technique, called *Sensitive Robot Metaheuristic (SRM)* based on the *Ant Colony System* with autonomous mobile robot features. Section III gives a brief review of *Artificial Immune System*. In Section IV, we study the similarities between the proposed systems. Sensitivity in the Immune Network is tackled in Section V, which includes an existing model of sensitivity in AIS. In Section VI, we present several examples as well as discuss the sensitivity mechanisms of the Immune and Ant Colony Systems. Finally, the conclusions are given in Section VII.

II. Sensitive Ant System towards Robotics

In Pintea et al. [22] a sensitive metaheuristic is introduced, namely a robotic system inspired by an ant-system for solving a large optimization problem, the drilling problem. The metaheuristic addresses difficult problems including a robotic travel problem by optimizing the drilling operations time on the printed circuit board. The hybrid technique called *Sensitive Robot Metaheuristic* was based on the *Ant Colony System* [7] with autonomous mobile robots features. A collection of robots endowed with a *Stigmergic Sensitivity Level (SSL)* was used. A short notations is used here: *Sensitivity Level (SL)*. Stigmergy provides the following mechanism: an individual robot behavior modifies the environment and the environment will in time modify the behavior of other individuals.

The robot communication relies on local environmental modifications that can trigger specific actions. The set of micro-rules used by a colony of stigmergic robots defines the behavioral repertoire of the group of robots; see [8] for more information.

Sensitive robots refers to artificial agents with a *Sensitivity Level (SL)*; $SL \in [0,1]$. The extreme situations are: $SL = 0$ indicates that the robot completely ignores stigmergic information (is a 'non-stigmergic' robot); $SL = 1$ means that the robot has maximum stigmergic sensitivity.

The independent explorer robots are considered the ones with small *SL* values, *sSL*; their role is to sustain diversification. The exploiters robots are the robots with high *SL* values, *hSL*; their role is to intensify the search in a promising space. The robots will change their sensitivity level based on their encoded "experience". In the same context, Figure 1 shows how the sensitive agents are grouped in the *Sensitive Ant algorithm for Denial Jamming Attack on Wireless Sensor Network* [26].

A generalization based on agents was also proposed [27]. The *Sensitive Agent Algorithm for Jamming Attack on Wireless Sensor Network* (*SAA-DjaWSN*) includes indirect, artificial "pheromone" and direct communication between agents through *Agent Communication Language ACL* messages [13], information related to the security attacks and the routes found. A conceptual model for sensor networks security based on sensitive robots agents was introduced in [23].

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Fig. 1. Illustration of grouping sensitive agents based on their level of sensitivity (SL): agents with a high level of sensitivity, *hSL* and agents with a low level of sensitivity, *sSL* [26], [27]

The *Hybrid Sensitive Robot Algorithm for Intrusion Detection* was used to solve the intrusion problem; see the general description in Algorithm 1. For further details we refer to [23] and discussions about this hybrid approach are presented in Section VI-B.

Algorithm 1. Sensitive Robot Algorithm

```
Set parameters, initialize stigmergic values of the trails
while not chosen all robots do
    Place a robot on a randomly chosen node from a randomly chosen cluster
    while not chosen all nodes do
        Each robot incrementally build a solution
        based on autonomous search sensitivity
        sSL robots are characterized by the inequality
        q > q0 while for hSL robots q ≤ q0 holds
        sSL robots probabilistic choose the next node
        hSL-robot uses information supplied by sSL robots to find a new node j
        Local update rule
    end while
    Global update rule applied by elitist robot
end while
```

Parameter $0 \leq q_0 \leq 1$ is used to control the level of exploration undertaken by the robots, and q is a random number uniformly distributed over $[0, 1]$.

III. Artificial Immune System towards Robotics

Artificial Immune Systems [24], [15], [25] are inspired by the natural immune system. In particular, the computational intelligent algorithms use the ideas of the natural immune system's characteristics of learning and memory in order to solve particular problems emerging in the fields of computer science and engineering [29].

A recent and up to date review on *Artificial Immune System* is presented in [28] by Raza & Fernandez. Clonal selection theory [2] is the oldest definition that interprets the working of B cells in a BIS. The B-cell activation process results in the generation of plasma cells and antibodies; to capture similar antigens that are released into the bloodstream. The main components of *AIS* are: antibodies, cloning and hypermutation, and affinity measure and selection [29]. To give rise to the self-nonself theory, the clonal selection was augmented by negative selection when the BIS chooses not to respond [1], [4], [28].

Immune network theory [19], most commonly used in robotic applications, defines the working of an antibody network that enables antibodies to recognize each other [28]. In particular, the algorithm works based on the fact that antibodies trigger an immune response not only when they interact with antigens but also with other antibodies. The antibodies either respond positively (leading to cell activation and differentiation) or negatively (leading to tolerance or suppression) to a recognition signal [29].

Recent major development in immunology concern the inclusion of danger theory [20] in order to construct a three signal approach to handle invading pathogens in dangerous/stress situations. The immune system differentiates only what is harmful and what is not harmful to the body. An alarm signal is activated into the Danger Theory when harmful invaders enter the body, and thus, an adaptive immune response is triggered [28].

Algorithm 2. General Immune Network Algorithm

```
while not goal do
    Collect Antigen
    Affinity: between Antigen and Antibody
    Network: Stimulation and Suppression (Some or all)
    – Stimulus 1: between antibodies
    – Stimulus 2: between antigen and antibodies
    – Suppression: between antibodies
    Antibody Network Dynamics
    Cloning
    Metadynamics
    Return Network
end while
```

Algorithm 2 presents the pseudo-code of the *Immune Network* algorithm [28]. Furthermore, some similarities between ant algorithms and immune systems are shown followed by the *AIS* sensitivity approach.

TABLE I
COMPARATIVE STUDY: ANT ALGORITHMS AND IMMUNE ALGORITHMS

Ant Algorihtms	Immune Algorihtms
Initialize	
Pheromone value decreases over time, due to pheromone evaporation	Negative selection: a pool of antigens (not empty) start with a certain concentration value that decreases over time.
To find good solution eliminate other possibilities	
The trails with low pheromone are abandoned in time.	To *saturate* the antibodies with a high concentration, the others are removed.
Discrete update	
Local update of pheromone trail.	The stimulation is done by matching an antigen, an antibody increase its concentration; in a discrete setting it is regarded as 'cloning'.
Global update	
A global update of pheromone.	AIS will reduce the stimulation until at least one antibody drops out, when there are enough antibodies in the system; a new antibody is added.
Stopping criterion	
When the solution is stable for a certain period of time.	For example when there are no more drop-outs in AIS.

IV. Similarities: Immune Systems and Ant algorithms

The current section highlights, for the first time as far as we know, the similarities between *Artificial Immune System* [10] and Ant algorithms [6] (Table 1).

In negative selection, a pool of antigens (not empty) start with a certain concentration value that decreases over time. The other users are considered antibodies. *AIS* receives one candidate antibody at a time [10].

$$\frac{dx_i}{dt} = k_2(\sum_{j=1}^{N} m_{ji} x_i y_j) - k_3 x_i \quad (1)$$

At each iteration the concentration of the antibody is "increased by an amount dependent on its matching to each antigen". An AIS iteration is based on the following equation given by Farmer et al. [12]. When no matching is possible the concentration of the antibody decreases. Equation (1) uses the following notations: N is the number of antigens; x_i is the concentration of antibody i; y_j is the concentration of antigen j; k_2 is the stimulation effect, and k_3 is the death rate [10].

Section V includes several sensitive models of AIS.

V. Sensitivity in Immune Network

Watanabe et al. [33] proposed a "quick improvement" of the immune network inspired by the *Biological Immune System (BIS)*. They introduced a new "selection mechanism by modeling the function in thymus". The number of antibodies is N, m_{ji} is the affinity between antibody j and antibody i, m_i is the affinity between antibody i and the detected antigen.

The considered immune network has N antibodies generated with gene recombination and given one state variable named concentration of B-cell. To relate this variable to the action selection process, the concentration of the i-th antibody (a_i) is calculated as in Equation (2).

$$\frac{dA_i(t)}{dt} = \{\alpha \sum_{j=1}^{N} m_{ji} a_j(t) - \alpha \sum_{k=1}^{N} m_{ki} a_k(t) + \beta m_i - k_i\} a_i(t) b_i(T) \quad (2)$$

where $\alpha \sum_{j=1}^{N} m_{ji} a_j(t))$ is the stimulation, and $\alpha \sum_{k=1}^{N} m_{ki} a_k(t))$ is the suppression from other antibodies; βm_i is the stimulation from antigen, and k_i is the dissipation factor.

$$a_i(t+1) = \frac{1}{exp(0.5 - A_i(t))} \quad (3)$$

Equation (3) is used to maintain a stable concentration. Roulette-wheel is used to select the antibodies using their magnitude of concentrations. Only an antibody will be activated.

The concentration of B-cell i in the T-th time step is denoted by $b_i(T)$. If the antibody receives a signal of reinforcement after its action, the concentration of the B-cell varies:

$$\frac{db_i(T)}{dT} = r_i \Delta - K b_i(T) \quad (4)$$

where K is the dissipation factor of the B-cell; r_i=1 if the antibody is *selected*; r_i=0 if the antibody is *not selected*; r_i=-1 if the antibody receives a *penalty signal*. When $b_i(T) < 0$ the corresponding antibody is removed and another antibody is incorporated through the proposed selection mechanism.

The role of sensitive factors through the selection mechanism is pointed out. As is known, each antibody has stimulation and suppression as interactions. Sensitivity factors are introduced for both interactions.

Description of the sensitivity based model.

Step 1. Randomly generate m candidates for antibodies by gene recombination process.

Step 2. Compute the sensitivity denoted σ_i between each new antibody and the existing immune network. Sensitivity σ_i represents the sum of stimulation from the existing network,

$$\sigma_i = \sum_{j=1}^{N} m_{ji} a_j \quad (5)$$

Step 3. Compute the sensitivity denoted δ_i between each new antibody and the existing immune network. Sensitivity δ_i is the sum of suppression,

$$\delta_(i) = \sum_{j=1}^{N} m_{ij} a_j \quad (6)$$

Step 4. Based on both sensitivity parameters σ_i and δ_i only an antibody will be incorporated using the predetermined criterion, in particular $max\ \sigma_i$, and $max|\sigma_i - \delta_i|$ as criteria.

In order to demonstrate the role of sensitivity, we emphasis the importance of this selection mechanism in the Immune Network for solving problems.

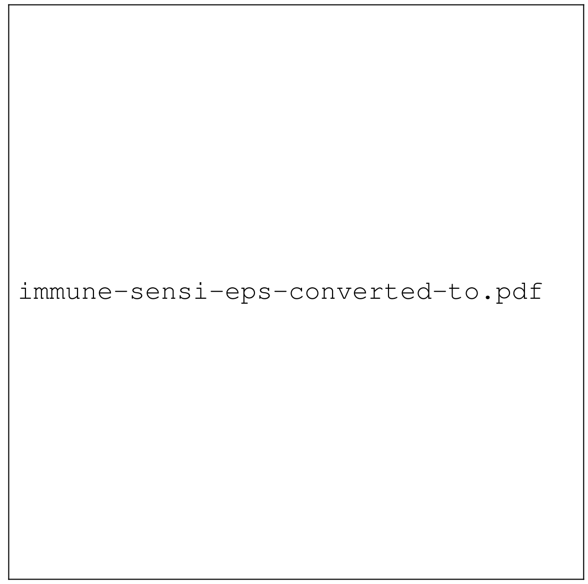

Fig. 2. Avoid obstacles problem: simulation results for the network [33]

VI. Examples and Discussions

A. Example of the sensitivity mechanism in Immune System

The problem of avoiding obstacles is used to test and confirm the robustness of the sensitive mechanism in the Immune network. Figure 2 illustrates the problem simulation. In the simulated environment a charging station, an immunoid, and several obstacles are included. The immunoid explores, avoiding the obstacles, to the charging station in order to increase its energy level. The reward and penalty signals are shown in Table 2. *Parameters*: the number of antibody is $N = 50$, and the number of new antibody is $m = 20$.

To compare the results, both (b,c) and without (a) selection mechanisms cases are used (Figure 3). Both selection criteria (b,c) use sensitivity: with the maximum sum of stimulation, $max\ \sigma_i$ (b) and with the maximum of absolute difference between the sum of stimulation and the sum of suppression, $max|\sigma - \delta|$ (c) based on Equations (5)-(6); see further details [33].

Figure 3 illustrates the lifetime of a transition, the number of collisions with the obstacles, and the counting result of actions when moving-forward in the environment. ANOVA statistical analysis for fitness value, the lifetime of a transition, shows that the probability of the result, assuming the null hypothesis, is 0.0004, so the a), b), c) groups are different; the *Average Absolute Deviation from Median* for a) is 100, for b) is 98.2 and for c) is 36.4 variant, so variant c) has the most promising result.

B. Example of the sensitivity mechanism in Ant Algorithms

1) Sensitive Robotic System-Drilling problem: In order to apply *Sensitive Robotic Metaheuristic* for solving a complex drilling problem [22], a particular case of generalized traveling salesman problem, the robots are placed at the starting point and are going to search objects in a specific area. Assuming

TABLE II
THE REWARD AND PENALTY SIGNALS [33]

Reward	Penalty
• Immunoid approaches the charging station with low energy level. • Immunoid moves forward without collisions.	• Immunoid collides with an obstacle or a wall. • Immunoid does not move forward when there is no obstacle around it.

that each cluster has specific objects recognized by the robots, they choose a different cluster each time. The stigmergic values guide the robots to the shorter path–a solution of *Robotic Travel Problem*. The number of clusters is considered the integer part from the number of nodes divided by five [22].

The robots are in the small/large sensitivity group at the time; the placement in a group is based on the q variable, uniformly distributed over $[0, 1]$; q_0 is a constant, $0 \leq q_0 \leq 1$. The inequality $q > q_0$ include the robots in the group with small sensitivity; the others are in the group with high sensitivity. The *hSL-robots*, with high sensitivity level, use the information given by the *sSL* robots, with small sensitivity level, in order to intensify the search in the given area.

The parameters used are $\beta = 5$, τ_0=0.01, the number of robots is 25, $q_0 = 0.9$ [7], [21], [22]; the *sensitivity level* q for *hSL* robots is distributed in $(q_0, 1)$, and for *sSL* robots, the sensitivity level is in $(0, q_0)$. The Expected Utility Approach [14] was used as in [22] to rank the compared algorithms. The running time of *SRM* exceeded the other algorithms running time but the ranks over the optimal result were: *SRM*, followed by a version of *Genetic Algorithm* [32], *ACS for Generalized TSP* [21], a hybrid heuristic (GI^3) [30], and *Nearest Neighbor* [30].

2) Sensitive Robots-WSN problem: An analysis of the *Hybrid Sensitive Robot Algorithm for Intrusion Detection* follows. The artificial pheromone from the edges of the sensor network reveals the attacked zone within the network. Each robot uses its one specific property as its level of sensitivity in order to detect the intruders and the artificial stigmergy in order to find the attacked edges [21].

Table 3 illustrates how the sensitivity factor influences the groups of robots to search for intrusions in a sensor network. Diversification of the search is maintained by the robots with small sensitivity values, and the others are used to test and identify the attacked regions.

Sensitivity is presented in different cases for both ant algorithms and immune algorithms. The sensitive approach brings a helpful support to identify the better solution between the existing ones. The sensitive parameters values should be tested and should provide the most beneficial value to each particular problem.

VII. CONCLUSION

The field of artificial intelligence encompasses many different subfields ranging from machine learning and perception to game theory and complex mathematical analysis. At the heart lies the idea to investigate broad approaches in order to understand and engineer intelligent systems. Many new fields emerged including artificial life, evolutionary robotics, and swarm intelligence. All these new fields have in common that they question the validity of the assumptions made and methods applied by mainstream artificial intelligence for creating artifacts.

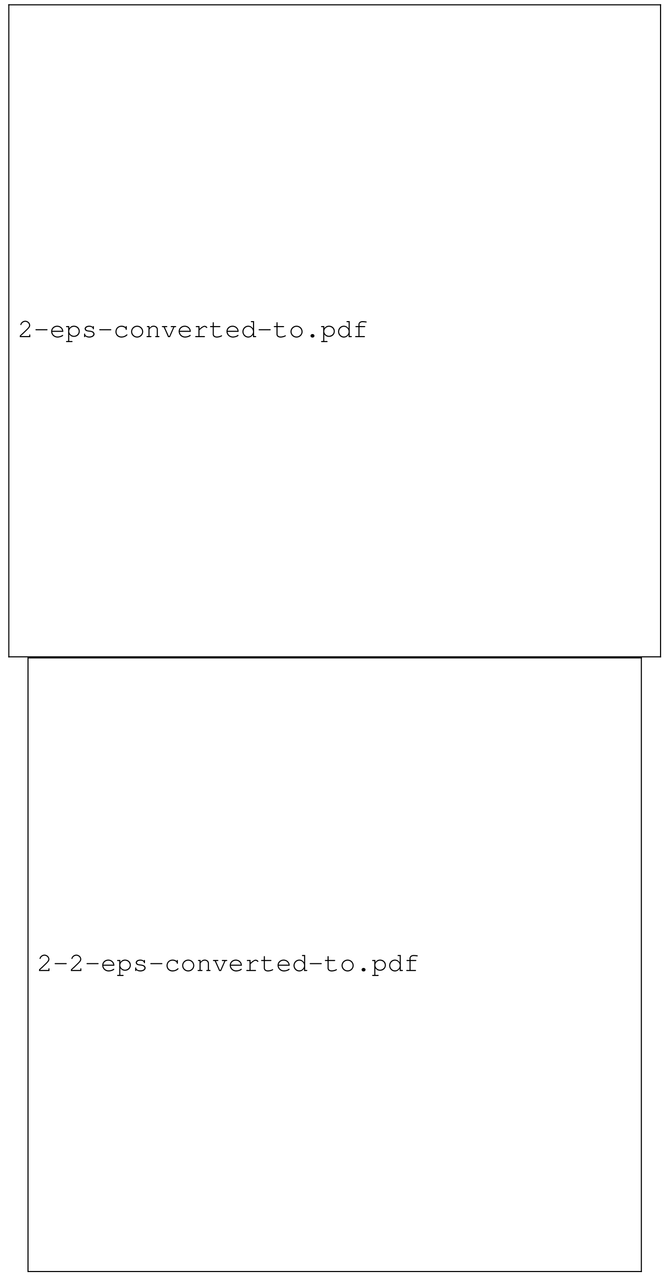

Fig. 3. Images of the simulation tests and results; included are different selection criteria: a) without selection mechanism, b) with selection using the sensitivity factor of $max\sigma_i$, where σ_i is the sum of stimulation between an antibody and the immune network (Eq. 5), c) with selection using the sensitivity factor of $max|\sigma - \delta|$); where δ_i is the sum of suppression, the sensitivity between each new antibody and the immune network (Eq. 5-6)) [33] .

The current paper studied the similarities of two natural

TABLE III
AGENTS-ROBOTS WITH DIFFERENT LEVELS OF SENSITIVITY ACTIONS IN A SENSOR NETWORK [22]

Agents search	**Intruders type**	**Sensitive Level**	**Detecting intrusion**	**Action Type**
sSL robots	explorers	low	no	continue to explore
		high	possibly intruders	notify the hSL-robots
hSL robots	exploiters	low	the attack is not certified	update pheromone trails
		high	attack is highly present	identify the affected path

algorithms inspired by immunity system and ant-based algorithms. Sensitivity approaches are also studied and several robotic related applications solved with both algorithms are presented. Further work involves the sensitivity analysis of immune algorithms based on the way the antibodies are grouped.

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