A Framework for Affect-Based Natural Human-Robot Interaction

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***Abstract*— In this paper we present a general framework for affective human-robot interaction that allows users to intuitively interact with a robot and takes into account their mental fatigue, thus simplifying the task or providing assistance when the user feels stressed. Interaction with the robot is achieved by naturally mapping user's forearm motion, detected with a smartwatch, into robot's motion. High-level commands can be provided by means of gestures. An approach based on affective robotics is used to adapt the level of robot's autonomy to the cognitive workload of the user. User's mental fatigue is detected from the analysis of heart rate, also measured by the smartwatch. The framework is general and can be applied to different robotic systems. In this paper, we consider its experimental validation on a wheeled mobile robot.**

I. Introduction

Affective robotics is a growing research area that refers to the combination of robotics and affective computing, thus enhancing the interaction of a human with a robot by recognizing her/his affect, such as mood and emotion. Indeed, in recent years it has been found that monitoring and interpreting nonverbal communication can provide important insights about a human interacting with the robot, thus making it possible to achieve implicit feedback about the interaction [1]. To this end, eye gaze [2], facial expression [3], voice, linguistic and paralinguistic (e.g., utterances) features [3], and physiological signals such as heart rate, electrodermal activity, and facial electromyographic activity [4] have been investigated as indices of subject's affective state, focus, attention and intent.

The advantages of an approach based on affective robotics are, at least, twofold: on the one side, affective robots can engage people in an interpersonal manner, establishing a natural and smooth social communication with humans [1], [5]; on the other side, by monitoring users' anxiety and fear, those tasks requiring human-robot interaction (HRI) can be accomplished in a safer and efficient manner [4]. The first aspect refers to the so called socially interactive robots, which are designed to operate in human environments alongside people [1]. Plenty of literature has been dedicated to this theme and social robots have been proposed for a wide variety of applications, ranging from assistance to the elderly or the disabled [6], to educational robots [5] and entertainment robots [7], just to cite few application fields. As regards the second aspect, which, to the best of the authors' knowledge, has been less investigated in the literature, detecting user's emotions such as stress, anxiety or fear has been found to be useful for robotic rehabilitation tasks and for service robots [4], which are the focus of our research. Affect detection has been also considered in [8], but therein very little attention is given to how HRI can be adapted accordingly.

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In this paper we introduce a novel affective robotics approach that consists in adapting the behavior of the robot based on the cognitive workload of the user. In particular, the idea is that of tuning the level of autonomy of the robotic system, in order to assist the human operator. To ground this concept, we build upon our previously presented HRI approach based on natural interaction [9], [10] and develop a general framework for affect-based natural interaction with service robots.

A. Motivation and contribution

Achieving a different level of autonomy implies changing the workload for the user [11]. Consider a fully autonomous robotic system: in this case, the robotic system is able to perform its task without the intervention of the user, who hence is not requested to perform any work. Clearly, in this case, the objectives that can be achieved are limited by the control strategy implemented on the robot and this approach is suited only for highly predictable and repetitive tasks. Conversely, consider a robotic system that is completely teleoperated, or manually guided by an operator: in this case, it is possible to take full advantage of the flexibility that can be achieved thanks to the presence of the human operator. Thus, non repetitive precision tasks can be easily tackled by combining human's and robot's capabilities. This increased flexibility implies, however, an increased workload for the operator, which can become very high for complex or critical tasks.

Intermediate conditions represent a trade-off between complete flexibility and an acceptable level of workload for the operator. Our aim is then that of automatically relieving user's cognitive burden when the task to accomplish overloads her/his mental capabilities. Specifically, we aim at tackling also those conditions in which incipient stress causes a decrease in performance even before the user could detect it, or the user feels discriminated to admit that she/he is experiencing trouble and needs some assistance. This can be achieved by implementing a sufficient level of autonomy in the robotic system by means of different assistive strategies, which depend on the specific application under consideration, as discussed hereafter.

Assistance to the user can be provided exploiting the concept of shared autonomy [12], which consists in combining user input and robot autonomy to control a robot to achieve a goal, aiming to reduce the cognitive and physical burden on the user [13], [14]. Classical approaches consist in predicting user's goal and providing assistance for that goal by exploiting methods such as potential fields and motion planning. However, differences in user's abilities and desired amount of assistance are not considered, since non user-driven optimization metrics are typically considered. In [15] user-driven customization of the amount of assistance is considered for an assistive robotic arm: verbal cues about the desired level of assistance expressed by the user are translated into proper input for the control algorithm of the robotic system. In the framework considered in this paper, we aim at selecting the optimal level of assistance to provide to the user by taking into account her/his mental fatigue during the execution of the task and relieving the user when the task overloads her/his capabilities. In particular, such mental fatigue might lead to anxiety and a decrease of overall performance and abilities, inducing distress in the user.

In order to achieve such affect-based adaptation, the user's cognitive workload needs to be measured in order to detect incipient fatigue. One of the most well known methodologies for measuring the cognitive workload is represented by the analysis of the variability of the user's heart rate [16]. Nowadays heart rate is customarily measured by commercial smartwatches or wristbands for activity tracking. Thus, the smartwatch-based approach to natural HRI presented in [9], [10] lends itself to the purpose of this paper.

The contribution of this paper is the introduction of an approach to HRI that allows users to intuitively interact with a robot and takes into account user's mental fatigue, providing adequate support when necessary. Being general, the approach represents a framework for HRI, since it can be applied to different working scenarios, as discussed hereafter considering industrial manipulators, wheeled and aerial robots and multi-robot systems. The rule for mental stress detection based on non-invasive monitoring of heart rate is presented and experimentally validated. Additionally, the experimental validation of the framework is presented considering the interaction of different users with a mobile robot.

II. Background on stress detection based on heart rate variability

Heart rate variability (HRV) refers to the variation over time of the interval between consecutive heart beats [17]. It is an established quantitative index to assess autonomic nervous system function, noninvasively. The normal variability in heart rate is due to the autonomic neural regulation of the heart and the circulatory system. In particular, short-term oscillations of beat-to-beat intervals reflect changes in the relative balance between the sympathetic and parasympathetic branches of the autonomic nervous system, which is the so called sympathovagal balance [18]. Thus, the analysis of HRV has been found to be related to a great variety of pathological and physiological conditions [18].

The analysis of HRV relies on the analysis of RR interval time series, which is the series of occurrence times of heart beats. The expression RR series is due to the fact that, with reference to the electrocardiographic (ECG) recording of heart electrical activity, R peaks are usually considered as the fiducial marker of each beat, since they are the portion of ECG signals exhibiting the highest signal-to-noise ratio [19]. Denoting by R_k the instant of occurrence of the $k-$th heart beat, the RR series is then defined as:

$$RR_k = R_{k+1} - R_k, \qquad k = 1, 2, \dots \tag{1}$$

Many metrics for HRV analysis have been described in the literature. In general, HRV metrics are classified into time domain metrics, which can be statistical or geometrical, or frequency domain metrics, which evaluate power, or ratios of power, in certain spectral bands. In particular, the most common statistical time domain metrics are: the mean value and the standard deviation, denoted by $\overline{RR}$ and *SDRR* in the following, of the RR series, the root mean square of successive differences (*RMSSD*), and the percentage number of consecutive (normal) intervals differing by more than 50 ms in the entire recording (*pNN50*). As regards the frequency domain metrics, the most used ones are the power in the low frequency band (*LF*, $0.04 - 0.15$Hz), the power in the high frequency band (*HF*, $0.15 - 0.40$Hz) and their ratio (*LF/HF ratio*). More details can be found, for example, in [17]. Furthermore, clinical standards require that metrics are calculated either on a short time scale (namely short-term HRV) of about 5 min duration, or over extremely long periods of time (namely long-term HRV) usually lasting 24 hours [17].

As regards mental workload, there is large part of literature showing that stress, in general terms, and cognitive processing in particular, influence HRV [4], [8], [16], [18]. However, there is a lack of consensus on the meaning and operationalization of the concept of stress. In the rest of the paper we will make no distinctions among the terms stress, mental stress and fatigue and cognitive workload; however, the kind of stress we measure is mental stress caused by increased mental fatigue due to complex tasks and anxiety due to situational pressure and/or poor user's experience in the task. Intense mental fatigue is typically induced by means of arithmetical tasks, cognitive tests (such as the Stroop color and word test [20]), or oral examination. In some works the joint effect of other stressors, such as physical exercise or verbalization, is considered.

The effect of stress on HRV is due to the fact that mental stress is one of the factors contributing to sympathetic stimulation, which is associated with the low frequency range of heart rate. Thus, it has been found that *LF* is reduced in mental stress condition, while *HF* is increased [8], [18]. As regards time domain metrics, the main reported changes regard $\overline{RR}$, *SDNN* and *RMSSD*, which are decreased under mental stress [16].

III. Proposed framework and working scenarios

In this paper we propose a general framework for natural HRI, implementing an adaptive behavior that assists the user by relieving her/his mental fatigue when needed. To this end,

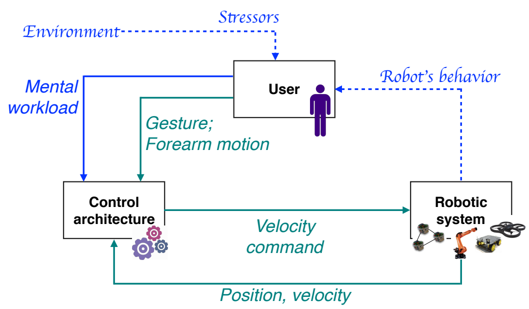

Fig. 1. Architecture of the proposed framework for natural affect-based HRI. Mental workload is contributed by both environmental factors related to the social and physical context (e.g., rushed, noisy, etc.), and the robot's behavior, meant as level of autonomous behavior and task to accomplish (e.g., precision task, presence of obstacles).

the user is supposed to wear a smartwatch (or an activity tracker wristband), which is used to acquire the motion of her/his forearm and the heart rate. The benefits of using a smartwatch-based system have been discussed in [9]. Fig. 1 shows the architecture of the proposed system. Specifically, the key features of the proposed framework are twofold:

1) with respect to the control of robot's motion, it allows an intuitive and comprehensive interaction with a robot such that any subject can use it, without any specific experience. This is achieved by means of
   - a natural mapping between the user's and the robot's motion, and
   - gestures used for imposing high-level commands to the robot;
2) it implements an approach based on affective robotics that adapts the level of robot's autonomy according to the cognitive workload of the user.

The rationale behind the natural interaction has been firstly presented in [9], [10], where the use of a quadrotor and a wheeled mobile robot, respectively, were considered. Generally speaking, rotations of user's forearm are detected by the smartwatch and translated in velocity commands for the robot. While the exact mapping between the motion of the user's forearm and the velocity command for the robot depends on the specific operational scenario under consideration (e.g. a flying robot and a ground robot move in a completely different manner), some general concepts are depicted in Fig. 2. In particular:

- changing the *roll* angle of the forearm is mapped into a left/right motion command for the robot,
- changing the *pitch* angle of the forearm is mapped into a forward/backward motion command for the robot,
- changing the *yaw* angle of the forearm is used for changing the orientation of the robot.

Moreover, the system is able to recognize some gestures from a predefined set [9]. These allow the user to change among different *operational modes* of the robot: by performing a gesture the user can command the robot some predefined semi-autonomous behaviors, such as follow a trajectory or create a map of the environment, or switch to teleoperated mode, in which velocity commands for the robot are directly computed as a function of the motion of the user's forearm, as shown in Fig. 2.

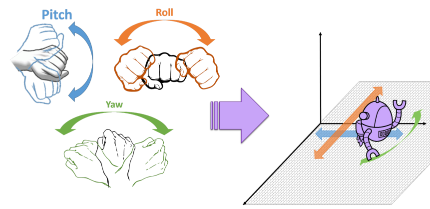

Fig. 2. Mapping between user's and robot's motion.

The intuitiveness of such HRI approach extends the possibility to command a robot, in principle, to *any* subject, without restriction of age and prior acquaintance with robots. However, a non negligible mental fatigue might be put on the user, depending on the task and her/his attitude towards the use of robots. To this end, we propose to enhance the natural interaction approach by taking into account the user's mental fatigue and changing the behavior of the robot accordingly. In particular, the subject's heart rate is monitored through the smartwatch and incipient mental fatigue is detected, as discussed in Sec. IV. In this case, the behavior of the robot is adapted by taking into account user's mental fatigue and simplifying interaction when it is exceeding her/his capabilities, thus generating discomfort. Assistance is provided by adapting the level of shared autonomy between the user and the robot and assigning a (quasi-)autonomous behavior to the robot, which relieves the user's stamina. The way such assistance is implemented strictly depends on the interaction task, the goal, and the considered robot. Just to cite some examples, assistance can be provided in terms of reduction of robot's maximum velocity, activation of obstacle avoidance, or movement along a predefined trajectory.

These solutions are meant as a trade-off between system flexibility and an acceptable amount of workload for the user. Indeed, when at rest, the user is left free to interact with the robot with no limitations, since she/he is considered to be fully aware of the interaction task. When mental fatigue is detected, a reduced effort is put on the user, but, on the other side, the objectives that can be achieved are limited by the robot control strategy.

In the following, we consider some specific working scenarios, providing some examples of adaptation of the level of shared autonomy to the user's mental stress.

Mobile robots: Driving a mobile robot by the proposed approach has already proved being advantageous in [10] and [21]. The use of natural mapping for motion control according to Fig. 2 is straightforward, whereas gestures can start predefined behaviors such as building a map of the environment, parking in a given position, reaching a target or following a trajectory or the walls. In particular, in [10] it has been shown that such interaction approach proves more effective than the use of a classical haptic device for robot teleoperation.

As presented in Sec. V, assistance to stressed users can be provided by implementing collision avoidance and reducing velocity when obstacles are detected. Results in this regard are shown in Sec. V.

Aerial robots: The case of interaction with aerial robots has been preliminarily considered in [9]. It represents a very interesting case of interaction with a robot by the proposed framework, since the natural mapping described in Fig. 2 directly recalls the motion of a quadrotor and *Up* and *Down* gestures can be given the physical meaning of taking off and landing. Indeed, compared to a haptic device, a joypad and a smartphone, it proved being easier to use [9].

Despite the intuitiveness of the interaction mode, considerable cognitive workload might be induced by the task (i.e. piloting an aerial robot), which is intrinsically complex, in particular for untrained and non expert users. In this regard, relieving the user by introducing prudential measures might be beneficial when the task is getting too difficult, that is when mental fatigue is detected. Examples are reducing the maximum velocity of the robot, limiting the maximum height, hindering hazardous manoeuvres, or activating obstacle avoidance. Depending on the application scenario and in the case of highly increased cognitive stress, forcing hovering might also be considered.

Manipulators: The proposed framework applies also to interaction with industrial manipulators. The natural mapping provides a means to intuitively teleoperate the robot: using position, rather than velocity, control, this might be the case of programming the robot by teaching a trajectory when physical interaction is not possible, or moving it in pick and place tasks among unknown and unforeseen positions, when support by a vision system is not available. Assistance to the user when mental fatigue is detected can be provided by implementing semi-autonomous behaviors or virtual fixtures that guide the user along predefined paths.

Moreover, in the case of physical HRI with industrial manipulators for walk-through programming [22], the parameters of the robot controller can be dynamically adapted to increase the stiffness of the robot, thus helping the operator to increase the precision, while reducing the overall execution speed.

Multi-robot systems: Control of multi-robot systems has typically been addressed considering that the robots in the team operate autonomously. As a consequence, the objectives that can be achieved are limited by the robots control strategy and usually amount to basic and simple cooperative behaviors, such as aggregation, synchronization, coverage, or formation control. The presence of a human operator is marginal in classical approaches. Recently, a few works have appeared in the literature that consider the possibility of having a human operator interacting with the multi-robot system, thus increasing the capabilities of the system by taking full advantage of the user's flexibility and skills [23]. However, as a consequence of such an interaction, a high cognitive burden is put on the human operator, who is asked to supervise and interact with a complex system.

In this regard, controlling and interacting with a fleet of robots in a natural manner alleviates the communication gap between the user and the robots and increases situation awareness [24]. Moreover, considering, as an example, exploration tasks, when the user is not overloaded by the task, she/he can command one or few robots (e.g., driving it/them to a specific area), while the others can autonomously explore the remaining areas. However, this increases the complexity of the task since, while being directly involved in the interaction with one or few robots, the user is requested to pay attention also to the other ones. Thus, in the case of mental fatigue, aggregated behaviors, such as the user driving a robot and the others following it, can simplify the task, letting the user focus on the team of robots acting as a single one [24].

IV. Real-time non-invasive stress detection based on HRV

In this section we introduce a method for real-time detection of mental stress by means of a smartwatch (or a similar wrist-worn device). Following the discussion reported in Sec. II, mental stress detection is based on HRV analysis: in particular, we measure HRV in terms of mean value of successive RR intervals, namely $\overline{RR}$, computed on sliding windows of fixed duration.

While standard short-term HRV analysis is usually performed on 5-min recordings [17], research is considering the opportunity of measuring HRV from shorter recordings, aiming at a faster detection of cardiovascular associated diseases or physiological conditions [25]. Moving along these lines, we propose to consider non overlapping sliding windows collecting the inter-beat intervals that have occurred in the last $T^{(w)} = 150$ s. Thus, the mean value of each window, namely $\overline{RR}_i$, where i refers to the current window, is computed as:

$$\overline{RR}_i = \frac{1}{N_i} \sum_{k \in w_i} RR_k \tag{2}$$

where w_i is the $i-$th window of duration $T^{(w)}$, whose cardinality is N_i.

Mental workload is then detected by comparing the quantities $\overline{RR}_i$ and $\overline{RR}_{i-1}$, since an increase in the mental stress level is reflected in a decrease of $\overline{RR}$. Specifically, we introduce the following stress detection law:

$$(\overline{RR}_i < \overline{RR}_{i-1} - \Delta_{r\to s}) \wedge (\overline{RR}_i < \Gamma_r) \implies rest \to stress \tag{3}$$

$$(\overline{RR}_i > \overline{RR}_{i-1} + \Delta_{s\to r}) \wedge (\overline{RR}_i > \Gamma_s) \implies stress \to rest \tag{4}$$

where $\Delta_{r\to s}$ and $\Delta_{s\to r}$ are constants denoting the minimum variation required to detect a change in mental workload level (from rest to stress and vice versa, respectively), and Γ_r and Γ_s are constants denoting a threshold on the value of $\overline{RR}$: all these parameters were defined experimentally.

In particular, 21 volunteer subjects (15 males, 6 females, age 28.4 ± 4.1 y.o.) were involved in experimental tests[1]. Each test was composed of two parts, of duration 5 min,

[1]Each subject was asked to read the description of the experiments, and to sign an informed consent form.

during which heart rate was recorded. In the first part, the subject was asked to sit and rest (i.e., she/he was not involved in any physical nor mental activity), while in the second part the subject was exposed to commonly adopted stressors, namely arithmetical tasks and fast counting tests while listening to loud music [8], [16].

Acquired data were then analyzed according to the methodology considered in [25], extracting random segments of duration 2.5 min from the recorded RR series, and computing the value of $\overline{RR}$. The analysis of 1000 Monte Carlo trials (obtained randomizing the beginning of the 2.5 min RR series) provided statistically significant difference[2] between the rest and stress conditions:

$$\begin{array}{rl} \text{rest:} & \overline{RR} = 0.871 \pm 0.135 \\ \text{stress:} & \overline{RR} = 0.844 \pm 0.149 \end{array} \quad (p = 0.02 < 0.05) \tag{5}$$

averaged over the extracted 21×1000 segments of RR series of duration 2.5 min.

These data allowed us to define the parameters for the stress detection algorithm. In particular, considering the difference between the rest and stress conditions reported in (5), we set $\Delta_{r \to s} = 0.02$ s, and $\Delta_{s \to r} = 0.5 \Delta_{r \to s}$ to take into account the hysteresis of human body to switch between rest and stress [19]. The values Γ_r and Γ_s are introduced to reduce misdetection of stress: namely, if $\overline{RR}$ is too high (low), a condition of rest (stress) is identified, without considering increase or decrease with respect to the previous time window. The values of the thresholds were set to the 70th percentile of the $\overline{RR}$ values for the rest and stress conditions recorded during the experimental tests, resulting in $\Gamma_r = 0.94$ s and $\Gamma_s = 0.74$ s.

V. Experimental validation of the framework

For the experimental validation of the proposed affective interaction approach, we considered a Pioneer P3-AT mobile robot mounting a laser scanner on the front and a Samsung Gear S smartwatch, which embeds an accelerometer and a magnetometer and a heart rate monitor sensor providing heart rate in terms of beats per minute and successive RR intervals. Movement of the user's forearm and gestures were used to move the robot as presented in [10]. Two different experiments were carried out, considering different setups and assistance strategies to the user. All involved subjects volunteered to participate in the tests and were properly informed of the experimental protocol.

Due to the limited computation capabilities of the elaboration unit utilized for the control of the mobile robot, gesture recognition and HRV analysis were performed on an external computer, and the architecture was implemented by means of ROS. Wi-Fi was used for communicating with the robot and the smartwatch.

In the first experiment, 12 first time users (2 females, 10 males, age 26.7 ± 3.6 y.o.) were asked to drive the mobile robot through the tight cluttered environment shown in Fig. 3, consisting of seven plastic pins placed on the ground. In particular, the users were instructed to follow the red path, without touching any pin or barrier. The experiment was organized in two parts, which are represented in Fig. 4. In each of them, the users were asked to drive the robot along the path for three continuous laps, for a total of six laps. In the first part, no adaptation of the robot's behavior was considered; thus, the robot was controlled according to [10]. In the second part of the experiment, the robot's behavior was adapted on the basis of the detected user's mental workload and its velocity was halved when mental stress was found. Additionally, the second part of the experiment was anticipated by an initial baseline recording of duration 2.5 min, aiming at recording the subject specific value of $\overline{RR}$ at rest. The order of the two sessions was randomized to compensate any learning effect. In the session of the experiment when adaptation of the robot's behavior was provided, HRV was computed on recording windows of 2.5 min.

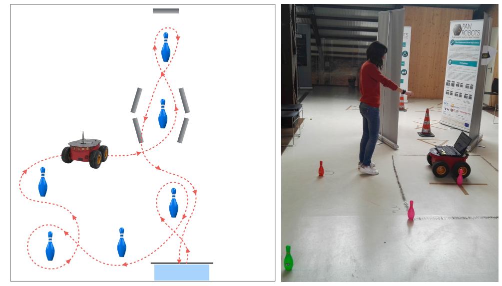

Fig. 3. Experimental setup of the first experiment.

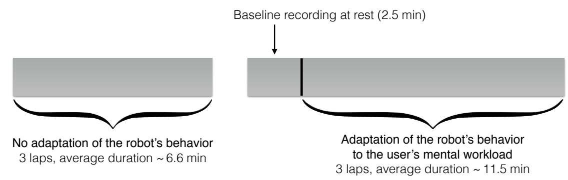

Fig. 4. Test session with the robot in the first experiment.

Fig. 5 shows the detected cognitive status of each user during the experiment in the scenario of affective robotics[3]. The green rectangles denote the time windows following the detection of a stress level, during which the robot's velocity was limited. The white rectangles denote the rest condition. The duration of the task was variable depending on the detected rest-stress pattern and on the driving attitude of the involved users. The figure highlights that, for all the users, an increase in mental workload was measured 2.5 min (8 users out of 12) or 5 min (4 users out of 12) after the beginning of the driving task. This is due to the fact that a noticeable amount of concentration is required to move the robot in such a tight area. For the majority of the participants, the adaptation of the robot's behavior to the detected increase of stress was beneficial since it took to a reduction in stress during the following monitoring time window. With reference to Fig. 5, this means that all the participants could recover to a rest condition, exception made

[2] $p < 0.05$ in 854 out of 1000 runs, of which 436 gave $p < 0.01$

[3] Each driving session was started considering users at rest.

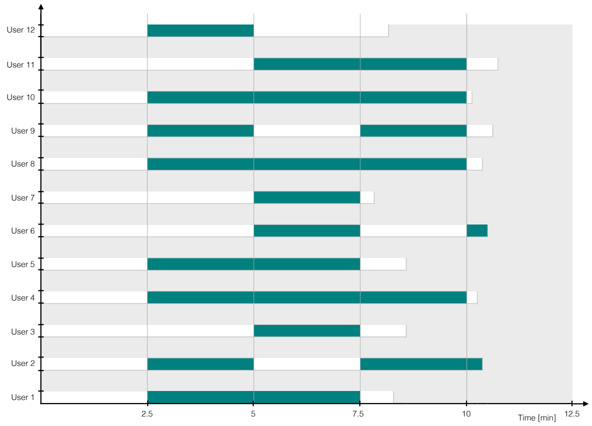

Fig. 5. Detected cognitive stress levels during the robot driving task. Green areas start after the detection of mental stress condition and end when the user returns to a sustainable mental workload.

TABLE I
RESULTS OF ADAPTING ROBOT'S BEHAVIOR DUE TO STRESS DETECTION WHILE DRIVING THROUGH A CLUTTERED ENVIRONMENT IN THE FIRST EXPERIMENTAL SETUP.

	Rest *robot's velocity as in [10]*	**Stressed** *reduced robot's velocity*
Touched pins	32	6
Visited pins	186	174
Ratio	17.2%	3.4%

for users 2 and 6 who completed the experiment in the stress condition.

To quantitatively assess the effectiveness of the proposed affective interaction system, we considered the number of touched pins over the total of visited pins, both in the case of calm user (robot's velocity given by [10]) and stressed user (reduced robot's velocity). The results are summarized in Table I, which shows that, when the user is experiencing mental stress, she/he finds it difficult to accomplish the task correctly. Reducing the robot's velocity is of help since the user is then able to accomplish the task more effectively, i.e., touching a much smaller number of pins. However, the reduction of robot's velocity has the clear drawback of requiring more time to accomplish the task, thus reducing the user's efficiency. In this regard, adapting the robot's behavior according to the user's needs represents a more appropriate solution than considering a fixed reduced robot's velocity.

In the second set of experiments, 15 first time users (2 females, 13 males, age 26.1 ± 6.7 y.o.) were asked to drive the mobile robot through a tight cluttered environment, consisting of 11 gates placed on the ground, as shown in Fig. 6. In particular, the users were instructed to move along a slalom path, visiting the gates without touching any pin. Each experiment lasted 10 min, during which users were able to complete from 3 to 5 laps, depending on their own confidence with the system. The experiment was anticipated by an initial baseline recording of duration 2.5 min, aiming at recording the subject specific value of $\overline{RR}$ at rest. When an increased mental strain was found according to (3), obstacle avoidance was activated: in particular, when an obstacle was detected by the laser scanner, linear and angular velocities of the robot were reduced to $1/3$ of their nominal value if the distance d between the robot and the obstacle was less than 70 cm; the linear velocity was then put to zero for $d \leq 30$ cm.

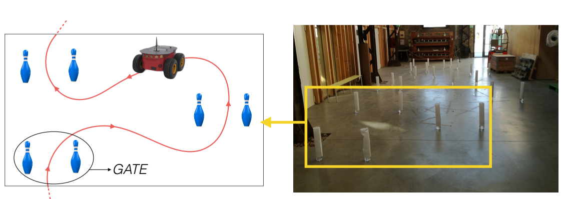

Fig. 6. Experimental setup of the second experiment.

To characterize in quantitative terms the experiments, we considered the task speed s, measured as average number of gates visited per minute, and the error e, measured as average number of touched pins per visited gate, per minute.

Fig. 7 depicts, as an example, the performance of a user among those considered in the tests. In the first 2.5 min of the experiment, the motion of the robot was unrestricted, since the experiment started considering the user at rest for all test subjects. The user performed quite well since he visited a large number of gates (11 gates, panel (b)), although he hit 3 obstacles (panel (c)). No increase in mental strain was measured in this first recording window, thus unrestricted motion was continued until the next computation of stress. The user was fast also in the second temporal window, since 10 gates were visited, but 5 touched pins were recorded and an increased mental strain, due to intense focusing on the task, was found according to (3). Thus, after 5 min from the beginning of the experiment obstacle avoidance was activated (as shown at time 5 min in panel (a)). This helped the user to perform the task more carefully, while reducing the necessary concentration. Indeed, no pins were touched from time 5 min to the end of experiment, when rest condition was restored, and 8 gates were visited in each of the two windows.

Moreover, we considered the average execution speed and error achieved by all the test subjects. We compared them to the same quantities computed extracting the temporal windows in which the users were found at rest and affected by mental strain. Given a total of 60 temporal windows during which affective robotics was considered (15 test subjects, duration of the test 10 min, duration of a temporal window for stress detection 2.5 min), 40 temporal windows with users at rest were found, whereas mental strain was measured in 20 windows. Table II reports the achieved results, which show that adapting the behavior of the robot to the detected user's affects provides a trade off, in terms of execution speed and error, between the two alternative conditions of no support given to the user (when the user is at rest) and support provided in terms of obstacle avoidance (when mental stress is measured).

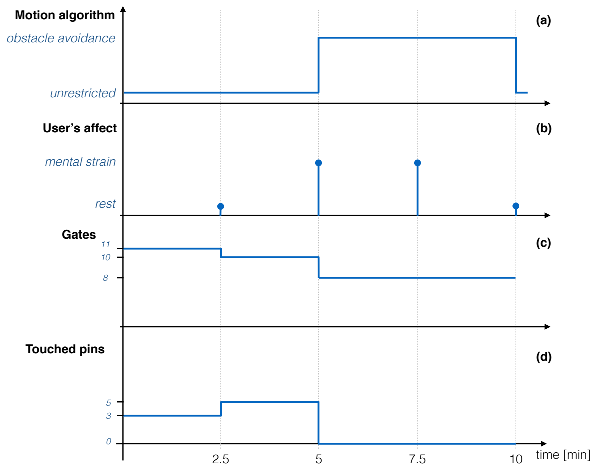

Fig. 7. Example of performance in the second experiment.

TABLE II

RESULTS OF ADAPTING ROBOT'S BEHAVIOR DUE TO MENTAL FATIGUE DETECTION WHILE DRIVING THROUGH A CLUTTERED ENVIRONMENT. TASK SPEED AND ERROR ARE IN $[\text{MIN}^{-1}]$.

	No support	Obstacle avoidance	Adaptive behavior
Speed s	3.38	2.66	3.14
Error e	0.13	0.03	0.1

VI. CONCLUSION

In this paper we presented a framework based on affective robotics for natural HRI. Interaction with the robot is enabled by a smartwatch that is worn by the user and allows a natural mapping between user's and robot's motion. Thus, the user can intuitively interact with the robot. Moreover, the behavior of the robot is adapted based on the user's cognitive workload: when an increase is measured, assistive strategies are activated in order to simplify the task. The framework is general and can be applied in different working scenarios. In this paper we considered its application with industrial manipulators, wheeled and aerial robots and multi-robot systems.

The algorithm for detecting increased user's cognitive workload was presented. It relies on the analysis of the variability of user's heart rate, which is measured by the smartwatch in a non-invasive manner. Experimental results showed that the algorithm is able to detect changes in mental workload. The framework was tested considering, as a case study, the interaction with a wheeled robot.

Further studies will aim at considering more intriguing task scenarios, thus assessing the effect of lack of interest and physical fatigue during the execution of the task.

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