

Attentive Monitoring and Adaptive Control in Cognitive Robotics

E. Burattini, A. Finzi, S. Rossi and M. Staffa

Universita' degli Studi di Napoli "Federico II" - Italy.

email: {ernb, finzi, srossi}@na.infn.it, mariacarla.staffa@unina.it

Abstract

In this work, we present an attentional system for a robotic agent capable of adapting its emergent behavior to the surrounding environment and to its internal state. In this framework, the agent is endowed with simple attentional mechanisms regulating the frequencies of sensory readings and behavior activations. The process of changing the frequency of sensory readings is interpreted as an increase or decrease of attention towards relevant behaviors and particular aspects of the external environment. In this paper, we present our framework discussing several case studies considering incrementally complex behaviors and tasks.

Introduction

An autonomous robotic agent is expected to operate in complex dynamic environments by continuously monitoring the internal processes and the external environment. The robot executive system is to coordinate different low-level strategies (such as obstacles avoidance, walls follow, gates crossing, etc.) with high-level activities (such as achieving a goal, picking up an object, etc.), giving them, from time to time, different priority values both for allocation of resources and for action selection processes. The low-level activities are usually safety critical and are managed in a reactive way. On the other hand, high-level activities are generally achieved by processing more complex tasks, and, therefore, require high computational costs for both the inputs processing and data acquisition from the environment.

In this context, attentional mechanisms balancing sensory elaboration and actions execution can play a crucial role. In particular, attentional mechanisms have two main roles: direct sensors towards the most salient sources of information; filter the available sensory data to prevent unnecessary information processing. As a result of the application of these mechanisms, the robot behavior should be enhanced: the robot is to react faster to task-related or safety critical stimuli because processing resources are focused on not relevant stimuli.

Attentional mechanisms applied to autonomous robotic systems have been proposed elsewhere (e.g. (Mitsunaga and Asada 2002; Carbone et al. 2008; Frintrop, Jensfelt, and Christensen 2006)), mainly for vision-based robotics. In

contrast, in our work, we are interested in artificial attentional processes suitable for the executive control. In particular, our aim is to provide a kind of supervisory attentional system (Norman and Shallice 1986; Cooper and Shallice 2000) capable of monitoring and regulating multiple concurrent behaviors at different level of abstraction. The notion of *divided attention* (Kahneman 1973) suggests that a limited amount of attention is allocated to tasks, with the resources involved in multi-task performances, and can be available in graded quantity. In an artificial setting, this can be obtained by introducing suitable scheduling mechanisms.

In this work, we present a behavior-based control architecture endowed with attentional mechanisms which are based on periodic releasing mechanisms of activations (Burattini and Rossi 2007; 2008). In this context, each behavior is equipped with an adaptive internal clock that regulates the sensing rate and the resulting action activations. The process of changing the frequency of sensory readings is interpreted as an increase or decrease of attention towards relevant behaviors and particular aspects of the external environment: the higher is the frequency, the higher is the resolution at which a process is monitored and controlled. Here, we present our framework providing several case studies where we discuss the effectiveness of the approach considering its scalability and the adaptivity with respect to different environments and tasks.

Attentive Executive Control

Our goal is to develop a behavior-based control system endowed with attentional mechanisms which focus sensory acquisitions and processing and modulates behaviors activations. The executive system should be enhanced with a supervisory attentional system (Norman and Shallice 1986) to suitably combine deliberative and reactive activities, monitoring and regulating multiple concurrent behaviors (Kahneman 1973). Our working hypothesis is that attentional behaviors are affected by internal self-regulating mechanisms and external sources of salience. The attentional global behavior should emerge from the interrelation of the attentional mechanisms associated with each single behavior.

Design Principles

The attentional control system we consider in this work combines the following design principles:

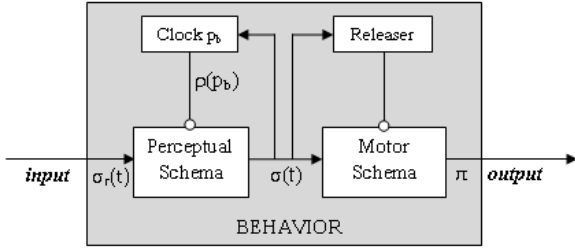


Figure 1: Each behavior is composed of an adaptive clock, a releasing function, a perceptual schema and a motor schema.

- *Behavior-based control system.* The attentional control is obtained from the interaction of a set of multiple parallel attentional behaviors working at different levels of abstraction.
- *Attentional monitoring.* Attentional mechanisms are to focus monitoring and control activities on relevant internal behaviors and external stimuli.
- *Internal and external sources of salience.* The sources of salience are behavior and task dependent; these can depend by either internal states (e.g. hunger, fear) or external stimuli (e.g. obstacles, unexpected variations of the environment).
- *Adaptive sensory readings.* For each behavior, the process of changing the rate of sensory readings is interpreted as an increase or decrease of attention towards a particular aspect of the environment the robotic system is interacting with: the higher is the frequency, the higher the resolution at which an activity is monitored and regulated.
- *Emergent attentive behavior.* The overall attentional behavior should emerge from the interrelations of the attentive mechanisms associated with the behaviors.

Attentive Monitoring in the AIRM Architecture

In (Burattini and Rossi 2007; 2008), we connected the concept of IRM (Innate Releasing Mechanisms) (Lorenz 1991; Tinbergen 1951) to the concept of periodical activations of behaviors (Pezzulo and Calvi 2006; Stoytchev and Arkin 2001; 2004) introducing the Adaptive Innate Releasing Mechanisms (AIRMs). An AIRM is a *releasing mechanism* endowed with an internal *adaptive clock*.

In Figure 1 the AIRM is represented through a Schema Theory representation (Arbib 1998). Each behavior is characterized by a schema composed of a Perceptual Schema (PS), which elaborates sensor data, a Motor Schema (MS), producing the pattern of motor actions, and a control mechanism, based on a combination of a clock and a releaser. In particular, the releaser enables/disables the activation of the MS, according to the sensor data $\sigma(t)$. For example, the presence of a predator releases the motor schema of an escape behavior. Instead, the adaptive clock is active with a base period and it enables/disables data flow $\sigma_r(t)$ from sensors to PS. Therefore, when the activation is disabled, sensor

data are not processed (yielding to sensory readings reduction). Furthermore, the clock regulates its period, hence the frequency of data processing, using a feedback mechanism on the sensor data $\sigma(t)$.

We assume a discrete time model - with the machine cycle as the time unit - where each behavior is endowed with a clock regulating its own activations. This regulation mechanism, that we call *monitoring strategy*, is characterized by:

- An initial period p_b called base period, ranging in an interval $[p_{min}, p_{max}]$,
- An *updating function* $f(t) : \mathbb{R}^n \rightarrow \mathbb{R}$ that changes the clock period p , according to the parameters the behavior depends on (sensors used, internal state, special features of the environment, and the behavior goal).
- A trigger function $\rho(t, p_{t-1})$, which enables/disables the data flow $\sigma_r(t)$ from sensors to PS, at each p time unit. More formally:

$$\rho(t, p_{t-1}) = \begin{cases} 1, & \text{if } t \bmod p_{t-1} = 0 \\ 0, & \text{otherwise} \end{cases} \quad (1)$$

- Finally, a support function $\phi(f(t)) : \mathbb{R} \rightarrow \mathbb{N}$ maps the values generated by the updating function $f(t)$ in a range of allowed values for the period $[p_{min}, p_{max}]$. More precisely:

$$\phi(x) = \begin{cases} p_{max}, & \text{if } x \geq p_{max} \\ \lfloor x \rfloor, & \text{if } p_{min} < x < p_{max} \\ p_{min}, & \text{if } x \leq p_{min} \end{cases} \quad (2)$$

Now, starting from the clock period at time 0,

$$p_0 = p_b \quad \text{with } t = 0 \text{ and } p_b \in [p_{min}, p_{max}]$$

The clock period at time t is regulated as follows:

$$p_t = \rho(t, p_{t-1}) * \phi(f(t)) + (1 - \rho(t, p_{t-1})) * p_{t-1} \quad (3)$$

That is, if the behavior is disabled, the value of the period calculated at time t remains unchanged at the last computed value p_{t-1} . Instead, when the value of trigger function is equal to 1, the behavior is activated and, subsequently, its activation period changes according to the $\phi(f(t))$ function.

Attentive Monitoring and Control. The *monitoring strategy*, i.e. the process of changing the clock sampling rate, can be associated with the increase or decrease of attention towards a particular behavior. Namely, the more salient is the behavior, the higher is the clock frequency and the resolution at which a behavior is monitored and regulated. Notice that, the frequencies of the adaptive clocks provide also a divided attention mechanism: the monitoring activity is distributed over the concurrent behaviors depending on the frequencies of their associated clocks.

Following this approach, we can obtain different attentional mechanisms associated with each behavior once we define the associated *monitoring strategy*. Therefore an attentive behavior will result from the combination of the initial period p_b , the permitted values range $[p_{min}, p_{max}]$ and the updating policy $f(t)$. In order to obtain a good

monitoring strategies, it is necessary to balance the cost of monitoring a behavior against the risk of acquiring inaccurate/degraded information about the environment.

These attentive monitoring strategies are introduced to provide the following main benefits:

- the periodical activation can reduce the number of activations of the perceptive system causing a relative decrease in the computational burden, and improving performance of the entire system;
- the use of adaptive activation mechanisms allows us to obtain a behavior that adapts itself to the specific environmental conditions (e.g. the robot reads sensors more often if there is a dangerous situation and less often in cases of a safe operational situation).

Example. Consider the example of a person who is crossing a street. Depending on the traffic intensity, this person has to pay more or less attention while crossing the street, turning his head left and right. Here, the monitoring frequency should be regulated according to the speed of the passing cars. The pedestrian has to react according not only to the environmental change (a car passing on the street) but also to the speed at which this happens (fast or slow cars). Intuitively, we can associate the speed of the pedestrian and his monitoring activity to the speed of the passing car. Following this approach, in (Burattini and Rossi 2008), we provided an example of a robot whose task was to cross a street avoiding moving obstacles. In this case, the updating policy has a frequency that is directly proportional to the speed of the moving obstacles: the higher the speed, the smaller the sampling period.

Case Studies Overview

In this section, we present and discuss our framework deployed in different scenarios and setting, both in simulation and in the real world, from simple scenarios to more complex settings. Our aim is to discuss our approach considering its effectiveness efficiency, adaptability (in different scenarios), and scalability (considering increasingly complex behaviors and tasks).

For the simulated experiments we used the *Stage* tool of the *Player* project (Gerkey, Vaughan, and Howard 2003), while for the real one we used the *PIONEER 3DX* robotic platform *Active Media Robotics*, endowed with a blobfinder camera, and sonars.

Conflicting tasks

In previous work (Burattini and Rossi 2010; Burattini et al. 2010), we investigated the application of the AIRM attentional mechanisms in simple cases of conflicting behaviors. In the following we provide an overview of two scenarios presented in (Burattini and Rossi 2010) and (Burattini et al. 2010) respectively.

Emergent Action Selection in Conflicting Tasks. In (Burattini and Rossi 2010), we describe a simple case study involving two conflicting attentive behaviors: *ESCAPE*, representing predator avoidance, *FIND_FOOD*, representing the

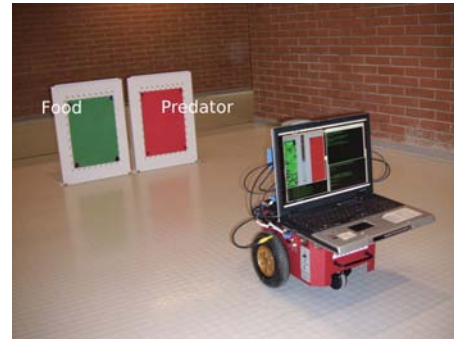


Figure 2: Conflicting tasks: food and predator.

search for food. *FIND_FOOD* has an updating policy that depends on the risk of starvation, and it is regulated by a linear time-dependent function representing hunger: the higher the hunger, the higher the attention towards the food. *ESCAPE* changes its clock period following the Weber-Fechner law of perception which is used to represent fear: the higher the fear, the higher the attention towards the predators. When *FIND_FOOD* is enabled and the robot perceives a green object (representing food), it activates a movement towards the food. When the *ESCAPE* is enabled and the robot perceives a red object (representing a possible threat), it activates a movement opposite to the threat and a velocity inversely proportional to the clock period.

When the robot encounters a red object close to a green object (see Figure 2) we have a conflicting behavior. In this case, the attentional mechanisms implemented with the adaptive clocks allow to balance the trade off between the risk of predation and the risk of starvation. This can be obtained avoiding the introduction of explicit action selection mechanisms. Indeed, if the threat stand still, as soon as the risk of starvation increases more than the value of the *ESCAPE* clock, the robot starts moving towards the food, escaping in the case an abrupt movement of the threat. The combination of these two behaviors, elicited by the risk of starvation and the risk of predation, is an oscillating movement that will lead, eventually, to reach the position of the food.

Parallel Execution of Conflicting Task. Inspired by studies (Patten et al. 2004; Harbluk, Noy, and Eizenmann 2002) on cognitive distraction while driving (i.e., talking over a mobile phone), (Burattini et al. 2010) considers a case study including two behaviors that, although conflicting, can be simultaneously carried on. (Harbluk, Noy, and Eizenmann 2002) shows that drivers, under a high cognitive load, execute less saccadic movements consistently with an increase of fixation time and a smaller exploration of the visual field. These results suggest that parallel tasks can be accomplished, but the resources allocated to each task are dynamically distributed according to environmental conditions and to cognitive and physical capabilities.

To investigate our framework in an analogous setting, in (Burattini et al. 2010), we designed the case study of a mo-



Figure 3: The hallway domain.

ble robot that is to run across a hallway in the shortest time possible, while counting green blobs distributed on walls and arranged into clusters (Burattini et al. 2010) (see Figure 3). The two tasks of running and counting conflict on the speed of the robot. Indeed, the first task requires a high speed, while the second require a slow speed to effectively count all the blobs.

In order to accomplish the two tasks we implemented a robotic system endowed with three behaviors: RUN, SEARCH, and SCAN. SEARCH looks for green blobs on the left and right wall. This behavior works with a maximal frequency until at least one green blob is detected, then the period is increased proportionally to the amount of green blobs. SCAN counts the blobs once a salient area is identified and the clock period is proportional to the SEARCH activation frequency. RUN sets the speed of the robot that is in inversely proportional to the period. The clock period of the RUN is directly proportional to the period of SEARCH.

The observed system behavior is the following. The robot starts running with a medium speed, looking for green objects on the walls of the corridor. When the system detects a cluster of blobs, the period of SCAN decreases, allowing the robot to slow down its speed and to count the objects it detects. Similarly, if no green objects are detected, the period of the RUN become smaller, allowing a more accurate exploration (moving several times the camera looking for objects), and increasing the system speed to reach the end of the corridor as soon as possible.

In (Burattini et al. 2010), we compared the system performances with respect to an analogous system with non adaptive clocks (i.e. activation at each machine cycle). The experiments show that the proposed architecture performs better compared to the non attentional setting in terms of: number of detected blobs (effectiveness); tradeoff between time and counted blobs (cost/benefit); error of detection (precision); less activations of the perceptual schema (efficiency). The attentive system is effective in counting blobs because it can coordinate and modulate speed and pan-tilt control, focusing the visual exploration on the region of interest. The overall attentional coordination increases the time needed to

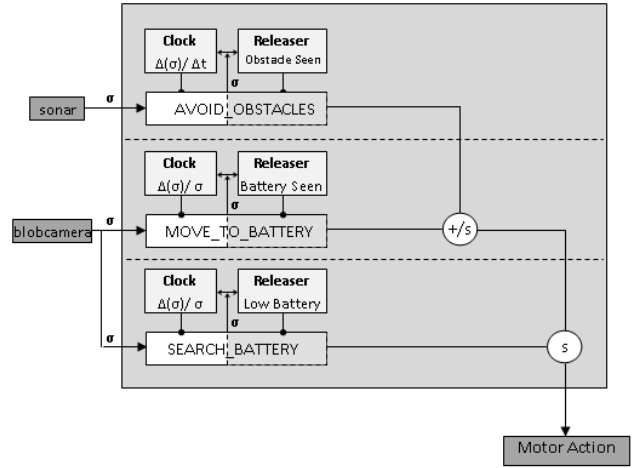


Figure 4: Control architecture.

accomplish the task, but this additional time is spent in the counting phase, effectively trading off between time and precision. Basically, the system can modulate the activation frequencies on the basis of the available resources and external conditions. Indeed, using the adaptive clocks, the number of behaviors activations substantially decreases compared to the case where each behavior is enabled at each machine cycle, and this results in a substantial gain in performances.

Foraging domain

In this scenario, we consider a robot whose aim is to explore a dynamic and unknown environment avoiding obstacles and seeking sources of energy to recharge its batteries in a fixed amount of time.

In this scenario, we evaluated the performances of our attentive system with respect to the performances of analogous behavior-based systems not equipped with adaptive clocks. In particular, to better assess the gain due to the attentional mechanisms, we compared the system with respect to two different versions of the control system:

- a *cautious* version of the system, that we call *without clocks* (STD): where each behavior can be activated at each machine cycle, depending on the releasing function (as in a standard non adaptive behavior-based architecture);
- a *brave* version of the system with *periodic clocks*: where behaviors are associated with periodic, but fixed, activation periods. In this case, each behavior has its own clock without attentional adaptivity.

In this setting, we want to prove the scalability of the attentive mechanism with respect to the system complexity (system with more behaviors) and different environmental conditions (obstacles configurations). Our aim here is to demonstrate the ability of our attentive monitoring strategies to regulate the resources distribution among the different behaviors.

Behavior-based control. The robot behavior is obtained as the combination of the following primitive behaviors (see Figure 4): AVOID, SEARCH_BATTERY, MOVE_TO_BATTERY.

The AVOID behavior is responsible for obstacle avoidance. This behavior is safety critical and needs an updating policy for its adaptive clock which is able to timely react to dangerous situations. In this case, the AVOID clock period changes according to the first derivative of the input percept. More formally, the AVOID clock period is updated according to (3), with the following updating function:

$$f(t) = \left(\frac{\alpha_{avoid} * p_{t-1}}{\Delta\sigma(t) + k_{avoid}} \right)$$

where $\Delta\sigma(t)$ is equal to $\sigma(t) - \sigma(t - p_{t-1})$ that is the difference between the actual data perceived by the sensor $\sigma(t)$ and data received at the previous sampling time $\sigma(t - p_{t-1})$. In this way, the AVOID activations frequency adapts itself not only to the environmental changes, but also to the speed at which these changes take place. α_{avoid} and k_{avoid} are two attenuation parameters. These two parameters are context dependent and can be tuned by a suitable learning algorithm.

The AVOID behavior is responsible not only for the robot orientation, but also for its speed variations. In particular, speed is related to the period according to the following relation:

$$speed_t = \frac{max_speed \times p_t}{p_{max}}$$

where $speed_t$ is the current speed, max_speed is the maximum value allowed for the robot speed. The range of values for the speed is $[0, 0.3]m/s$. In this way, if the period is relaxed, the robot moves at a maximum speed, otherwise, it slows proportionally to the decrease of the period. This allows the agent to avoid obstacles in a smooth way (see the next paragraphs for details).

The SEARCH_BATTERY behavior provides a random search of sources of energy in the environment. The frequency of this behavior activation is related to the level of charge of the robot's battery. The lower the battery, the greater the activity of the search behavior. Since we assume that the energy need is represented by a function $e(t)$ that grows with time, the updating function can be defined as follows:

$$f(t) = \frac{k_{search}}{e(t) + h_{search}}$$

where k_{search} and h_{search} are two context dependent parameter to be suitably tuned by a learning algorithm. The output of this behavior is a random pattern of orientations for the motor action.

The MOVE_TO_BATTERY behavior guides the agent towards the battery when this has been identified. So the releaser is activated by battery detection using the blob camera. Analogously, to the previous updating function, the period of this behavior activation also depends on the level of the battery charge and can be defined as:

$$f(t) = \frac{k_{move}}{e(t) + h_{move}}$$

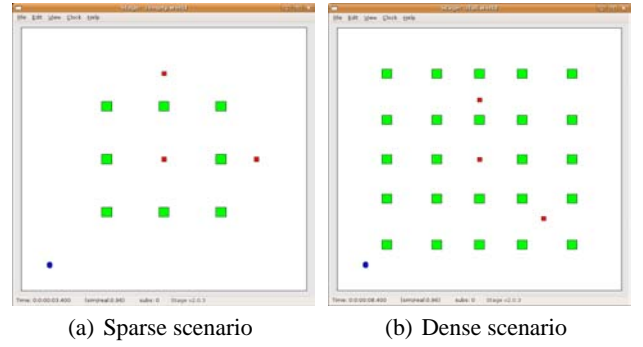


Figure 5: Map of the environment in two scenarios. Energy sources and obstacles are, respectively, the small red boxes and the big green boxes. The robot is the blue rounded square at the left bottom.

Namely, the adaptive clock period is regulated by a time-dependent function that represents the agent need of energy.

If the releaser is on and the agent can perceive the battery, the output will be a movement towards it, otherwise the agent will rely on the SEARCH_BATTERY behavior. The trajectory towards the battery is calculated with respect to the centroid of the red blob, which identifies the battery charge in the scene.

Testing Scenarios. The robotic system works in a foraging domain characterized by an area of $20m \times 20m$ ($400 m^2$). In this environment we considered two possible configurations: (1) a sparse scenario with few obstacles (Figure -(a)) and (2) a dense scenario with many obstacles (Figure -(b)). The size of the robot with respect to the environment is $0.2 m \times 0.1 m$ ($0.2 m^2$). Obstacles are represented by a green square ($0.7m \times 0.7 m$), while the energy source by red square in size $0.3 m \times 0.3 m$. We performed the experiments in simulation using the Stage tool.

In these scenarios, we considered the system performances by incrementally adding behaviors and tasks. From only one behavior (AVOID) to a combination of three behaviors (AVOID, SEARCH_BATTERY, and MOVE_TO_BATTERY). For each setting, we collected the data of 10 runs.

Avoiding Obstacles. First of all, we considered a robot equipped with the AVOID behavior, whose task is to safely navigate into the environment with obstacles, for a fixed interval of time (5 minutes). This test has been performed in both the sparse and dense scenarios.

In Table 1, the results of the attentive system are compared with respect to the caution version (case (a)), *without clocks*, and brave version (case (b)), *with periodical clocks*.

The collected parameters are: the number of activations of the avoid behavior, the number of possible dangerous situation (minimum distance from the obstacle detected by sonar less than $0.3m$), and the average speed of each run.

In Table 1, we see that both in the case of sparse and dense obstacles, the number of the different behaviors activations is radically reduced in the case of the attentive system. Less behavior activations determines a reduction in the computa-

	AVOID		dangers		speed (m/s)	
	avg	st.dev	avg	st.dev	avg	st.dev
SPARSE adaptive	403	18	6,8	6,7	0,2874	0,0045
SPARSE periodic	621	14	24,3	27,4	0,2886	0,0053
SPARSE without clock	1203	4	0	0	0,2078	0,0312
DENSE adaptive	476	30	3,6	5,5	0,2696	0,0075
DENSE periodic	625	3	45,3	49,8	0,2748	0,0136
DENSE without clock	1279	25	0	0	0,1704	0,0118

Table 1: Attentive, Periodic and STD architectures endowed with the AVOID behavior and compared in the sparsity and density scenario.

tional time spent for sensory data acquisition and processing.

Furthermore, these results show that by improving the complexity of the environment we do not lose the benefits of the attentive setting in term of low activations and high average speed.

The results obtained with periodic clocks represent a medium case. Indeed, the periodic setting reduces the behavior activations with respect to the setting without clocks, however, without adaptability we cannot ensure the robot safety (note the increment of possible dangerous situations in the case of periodic clocks).

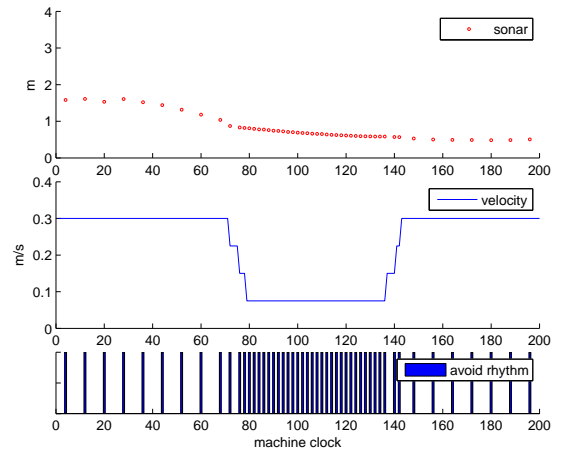
Avoiding Obstacles and Reaching a Source of Energy. In a second set of tests, we enhanced the functionality of the control system by adding the SEARCH_BATTERY and MOVE_TO_BATTERY behaviors. Here, the robot task is to safely navigate the environment trying to reach the source of energy according to its needs in a fixed amount of time. The amount of time chosen for the experiments is 3 minutes. As before, we compared the performances of the three architectures both in the sparse and in the dense environment.

In Table 2, in addition to the data presented in the previous test, we show also the average number of sources of energy reached.

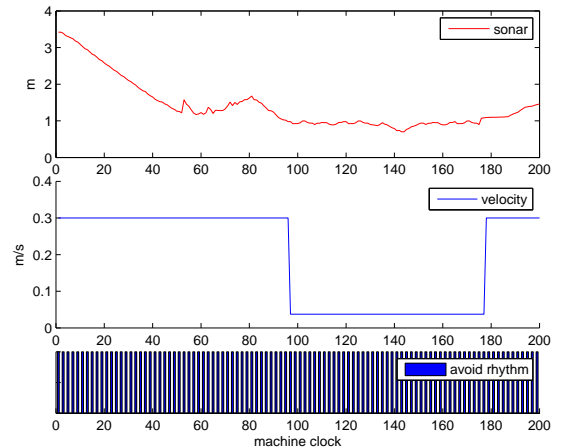
Differently from previous case, the number of MOVE_TO_BATTERY activations is minimal with a periodic system, however, here we have also a decrease in the average number of batteries reached. This happens because the MOVE_TO_BATTERY behavior is responsible of directing the robot toward the source of energy, hence, the smaller the number of the activations the lower the chance of finding battery and the precision of the robot maneuvers during the battery approach. Moreover, in the periodic setting, the number of possible dangers grows dramatically with respect to the attentive one, where we find more sources of energy and less dangerous situations.

If we compare the attentive architecture with respect to the one without clocks, we see less activations (Table 2), more energy found, and less crashes despite the average speed the robot remains high. This means that the attentive robot can reach its goals earlier with less effort.

Moreover, the attentive behavior appears smoother and more natural than the one of the non adaptive versions; this also affects safety. For example, in the attentive case the agent can avoid obstacles in a smooth way (Figure 6-(a)), because the AVOID behavior, responsible for the speed vari-



(a) Attentive avoidance



(b) Non-adaptive avoidance

Figure 6: Comparing avoidance behaviors.

(S=Sparse/D=Dense)	AVOID		MOVE_TO_B		SEARCH_B		dangers		speed (m/s)		energy	
	avg	st.dev	avg	st.dev	avg	st.dev	avg	st.dev	avg	st.dev	avg	st.dev
S adaptive	310,7	10,4	132,6	67,0	45,2	5,1	39,4	25,8	0,282	0,003	1,1	0,6
S periodic	560,2	62,4	17,5	37,0	113,6	22,8	136,9	77,1	0,167	0,003	0,2	0,4
S without clock	968,8	69,8	417,8	197,0	302	101,7	87,7	40,9	0,175	0,012	1,9	0,7
D adaptive	330,3	6,8	250,5	114,4	32,6	7,0	15,2	9,9	0,238	0,018	0,8	0,4
D periodic	605,2	175,1	28,7	59,4	93,9	29,1	72	111,4	0,162	0,007	0,4	0,8
D without clock	1054	43,9	106,5	50,5	408,2	124,9	49,5	15,2	0,169	0,021	1,1	0,6

Table 2: Attentive, Periodic and STD architectures endowed with three behaviors and compared in the sparsity and in the dense scenarios.

ations, can modify the robot speed proportionally to the relevance of the situation. Instead, in the non-adaptive case, the speed is very high if there is no danger, very low otherwise; this produces drastic speed variations (Figure 6-(b)) that can determine unsafe behaviors.

Related Works

Attention-based control is an emerging issue, in particular for vision-guided mobile robots. Several approaches in literature address the problem of feature extraction to support task execution (Minato and Asada 2001), localization, mapping, and navigation (Mitsunaga and Asada 2002; Frintrop, Jensfelt, and Christensen 2006; Carbone et al. 2008). For instance, in (Minato and Asada 2001) an attentive behavior is learned by pairing actions and image features.

Mechanisms for executive and divided attention in robot execution monitoring are less explored. In (Garforth, McHale, and Meehan 2006), the authors investigate executive attention in mobile robotics tasks proposing the deployment of a supervisory attentional system inspired by (Norman and Shallice 1986). Concurrent tasks interacting with the attentive processes are considered in (Wasson, Kortenkamp, and Huber 1999) where we find a robot architecture integrating active vision and tasks execution. However, here divided attention is not considered while attentive and goal-directed behaviors are integrated and coordinated using a perceptual memory.

Closely related to our system, in (Stoytchev and Arkin 2001) Stoytchev and Arkin propose an hybrid architecture combining deliberative planning, reactive control, and motivational drives. In this context, the internal state is represented by motivational variables affecting action and perception. Analogously to our framework, periodic activations of behaviors as circadian rhythms and time-dependent motivational processes are deployed, however, here internal clocks are not directly used for attention selection and behavior modulation.

Other authors dealt with flexible/adaptive behavior realized through timed activations. For example, (Pezzulo and Calvi 2006) presented a parallel architecture focused on the concept of activity level of each schema which determines the priority of its thread of execution. A more active perceptual schema can process the visual input more quickly and a more active motor schema can send more commands to the motor controller. However, while in our approach such effects are obtained through periodic activation of behav-

iors, in (Pezzulo and Calvi 2006) the variables are elaborated through a fuzzy based command fusion mechanism.

Our attentive sampling can be also related to flexible scheduling for periodic tasks in real-time systems (Buttazzo et al. 2002; Beccari, Caselli, and Zanichelli 2005). Here, analogously to our system, period modulation is exploited to degrade computation and keep balanced the system load. For example in (Buttazzo et al. 2002), the authors propose an elastic model to decide how to change the sampling period associated with a task. Similar techniques can be incorporated in our framework, however, in our case sampling rate depends not only on the computational load, but also on salience due to environmental changes, motivations, and goals.

Conclusions and Future Work

In this paper, we illustrate an attention-based control architecture for a robotic system capable of adapting its emergent behavior to the surrounding environment and to its internal state. While attention-based robot control has been already considered in literature, mainly for vision-based robots, mechanisms for executive and divided attention in robot execution monitoring are less explored. In the context of a behavior-based executive system, we introduced simple attentional mechanisms which are based on the periodic releasing mechanisms of activations introduced by (Burattini and Rossi 2007; 2008).

In the proposed attentional system, each behavior is equipped with an adaptive clock and the process of changing the frequency of sensory readings is interpreted as an increase or decrease of attention towards relevant behaviors and particular aspects of the external environment.

To validate our approach, we experimented the control architecture in different case studies. In particular, we tested the scalability and the adaptivity of the approach with respect to different and heterogeneous environments and tasks. Furthermore, we evaluated the performances of the attentional system with respect to the performances of other behavior-based systems not provided with attentive and adaptive mechanisms. The collected results show that attentional mechanisms permit a smooth and natural emergent behavior in all the considered scenarios trading off between adaptivity and performances. We are currently investigating suitable learning mechanisms to set the parameters associated with monitoring strategies and attentional mechanisms to combine deliberative and reactive processes.

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