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Immune robustness from top to down: bio-inspired immune-based behavior coordination for autonomous mobile robot navigation

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Abstract

Behavioral robustness at antibody and immune network levels is discussed. The robustness of the immune response that drives an autonomous mobile robot is examined with computational experiments in the trajectory generation context in unknown environments. The immune response is met based on the immune network metaphor for different low-level behaviors coordination. These behaviors are activated when a robot sense the appropriate conditions in the environment in relation to the network current state. Results are obtained over case studies in computer simulation as well as in laboratory experiments with a Khepera II microrobot, and also when such an immune response is externally perturbed at network or low-level behavioral modules for behavioral robustness. Results indicate that robust behavior and immune responses relate to the coupling between behavioral modules that are selectively engaged with the environment based on

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immune response. The importance of results is that such a demonstration, because of the simplicity, leads discussions on a dynamical systems perspective of behavioral robustness in artificial immune systems that goes beyond the isolated immune network response, but the antibody self-response with implications on bio-inspired systems research. Challenges and limitations of the proposed approach are also identified for future studies.

Index Terms: Bio-Inspired Immune-Based Systems; Complex Adaptive Systems; Behavior-Based Robotics; Autonomous Mobile Robot Control.

I. Introduction

One of the unanswered questions facing scientists since von Neumann (1956) noted the complexity of such a problem is 'the synthesis of reliable organisms from unreliable components'. Reliability in this context refers to the ability of artificial or biological organisms to maintain its capacities (functionalities) in normal situation, as well as under unexpected internal or external factors (or perturbations), which associates to biological robustness research [16]. Despite the lack of a formal definition, robustness usually refers to the continuation of function in the presence of perturbations [15][16][17]. Robustness is a systemic property commonly attributed to living organisms [20][2].

Studies in complex adaptive systems, neuroscience, and systems biology generally propose organism-centred accounts of robustness. However, the partition between organism and environment is not always helpful for thinking on organisms as 'highly-interdependent'. This is because the division focuses only on one-third of the potential behavioral interactions between internal control systems, body, and environment, giving special emphasis on the former component (e.g. internal control mechanisms, brains, or nervous systems). In fact, internal properties like modularity, decoupling, and redundancy are conventionally thought to be necessary for robustness in systems biology [17]. Structural properties like these may be required to support systemic functionality to certain perturbations between internal control systems and body, but they do not in themselves 'ensure' robust traits (see [15][17]) for complementary discussions). As an example of this last point, neural network models have been used to explore how modularity can lead to more efficient task management [3][4]. Despite recognized robust properties of most modular neural networks to noisy data [3], a considerably high amount of noise still reduces drastically their filtering capacity. Another example relates to the immune systems metaphor, in which immune robust coordination *cannot* be understood as the work of a general coordination solver capable of dealing with a variety of situations (i.e. antigens). However, this robust coordination can be understood as the result of highly individual problem solvers with the capacity for robust behavior based on self-training history of interactions with the environment (i.e. antigens). Therefore, is it adequate to see robustness as internally generated in immune-based systems?

Answers to what is required for robustness at behavioral level (behavioral robustness) could guide better scientific descriptions of habits, coherent experience, and adaptation to changing environments, which could also beneficiate to bio-inspired systems research. This will follow a small step in the understanding of how operates the two great complex adaptive biological systems that humans have to deal with the diverse world that surrounds us. These systems are the central nervous system, where the brain is the main 'component', and the immune system, which operates below the level of consciousness as a relational phenomenon.

This article promotes that *only* understanding organism-environment coupling, behavioral sciences and researchers in bio-inspired immune systems in situated and embodied organisms can understand how immune idealizations control organisms' movements for robust traits. Thus, it is possible to better understand what goes wrong after organism failures or damage in artificial (or eventually biological) contexts, and to develop better ways to deal with associated outcomes.

This article provides experiments on the autonomous navigation of robots through different computational simulations and physical robotic configurations (see also [9]). After obtaining the elemental traits for navigation tasks based on the Evolutionary Robotics paradigm (see [8]), we evaluated an immune based coordination model of these behaviors. The importance to develop an AIS coordination based on robust low-level behaviors is relevant to be analyzed despite the fact that immune coordination is robust in itself if it is well implemented. The emergent global behavior in our experiments not only has demonstrated its viability for solving robot's navigation, but also its robustness. After analyzing the performance of behavioral coordination under the effects of sensorimotor perturbations, in fact, it is when we analyze robustness against environmental perturbations of the proposed behavioral coordination.

The development of low-level behaviors cannot be considered as a minor problem in behavior-based coordination (e.g. immune coordination) as well as the set of contingencies that complement them, because the interaction between low-level modules determines global traits in our model. This is especially so in the case of sensorimotor control in physical scenarios because low-level behaviors are thought to be suited for dealing with physical environments to obtain the expected performance (i.e., autonomous navigations in unknown, but semi-structured environments).

By limiting experimental analyses to concrete case studies, this article highlights behavioral robustness as a dynamical process in immune-based models, being in any case certainly incomplete if we do not focus on engaged organism-environment dynamics. In fact, the described studies show us that behavioral robustness is better understood in the context of dynamical couplings, not in terms of immune mechanisms (i.e. 'ensuring' immune network response).

II. Related works

During the last decade, several works have been done over the behavior coordination in robots that use bio-inspired models, many of them inspired in the immune system [18][5][14][21][22]. The guidance and control systems (GCS) of these robots may be associated to the concept of an ‘organism’, with the ability to detect situations in the robot’s surroundings and then react against them. The information about the environment that is coming from sensors is associated with ‘antigens’, to be classified by the organism. Such classification is carried out by an ‘antibody network’. When an antigen is detected, a response from the immune system (in this case an artificial immune system, or AIS) is generated. This response defines a particular action of the organisms in its environment. In this way, a condition-action pair in the GCS is linked to each antigen-antibody interaction [5]. Hence, the dynamic of the AIS is responsible of selecting the action to be executed in each situation associated to an activated antibody.

The dynamic for the AIS in the present approach is inspired from [7], where the final action decision to be applied to the robot’s actuators is determined by the antibody concentration within the organism. Note that this AIS is an adaptive and distributed information system. The work presented in this article is also based on previous proposals as described by Whitbrook (2005, 2007), while the model of the immune network is inspired by the approaches in [21] and [7] (see also [13]). The main objective of the present study is referred then to the development of a robust GCS that gives priority to secure navigation in unknown environments, advancing previous works in immune based control [10].

Next sections are organized as follows. Section III shows the main ideas governing the dynamics of AIS and section IV describes the application domain of this work. Section V presents experimental results, and finally, some conclusions about in sections VI and VII are given.

III. Dynamics of the implemented AIS

The process of antibody concentration variation is an essential feature for the analyzed behavior coordination and then, for the final trajectory generation. The antibody concentration is modeled by a time dependant ordinary differential equation. According to antibody concentration, this can stimulate or depress other antibodies within the organism [9]. Hence, the highest level of a particular antibody concentration determines the action to be done by the robot, also codified in the antibody. Then, the most ‘concentrated’ antibody (winner) is selected exclusively in each sampling time to take the entire control of the robot.

In this work, initial values of antibody concentration were set to zero and bounded to be included in the interval [0;1]. The concentration of a particular antibody depends on: (a) the state of the environment in each sampling time, reported by antigens, and (b) the concentration of other antibodies in the AIS. This is due to the connections among antibodies, called ‘idiotopes’. As every antibody is linked to a simple behavior, the connectivity pattern allows the appearance of more complex (emergent) behaviors [6][21].

$$\frac{da_i^{t+1}}{dt} = \left(\sum_{j=1}^{N} m_{ij} a_j(t) - \sum_{k=1}^{M} m_{ik} a_k(t) + m_i - k_i \right) . a_i(t) \qquad (1)$$

$$a_i(t) = \frac{1}{1 + \exp(0.5 - a_i(t))} \qquad (2)$$

The equations (1) and (2) represent the antibody concentration level of *i-th* antibody in the AIS [7]. This concentration is evaluated in the instant t, being $N+M$ is the total number of antibodies integrating the AIS; m_i, is the affinity between the antibody i and a determined antigen; m_{ji} is the affinity between the antibody j and the antibody i (the stimulation degree); m_{ik} is the affinity between the antibodies k and i, (the suppression degree); k_i represents the natural death coefficient of antibody i. Equation (2) is the function employed to set the concentration levels for each antibody a_i.

As proposed in [14], in next sections it is evaluated the AIS performance in the dimension of the adjustment mechanism, and not regarding innovation (see [18][14][21] for a detailed classification). Innovation refers to the system ability to include unknown new situations from a generalization of the antibodies network, in a process similar to inductive learning. Due to the learning abilities associated to the antibodies, stimulation or suppression processes were not considered. Our decision is based on the hypothesis that it is more efficient to consider in each sampling time the interaction of the robot with its environment to determine the selection of the adequate antibody (short term learning), instead of doing this selection based on a ‘history of interactions’ (long term learning). In other words, this history integration would not allow the AIS to forget opportunely previous actions for a particular situation in the environment and then would inhibit a reaction for such situation, which is not adequate in physical world for our experimental purposes.

IV. Description of the application domain

The considered robots had available infrared sensors (Figure 1) to measure distances and light intensity, to determine the presence of an approaching goal in the face of a light source in the environment. This information is mapped as antigens; hence, antigens represented the current state of the environment. The behavior of the robot in response to environmental conditions is analogous to external matching between antibodies and antigens. An internal matching between antibodies is required as part of the immune response in order to select the most appropriate action to perform.

Figure 2 and Figure 3 show the adopted structure of antigens representing the information provided by sensed environmental situations. The representation of Figure 2 codifies the robot's sensor signals regarding the location of objects in the environment. The references to elements such as waypoints, pipelines, zones, and obstacles is due to a possible application of this approach to the preventive maintenance of structures for related project with underwater vehicles, further described in [1].

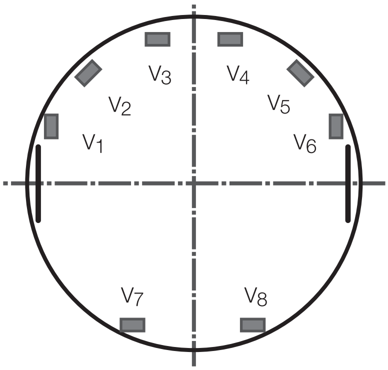

Fig. 1 | Sensors V_i deployment for the experimental robot.

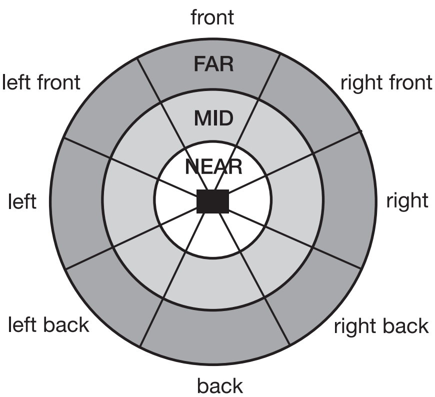

Fig. 2 | Definition of zones for antigen recognition based on waypoints, pipe segments, zones, and obstacles recognition.

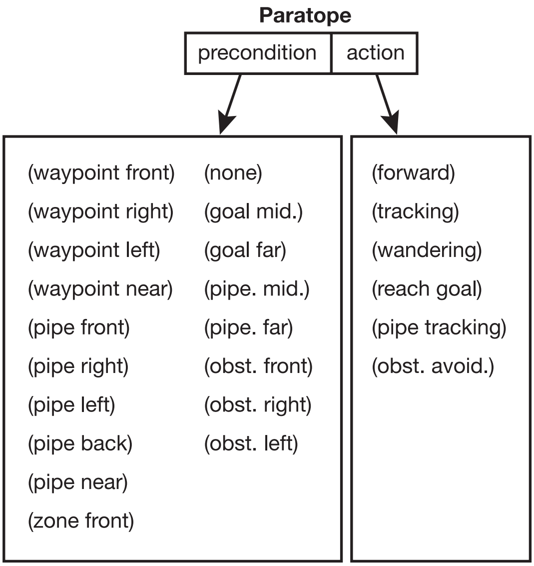

Fig. 3 | Definition of zones for antigen recognition.

The relationship between sensed information and situations to be recognized by the immune control system in each zone defines the incoming signal for the immune response. This information is mapped to a binary vector representing the presence or absence of recognized situations. These situations are an obstacle in the environment, tracking an object (pipeline or wall), or free space around the robot. Antigens are then linked to the direction in which the obstacles are located (obstacle avoidance task) based on Fig. 2, the light sources to approach (waypoints to follow provided by the guidance task), and the distance and direction of the tracking objects (tracking task). The possible actions to be performed by the robot are: to go forward, to turn left/right or wandering, to avoid obstacle, and to reach the objective. These actions may be caused by the simple behaviors of: (1) object tracking, (2) object searching and (3) obstacle avoidance. Each one of them is supported by a feed-forward artificial neural (ANN) trained with an evolutive algorithm as explained in [8] (see also [9]).

V. Results

A. Computer simulation results

Although still far from an exhaustive analysis, several variations of the behavior coordination are tested in [9] to analyze the relative appropriateness of the described immune coordination. In this article, we only show a couple of experimental sets that support our research hypothesis as explained in the introductory section. The environment is unknown for the robot, but structured. The variations under study are:

(a) coordination based on the evolution of relationships among simple behavior modules, named evolutive coordination introduced in [12];
(b) coordination based on the AIS (immune coordination);
(c) immune coordination of behaviors obtained after introducing Gaussian noise in the output of the ANN supporting each simple behavior, like in [10][11].

The experiments presented in this section are done over a micro-robot model in computer simulation with the capability to move freely in the exploration of the environment during a limited time. This maximum time is upper bounded by the evolution of 300 generations in the ANN training. Experimental settings are similar as the one presented in [14][21][24]. The task to be carried out by the robot is to go through the gate A-B in a secure way (without collisions), reaching a light source or its neighborhood, as a stopping point. Three starting points were set, P0, P1 and P2. This is depicted in Figure 4. A record of every case was done, and when they were successful, the time in which the task was fulfilled was recorded. After trials, four sets of faulty situations were observed:

(case 1) – the robot did not reach the goal but the robot did appropriate gate passing;
(case 2) – the goal was reached but the robot did not pass through gates AB;
(case 3) – the robot passed through the gate but stopped (stuck) near the gate;
(case 4) – the robot became trapped and could not escape before passing the gate.

All significant tests were at the 95% confidence level using a *t*-test. A *t-test* is any statistical hypothesis test in which the test statistic has a Student’s *t* distribution if the null hypothesis is true. Normally distributed values are assumed. Thirty (30) experiments are done, 10 from each starting point. Table 1 and Table 2 summarize the results of these trials. In Table 1, the faulty situations are presented, describing the number of occurrence of each one (number of failures column), and the percentage of faulty situations over total observed ones (% failed trials column).

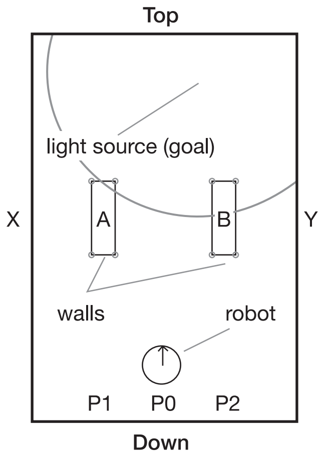

Fig. 4 | Experimental settings for the comparative analysis of different coordination approaches.

It was found that the performance of the task completion was affected by the following parameters:

D – the distance between the obstacles and the robot;
S – the measuring scope of the sensors;
B – the previous performance of the simple behaviors employed in obtaining the emergent behavior;
C – the coordination approach.

Table 1: Frequency of failure in robot performance considering 30 experiments from different starting positio

Coordination approach	Error code	Causes of failures (Freq.)	% All failed trials	% Causes of failure
Layered-Evolutive (ruled-based)	1	8	26.6%	39.9%
	2	12	40.0%	60.1%
	3	0	0%	0%
	4	0	0%	0%
AIS (no noisy modules)	1	0	0%	0%
	2	10	33.3%	100%
	3	0	0%	0%
	4	0	0%	0%
AIS (noisy modules)	1	2	6.6%	18.1%
	2	9	30%	81.9%
	3	0	0%	0%
	4	0	0%	0%

Table 1 also shows that immune based coordination of behaviors exhibited the lower number of failed cases (fourth column). The robot needed an average of 96 CPU cycles to reach the objective. By the other side, evolutive coordination do not allow the robot to cross the gate A-B with a high success rate due to its difficulties to activate in effective time the appropriate behavior. Effectively, inhibitory and excitatory links are generated among behavior modules. The gains of these links, within the interval [0;1], did not change during experiments after evolution. However, with the immune coordination there was a continuous adaptation during experiments that took into account the history of the emergent behavior. This adaptive capability of coordination compensated any faulty performance of simple behaviors. For instance, if some noise was introduced in the sensors' measurements, the immune coordination may activate them in the same way by remembering its previous recent activations, solving the loss of sensory ability.

Table 2: Summary of statistics for time (CPU cycles) to reach the goal using the simulator considering only successful cases.

Coordination approach	Mean			Standard deviation			95% confidence interval		
	P0	P1	P2	P0	P1	P2	P0	P1	P2
Layered-Evolutive (ruled-based)	185.43	233.7	249.7	27.6	21.14	15.1	[212.01;287.3]	[159.8; 211]	[200.1;267.2]
AIS (no noisy modules)	98.9	119.	69.6	56.	41.40	13.38	[58,5;139.3]	[90.2;149.4]	[60;79.2]
AIS (noisy modules)	95.8	109.2	65.2	49.4	31.	8.6	[60.4;131.1]	[85.4;133]	[58.6;71.8]

B. Experimental results over the physical robot

The experiments reported in the previous section are repeated with a Khepera II microrobot, with the sensor configuration depicted in Figure 1. The environment is also the same in terms of structure. Figure 5 shows such a structure with a considerable influence of variability in zenith light sources. That influence is originated by two zenith light sources (fluorescent) as environmental light, and uncontrolled light influence from other light sources in the room (e.g., windows and secondary environmental lights). The target during tests is a light source of 60 Watts (fluorescent) placed on top-right side of the arena.

The time to finish the task and the possible reasons for not comply with it, are recorded in a similar manner to that described in the previous section. All experiments with the physical robot are stopped in the case of detecting a faulty situation (i.e. if a collision with one of the internal walls was foreseen). In addition, if the robot hit a wall during its internal navigation task, this situation is also registered, generating a new error, which is coded as 0 in next Table 3. Thus, error conditions for experiments on the real robot are the same as for computer simulation experiments, adding only this case 0. The maximum error situations allowed for each test from each starting position is 20 for the 30 independent experiments.

It is also important to note that in the case of the computer simulation tests, the robot is allowed to continue his career after a collision occurred, representing new opportunities for the robot to correct its actions. This does not occur during experiments with physical robots because after such collisions, the experiment is stopped and in this way, there is an increment in the failure rate for these experiments. This is done to protect the physical integrity of the robot. Hence, during these trials, the failure rate is high (52%). Another important cause of failures is due to environmental influence on the sensors. The characterization of each sensor reading including variability with noise, allowed to significantly decreasing the failure rate. For example, two qualitatively identical sensors show differences in their readings during experiments with obstacle avoidance, due to light changes. The time elapsed for perception and the action is different in both identical sensors. This is the reason for also experimenting with the physical robot. Similar differences between the performance in computer simulation and the physical robot with real sensors are reported in the reference [24]. The results indicate that the failure rate after corrections including the variability of sensor reading is then decreased (at 37%).

Particularly, the obstacle avoidance behaviour, when approaching the sides of the internal walls, does not work as expected in comparison with computer simulation results. In this situation, the Khepera II robot is too close to the limits of the internal walls and got trapped. Internal walls generated shadow cones which do not allow the sensors to work properly (please refer to Figure 5). Table 3 summarizes statistics on the failure rate during experiments with the physical robot. The results indicate a greater number of failures (about 20%) when the robot approached the end of the internal walls but not when crossing the gate AB, generating 60% of all the faulty situations. There is no significant difference between the simulated and physical tests in terms of failure rates and difficulty in completing the task. The average number of actions towards the objective within the corridor A-B from all initial positions was of 33% in the physical experiments, compared with 59% obtained in the simulation experiments.

As usually presented in the literature of technological research, computer simulation represents physical world idealizations. In the case of robots, in the simulated world there are more precise sensorimotor actions. As it is reported, AIS based coordination in physical robots exhibits no significant differences between the same computer simulation results. Hence, it might be inferred that this coordination is the one that better suits in the physical world. Anyway, to support this claim it is still needed a greater number of statistically significant evidence, as well as analysis of global stability, or at least convergence of coordination in a non-erratic behaviour.

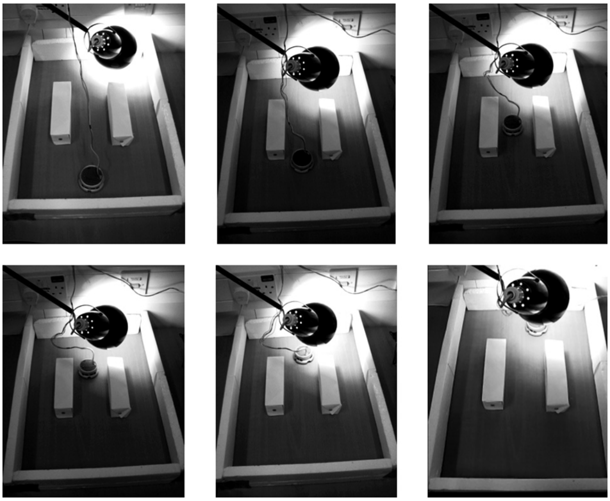

Fig. 5 | Experimental settings in real confined physical environment for testing short-term goal-seeking problem navigation using AIS behavior coordination for a Khepera II robot.

Table 3: Frequency of Robot Performance Failures using AIS, considering 30 experiments from different starting points.

Initial position	Unsuccessful code	Causes of failures (Freq.)	% All failed trials	% Causes of failure
P0	0	3	10%	20%
	1	0	0%	0%
	2	12	40%	80%
	3	0	0%	0%
	4	0	0%	0%
P1	0	4	13.3%	21%
	1	2	6.6%	10.5%
	2	10	33.3%	52.6%
	3	2	6.6%	10.5%
	4	1	3.3%	5.3%
P2	0	4	13.3%	21%
	1	0	0	0%
	2	11	37%	57.8%
	3	2	6.6%	10.5%
	4	2	6.6%	10.5%

C. A comparative fitness analysis of AIS in long-term tests

This section evaluates in computer simulations the immune performance obtained in previous experiments based on a specific fitness metrics. We evaluate the immune coordination using non-noisy behavioural modules because this coordination presented a relatively better performance in comparison the other analysed behavioural coordinations that we have evaluated in [9].

Five situations are settled for experiments as named in Figure 6 (see figure's caption). Similarly to Ishiguro et al.'s (1996) work, in the following, it is evaluated the performance of the AIS coordination only using an adjustment adaptation mechanism as explained in previous sections. We allocated the simulated robot to perform the same experiments as in Figure 7 (navigation in a labyrinth). The following equation describes the fitness function used for the evaluation process.

$$fitness = \alpha.(1-lt) + \beta.(rz) + \chi.(1-ss) + \varsigma.(1-wt)$$

where lt is the time spent into a light zone over the total time; rz is the amount of reached zones over total zones; ss is the time spent in a trapped situation over total time; and wt is the time spent as wandering behaviour over total time. Parameters α, β, χ and ς are defined for weighing the contribution of each term, but defined as 1 for every experiment in this section. The higher the fitness is, the better performance robots reached. This measure criterion directly increased accordingly the number of special zones that the robot approached, and decreased directly with more time the robot spends without tracking the line (i.e., performing wandering behaviour or becoming trapped). The fitness value is clamped in range [0;1].

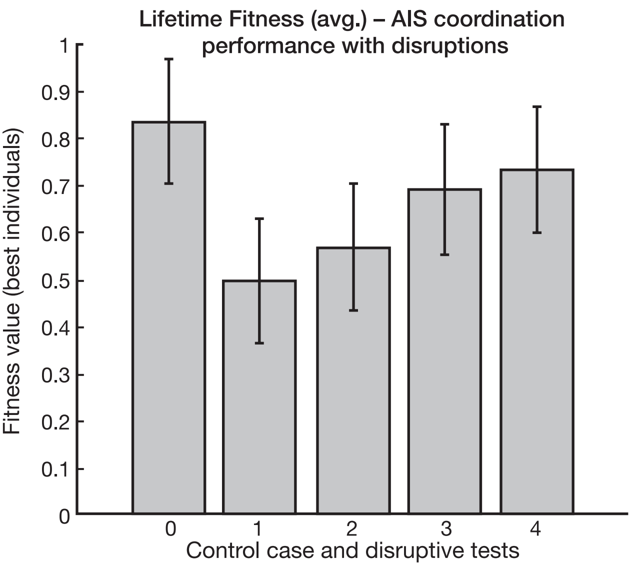

Fig. 6 | Mean performance (y-axis) against perturbation tests of the AIS coordination for non-noise behaviors. 10 independent tests per plotted bar. X-axis represents performed experiment: *test 0:* control case; *test1:* sensors gain ±5%; *test 2:* motor gain ±5%; *test 3:* random noise in affinities (m_i) among antibodies ±50%; *test 4:* random noise in antibody concentrations (a_i) ±50%.

Figure 6 shows that the fitness measurement of *test1* and *test2* was considerably lower (0.499 and 0.569, in that order) than the one obtained in the control case (0.836). The efficiency (avg.) for performing the task in relation to the control case is 59%, 68%, 82%, and 87% for *test1*, *test2*, *test3*, and *test4*, respectively. It means that the immune coordination present fragility in experiments against sensorimotor perturbations. However, we obtain a considerably high performance against structural perturbations in affinities and antibody concentrations (0.692 and 0.733, respectively). In average, the performance of the immune coordination is 64% effective for sensorimotor perturbations in relation to control case, while for structural perturbations is 85%.

Due to the proposed fitness measurement, terms *ss* (the time spent in a trapped situation over total time) and *wt* (the time spent as wandering behaviour over total time) have obtained a considerable influence in sensorimotor perturbation tests. For example, the effect of sensors and motor perturbations generate constant errors in movements. This produces that the special tracking zones behaviour is lost, or robots actions consume more time in special tracking zones as correcting actions for tracking the line. The immune coordination approach does not surpass satisfactorily this inconvenience for *test1* and *test2*. However, the immune coordination obtains a relative good performance in relation to structural perturbations on affinities among antibodies and in antibody concentrations (*test3* and *test4*). In general, results of this section support that the immune coordination was considerably more sensitive to sensorimotor perturbations on low-level behaviours than to perturbations in immune coordination of behaviours.

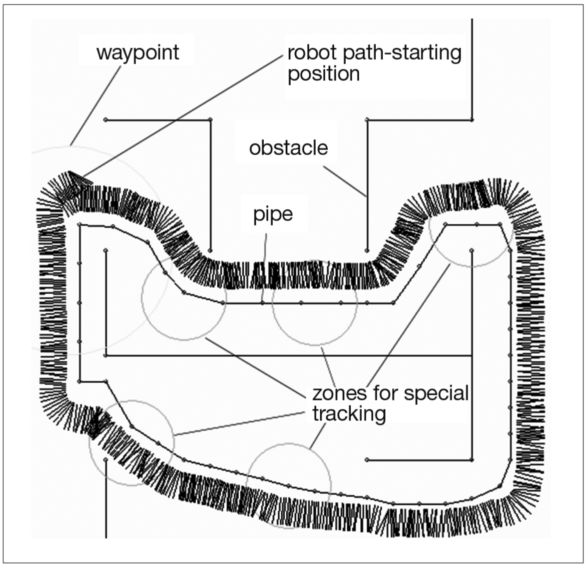

Fig. 7 | Example of tracking trajectory generation using immune coordination without neural and environmental noise during tests. Situation where the robot tracks segments of a line.

VI. Experimental discussions

From a simulated perspective, we describe in previous sections some behavioral analysis of the appropriateness of different immune-based behavior coordination over similar behavioral modules. In addition, we evaluated the navigation task in unknown environments through physical environments. Internal variability in the face of neural noise in behavioral modules during the evolutionary process was also analyzed in behavioral tests. In physical experiments, behaviors needed to deal against environmental variability (noise) that comes into the robot controller through sensorimotor signals (full experiments not shown here). This aspect of the work was interesting for a number of reasons. Firstly, very little work has been done in literature with AIS coordination that relates neurocontrollers focusing on internal variability as perturbations. Our experiments demonstrated that AIS could deal with non-reliable components in behavioral terms to complete proposed tasks. Secondly, actions in the near past not necessarily define future actions in short term, but they restrict the set of behaviors to apply. In other words, there exists a higher probability for maintaining a pre-stimulus activity (behavior) than behaviors without relation to current situation. Finally, the immune coordination of behaviors could deal with environmental noise in restricted situations (i.e. arenas). We characterized the immune system approach by adapting to environment conditions in short and long term. In comparison with the evolutionary coordination approach [8] [9], which represents a coordination network that can be accomplished with the navigation task after evolution [12], the immune coordination was not seriously affected during perturbation tests (internal and external). We mainly based this capacity for dealing with perturbations on its intrinsic adaptive properties in the immune network dynamics.

Relatively well-tuned behavioral modules affected that performance. Results indicated that immune coordination increased the network dynamics performance based on behaviors to coordinate, endowing it with additional robustness. We understand this as an improved flexibility in the adaptation to new situations. The knowledge-based approach implies, however, more effort for discovering how to coordinate action-behaviors based on a trial-error process in comparison with evolved and immune coordination. In general terms, results show that the immune network could deal with an expected robot performance in simple and complex tests. The robot was capable of developing all its dedicated tasks, as well as it was also capable of maintaining its integrity. Despite satisfactory results, further analyses must be carried out to give the robot control additional robustness. A more flexible control among behaviors could be beneficial in unknown environments.

VII. Conclusion

This article presents results of the study in bio-inspired behavior coordination from two experimental perspectives: computer simulation and physical robot in partially controlled environment tests. The different analysis performed over the guidance and control systems (GCS) of an autonomous mobile robot showed the feasibility of using immune-based techniques for coordination of simple behavior modules. The influence of Gaussian noise in the construction process of simple behavior modules was also analyzed and it was demonstrated that AIS based coordination was the best to deal with the real environment due to its better capability to adapt, even in the presence of such noise (see [9]).

A first conclusion is that the immune-inspired is a more robust approach for behaviors coordination than the evolutive one (see also [12] and [13] for further arguments). Effectively, based on the described experimental configuration, this last approach is able to yield an emergent behavior, but without the possibility to adapt in effective time to the sensorimotor inaccuracies that were not given during the evolutionary process. In particular, AIS based coordination was not seriously affected by noise. The results suggest that immune-inspired coordination has the potential to improve over time the performance of the robot's emergent behavior. The immune coordination of behaviors, in consequence, was in some sense robust to maladaptations of isolated behaviors in how they solve a task. If not so, maladapted behaviors negatively affected the immune coordination.

Behaviors were difficult to obtain covering a wide range of changing and unknown situations. Ideally, an immune coordination system should be 'decoupled' then in relation to the task to solve, but only coordinating low-level behaviors that were pre-evolved for solving certain tasks. Our implemented immune coordination presented robustness in relation to low-level behaviors at different contexts (e.g., behaviors under noisy and non-noise evolutionary processes), and in simulated and physical experiments.

Summarizing, one of the main conclusions raised on this work is that the performance of the immune coordination (systemic behavior) not only emerges from low-level behaviors, but also its dynamics with the environment through low-level behaviors also effects the coordination of behavioral modules regarding sensorimotor interactions.

The immune 'decision' generating the immune coordination for activating low-level behaviors, defines in fact the subsequent systemic states. For example, activating the behavior of goal approaching will generate further incoming signals associated with sensing that goal in next time steps. This indicates that the performance of low-level behaviors is essential to obtain better immune performance. This idea however is sometimes given for granted rather than discussed in literature, because the dynamics of the immune response receives more interest than the whole set of low- and high-level behaviors.

Finally, experiments showed that AIS based behavior coordination could generate safe trajectories for the robot when reaching a target, maintaining its physical integrity. Despite the satisfactory results, a further analysis on the relevance of these results is still pending, in order to achieve a greater level of robustness against disturbances in coordination for real world environments, like underwater or open field missions. It is also needed more evidence statistically significant, and an analysis of the robot's global control stability, or at least convergence of the coordination in a predictable pattern and adapted to the environment. Only in this situation, this technology would be mature to meet the challenge of navigating in a completely unknown environment.

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