Relieving Operators' Workload: Towards Affective Robotics In Industrial Scenarios

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Abstract

This paper proposes a novel approach based on affective robotics that can be applied to industrial applications. Considering a human-robot interaction task, we propose to analyze the mental workload of the operator, and subsequently adapt the behavior of the robotic system, introducing assistive technologies. These technologies would prevent the performances deterioration caused by the human stress, helping him/her only when needed and decreasing the user's mental workload. This represents a general methodology, which can be applied to several industrial applications, leading to increase the overall performances of human-robot interaction exploiting principles of human-centered design. As a case study, we consider a teleoperation task, where virtual fixtures are utilized as an assistive technology. The stress of the operator is monitored in terms of heart rate variability, measured by means of a wearable sensor tied at the operator's wrist. Experimental validation of the proposed architecture is performed on a group of 15 users that teleoperate an industrial robot for performing a pick and place task.

Keywords: Affective robotics, Human-robot interaction, Industrial robotics, Human-centered workplaces

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1. Introduction

In the recent years, robots are becoming key elements to achieve manufacturing competitiveness, especially if they are able to collaborate with humans in a shared workspace, creating a co-working partnership. To this end, the initial paradigm for robot usage has changed during the years from an idea in which robots work with complete autonomy in a separate cell, to a scenario in which robots and humans can work together and interact.

Human-Robot Interaction (HRI) is a growing research area: main researches focus on construction, healthcare and assistive robotics, aerospace, edutainment and entertainment, home service, military and industrial applications [1, 2]. Robots can help humans in relieving physical effort tasks, carrying heavy loads and conducting repetitive tasks: in [3] authors describe a human-robot dialogue system that allows a human to collaborate with a robot during an assembly task; in [4] authors present a mobile construction robot that performs accurate and delicate building tasks with a new real time framework of "sense and act"; in [5] authors propose a mobile robot that can handle an object in cooperation with a human, sharing the load. With respect to healthcare and assistive robots, applications of HRI have been proposed for assistance for blind people [6, 7], social interaction for autistic children [8], elderly care [9, 10] and intelligent and autonomous wheelchairs [11, 12]. In the space field, robots are used for the exploration of planets [13] and construction of space stations [14]. Another field where robots support and take over for humans is urban search and rescue [15, 16]: they can more easily explore and move in collapsed buildings thanks to their small dimensions [17], looking for human victims, in combination with aerial robots to monitor areas from above, after natural disasters [18]. Edutainment and entertainment robots have been employed as tour guides in museums [19], dance partners [20], robotic pets [21] and story tellers [22]. Moreover, for home service, robots are used as vacuum cleaners, home security and household devices [23]. In military field, robots are used as soldiers in remote operations or dangerous ones like bomb disposal [24]. Cooperation with robots is also useful in small-scale tasks, as microassembly and microsurgery, where a high precision is required [25].

As regards industrial applications, in the last years the increasing need for collaborative robotic solutions has been mainly driven from the automotive and electronics industry [26]. Most of the applications in the automotive domain refer to assembly processes, where robots are in charge of those tasks requiring high precision or causing workers repetitive strain injury when done by hand, such as carrying heavy objects [27]. Just to cite few examples, in [28] robots assist humans on physically demanding operations like door removal or seat loading, or they can load and transport heavy wheels in tire workshops [29]. Another interesting application field is the oil and gas industry: in [30], HRI is exploited to remotely control a mobile robot for inspection of plants and repairing tasks. Further industrial applications of human-robot collaboration and interaction refer to handling and welding tasks and in [31] the case of assembly of biomedical products is considered. A detailed review on human-robot collaboration in industrial settings can be found in [32].

It is worthwhile noting that the use of collaborative robots in industrial working environment enjoys two major advantages. First, human workers and robots share their complementing skills, such as robots precision, accuracy and repeatability, which are impossible to achieve by humans, and humans innate flexibility and ability to adapt to unforeseen events. Second, using collaborative robots allows to relieve human workers of tiring and physically demanding tasks, which are delegated to robots. However, the introduction of such robotic systems in industrial applications poses also two major issues, which cannot be ignored. Specifically, issues related to safety must be considered, since any harm to the human worker due to proximal interaction with the robot must be prevented. In this regard, a large body of the literature has been devoted to this topic and several technical and governmental regulations have been issued, as recalled in [32]. Additionally, issues related to human factors and cognitive workload for the user have to be considered. Indeed, shopfloor workers, who typically are neither expert nor confident with the use of robots, are requested to work close to such complex systems: this generates anxiety and fear. In particular, an increased operators mental strain in collaborative robotic assembly tasks was reported in [33]. Moreover, in most cases, the introduction of robots changes the way workers are used to perform a task, thus requiring that workers adapt to the new workflow and learn again the task from scratch. These thoughts add to the fact that, in typical industrial work tasks, shopfloor workers have often to accomplish repetitive jobs, or they work in adverse conditions, either environmental, such as noisy places, dangerous environments, dark views, or psychological, due for example to tight time constraints, presence of supervisors and electronic monitoring of job performance [34, 35]. Ultimately, in [36] it was proven that there is an association between work stress for industrial employees and the risk of death from cardiovascular disease. Thus, human factors, meant as mental stress induced by close and prolonged interaction with the robot, have to be taken into account when considering and designing robotic industrial applications.

A promising way to achieve this is tuning the interaction with the robot depending on the worker's skills and her/his instantaneous stamina. Indeed, while the former can be considered as constant during the interaction session, stamina varies depending on situational conditions, such as stress, fatigue and specific working environment and tasks. In order to adapt HRI task according to the worker's stamina, an approach based on affective robotics can be exploited. Specifically, affective robotics consists in enhancing the interaction of a human with a robot by recognizing her/his affect [37]. By supervising non verbal communication towards the robotic system during the interaction, such as emotions and feelings, an implicit feedback can be obtained. This implies that, when worker's stamina is increased, human weakness can be detected and the robot can adapt its behavior and compensate the human temporary lack, reducing the user's cognitive load. Affective robotics has been mostly used in the context of social robots [37], where an interpersonal human-robot communication is desired. For example, in [38] affective robotics is exploited to reach a smooth and natural HRI, considering a model of affect that gathers emotions, moods, and attitudes, particularly with regard to long-term responses. Few works exist with respect to service robots. In [39], authors develop a Hidden Markov Model to estimate the human affective state in real time, using robot motions as inducements, to obtain a more natural HRI. Moreover, in [40] an approach to HRI is presented that allows users to intuitively interact with a robot and takes into account mental fatigue, providing adequate support when necessary. The idea of implementing affective computing for interacting with automatic machines has been considered in the European project INCLUSIVE, which has recently started [41]. However, to the best of the authors' knowledge, no attempts have been considered yet on integrating affective robotics in industrial applications, where situational constraints (such as stress and psychological pressure) make the interaction more critical and tend to reduce human operator's acceptance of robotic systems.

Rather than adapting the interaction to the current psycophysiological condition of the worker, classical approaches used in industrial practice resort to user profiling, that is off-line measuring the skills and capabilities of the user and adapting the user interface accordingly (see, e.g., [42] and references therein). Off-line profiles can be built upon analysis of worker's skills (like experience, knowledge, training, competence and education), information processing ability and cognitive and physical impairments. However, this approach does not take into account the online evolution of the user's aptitude and her/his mental workload. Furthermore, it is worthwhile noting that workers' physical fatigue is considered in [43] and it is explicitly taken into account in the design of a collaborative robotic cell for manufacturing tasks. In particular, tasks are assigned either to the robot or the human operator depending on the level of his/her physical fatigue.

Recently, support tools based on augmented or virtual reality have been proposed to assist workers and guide them in the interaction with robotic systems. Both of these approaches result into augmenting natural feedback to the operator with simulated cues [44]: with augmented reality, the user maintains a sense of presence in the real world and only virtual elements are added; with virtual reality, the user is totally immersed in a virtual environment and her/his senses are under the control of the system. Specifically, several solutions have been proposed aiming at assisting workers in tasks related to planning [45], maintenance [46] assembly design [47], where the optimal operation sequence that minimizes completion time and effort must be found. However, neither these methods make any distinction between different cognitive capabilities of the users or their experience and sensitivity toward the system.

1.1. Contribution and organization of the paper

To overcome the above mentioned limitations, we propose to combine industrial and affective robotics to design an anthropocentric industrial robotic system, whose behavior changes according to the worker's feelings and reactions, becoming flexible towards different typologies of users and tasks. On the one side, the proposed approach is intended to relieve the user's mental workload when the interaction with the robot becomes not sustainable for the worker. On the other side, we ultimately aim at making industrial robots accessible also to inexpert users, who do not feel confident or do not have experience of interactive tasks, and thus are excluded when creating employments in this field.

Generally speaking, affective robotics is based on real-time measurements of physiological parameters that are indicators for mental strain, such as blood volume pulse and heart rate variability, electrodermal activity, body temperature, electroencephalography, hormonal balance and the analysis of oculomotric functions or speech. Specifically, we propose to monitor worker's mental strain from the analysis of heart rate variability, which is a reliable marker of cognitive stress, as detailed in the next section. Moreover, monitoring operator's cognitive workload in working environments requires the use of unobtrusive tools, which do not limit her/his freedom of motion and not interfere with the task to accomplish. To this end, we propose to measure heart activity, and hence heart rate variability, by using a commercial smartwatch, which embeds a heart rate sensor.

The system, starting from a nominal common condition (i.e., without any change from the original task), monitors the worker's stamina and, when a stressful situation is detected, adapts itself, by simplifying the execution of the task. Examples of task simplification in response to an increased mental stress are represented by reducing the movement velocity, forbidding hazardous manoeuvres or providing the user with assistive forces that help her/him to command the robot towards a target or far from an obstacle. Such a change in the robot behavior aims at reducing the user's mental workload, so that when the mental stress is relieved or she/he feels more confident, the system can restore the nominal conditions. It is worthwhile underlying that the adaptation of the robot behavior to a simplified task is temporary: when an increase in mental stress is measured, the standard interaction task cannot be performed efficiently by the user, since it overloads her/his stamina. In this regard, although the simplified task *per se* represents a reduction of performance of HRI (e.g., reduced velocity implies longer execution times, assistive forces limit user's freedom of motion, hindering hazardous manoeuvres implies limiting movements of the robot), it still leads to an overall improvement of HRI, given the (temporary) reduction of the effort required to the worker. As soon as worker's faculty is restored, the standard HRI task can be restored as well, in order to exploit the standard operation mode of the robot.

The proposed control strategy represents a general methodology, that can be applied to industrial applications. In this paper, as a case study, we consider the teleoperation of an industrial manipulator, although the general approach holds true for any HRI task. Teleoperation refers to the possibility for the user to command a remote system or machine at a distance: since the early days of robotics, it has been implemented in several industrial applications [48], which typically involve work conditions inappropriate for humans. Specifically, it proves useful when the environment is dangerous or unpleasant, or the required forces or accuracy are greater or smaller than the human can directly provide. Under these circumstances, in the case the task is difficult to model or the judgment and skills of a human are needed, the use of a teleoperation

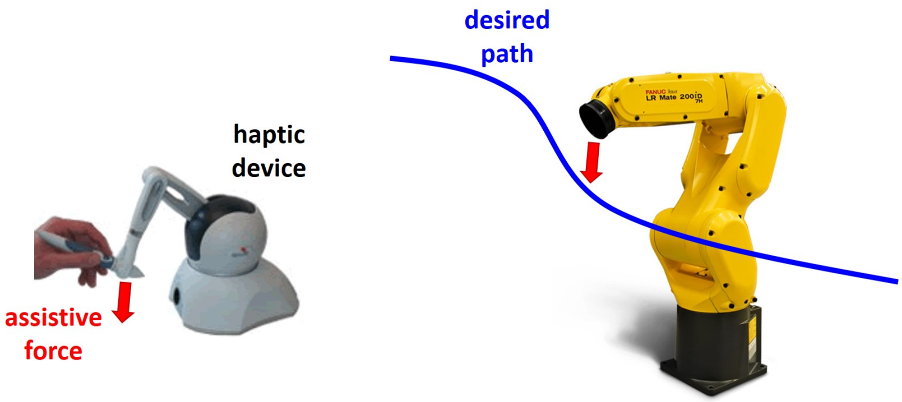


Figure 1: Example of guidance virtual fixtures: the teleoperated robot has to follow the desired path (blue line). An assistive force is applied to the haptic device (red arrow) to make the user teleoperating the robot towards the desired path.

system should be considered, since in this way the operator can exercise her/his abilities in completing the task, even in the face of unforeseen circumstances [49]. Examples of industrial applications are forging, the metal industry or mining tasks. Moreover, teleoperation systems can be used to handle nuclear waste or radioactive materials [49].

As a support strategy that assists the worker when mental stress is detected, we consider virtual fixtures, which are applied to the haptic device used for teleoperation [50]. Such virtual fixtures can be designed to restrict the motion of the haptic device to desired subspaces or volumes in its operational space (*forbidden region virtual fixtures*), or to guide the user towards a desired target, which can be either a specific operating point or a more complex geometric path (*guidance virtual fixtures*) [51]. In this paper, guidance virtual fixtures are considered as the support strategy to assist the worker in case of mental stress. They are achieved defining an artificial potential that creates a virtual force to be applied to the haptic device in order to guide the user towards the desired target. The concept of guidance virtual fixtures is shown in Fig. 1, where the desired path is indicated in blue, while the assistive force applied to the haptic device is shown in red.

The paper is organized as follows. In Section 2 we present an overview of the background on heart rate variability for mental stress detection. Subsequently, Section 3 introduces the architecture of the proposed affective teleoperation system. The experimental validation of the system is reported in Section 4 and, finally, Section 5 contains some concluding remarks.

2. Background on heart rate variability and mental workload

Heart rate variability (HRV) is the physiological phenomenon of variation over time of the period between consecutive heart beats and it is predominantly dependent on the extrinsic regulation of the heart rate [52]. HRV is thought to reflect the heart's ability to adapt to changing circumstances by detecting and quickly responding to unpredictable stimuli.

The analysis of HRV allows to assess overall cardiac health and the state of the autonomic nervous system, which is responsible for regulating cardiac activity. The normal variability in heart rate is due to autonomic neural regulation of the heart and the circulatory system. The balancing action of the sympathetic nervous system and parasympathetic nervous system branches of the autonomic nervous system controls the heart rate. In particular, increased sympathetic nervous system activity or diminished parasympathetic nervous system activity results in cardio-acceleration. Conversely, a low sympathetic nervous system activity or a high parasympathetic nervous system activity causes cardio-deceleration [52].

HRV analysis relies on the analysis of the fluctuations of the RR intervals. These RR intervals are obtained from electrocardiogram (ECG) recordings, where 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 [53]. Denoting by R_k the instant of occurrence of the k-th heart beat, the RR series is then defined as:

$$RR_k = R_{k+1} - R_k, \quad k = 1, 2, \ldots \tag{1}$$

The most widely described methods in literature for HRV analysis can be grouped under time-domain and frequency-domain. Other methods have been proposed, such as non-linear methods [54]. The most simple parameters are the time-domain metrics that can be computed directly from the raw RR interval time series. The most common time-domain measures are the mean value ($\overline{RR}$), the standard deviation ($SDRR$) of the RR time series, the root mean square of the differences between consecutive RR intervals ($RMSSD$) and the percentage number of consecutive (normal) intervals differing more than 50 ms in the entire recording ($pNN50$). In the frequency-domain analysis, power spectral density (PSD) of the RR series is calculated. The PSD is analyzed by calculating powers and peak frequencies for different frequency bands. The commonly used frequency bands are very low frequency (VLF, 0-0.04 Hz), low frequency (LF, 0.04-0.15 Hz), and high frequency (HF, 0.15-0.04 Hz). The most common frequency-domain parameters include the powers of VLF, LF and HF bands in absolute and relative values, the normalized power of LF and HF bands, and the LF to HF ratio. For further details, the reader is addressed to [54, 55].

During the last few decades, researchers have used HRV to measure mental stress since it has been shown that stress, in general terms, and cognitive processing in particular, influence HRV [52, 56, 57]. In this paper, we will make no distinctions among the terms stress, mental stress and cognitive workload, since in an industrial environment the joint effect of several stressors could arise. The effect of stress on HRV is due to the fact that, when a person is exposed to a stressor, the parasympathetic nervous system is suppressed and the sympathetic nervous system is activated, resulting in cardio-acceleration and low frequency range of heart rate. Thus, it has been found that LF is reduced in mental stress condition, while HF is increased [52, 58]. Regarding time-domain metrics, the main reported changes involve $\overline{RR}$, $SDRR$ and $RMSSD$, which are decreased under mental stress [59, 60].

It is worthwhile noting that several studies have used also other physiological measures to classify operator state with regard to mental workload. In addition to cardiac activity, recorder by heart rate, most of these studies have employed brain, respiratory, skin conductance and eye (pupil dilatation) data. Examples in this regard are [61, 62, 63, 64, 65]. However, recording these signals requires that obtrusive instrumentation is used, which makes it impractical in real operational environments. Our goal, indeed, is that of monitoring operator's mental fatigue in real working scenarios, that is in a manner that is transparent to the user, being non-invasive. To this end, the use of heart rate and skin conductance proves convenient, since they can be recorded by means of non-invasive wrist-worn devices. Specifically, heart rate can be easily recorded by using everyday commercial devices, as will be discussed in the next section.

3. Proposed affective teleoperation system

In this section we describe the proposed affective robotics methodology, applied to a teleoperation scheme. Traditional teleoperation systems typically consist of a user that is interacting with two robots, the (local) master and the (remote) slave, interconnected by means of a control architecture. Master and slave exchange then information over a communication channel: in particular, the motion of the master is sent to the slave, which replicates it. Specifically, the master robot sends its current Cartesian position to the control system, which transforms it in the slave reference frame and executes the inverse kinematics, sending the corresponding commanded joint position to the low-level controller. The communication channel introduces time delays that may be, in general, non-negligible and may lead to unstable behaviors. However, since several strategies have been developed in the literature to cope with such issue [66, 67] and since teleoperation itself is not the focus of this paper, we will hereafter not consider the time delay. In a bilateral teleoperation architecture, such as the one depicted in Fig. 2, the slave robot reflects back to the master reaction forces, which provide the operator with information about the task being performed.

In an affective robotics perspective, we propose to enhance the exchange of information, by including:

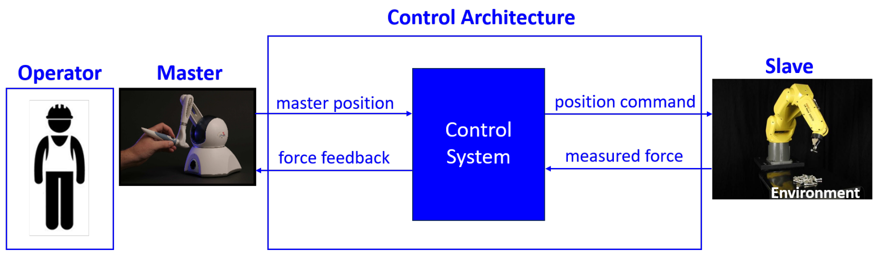


Figure 2: Standard bilateral teleoperation architecture.

1. data regarding the mental stress of the operator,

2. additional force feedback to assist the operator when needed.

Force feedback is generally computed, in traditional teleoperation schemes, based on the task the slave robot is performing: typically, force feedback is proportional to the force exchanged by the slave robot and external objects, such as objects being manipulated or obstacles (i.e., the environment). Such feedback provides the operator with information about the current status of the task performed by the robot, making her/him feel as if she/he were directly performing the task (telepresence). When the task is particularly complex, additional force feedback can be introduced to provide assistance to the operator [68]. In particular, we implement such an assistive system utilizing virtual fixtures, namely forces applied to the master device, that guide the operator towards a desired target.

Virtual fixtures provide a guide for the operator, influencing her/his movement towards predefined configurations, thus reducing the possibility of execution errors. Moreover, they may help the user if she/he cannot directly access the work environment (e.g., if it is dangerous or cannot be contaminated) and she/he must use a camera or a vision system with a possibly disturbed view (e.g., due to dust in the environment). At the same time, however, virtual fixtures impose constraints on the freedom of execution of the operator, which may be felt as unnecessary or disturbing.

The proposed affective robotics approach consists in activating the assistive system (i.e., the virtual fixtures) only when the mental stress of the operator is excessively high. We assume that the environment at the slave side is mapped, possibly after scaling, to the master side so that the forces generated by the fixtures can be computed locally (i.e., with respect to the workspace at the master side). In order to keep the notation simple, we will heareafter consider virtual fixtures generating translational forces only, as proposed in [69]: however, we would like to remark that the proposed method can be easily extended to consider rotations as well.

Virtual fixtures are achieved defining an artificial potential field, which generates a virtual force on the master robot, which attracts it towards a reference configuration. Specifically, such a potential field can be defined as follows:

$$V(x) = \frac{1}{2}k\,(x - x_d)^2 \tag{2}$$

where $x \in \mathbb{R}^3$ is the Cartesian position of the end-effector of the master robot, $x_d \in \mathbb{R}^3$ is the target point and $k > 0$ is a tunable gain. The target point x_d is defined as the configuration of the master robot that corresponds to having the slave robot in the desired configuration (e.g., pick/place position).

The corresponding attractive force is defined as the negative gradient of the potential function, expressed as:

$$F(x) = -\frac{\partial V}{\partial x} = -k\,(x - x_d) \tag{3}$$

Such a force attracts the end-effector of the master towards the desired point x_d. If point x_d is replaced with a sequence of way-points, it is possible to attract the end-effector of the master robot to follow a reference path.

As regards stamina detection, among the methods described in Section 2, we exploit the average of the RR series, namely $\overline{RR}$, as a measure of mental stress. The choice is motivated by the ease of implementation, and by the well documented reliability of such a metrics [59]. In classical clinical applications, heart rate is measured by means of intrusive and cumbersome instruments (e.g., electrocardiograph), which are however not practical to be applied in the considered scenario. Hence, in order to reduce the interference with the main task of the operator (i.e., interaction with the robot), a wearable device is exploited for measuring the HRV. While we utilized a commercial smartwatch, any wearable device equipped with heart rate sensors can be used as well. Such a wearable device is tied at the operator's wrist, while she/he is performing the teleoperation task. The control system is then adapted, based on the analysis of the HRV.

To assess the suitability of heart rate recorded by means of the smartwatch to detect mental fatigue, we performed some tests in which subjects were exposed to sustained mental workload and their heart rate was recorded. 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 minutes, during which heart rate was recorded by means of the smartwatch. 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 [64, 70].

Acquired data were then analyzed according to the methodology considered in [71], extracting random segments of duration 2.5 minutes 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 newly extracted RR series) provided statistically significant difference[2] between the rest and stress conditions:

$$\begin{array}{rl} \text{rest:} & \overline{RR} = 0.871 \pm 0.135 \\ \text{stress:} & \overline{RR} = 0.844 \pm 0.149 \end{array} \quad (p = 0.02 < 0.05) \tag{4}$$

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

The overall proposed affective teleoperation scheme is then depicted in Fig. 3:

[1] Each subject was asked to read the description of the experiments, and to sign an informed consent form: subjects were involved in the experimental tests only afterwards.

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

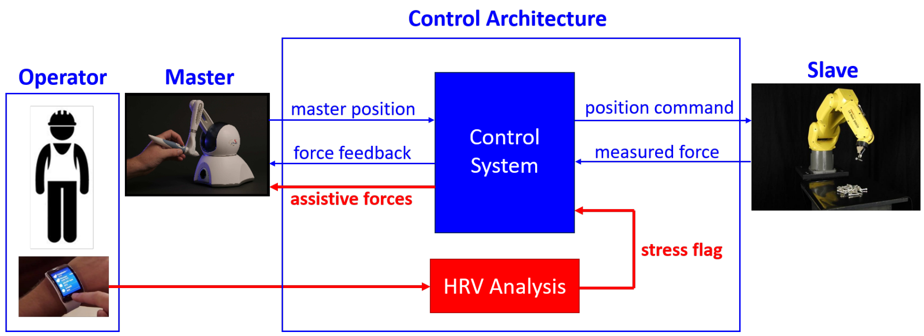


Figure 3: Proposed affective teleoperation architecture.

the HRV of the operator is measured in terms of variation of $\overline{RR}$, to define a *stress flag*, that indicates whether the operator is in a mental stress condition. In particular, as depicted in Fig. 4, the HRV analysis computes the mean value of successive RR intervals over time windows of duration 2.5 minutes, and computes then the stress flag: specifically, in a given time window, the operator is considered in a stress condition if the value of $\overline{RR}$ decreases with respect to the previous time window, in a rest condition if the value of $\overline{RR}$ increases. The stress flag is then raised to one if the operator is in a stress condition: the virtual fixtures are subsequently activated. Conversely, if the operator is in a rest condition, the stress flag is put to zero, and virtual fixtures are disabled.

4. Experimental validation

Experiments were performed using a Fanuc LR Mate 200iD as the slave robot and a Geomagic Touch haptic device as the master one. To monitor the user's mental workload we exploited a Samsung Gear S smartwatch embedded with a heart rate sensor, which allows to measure HRV. The software components dedicated to the system control have been developed using Orocos realtime framework [72] and they run with a period of 30 ms; the HRV analysis has been developed exploiting ROS framework [73].

To demonstrate the effectiveness of our proposed system we implemented a pick and place task. The experimental setup is shown in Fig. 5 : the human

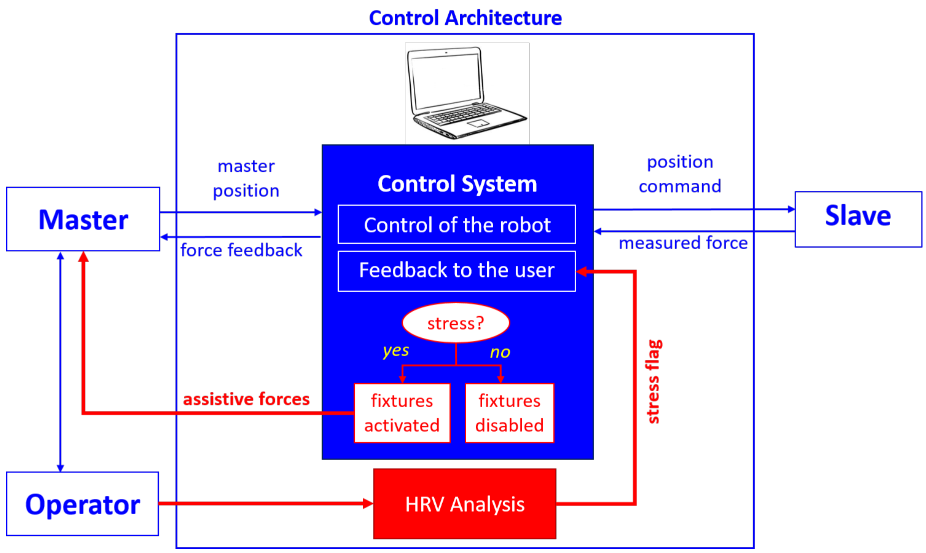


Figure 4: Control architecture.

operator, with the smartwatch at her/his wrist, teleoperates the robot looking at a display where the image is dark and the sense of depth is lost. On the working area, two separate locations are assigned to the picking phase and the placing one. A magnet, placed under the robot end effector, is used to get each object, which has to be placed inside the box. This has been designed to represent a simplification of industrial teleoperation tasks in which the operator is compelled to work from the remote since the environment is dangerous or inaccessible. From the teleoperation point of view, this is a basic task, in which the interaction force between the slave robot and the environment does not provide any interesting information to the operator: hence, we did not provide such a force feedback. Therefore, the only forces perceived by the human operator are the virtual fixtures, while the measured forces are not provided back, in order to avoid possible misunderstandings. For more complex tasks (for example, if obstacles are placed along the desired path), having a force feedback from the environment becomes relevant: in this case the time delay has to be considered and the stabilization of the communication channel has to be guaranteed using,

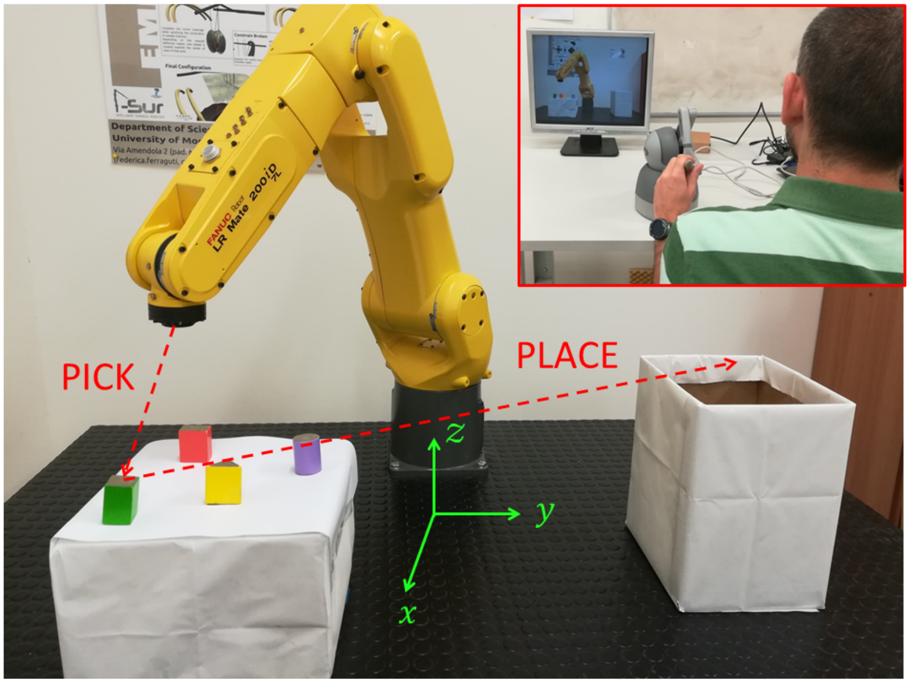


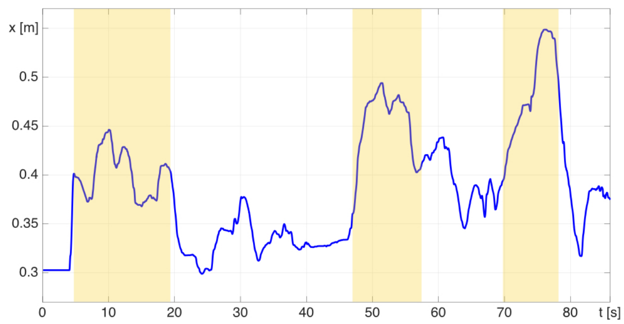
Figure 5: Experimental setup. The red square shows the user teleoperating the robot looking at a display where the image is dark and the sense of depth is lost. When the stress is detected, the virtual fixtures attract the user above an object and, once it has been picked, they drive her/him towards the placing box (dashed red lines).

for instance, the technique proposed in [67].

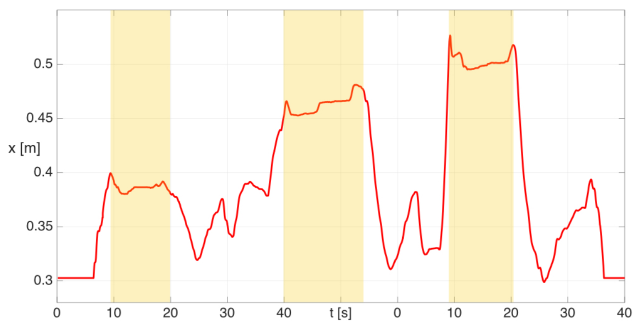
In nominal conditions (i.e., without the application of virtual fixtures) the human operator grasps the objects from the pick position and places them into a box on the opposite side of the table: she/he can choose the picking order and freely move the robot in the workspace. When the smartwatch at her/his wrist detects the stress condition, mainly induced by the lack of sense of depth and the mapping of master movements into slave motion, the virtual fixtures are activated. As is well known in the literature, when teleoperation is performed in challenging situations, virtual fixtures can help the human operator to perform the task effectively [51]. Such an external help in performing the task counteracts with a downside: the objects to be picked have to be placed in fixed and unvaried positions. In our experiment, the virtual fixtures attract the operator on the first object and, once it has been grasped, a force drives the operator to the place-box, and so on for each element. With the introduction of such an additional help, the performances of the overall system are guaranteed. However, the user's freedom of choice is reduced and the robot movements are constrained by virtual fixtures.

Trajectories along the most significant directions of picking (i.e., x and y in Fig. 5) are depicted in Figs. 6 and 7: three objects, placed approximately at $P_1(x = 0.386\ m$ and $y = -0.212\ m)$, P_2 $(x = 0.465\ m$ and $y = -0.280\ m)$ and P_3 $(x = 0.501\ m$ and $y = -0.330\ m)$ are grasped without and with the help of the virtual fixtures, respectively. Yellow areas in the figures refer to the portion of the trajectory related to the picking operations. In the first case (blue lines) the user does not perceive the space depth and several trials are required to catch the object. In the second one (red lines) the user is directly driven above the object, reducing the picking time and the number of trials required. This results in a smoother trajectory in the picking phase, as can be seen in Figs. 6(b) and 7(b). This is a clear evidence of the difficulties that can arise for an operator when the sense of depth is partially unavailable, even for a very simple teleoperation task.

The novelty of the proposed approach is to take into account the human stress during the execution of the task, generating an adaptive system that helps the operator when she/he is in a stressful condition. To show the effectiveness of this method we evaluated the performances of 15 users during the above mentioned pick and place task. The set of users considered in our experiments was composed of people between the age of 20 and 35, 6 females and 9 males, both expert and unskilled users. Each user started the experiment with 2.5 minutes of rest, during which the system recorded and analyzed the RR intervals in a non stressful situation. This was used as a baseline reference value of subject's heart rate at rest. After this system training phase, each user performed the pick and place task for 10 minutes and, after every 2.5 minutes, the HRV analysis determined if the operator was stressed and the virtual fixtures



(a)

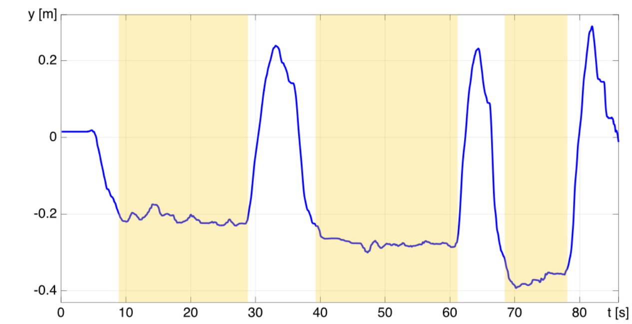


(b)

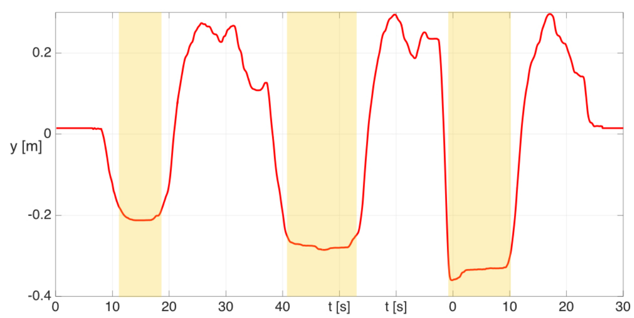
Figure 6: Trajectory along x axis without (a) and with (b) the virtual fixtures. Yellow areas refer to picking tasks.

were consequently activated.

In particular, as shown in Fig. 8, four stress-flags were detected, one every 2.5 minutes: if the user had already been trained or she/he felt confident with the haptic device, the flag remained false (e.g., users 11 and 13). Instead, if the user felt insecure or stressed or was not used to teleoperation tasks, the flag was raised. In this case, most of the times the virtual fixtures helped the operator to reduce the stress and to become familiar with the haptic device, restoring the flag to false value. Other times, if the 2.5 minutes of the external help had not been enough and she/he was still insecure, the stress flag raised again and the assistive virtual fixtures were kept active. It is worthwhile noting that, in the last minutes of the task, that is before the last flag was raised, several



(a)



(b)

Figure 7: Trajectory along y axis without (a) and with (b) the virtual fixtures. Yellow areas refer to picking tasks.

users reported fatigue and annoyance towards the task, which indeed was quite repetitive. Thus, we suspect that such feelings mainly contributed to the stress flag that was measured in the last recording window for users 3, 7, 8, 10 and 15. In other words, we believe that such stress conditions resulted mostly from fatigue and lack of interest in the task, rather than increased mental workload. Further investigations are required in this regard.

Further, to quantitatively assess the effectiveness of the introduction of assistive forces to reduce user's strain according to the proposed approach, we considered the effort that test subjects put in the task. Specifically, this was quantified in terms of time needed for the picking task and variability of the trajectory of the end effector of the slave robot along the x axis, which is the most

User	Flag after 2,5 min	Flag after 5 min	Flag after 7,5 min	Flag after 10 min
1	Stressed	Rest	Rest	Rest
2	Stressed	Rest	Rest	Rest
3	Stressed	Stressed	Rest	Stressed
4	Stressed	Stressed	Rest	Rest
5	Stressed	Rest	Stressed	Rest
6	Rest	Rest	Stressed	Rest
7	Stressed	Rest	Rest	Stressed
8	Rest	Rest	Stressed	Stressed
9	Stressed	Rest	Rest	Rest
10	Rest	Stressed	Rest	Stressed
11	Rest	Rest	Rest	Rest
12	Rest	Stressed	Rest	Rest
13	Rest	Rest	Rest	Rest
14	Stressed	Rest	Rest	Rest
15	Stressed	Rest	Rest	Stressed

Figure 8: Stress flags detected every 2.5 minutes.

challenging direction for the user since it represents the depth in the robot reference frame (see Fig. 5). Furthermore, regarding the trajectory, we considered only the portion related to the picking operation (i.e., the yellow areas in Figs. 6 and 7), since it was the most difficult one, as the pieces to pick were quite small and accurate displacements of the robot were needed. Time and variability of trajectories were computed for picking tasks, both when users were at rest or when mental stress was measured, that is without and with assistance by virtual fixtures, respectively.

To quantify variability, firstly we manually selected the trajectories of the robot during picking tasks with and without assistive forces. With respect to Fig. 7, we considered as movements pertaining to picking those portions of trajectories belonging to time intervals in which small displacements along y

axis were recorded. Indeed, given the layout of the experiment, the picking movement was arranged in two main steps: when the user intended to pick a part in a given position, namely $(\bar{x}, \bar{y})$, she/he drove the robot towards $\bar{y}$ at first, since the y direction was unaffected by lack of sense of depth. Then, the user started exploring the x direction, while keeping $y = \bar{y}$ almost constant. Thus, variability of robot trajectories along the x axis was measured as the displacements $\delta_x = x - \bar{x}$ during the segmented picking time window. Fig. 9 shows the histogram of δ_x for $N = 30$ picking tasks without assistive forces (left) and N tasks with virtual fixtures assisting stressed users (right). Picking tasks have been extracted from 5 different subjects involved in the experiment (namely, 4, 5, 6, 8 and 12, with reference to Fig. 8).

Two considerations come in handy. First, the histogram of displacement when assistive forces are not provided (left) is much more spread than when the user receives assistance (right). This is due to the fact that a much smoother trajectory is achieved when virtual fixtures are used, as shown in Fig. 6. This result is corroborated by the analysis of the coefficients of variations (CV) of displacements in the two experimental situation, as shown in Fig. 10. The CV represents the normalized dispersion of a variable, computed as the ratio between its standard deviation and its mean value. Thus, it takes into account the amplitude of displacements, irrespective of the position of the parts considered in our experimental setup. As Fig. 10 shows, the median of the CV when virtual fixtures are used is much smaller than the median achieved when virtual fixtures are not used. A statistically significant difference was found between the CV computed over all the trials, in the two different conditions (without and with assistive forces, $p \approx 10^{-7}$).

Second, with reference to Fig. 9, the histogram related to the use of virtual fixtures exhibits much less occurrences: although the same number of picking task was considered for the two experimental conditions, picking with virtual fixtures was completed with much shorter trajectories, i.e., with much less displacement. Specifically, the mean time for picking when virtual fixtures were not provided was 1723 s, whereas when virtual fixtures were used the mean

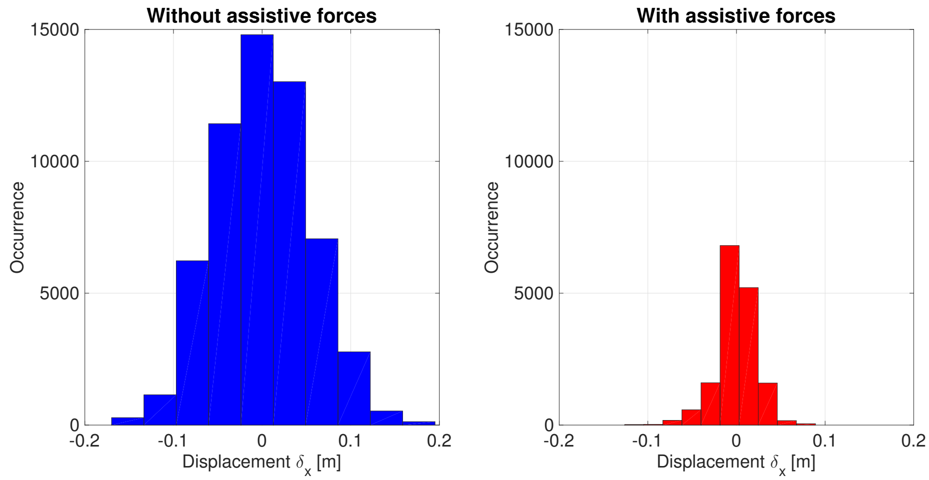


Figure 9: Histogram of displacements δ_x along the x direction in the picking task without (left) and with (right) assistance in terms of virtual fixtures.

time for picking was 487 s. These results suggest that guiding the operator towards the picking position by means of virtual fixtures provided a significant simplification in the task, thus decreasing the required mental strain.

5. Conclusions and future works

In this paper we proposed a novel affective robotics scheme, to be applied to industrial robotics applications. The proposed method relies on analysis of HRV as a method for supervising the human mental workload. The proposed system adapts the robot behavior depending on the current user's affect, while improving the performance of the interaction task.

The proposed methodology is general, and can be applied to a wide range industrial applications, moving a step towards human-centered design of robotic systems in industrial workplaces.

As a relevant case study, we considered a teleoperation task, since it has been largely used in several industrial applications since the early days of robotics. In particular, we proposed an affective robotics methodology applied to a teleoperation scheme: the average of the RR series (i.e., a measure of the heart rate

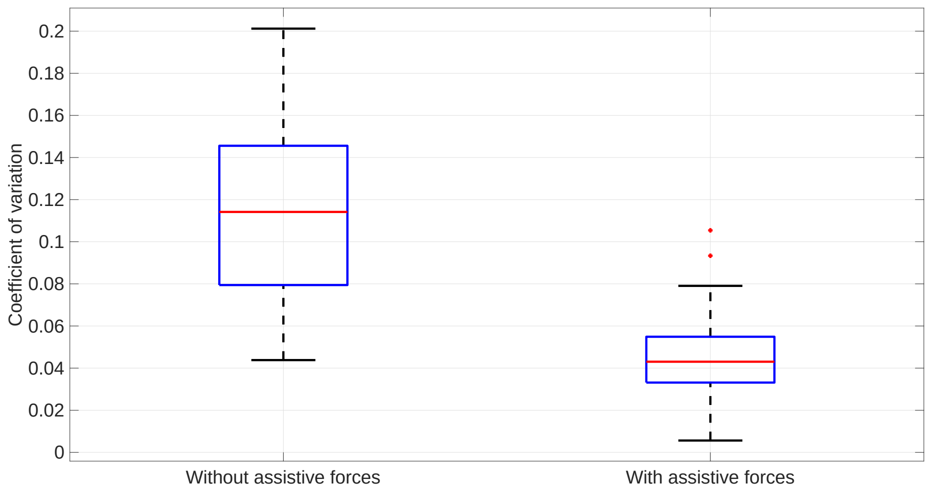


Figure 10: Coefficient of variation of displacements δ_x without (left) and with (right) virtual fixtures. In the figure, red lines denote median values.

variability) is monitored and when an excessive increase in the mental stress of the user is detected, then an assistive system based on virtual fixtures is activated in order to reduce her/his mental workload.

The proposed system has been experimentally validated on a group of 15 users that teleoperate a FANUC industrial robot for performing a pick and place task. The experiments showed that, when the interaction task overloads the user's sustainable mental workload, the assistive system based on the virtual fixtures can help the majority of the users to reduce the stress and to become familiar with the haptic device. Moreover, it was shown that guiding the operator by means of assistive forces provides a significant simplification in the task, measured both in terms of reduced time to pick a piece and smoother trajectories to approach it, thus decreasing the mental strain required by the task.

Future work aims at investigating the possibility of shortening the window of 2.5 minutes for mental stress detection, to discover if this reduction would allow a faster adaptation of the robot behavior to the worker's stamina. An extensive experimental validation on complex tasks, with a larger number of operators, would allow a deeper investigation on the effectiveness of the proposed system in relieving the user's mental workload. Moreover we aim at implementing the proposed control system on a real industrial setup. Finally, we aim at developing an affective robotics system for physical human-robot interaction, thus extending the proposed approach to further applications of collaborative robotics.

Acknowledgment

The authors would like to thank FANUC Italia for the support and for providing the experimental equipment.

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