

Adaptive behavior-based control for robot navigation: a multi-robot case study

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Abstract—The main focus of the work presented in this paper is to investigate the application of certain biologically-inspired control strategies in the field of autonomous mobile robots, with particular emphasis on multi-robot navigation systems. The control architecture used in this work is based on the behavior-based approach. The main argument in favor of this approach is its impressive and rapid practical success. This powerful methodology has demonstrated simplicity, parallelism, perception-action mapping and real implementation. When a group of autonomous mobile robots needs to achieve a goal operating in complex dynamic environments, such a task involves high computational complexity and a large volume of data needed for continuous monitoring of internal states and the external environment. Most autonomous mobile robots have limited capabilities in computation power or energy sources with limited capability, such as batteries. Therefore, it becomes necessary to build additional mechanisms on top of the control architecture able to efficiently allocate resources for enhancing the performance of an autonomous mobile robot. For this purpose, it is necessary to build an adaptive behavior-based control system focused on sensory adaptation. This adaptive property will assure efficient use of robot's limited sensorial and cognitive resources. The proposed adaptive behavior-based control system is then validated through simulation in a multi-robot environment with a task of prey/predator scenario.

I. INTRODUCTION

In this paper, we investigate the application of certain biologically-inspired computation methods in the field of robotics, with particular emphasis on autonomous mobile robots. Different types of tasks, starting from industrial applications to planetary exploration, have been more or less successfully accomplished using single robot systems [2]. Many of these tasks can be carried out faster, more efficiently and on a larger scale using a cooperating group of autonomous mobile robots rather than a single one. Compared to a single autonomous robot, multi-robot [5],[14],[16] systems can perform a mission better in terms of time and quality, can

achieve tasks not executable by a single robot (e.g. moving a large object, exploring different types of environment) or can take advantages of distributed sensing and actuation. Based on all that with multi-robot systems we can increase the system effectiveness in general [6]. In any case, one of the main issues in designing a control system is to make an autonomous mobile robot able to react and adapt in useful time to the environmental changes.

The underlying paradigm of all the work is the behavior-based approach [1],[9] which is rooted in biology and is well suited for coping with rapidly changing (unstructured) dynamical environments [3],[7] and [8]. As mentioned above, the ability to operate in such environments is particularly important for autonomous mobile multi-robots which are expected to operate together in a group towards a common goal handling unpredictable events. Moreover, the robotic platforms have limited computational power similarly to the physical constraints of humans: at one point in time, they can only go toward a particular location, choose one interesting object, interact with an operator and grasp one or a few objects. Thus, a mechanism that selects the relevant parts of the sensory input and decides what to do next is essential. This work addresses this issue tackling the problem of efficiently allocating resources for enhancing the performance of cooperating autonomous robots. One of the most relevant issues is how to coordinate different low and high-level behaviors managing resource allocation and action selection.

The main problem in achieving this requirement is that the number and complexity of the stimuli received by each behavior may be quite high and also the effects on the emerging activity may be very hard to foresee. For this reason we will endow our behavior-based architecture with an adaptive mechanism based on sensory adaptation so that we can focus on particular stimulus and in this way save the resources and computational power of the autonomous multi-robot system by

the use of a potential field approach to determine the level of the robot attention. In particular the attentional level is chosen to be proportional to the resulting force of the environment potential fields. If the resulting force is high the attention is high (i.e. robot is close to a target or to an obstacle); if the resulting force is low the robot attention can be low (robot can save computational resource for other tasks/behaviors).

II. BACKGROUND AND MODELS

In this section, we present a background on potential fields [11] and the attentional allocation models used in this paper [21] along with our proposal to connect robots' environment objects to attentive bursts exploiting the relative distances.

A. Frequency-based model for attention allocation

The Adaptive Innate Releasing Mechanisms (AIRM) architecture combines innate releasing or inhibiting mechanisms (IRM) and simulated biological clocks in order to produce attentional mechanisms. We will use the approach and notation as proposed in [19],[20],[21] to define the attentional mechanisms for our control architecture. First of all, we will define these two concepts; IRM and adaptive clocks.

Innate releasing or inhibiting mechanisms present a mechanism able to control and coordinate behaviors. An IRM is based on a specific stimulus that releases a pattern of actions. For example, an animal may have a prey as an IRM, i.e. the stimulus coming from the view of the predator which activates the escape behavior. IRMs were included in the representation schema of behaviors in the form of releasers, controlling when behaviors must be activated or deactivated. A releaser is an activation mechanism that depends on exogenous factors (e.g. presence of a predator) and/or endogenous factors (e.g. hunger). Simulated biological clock represents the releaser function (internal clock) responsible for activating motivational states for a robot (for example, hunger or sleep). In fact, an internal clock, similarly to a releaser, represents an internal mechanism which regulates behaviors activations [21] depending on endogenous and/or exogenous factors. There are substantial differences between IRMs and AIRMs; one of the most important is that while a releaser is an instantaneous activation mechanism, the internal clock is periodical and adaptive. An internal clock implies periodical activations of the associated behavior. Such activations may be predicted in time, while the activity of a releaser depends only on contingent factors. In this way no computational resources are spent for elaborating unneeded stimuli, because the corresponding control systems is not active until a new periodical activation takes place. At the same time we are able to control the amount of resources spent in the elaboration of the sensor inputs. In the following part, we will present formalization of the AIRM model. For the representation of the AIRM, we will use the Schema Theory approach [18]. Figure 1 shows the AIRM model [21].

Each behavior is characterized by a schema composed of a Perceptual Schema (PS) which elaborates sensor data from the perceptual part of the architecture and a Motor Schema (MS) producing the pattern of motor actions, and control mechanisms, based on a combination of a clock and a releaser. The releaser enables or disables the activation

of the MS according to the sensor data. For example, the presence of a predator releases the motor schema of an escape behavior. In this way the MS is activated only in the presence of the stimulus, while sensor data are always (i.e. in each machine cycle) processed by PS. Instead, the adaptive clock is active within a base period and enables or disables data flow from sensors to PS. Therefore, when the activation is disabled, sensor data are not processed (yields to the sensory reading reduction). Furthermore, the clock regulates its period (frequency of the activation), hence the frequency of data processing, using a feedback mechanisms on the processed sensor data $\delta(t)$

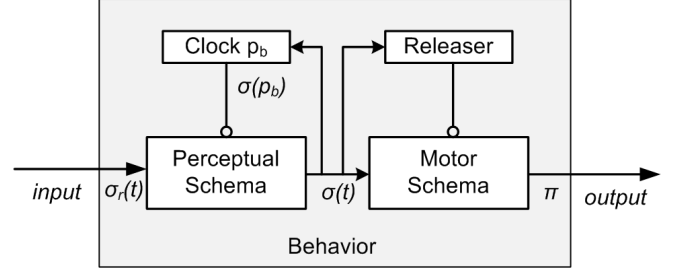


Fig. 1. The Adaptive Innate Release Mechanism model

The releasing mechanism works as a trigger for the MS activation, while the clock regulates sensors' sampling rate and behaviors' activations. The clock regulation mechanism is our frequency-based attentional mechanism: it regulates the resolution at which a behavior is monitored and controlled, moreover, it provides a simple prioritization criteria. This attentional mechanism is characterized by:

- A period p ranging in an interval $[p_{bmin}, p_{bmax}]$,
- An *updating function* $f_{a,d}(\sigma(t), p_b^{t-1}) : R^n \rightarrow R$ that adjusts the current clock period p_b^t , according to the internal state of the behavior and to the environmental changes.
- A *trigger function* $\rho(t, p_b^t)$, which enables/disables the data flow $\sigma_r(t)$ from sensors to PS at each p^t time unit.
- Finally, a *normalization function* $\phi(f_{a,d}(\sigma(t), p_b^{t-1})) : R \rightarrow N$ that maps the values returned by $f_{a,d}(x)$ into the allowed range $[p_{bmin}, p_{bmax}]$.

The clock period at time t is regulated as follows:

$$p_b^t = \rho(t, p_b^{t-1}) \times \phi(f_{a,d}(\sigma(t), p_b^{t-1})) + (1 - \rho(t, p_b^{t-1})) \times p_b^{t-1} \quad (1)$$

that is, if the behavior is disabled, the clock period remains unchanged, i.e. p_b^{t-1} . Otherwise, when the trigger function is 1, the behavior is activated and, the clock period changes according to the $\phi(x)$.

B. Potential fields

The Artificial Potential Field (APF) method was first proposed by Khatib [11] in the middle of 80's, as an on-line (real-time) collision avoidance approach, applicable for dynamical environments, when the robot does not have a priori model of the environment and the obstacles, but it is possible to sense them during motion execution.

A potential field can be viewed as an energy field and so its gradient, at each point, is a force as illustrated in Figure 2. More formally it is defined as an array, or field of vectors.

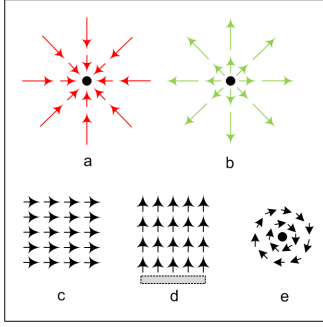


Fig. 2. Primitive potential fields: a.) attraction, b.) repulsion, c.) uniform, d.) perpendicular, and e.) tangential

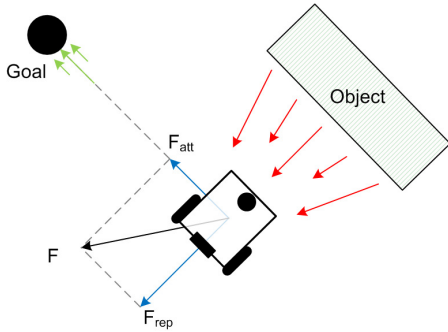


Fig. 3. Potential Field Control Approach

Let q represent the position of the robot, considered as a particle moving on a n -dimensional space $\mathbb{R}^n$.

For the sake of presentation simplicity we will assume that the robot is a point, robot's orientation θ is neglected, and the resulting potential field is only represented in $\mathbb{R}^2 (x, y)$ (see Figure 3). If we assume a differentiable artificial potential field function $U(q) : \mathbb{R}^2 \rightarrow \mathbb{R}$, we can find the related artificial force $F(q)$ acting at the position $q = (x, y)$.

$$F(q) = \nabla U(q) \quad (2)$$

where $\nabla U(q)$ denotes the gradient vector of U at position q .

$$\nabla U(q) = \left[\frac{\partial U}{\partial x}; \frac{\partial U}{\partial y} \right]^T \quad (3)$$

In order to make the robot be attracted toward its goal configuration, while being repulsed from the obstacle, U is constructed as the sum of two more elementary potential functions as in (4).

$$U(q) = U_{att}(q) + U_{rep}(q) \quad (4)$$

where $U_{att}(q)$ is the attractive potential associated with the goal configuration q_{goal} and $U_{rep}(q)$ is the repulsive potential associated with the C-obstacle region.

The repulsive potential results from the superposition of the individual repulsive potentials generated by the obstacles, and so (4) may be written as (5).

$$U(q) = U_{att}(q) + \sum U_{rep_i}(q) \quad (5)$$

where U_{rep_i} represents the repulsive potential generated by obstacle i .

We can consider that $U(q)$ is differentiable for every $q \in C_{free}$. At each q , the gradient of the potential field, denoted by $\nabla U(q)$, is a vector that points in the direction that locally maximally increases $U(q)$. In the potential field based robot navigation methods, the attractive potential is chosen to be zero at the goal and to increase as the robot is far away from the goal and the repulsive potential, associated with each obstacle, is very high (infinity) in the close vicinity of the obstacles and decreases when the distance to the obstacle increases. Along these principles, different attractive potentials may be chosen. Similarly, the forces can also be separated in a attracting and repulsing part as defined in (6).

$$F(q) = F_{att}(q) + F_{rep}(q) = -\nabla U_{att}(q) - \nabla U_{rep}(q) \quad (6)$$

where $F_{att}(q)$ and $F_{rep}(q)$ are called attractive and repulsive forces, respectively.

1) *Attractive potential*: To choose an appropriate attractive potential function the basic idea is that $U_{att}(q)$ should increase as q moves away from q_{goal} (like potential energy increases as you move away from earth's surface). $U_{att}(q)$ can, for example, be defined as a parabolic function, where the potential grows quadratically with the distance q_{goal} .

$$U_{att}(q) = \frac{1}{2} \xi \rho_{goal}^2(q) \quad (7)$$

where ξ is a positive scaling factor and $\rho_{goal}^2(q)$ denotes the Euclidean distance $\|q - q_{goal}\|$ of the robot q to the goal configuration q_{goal} .

The function $U_{att}(q)$ is positive or null, and attains its minimum at q_{goal} where $U_{att}(q_{goal}) = 0$. The gradient $\nabla U_{att}(q) = \xi(q - q_{goal})$ is a vector field proportional to the difference from q to q_{goal} that points away from q_{goal} .

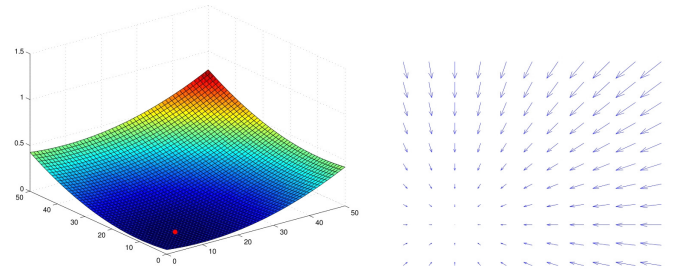


Fig. 4. Attractive Potential (left), Attractive Force to the goal (right)

The farther away the robot is from the goal, the bigger the magnitude of the attractive vector field as illustrated in Figure

4 where the attractive potential and the negative gradient force field is represented for a situation where the goal at position (10, 10) is marked by a red point.

As we saw before the attractive force is the negative gradient of the attractive potential.

$$F_{att}(q) = -\nabla U_{att}(q) = \xi(q - q_{goal}) \quad (8)$$

By setting the robot velocity vector proportional to the vector field force, the force drives the robot to the goal with a velocity that decreases when the robot approaches the goal. The force in (8) represents a linear dependence towards the goal, which means that it grows with no bound as q moves away from the goal which may determine a fast robot velocity whenever far from the q_{goal} . When the robot is far away from the goal, this force imposes that it quickly approaches the goal, i.e., that it moves directly to the goal with a high velocity. On the contrary, the force tends to zero, and so does the robot velocity, when the robot approaches the goal. Therefore the robot approaches the goal slowly which is a useful feature to reduce the overshoot at the goal.

2) *Repulsive potential*: As mentioned before the idea of using repulsive potential is to generate a force which will keep the robot away from the obstacles, both those a priori known and those detected in real-time exploration by robot perception [4],[17]. This repulsive potential should be very strong when the robot is close to the object (obstacle), but in the other case the potential should not influence the movement when it's far from the object. Given the linear nature of the problem, the repulsive potential results from the sum of the repulsive effect of all the obstacles as in:

$$U_{rep}(q) = \sigma U_{rep_i}(q) \quad (9)$$

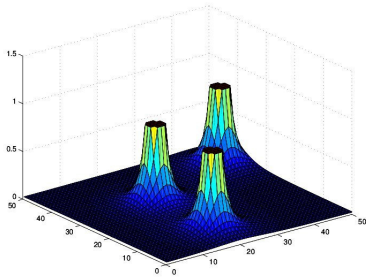


Fig. 5. An example of a repulsive potential field

The implementation of repulsive potential for the robot obstacle follows:

$$U_{rep}(q) = \begin{cases} \frac{1}{2}\eta \left(\frac{1}{\rho(q)} - \frac{1}{\rho_0} \right)^2, & \text{if } \rho(q) \leq \rho_0 \\ 0, & \text{otherwise} \end{cases} \quad (10)$$

where $\rho(q)$ is minimum distance from q and η is positive scaling factor also.

ρ_0 is a positive constance - the distance of influence of the object.

The repulsive potential function $U_{rep}(q)$ is positive or zero and tends to infinity as q gets closer to the object. The negative gradient of the repulsive potential, $F_{rep}(q) = -\nabla U_{rep_i}(q)$, is given as:

$$F_{rep}(q) = \begin{cases} k_{rep} \left(\frac{1}{\rho(q)} - \frac{1}{\rho_0} \right) \frac{1}{\rho^2(q)} \frac{q - q_{obst}}{\rho(q)}, & \text{if } \rho(q) \leq \rho_0 \\ 0, & \text{otherwise} \end{cases} \quad (11)$$

For the environment where the goal lead to the attractive potential represented in Figure 4, the repulsive potential for three obstacles is represented in Figure 5.

The sum of the attractive and repulsive potentials $U(q) = U_{att}(q) + U_{rep}(q)$ is plotted in Figure 6.

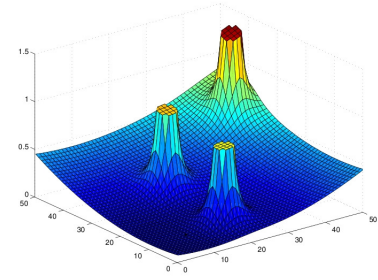


Fig. 6. Sum of two attractive and repulsive potentials

III. CASE STUDY

The aim of this case study is to evaluate the proposed architecture of adaptive potential fields with a multi-robot scenario where mobile predator and prey robots are "stalking" and "fleeing" in an open field, respectively [12],[15]. This predator-prey scenario is a so-called competitive co-evolution, wherein individuals of a particular population compete for the living space, delimited sources, or they even use individuals from other species for their own benefits and thereby decrease probability of their survival. The success of predator robots implies the failure of prey and vice versa. In our case study there will be four predator robots and one prey robot. The objective for the prey robot is to avoid being captured by at least one of the predator robots as long as possible. The objective for four predator robots is to capture the prey without striking into an object or between themselves. Here, capture means that one of four predator robots is simultaneously within one meter of the prey. The prey is successfully escaping as long as it avoids having one of the predator robots within this range. Functionally, each predator is the same in terms of movement and sensor capabilities. The predator robots can communicate with each other in order to exchange the relative positions of the prey trying to catch it. The simulated environment where the predators and the prey operate is unknown to the robots. The predator robot's behavior cannot know anything about how the prey robot's behavior works, and vice versa. In the environment, predators and prey can move in any direction in order to achieve their goals and ensure collision-free movement with fixed obstacles in the environment. The starting position of the predator robots and the prey is arbitrary position. All experiments have been done using the simulation package Player/Stage. Figure 7 shows Player/Stage screenshot

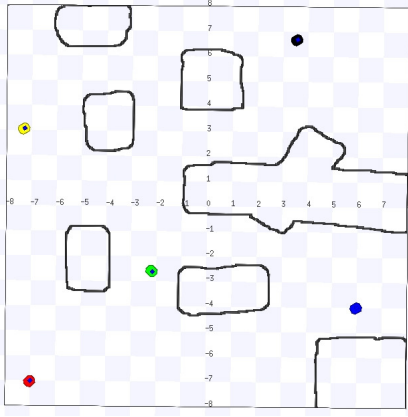


Fig. 7. Simulation environment (Stage simulator) for the predator-prey scenario

of the simulation environment. The colored objects represent the autonomous robots, the green one is a prey and the other colored ones are the predator robots. The black objects represent fixed obstacles in the environment.

However, prey and predator robots differ in several ways. First, the maximum speed of the prey is twice that of predator. This means, obviously, that the prey can outrun the predator. Since we will operate in a closed environment it is possible for a coordination movement at least of two predator robots to try to trap the prey robot if they properly coordinate. Second, the predator robots are endowed with a blob-finder camera as vision system to detect the prey (green color). Third, the prey is using sonar sensors (in total 16) to detect obstacles, instead of using sonar sensor predator robots use a laser which allows them to sense obstacles in a 180 degree field of view.

The predator emergent behavior is obtained as a combination of the following primitive behaviors: *AVOID-OBSTACLE*, *CATCH-PREY*, *WANDER* and *MOVE-TO-PREY*. The overall behavior design (control architecture) is shown in Figure 8. The proposed architecture consists of four primitive behaviors represented through a Schema Theory representation [18]. Every behavior is characterized by a schema composed of a Perceptual Schema (PS) which elaborates sensor data from the perceptual part of the architecture and a Motor Schema (MS) producing the pattern of motor actions, and control mechanisms, based on a combination of a clock and a releaser. The releaser enables or disables the activation of the MS according to the sensor data. Instead, the adaptive clock is active with a base period and enables or disables data flow from sensors to PS.

In the following paragraph we will briefly introduce all four basic behaviors of the predator robot architecture.

The behavior *AVOID-OBSTACLE* (B4) is the first basic behavior needed for an autonomous mobile robot. The obstacle avoidance behavior is responsible for making the mobile robot avoid obstacles on a certain distance away from itself. The motion of the mobile robot will be changed by the control of its velocity (v) and steering angle (θ). To perform obstacle avoidance, the robot needs to know the distances to objects around it. In our case we use a laser scanner with a sensing range from 0 to 180 degrees. The artificial potential field

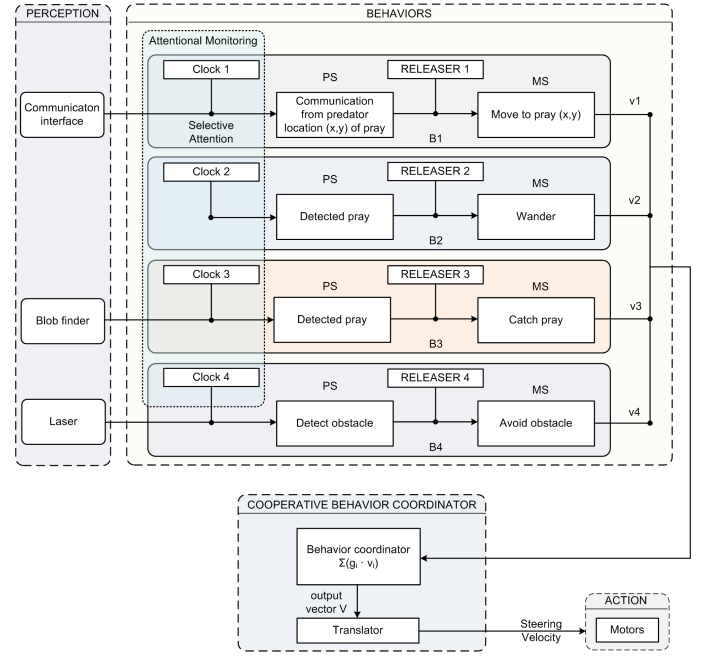


Fig. 8. Predator behaviours' control architecture

method is used to repulse the predator away from the obstacles and generate the control law for the velocity (v) and steering angle (θ).

The *CATCH-PREY* (B3) behavior is responsible for generating the control law for the predator to be able to navigate towards a moving prey. For this behavior, the perceptual input comes from a blob-finder camera. The predator robots are able to detect a prey by using the green color of the prey. The prey is captured when one of the four predator robots is simultaneously within one meter of the prey.

The *WANDER* (B2) behavior performs wandering of the predator robots in the environment by seeking out the prey. In fact, this behavior is an implementation of the random wander algorithm. It implements a randomly generated control law for the movement.

The last behavior *MOVE-TO-PREY* (B1) requires having predator robots communicate with each other when one of them finds the prey. The predator robot that finds the prey reports the prey's relative position to the other predators periodically, as long as that prey is being detected. The predator robot that receives the current relative position of the prey should then move towards the reported position of the prey, using the behavior *MOVE-TO-PREY*.

The perceptual activation is done using a communication interface; in our case the communication process is performed by writing in a global shared memory where all the predator robots have the same privileges to write and read.

The cooperative behavior [13] coordinator generates the emergent overall behavior of the predator robots. The cooperative coordinator applies a method which takes all the behavioral responses and generates an output which will be an input for the control of robots. The principal method is the vector summation such as artificial potential fields.

Behaviors which generate a stronger output will impose a greater influence on the final emergent behavior of the predator robots.

The translator is responsible for producing the control law: velocity (v) and steering angle (θ) for the motion of the predator robots which will be sent to the motors. Attentional monitoring of this mechanism is able to focus monitoring strategies towards particular aspect of the environment the predator robot is interacting with.

IV. SIMULATION RESULTS

In this section we will present some results obtained with the simulation software player/stage. The experimental setup task is based on the predator-prey scenario. Based on the *AIRM* we have analyzed the *CATCH-PREY* behavior as the most relevant for the attentional mechanism, so we will base our future experimental analysis on this behavior. First it is needed to setup the parameters of the monitoring strategy, as follows:

- the initial period $p_i = 10$ activation cycles;
- the range of allowed values for the period is in the interval $[1...10]$ where $p_{bmin} = 1$, $p_{bmax} = 10$;
- the upgrading policy for updating the period of activation is given as $p_b^t = p_b^{t-1} (\frac{1}{2}s - p_{bmax})$, where $p_b^0 = p_i$ and s is the size of the blob (distance of the obstacle/prey)

$$\phi(p_b^t) = \begin{cases} p_{min}, & \text{if}(p_b^t < p_{min}) \\ p_{max}, & \text{if}(p_b^t > p_{max}) \\ p_b^t, & \text{otherwise} \end{cases} \quad (12)$$

The range of allowed values for the period is in the interval $[1...10]$ where $p_{bmin} = 1$, $p_{bmax} = 10$.

The updating policy for updating the period of activation is given as reported in (12).

Figures 9-10 show the experimental results for two of four predators (Predator1 and Predator4) based on the *CATCH-PREY* behavior. In the Figure 9-10 a) we show the change of the period over the time. Figure 9-10 b) shows the size of the blob which is related to distance to the prey (e.g. as the prey is closer the size of the blob increases). Figure 9-10 c) shows the resulting speed of the predator over the time.

As shown in Figure 9 a) starting at the 9th second (90 tenth of seconds), as the size of the blob increases the period decreases according to (12). This means when the prey is far away from the predator the activation period of the *CATCH-PREY* behavior is greater. This adaptive mechanism allows the predator to save energy avoiding unnecessary behavior activations when it cannot catch the prey because of the long distance. In real application this means that we can save computational resources in extracting the blob [10] (prey) from a camera by reducing the acquisition frame rate. The linear speed of the predator is decreasing when it gets closer to the prey, in order to prevent to pass over.

In Tables I and II we present an evaluation of the activation period and the speed of the *CATCH-PREY* behavior.

TABLE I. CATCH PREY BEHAVIOR ACTIVATION PERIOD.

Robot	MIN	MAX	μ	δ^2	δ
Predator 1	1	10	8.5602	8.8708	2.9258
Predator 2	1	10	9.7463	1.7021	1.3046
Predator 3	1	10	9.5556	3.0062	1.7338
Predator 4	1	10	9.6366	1.8961	1.3770

TABLE II. CATCH PREY BEHAVIOR ROBOT SPEED.

Robot	MIN	MAX	μ	δ^2	δ
Predator 1	0.1153	0.9608	0.5352	0.0959	0.3097
Predator 2	0.1864	1.0000	0.5593	0.0272	0.1649
Predator 3	0.1720	1.0000	0.5905	0.0427	0.2068
Predator 4	0.1588	1.0000	0.5306	0.0242	0.1554

Tables I and II show for Predator 1 and Predator 4 (Figures 9-10) the minimum and the maximum period, the mean period, variance and standard deviation of the activations number and speed respectively.

V. CONCLUSION

In this paper, we have presented a behavior-based architecture for adaptive multi-robot system. The goal is to design and implement an adaptive reactive control strategy, able to control a cooperating group of mobile robots allowing them to operate in a weakly structured and dynamic environment. One of the main constraints of the autonomous mobile robot platforms is the limited resources, like the computational or the energy ones. In this paper, we have shown that Adaptive Innate Releasing Mechanisms allow us to save resources without significant loss in response speed. The experimental validation based on the predator-prey scenario performed in a simulated environment provides encouraging results about the effectiveness of the proposed multi-robot system.

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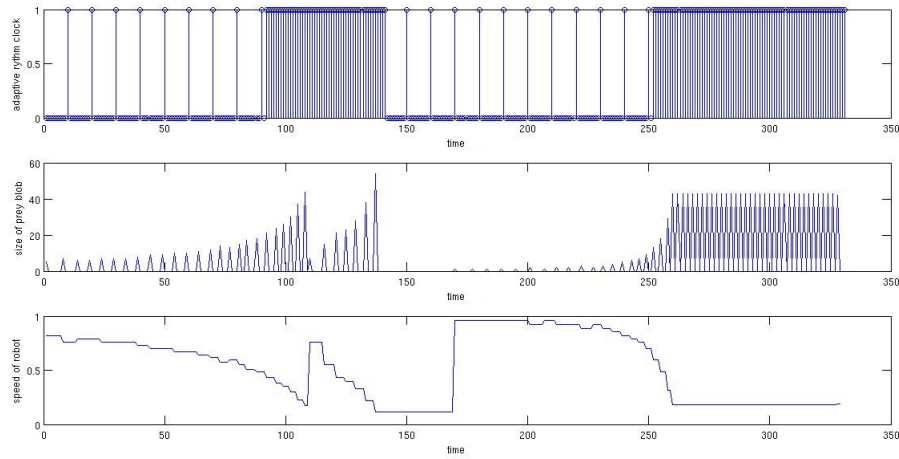


Fig. 9. Results of the *CATCH-PREY* behavior for the Predator 1 a) adaptive rhythmic clock b) size of the blob c) linear speed of the Predator 1

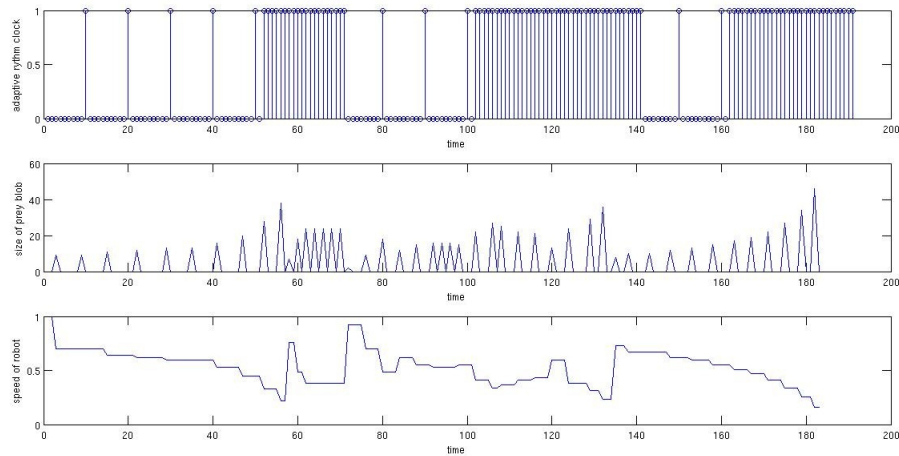


Fig. 10. Results of the *CATCH-PREY* behavior for the Predator 2 a) adaptive rhythmic clock b) size of the blob c) linear speed of the Predator 2

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