
Peer reviewed version

Link to publication record in Explore Bristol Research
PDF-document

University of Bristol - Explore Bristol Research
General rights

This document is made available in accordance with publisher policies. Please cite only the published version using the reference above. Full terms of use are available:
http://www.bristol.ac.uk/pure/about/ebr-terms
Attentive Monitoring for Team Coordination: a Human-Robot Convoy Example

Silvia Rossi, Mariacarla Staffa, Antonio Adaldo, Francesco Alderisio, Vito Magnanimo
Università degli Studi di Napoli Federico II
Department of Electrical Engineering and Information Technology - DIETI
via Claudio 21, 80125, Naples, Italy
{silvia.rossi, mariacarla.staffa}@unina.it

Abstract. Convoy driving requires both the leader and the follower to accomplish the task. Namely, also the leader has to monitor the following agents behavior and to adapt its own in order to not outdistance them. Our working hypothesis is that effective teamwork can be achieved by adapting periodic monitoring strategies. Inspired by the behavior of human beings, we adopted attentional mechanisms for filtering data and actively focusing the monitoring only on relevant information and agent behaviors. The robotic convoy task is accomplished via a behavior-based control architecture endowed with attentional mechanisms producing a variable frequency of the monitoring. In this paper, we consider a convoy task as a benchmark to evaluate and compare human and robot monitoring behaviors. We illustrate the various parts of the control architecture as well as present and discuss the results of experiments performed in a real world scenario with humans and robots.

Keywords: Teamwork, Agent Monitoring, Attention, Human-Robot Collaboration

1 Introduction

In the last two decades Human-Robot Interaction (HRI) emerged as one of the main topics in developing service robotics. While HRI includes the possibility of interacting with robots as intelligent tools to command (perhaps using speech or gesture [1]), real human-robot collaboration and teamwork is a relatively unexplored field [2]. A crucial factor to achieve an effective and safe HRI is the possibility of providing robotic system with autonomy (to handle the dynamic of the human-populated environments), social capabilities and information exchange (with direct or indirect communication [3]), and, finally, the possibility to act as a team member (in order to accomplish common objectives) [4]. Autonomy, information exchange and teamwork are concepts linked together by the awareness of the interaction, and so by the possibility of continuously monitoring activities of the other companions. Awareness and monitoring capabilities have
also affect in behavior generation [5] (i.e., a robot changes its action and movement, planning new trajectories), and in modulation of the execution [6] (i.e., the robot decides when to involve in an interaction with the human following cues from the observation of the human attention towards the robot). Moreover, in [7] the authors showed that a big number of damages in human-robot interactions occurs for the lack of awareness.

In order to monitor and to act in the surrounding environment, robots can be fully equipped with sensors. However, this comes with the drawback of sensors data fusion and with the impossibility to continuously process such amount of data in a sophisticated way. Bandwidth and computational limitations prohibit a monitoring agent from monitoring all other agents all the time [8,9]. Monitoring agent applications often relies on periodic monitoring, or ad-hoc policies [10,11] for updating the agent beliefs. Currently, a few approaches rely on the adaptation of monitoring strategies [12] or evaluation of the monitoring frequencies starting from the dynamics of the environment [8]. Finally, other approaches deal with different selectivity problems in teamwork. For example, in the work of [8], the authors focused on monitoring social relationships between teammates in order to detect failures. Hence, selectivity is on the agent to monitor starting from its role in the teamwork activities. Concepts related to attention were used in [13] to select agents and objects related to the task.

In this paper, the frequency of monitoring team actions is not constant or periodic, but adaptive. Our working hypothesis is that monitoring strategies can be adaptive and modulated by attentional processes that can be used to filter data and actively focus on relevant information. Inspired by the behavior of human beings, that pay frequent attention to timers while approaching deadlines when involved in dual tasks [14], we aim to provide robots with general strategies for attentional mechanisms. These attentional mechanisms allow to adaptively change the monitoring frequencies of the agent behaviors depending on salient stimuli in order to focus on the current relevant behaviors, while preventing unnecessary sensors/behaviors activation and processing. We consider a convoy task (led by a human or a robot) because it represents a good benchmark in order to evaluate and compare human and robot monitoring behaviors. Convoy driving requires, in fact, that both the leader and the follower accomplish the task. Namely, the leader (a robot or a human), as well as the follower (a robot), has to monitor the teammates behavior and to adapt its own in order to not outdistance them. Moreover, the human being’s monitoring strategy, while leading a convoy, can be observed. Our aim is to evaluate the monitoring strategies adopted by the different leader actors of the experiments, in order to see if there is a correspondence between the typical human behavior and the attentional strategies used by the robot.

The paper is organized as follows. In Section 2 we introduce the concept of attentional monitoring strategies, while in Section 3 we detail the general adaptive robotic control architecture. In Section 4 we introduce the convoy problem. We then describe our case studies, the first with a team composed only by robots, the second with the robot leader of the team substituted by a human being.
Finally, in Section 5 we present the evaluation of our system, by first analyzing the robot behavior with respect to different attentional policies (continuous monitoring, constant period monitoring, adaptive period monitoring) and then by comparing the robot and the human monitoring strategies. We discuss the results of our experimentation and we conclude in Section 6.

2 Attentive Monitoring

In these last years some researchers started to pay attention to the role of attentional processes in order to achieve an adaptive emergent behavior of robotics systems. In previous papers [12,15,16], we highlighted the opportunity of managing the frequency of processing the sensors inputs and action activations in an efficient way. This goal was achieved by introducing “internal clocks” in a robotic architecture, to regulate the frequency of sensors readings (see Section 3). We introduced a control system for the perceptual inputs that achieves a quasi-periodic activity (i.e. possesses at least an active and inactive phase) and is flexible (i.e. dynamically adapts its period to external and internal requirements). Moreover, we connected such control system to the activations of each single behavior, and related this mechanism to the process of the attention in human beings [15].

In the literature, different adaptive monitoring strategies, inspired by the human behavior, are proposed [14,17]. Applications of such strategies to behavior activations are related to the specific monitoring tasks the behavior is involved into. For example, a docking behavior that has a priori knowledge about the task to achieve (e.g., about the distance to cover for docking) may use strategies called of “Interval Reduction” [14,17]. Users involved in two simultaneous tasks, one that is engaging (such as playing video-games) and the other of monitoring (such as looking at the clock for checking the elapsed time), showed to adapt the frequency of monitoring the clock. In particular, they increase such frequency while the deadline is approaching. This means that, while a continuous monitoring in time will produce $T_{\text{max}}$ activations of a behavior, and a fixed periodical monitoring will produce a number that is proportional to $\frac{T_{\text{max}}}{T_{\text{const}}}$ activations, an interval reduction strategy will produce a number of activations that is equal to $\log_2(T_{\text{max}})$. It has been demonstrated that these latter strategies, asymptotically, are more effective than those characterized by a constant periodic monitoring in a wide class of problems. Differently from these approaches, our attentional monitoring strategy can be designed in a way that the behavior frequency can change in accordance with specific laws that do not diverge too far from the optimum case, and that are related to the obtained information from the surrounding environment.

In previous work [12], we compared 4 possible monitoring policies (continuous, constant periodic, interval reduction with a priori knowledge and adaptive periodic monitoring) by showing that the adaptive periodic one is the most suitable in case of absence of a priori knowledge and a dynamical environment. Moreover, we evaluated the performance of different adaptation strategies [12] and deployed learning algorithms to optimize such strategies [16] with the re-
results that, even with simple adaptive mechanisms, an increase of performance and a flexibility in the emergent behavior can be reached. However, in previous works, no real evaluation of possible relationship between human beings abilities in monitoring/tracking and the robots behavior strategies was performed on the same task. Hence, in this paper, we aim to compare the attentional strategy, as customized for the robots behaviors, with the one naturally showed by human users.

3 An Attentive Behavior-based Architecture

Our attentive architecture for robot control is built according to the Reactive Paradigm [19,20] and the Schema Theory [21].

3.1 Behavior Model

According to the Schema Theory representation, each primitive behavior, which describes a particular functionality, is characterized by a Perceptual Schema (PS) and a Motor Schema (MS) (see Figure 1). The PS extracts information from the sensory apparatus and stores what is relevant for the behavior $b$ into a data structure called $\text{percept}^{b}(t)$. The MS uses the $\text{percept}$ to calculate a contribution for the robot actions $a^{b}(t)$. For our mobile robotic application, such contribution is made up of a linear velocity ($v^{b}(t)$) and an angular velocity ($\omega^{b}(t)$). In our model each behavior is endowed with an internal mechanism able to attentively monitor the surrounding environment by adapting the sensors reading rates and consequently the behavior activations with respect to the events that are relevant for the behavior goal. Specifically, each time a primitive behavior is active, it evaluates the available inputs and calculates how long it has to wait before activating again (as will be detailed in the following sections). The behavior $b$ waiting time is indicated as $p^{b}$.

3.2 Monitoring Strategies and Adaptation

The emergent behavior will result from a combination of the following parameters:

- the initial period $p^{b}(t_{0})$;
– the range of allowed values for $p^b(t)$ \([p^b_{\min}, p^b_{\max}]\);
– the updating policy.

In particular, the combination of these parameters defines a monitoring strategy. A monitoring strategy is a policy for scheduling sensing activities and has to balance the cost of monitoring and the risk of inaccurate and partial information about the environment.

### 3.3 Behaviors Coordination

The coordination among the behaviors is realized via a particular combination (sum or subsumption) of the outputs of the primitive behaviors. At each control cycle possibly all the behaviors could be active at the same time. In our case, behaviors activation frequencies will produce output at different rates. At each control cycle only the output of active behaviors will be summed. This provides an emergent behavior where behaviors, which are more active, will have more influence in determining the output value. Details will be provided in the following sections.

### 4 Case Study: the Convoy Problem

A typical example of teamwork is the convoy problem. In this work we consider two main roles defining the responsibilities within the team: (i) the leader that takes up the heading position and determines the way the environment is going to be explored; and (ii) the follower role that has to follow the leader and maintain a certain distance from it.

Driving in a convoy is a teamwork behavior and requires monitoring (indirect communication) in order to keep the shared knowledge up-to-date. It differs from a formation maintenance, that can be considered as coordinated individual behaviors, where there is a separate distinction between the leader agent, which is in charge to decide the path and the following agents that have to keep a predefined position in respect to the leader and other agents. Driving in a convoy requires that both the leading and the following units accomplish the task, so the leader has to monitor the follower behavior and to adapt its own in order not to lose its follower [22]. On the other hand, the following units must be able to follow the path set by the leader and to maintain a semi-static distance with the unit before them. Furthermore, the follower must also be able to deviate from the set path in the case of dynamic conditions (i.e. an obstacle), and, after executing the deviation, it has to return to the path at the set distance. Hence, both the leader and the follower are aware of their own roles and of those of the other teammates. In this sense the tracking effort is a team-issue.

We consider two different case studies, one with the team composed only by two robots (case study A), and the other with a human being in the leader role (case study B). The team is required to navigate autonomously in a convoy in a straight corridor (see Figure 2a), while avoiding obstacles. In order to accomplish
the task the robots are allowed to look at each other (as an indirect exchange of information). Figure 2b shows the two robots while navigating. In case study A, we tested our monitoring approach by comparing the following different monitoring strategies: continuous monitoring, constant period monitoring and our adaptive period monitoring. In the second case study, we consider two settings. In one case the human subject is free to hear all sound signals (Figure 3a), while in the other setting the human participant (Figure 3b) is endowed with headphones (playing loud music). This was in order to cancel any sounds the human could hear from the robot and that can be used to indirectly infer the robot position. The convoy problem, with the human as a leader, allows to put the human in the robot framework: the human has to actively decide when to monitor the team activity and when to monitor the surrounding environment. Moreover, we can observe the monitoring strategies adopted by the human subject who will be forced to turn his/her head back in order to look at the robotic teammate and to look forward to check for obstacles.

A visual servoing approach is used for tracking robots and humans. Hence, robots and humans achieve a coordination that is observation-based [13,23]. The observations of the other agent activities can include simple information like relative distance, or location, or as well as complex information like joint-goal, or plan. Here, robot behaviors are not guided by the recognition of explicit internal states of the observed agents, but are achieved by reactive coordination (observations of other agents actions are directly mapped into actions).

4.1 Actors

Robots. The multi–robot system used in our experiment is made up of two wheeled robots Pioneer 3-DX (see Figure 2b). Each Pioneer is endowed with 16 sonar sensors. The Pioneers wheels actuators accept a linear velocity reference and an angular velocity reference. These references are calculated according to the robot behaviors as well as its role in the team. Each robot has also been
provided with a computer webcam and one or two colorful landmarks. These are necessary to make the robots capable of looking at each other in order to recognize each other. The control system is implemented on regular laptop computers, via the Robot Operating System (ROS) tool for developing robotic systems, and all communications between the computers and the Pioneers are implemented via the RosAria wrapper of ROS.

Human Participants. 13 male and 7 female graduate students participated in the experiment. The average age of the participants was 23.2 years. Subjects were asked to perform the task of guiding the team only one time. The students were asked to guide the team through the corridor without outdistance the other team members. The participants were divided into two sets. The participants in the first set were only endowed with a colored landmark on their back, while the participants of the second set were also provided with headphones playing loud music (Figure 3). Finally, the users were asked to proceed looking ahead and turning their heads only to monitor the team behavior when they felt it is necessary.

4.2 Procedures

We empirically evaluated the presented control architecture in extensive experiments, with 20 human participants, who have been divided into two sets respectively of 10 subjects and correspondent to the two settings within the case study B (with or without headphones).

For the robotic experimentation, we tested our approach by repeating the experiment 10 times for each setting (continuous monitoring, constant period...
monitoring, adaptive period monitoring). The variability of the actors (robots) was, in this case, implicitly provided by the random movements provided by the robotic control system and by the outline information such as brightness variability, different orientation of the follower robots etc., which introduce indeterminism and unpredictable environment states.

4.3 Environment Description

The testing environment is a regular straight corridor. The corridor is approximately 4 meters wide and the navigation covers approximately 20 meters in length. Several pillars are located at fixed distances from each other and at the same distance from the corridor sides. The corridor floor is made up of a plastic material, flat enough to allow an undisturbed navigation and not so slippery to cause the robots to slide while navigating. On either of the two sides of a pillar the way might be blocked by a permanent obstacle, that forces the leader to follow a particular direction. The environment cannot be said to be cluttered, since the distance between two separate obstacles is at least twice as long as the Pioneer length. Figure 2a shows some partial views of the mentioned corridor.

4.4 Robot Behaviors Description

In order to accomplish the assigned task the following primitive behaviors have been implemented: Wander, FollowCorridor, AvoidObstacles and FollowMate.

Wander. The Wander behavior is for generating small rotations in the robot motion in order to find lost teammates. Regardless of the orientation percept, a constant forward linear velocity reference is assigned in order to keep the robot navigating ($v = \bar{v}$). This behavior has a fixed frequency of activation ($p^w = \bar{p}^w$).

FollowCorridor. Basically, this behavior allows the robot to keep itself as aligned to the corridor walls as possible. It uses the lateral sonar sensors for evaluating the robot orientation with respect to the corridor walls, and assigns a “straightening” angular velocity. If the difference between a sonar frontal and a back reading is below a certain threshold, no angular velocity is given at all. For example, let $s_f$ and $s_r$ be the readings from the front left sonar and the rear left sonar sensors respectively. We calculate $\omega$ as follows: $(s_f - s_r)\bar{\omega}$ if $|s_f - s_r| > d_{ths}$, 0 otherwise. Regardless of the percepts that were provided, a fixed forward linear velocity contribution is assigned in order to keep the robot navigating ($v = \bar{v}$).

The difference between the front sonar sensors reading and the back sonar sensors readings (normalized with respect to the maximum distance $D_{max}$ detectable by the sonar sensors) is used to establish the waiting time (or activation period $p^{fc}$) before the following activation of this behavior. A higher difference triggers a greater urgency to put the robot in the straight direction, therefore assigning a shorter waiting time. Specifically, we calculate the waiting time as follows:
\[ p_{fc} = p_{fc}^{\text{max}} - \frac{|s_f - s_r|}{D_{\text{max}}}(p_{fc}^{\text{max}} - p_{fc}^{\text{min}}) \] (1)

**AvoidObstacles.** The index \( h \) of the sonar \( s_h \) detecting the current lower distance from an obstacle is selected and used for regulating the velocity output. If \( s_h \) is greater than a certain threshold, no reaction is triggered at all. The smaller the distance from the obstacle, the smaller will be this contribution. More formally, we calculate this velocity as follows:

\[ v = -\frac{s_h - s_{\text{min}}}{s_{\text{max}} - s_{\text{min}}} \bar{v}, \] (2)

where \( s_{\text{max}} \) and \( s_{\text{min}} \) are respectively the maximum and minimum values perceivable from sonars. The robot steers in the direction of the sonar reading the greater distance. Let \( s_k, s_{k+1} \) be the couple of adjacent sonars yielding the higher difference, the angular velocity is calculated as follows:

\[ \omega = \begin{cases} \bar{\omega} & \text{if } s_k \geq s_{k+1} \\ -\bar{\omega} & \text{if } s_k \leq s_{k+1} \end{cases} \] (3)

The activation period \((p^a)\) of the AvoidObstacles behavior is computed in a way that the smaller the sonar sensor value, the smaller the period with which sensory data are sampled (thus the higher the monitoring frequency). It is computed as follows:

\[ p^a = p_{\text{max}}^a - \frac{s_{\text{max}} - s_h}{s_{\text{max}} - s_{\text{min}}}(p_{\text{max}}^a - p_{\text{min}}^a) \] (4)

This means that when an obstacle appears, the behavior increases its attention towards this stimulus by increasing its activation frequency. This increasing of the activation frequency is necessary in order to give more attention to the input coming from sonar sensors with respect to that of the camera (i.e. the FollowMate sensor). As we will see later on, in fact, it could happen that, when an obstacle very close to the robot appears, the safety issue requires an implicit priority above the other behaviors and sometime the follower robot can lose the leader.

**FollowMate.** This behavior is intended to make a robot follow another robot (or a human being) in the team. The follow-mate attitude is accomplished via visual servoing, since each member of the team wears a colorful landmark that identifies its role and that can be seen by the other robot webcam. Figure 2 shows an example of a configuration where Pioneers wear colorful landmarks. When a robot individuates the landmark it is supposed to follow (or monitor), it can adjust its velocity according to the landmark position and dimensions in its field of view. A landmark is perceived as a blob of a specific color. A larger blob solicits deceleration (or acceleration), while a smaller blob solicits acceleration (deceleration). At the same time, a blob perceived on either side of the follower
field of view solicits steering in the direction that would push the blob towards the center (not for the leader role).

The perceptual schema for this behavior reads information from the webcam. If a consistent blob is perceived, the motor schema provides a linear velocity according to the perceived blob height \( h \), assuming that such height is inverse proportional to the distance from the following robot \( v = \frac{\alpha}{h} \). Of course this contribution can be either positive (for smaller blobs) or negative (for larger blobs). The angular velocity contribution aims at keeping the blob as centered as possible in the robot field of view. If the absolute value of the \( x \) position of the blob center is below a certain threshold, the blob is considered as centered, and no contribution is given at all. Otherwise, a reference whose value is proportional to \( x \) is provided.

\[
\omega = \begin{cases} 
-\frac{\bar{\omega}}{x_{\text{max}}} & \text{if } |x| > x_{\text{th}} \\
0 & \text{otherwise} 
\end{cases}
\]  

(5)

If no consistent blob is perceived, no linear velocity is provided but the most recent value of \( x \) is taken into account. If its absolute value is over a certain threshold, it is assumed that the sheet has disappeared to either side of the robot field of view. Therefore a strong angular velocity is provided in order to push it back in the center \( \omega = \text{sgn}(x)\bar{\omega} \). If the most recent value of \( h \) is below a certain threshold, that is, if the followed sheet is perceived as too far, a slowing signal is sent by this behavior. Basically, such signal is a message addressed to the followed robot requesting it to slow down, but actually the robot that receives it can autonomously decide how to use such information.

This behavior has a variable frequency of activation. When the followed blob is perceived on either side of the robot field of view, a greater urgency to put it back to the center is triggered, and then a shorter waiting period is set. Specifically, we calculate the waiting period as follows:

\[
p^f_t = p^f_{\text{min}} + \frac{x_{\text{max}} - |x|}{x_{\text{min}} - x_{\text{max}}} (p^f_{\text{max}} - p^f_{\text{min}})
\]  

(6)

4.5 Behavior Interaction

The implementation of the two roles in the robot team can be achieved using a different combination of the primitive behaviors and a different combination of their outputs (e.g., they could make a different use of the velocity references provided by behaviors).

**Follower Role.** The follower Pioneer activates the Wander, FollowMate and AvoidObstacles behaviors. Of course the FollowMate behavior is tuned on the color of the landmark worn by the leader. When the FollowMate behavior provides a non-null velocity reference, this robot velocity is calculated by summing the references provided by FollowMate itself and AvoidObstacles. On the other hand, when FollowMate provides null references, the follower Pioneer velocity is
calculated by summing the references provided by Wandering and AvoidObstacles in order to search for the lost companion. The activation of AvoidObstacles prevent the robot from hitting obstacles. Besides, the alternation of the velocity references provided by Wander and FollowMate should allow the robot to follow the leader path.

**Leader Role.** The leader activates the FollowCorridor, FollowMate and AvoidObstacles behaviors (see an example of architecture in Figure 4). The FollowMate behavior is tuned on the color of the sheet worn by the follower, and as a consequence the webcam is oriented to look back at the following robot. The FollowMate velocity reference has a negative sign, and so will slow down the emergent behavior and, eventually, stop the motion. The velocity references provided by FollowCorridor, FollowMate and AvoidObstacles are summed.

### 5 Experimental Results

In this section we are going to introduce and discuss some experimental results for our case studies. Our aim is to evaluate the monitoring strategies adopted by the different leader actors of the experiments, in order to see if there is a correspondence between the typical human behavior and the proposed attentional strategies used by the robot. In particular, we will first describe an example of functioning of the system considering (i) the FollowMate behavior of the follower robot with respect to the possible different leaders (human or robot). We then analyze (ii) the FollowMate behavior of the leader Robot with respect to different attentional policies (continuous monitoring, constant period monitoring, adaptive period monitoring). Then, we provide some discussion about (iii) the comparison of the performance between the two settings of case study B (Human with/without headphones). Finally, we compare (iv) the FollowMate behavior...
provided by the leader actors in the two case studies and settings: only robots, human as leader without headphones, and human as leader with headphones. In the latter comparison, in order to have comparable results between the human and the robotic counterparts we consider the robot endowed with the adaptive attentional policy.

(i) FollowMate of the follower w.r.t. different leaders. Figure 5 shows data produced by the FollowMate behavior of the follower robot during a run for each of the case study A and B. The first plot in the figure represents the trend of the blob height as perceived by the FollowMate primitive behavior of the follower robot. In general, the more this height lies in the range 60-90px, the better the team member robot keeps a right distance from the companion (human/robot). We, thus, use the height parameter as an indirect measure of the following distance. High frequency variation of this value is tolerable, since it depends on a number of factors, that are hardly predictable and controllable, such as the diversity of brightness in different parts of the environment, the orientation of the followed robot, etc. The second plot is the slowing signal. Recall that such signal is sent when the robot perceives that the team member is too far away and asks it directly to slowdown. Finally, in the last row we show the trend of the period of the behavior FollowMate.

In the case of the human-robot team, the snapshots of the interactions are related to salient events in the time line. We notice that, during the first part of the navigation task, an high frequency variation corresponds to the first orienting phase. Then, the robot starts to correctly follow the human, but in correspondence of a barrier (the column in the hallway), that abruptly introduces parallel noise signals, it starts to turn causing the blob-camera to lose the blob for a while. After that, it is able to center the human again and follow him/her until the next narrow part of the corridor, where the follower robot again loses the leader for a while. Finally, the robot is able to identify the blob again and follow the leader until the end of the corridor.

A comparable trend is shown in Figure 5a, corresponding to an experiment where the robot is following another robot. However, the robot-robot runs usually took a little more time to accomplish the task.

When the robot loses the leader (human/robot) position it sends a slowing signal, in order to notify the leader that it is left behind. In the case study A, this is represented by a message published on a ROS topic, while in the case study B this is implemented as a loud ring. In the case study B of human participants without headphones this information obviously can help the human to regulate his/her gait velocity with the aim of helping the followers to maintain the convoy, while this will not affect the behavior of participants in the second setting. Note that, in principle, it does not matter how many times the slowing signal is generated, but its duration of each single peak. In fact, it means that the two robots or the human and the robot are recovering the distance they are supposed to be from each other in order to navigate correctly in the convoy. In the case of human-robot interaction the human (wearing headphones) was not able to hear the tone, so the peak is higher than in the robot-robot experiments.
For what concerns activations of the FollowMate behavior, these are distributed over time. In general, the follower robot has the attitude to decrease the period of monitoring particularly in dangerous situations (e.g., when an obstacle occurs) or when it is losing a teammate. When this occurs the behavior is able to adaptively increase its monitoring activity by enhancing its frequency of activation. While when it is confident about the behavior of the leader it relaxes the rhythm of activation. What emerges from the activation plots in Figure 5a is that, differently from the case of the human as a Leader, where the Midfielder robot seems to be more confident of the Leader behavior, in the case study A, the Midfielder robot loses the Leader more times.
Case Study A

Monitoring Policy | Case Study A
--- | ---
| p = 1 | p = k | p = f(x)

| Time (m) | 3.02 ± 0.36 | 2.86 ± 0.32 | 2.92 ± 0.24
| Activations | 909 ± 138 | 435 ± 53 | 340 ± 26
| Failures | 20% | 40% | 20%
| Monitoring Time (%) | 100% | 48% | 37%

Table 1: Leader robot FollowMate behavior performance with respect to different attentional policies.

ii. Comparison among the attentional policies of the leader robot FollowMate behavior. In order to assess the advantages introduced by the adoption of the attentional mechanisms, we report in Table 1 the performance produced by the FollowMate behavior of the leader robot (case study A) considering three different attentional policies:

- continuous monitoring (monitoring period set to 1);
- constant monitoring period (monitoring period set to \( k = 3 \));
- adaptive monitoring period (monitoring period updated with respect to the behavior attentional policy \( f(x) \) ∈ [1, 10]).

The Table 1 shows that, while the time (first row) to achieve the goal remains quite the same in the three cases, the number of activation of the FollowMate behavior is drastically reduced in the case of adaptive monitoring (third column). What is notable is that, in the case of periodic monitoring (second column), even if the number of activation decreases, the number of failures increases. Instead, in the case of adaptive monitoring, the attentional inspired monitoring strategy permits to obtain the dual advantage of saving computational load, while maintaining the efficiency. The number of failures in this latter case is, in fact, comparable with the case of continuous monitoring. Last row of Table 1 shows the monitoring time percentage, evaluated as the mean number of activations with respect to the mean number of activations of the continuous monitoring case.

iii. Comparison between the performance in the two settings of case study B (Human with/without headphones). Data of the human behavior is extracted by a video analysis and results are summarized in Table 2. The two groups of human beings (with or without headphones) showed almost the same behavior in the time to accomplish the task (first row). This could be due to the fact that human beings with the headphones compensate the lack of environmental sound awareness by checking the team for longer time. In fact, while the average number of times the human subjects turn their heads back to monitor the team is quite the same (second row) in the two cases, the average duration of the monitoring activity is greater for the subjects with headphones (forth row). In particular, the monitoring time is evaluated as the ratio of the time the subjects spent monitoring the team (i.e., time spent looking backward) with respect to
The total time of the task. Failures, in the case of human with headphones, are slightly less than in the other case. Also this behavior is a consequence of the greater monitoring time. The statistical correlation value, evaluated on the average of the monitoring time is equal to 0.0597, which means that in the 94% of cases this difference is not due to the case. This shows how the headphones affect the perceptive capabilities of humans and consequently the performance.

**iv. Comparison between the robot leader and the human leader monitoring strategies.** Here we compare the monitoring strategies adopted by the leader actors in the two case studies (adaptive monitoring period for case study A and with/without headphones for case study B), from data in Tables 1 and 2. As we expected, the time to accomplish the task and the number of failures are reduced in the case study B. Intuitively, this may be due to the most remarkable ability of adaptation and awareness of human beings that allows the entire team to finish the task with better performance, in terms of time to accomplish the task, and greater ability to maintain the convoy (hence, less failures).

The number of head turns cannot be directly compared to the number of the robot behavior activations, because the human monitoring activities have different duration in time. In order to avoid this problem we refer to the monitoring time. In particular, human participants without headphones spent only the 25% of their time in monitoring the team with quick checks (4s in the average) from time to time, mainly in the process of avoiding obstacles. Most of their checks are right after an obstacles waiting for the members of the team. On the contrary, subjects with headphones spent 32% of the execution time monitoring the team. This is because they cannot infer any clue of the team behavior hearing the sounds made by the robot moving around and the eventual slowing signal. This human behavior is more similar to the robot behavior that spent the 37% of its time in monitoring the followers. This is because the monitoring strategy is to balance the risk of obtaining inaccurate information with respect to the optimization of resources. Hence, our simple attentional policies allow an efficient use of computational resources comparable with the human monitoring behavior.

Beyond the better global performance obtained when human subjects are involved in the convoy task, what is interesting, from our point of view, is to observe the monitoring strategies adopted by the different leader actors of the experiments, in order to see if there is a correspondence between the typical
human behavior and the attentional strategies used by the robot. We conclude that both refer to a capability of adaptively distributing in time the activations of the behavior of checking/monitoring the convoy (i.e. when and how to activate the FollowMate behavior).

6 Conclusions

In this paper we presented a comparison between an adaptive monitoring strategy for a behavior–based architecture and the corresponding human behavior in a convoy task. One of the main problems in such a kind of task deals with the impossibility of continuously processing all the amount of sensor data, especially when more parallel tasks (check the followers, while avoiding obstacles and hearing music) have to be taken into account. Many approaches have been presented coping with this problem by proposing a periodic monitoring for elaborating the environment incoming signals. Our working hypothesis is that effective teamwork, in a convoy problem, can be achieved by adaptive periodic tracking strategies. Hence, inspired by the behavior of human beings, we designed a behavior–based control architecture where each behavior is endowed with an attention mechanism for filtering data and actively focusing the monitoring only on relevant information and agent behaviors. Our aim is to observe the monitoring strategies adopted by the different leader actors of the experiments, in order to see if there is a correspondence between the typical human behavior and the attentional strategies used by the robot. We observe that the behaviors of the robots and the humans are comparable in terms of the strategies adopted to guide the team. In fact, we can state that both refer to a capability of adaptively distributing over time the activations of the behavior of monitoring the convoy. Naturally in the case of human as leader, the awareness of the interaction is crucial in determining the task effectiveness and the less time in the task achieving. Comparisons of the monitoring strategy showed, in fact, that, the humans were more able to optimize their monitoring activities, especially in the case of having contextual clues to infer the team behavior (as the environmental sound). Humans with headphones showed a behavior in terms of monitoring similar to the robot, while still keeping the task optimized.

Our results show that the approach of attentive monitoring strategies is feasible and effective, and is reflected in human behavior. In particular, this can be used in a fruitful manner in robotics since it produces several advantages. In our experimentation, overall, the benefits brought by adaptive and periodical monitoring strategies are mainly two. First the use of adaptive mechanisms allows to obtain a behavior that adapts itself and focus its resources to the specific environmental conditions (e.g. the robot reads sensors more often if there is a salient situation and less often in cases of a typical operational situation). Second, these attentional strategies can reduce the number of activations of the behavior, causing a relative decrease of the computational burden, and improving performance of the entire system. We conclude that in this context, the human behavior can
be used as a model to implement efficient strategies to reduce and optimize the monitoring burden.

Acknowledgments

The research leading to these results has been supported by the SAPHARI Large-scale integrating project, which has received funding from the European Community’s Seventh Framework Programme (FP7/2007-2013) under grant agreement ICT-287513 and by the Italian Ministry of University and Research and EU under the PON OR.C.HE.S.T.R.A. project (ORganization of Cultural HEritage for Smart Tourism and Real-time Accessibility).

References


