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Human Robot Collaboration: Experimental Layout For New Algorithms Development

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Abstract

The diffusion of collaborative robots is deeply changing the way in which human operators and robot interact in industrial environments: collaborative robots share their workspaces with men, making necessary to ensure safety and mental wellness of the operators. These goals can be obtained by implementing new algorithms to avoid any kind of collision between man and robot, designing the trajectories in order to make the interaction as friendly as possible, keeping in consideration the expectation of the man in terms of maximum relative speed and preferred deviation path when a collision could occur. At the same time the mental fatigue during collaborative tasks should be kept under control in order to send alerts when dangerous working conditions could occur and, if necessary, to reduce the robot speed or definitely stop it to prevent accidents. The proposed layout of the collaborative cell will undergo testing to assess its suitability for the disassembly of large and complex Waste Electrical and Electronic Equipment (WEEE), as for example the battery of an electric vehicle. This evaluation aims to ensure the system effectiveness and safety under operational conditions.

Keywords: collaborative robotics; path conditioning algorithm; collision avoidance; mental fatigue

1. Introduction

The integration of robots in industrial settings has heralded a new era of technological advancement, redefining the dynamics between human operators and machines. In particular, the rise of collaborative robots, or cobots, has introduced a paradigm shift in the way humans and robots interact within shared workspaces. This evolution necessitates a profound consideration for ensuring the safety and mental wellness of operators, outlining a critical focal point for the evolving landscape of industrial robotics. As technological boundaries are pushed further, the convergence of human and robotic interactions demands innovative algorithms and design frameworks that prioritize both physical safety and psychological well-being. The advent of Industry 5.0, a progressive iteration beyond the efficiencies of Industry 4.0, underlines the imperative for manufacturing and industrial production to not only optimize processes but also to revolve around the welfare of workers (European Commission, 2021), posing the attention on three fundamental elements: human-centricity, sustainability, and resilience.

In parallel, the emergence of digital twins as robust instruments in the realm of human-robot interaction has been noteworthy. These virtual replicas facilitate visualization and simulation testing of robot motion algorithms, enabling meticulous evaluations of robot movements within industrial environments. For instance, in (Salamina et al., 2023), a digital twin was meticulously modeled for a mobile manipulator comprising an anthropomorphic arm mounted on a mobile robot, showcasing its instrumental role in assessing robot behavior within complex workspaces. The effect of non-ideal stiffness of parts and components can be considered in the development of models and digital twins considering the deformability of some relevant components in multibody simulation tools (Salamina et al., 2020). The advent of a novel cobots designed for collaborative work alongside humans, i.e. Human Robot Collaboration (HRC), enhances the prospects for successful cooperation (Villani et al., 2018), (Matheson et al., 2019). Current cobots primarily consist of anthropomorphic manipulators equipped with both passive and active safety features. Passive features involve design choices that inherently minimize the risk of injury during unintended contact, such as the use of lightweight materials and rounded edges. In the field of collaborative robots, innovative prototypes with non-traditional designs have emerged, exemplified by the development of the deployable soft robotic arm (Palmieri et al., 2021, 2022). This unconventional design, featuring inflatable links, holds promising potential for collaborative robotics activities. Advanced cobots additionally incorporate sensors at the joints or employ sensitive skin, complemented by dedicated software packages. These features actively respond to unexpected contacts by halting the robot when joint torques or contact forces surpass predefined thresholds.

The very challenging application requires a responsive collaboration, which means that human and robot work at the same time in the shared workspace and that they must coordinate to accomplish the task safely. If human's and robot workspaces intersect, the industrial application must be designed according to the standards (ISO/TC 299: ISO/TS 15066:2016). The speed and separation monitoring (SSM) does not specify limitation to the robotic system as long as it maintains a protective separation distance from the operator. In practice, if the operator is within the robot workspace, the SSM translates into online robot controlling to generate alternative collision-free paths. The use of human tracking systems is needed for the minimum distance monitoring and collision avoidance algorithms shall be implemented to update in real-time the robot trajectory. Recent works by (Scimmi et al. 2019a, 2019b; Melchiorre et al., 2019, 2021) have extensively explored the use of cameras for monitoring human movements in the collaborative robotics environment. These works highlight the capabilities of vision systems to enhance the safety and coordination between human operators and robots, in the context of collaborative robotics. In light of these advancements, the evolution towards Industry 5.0 underscores the imperative to not only optimize productivity but also revolve industrial production around the well-being of workers.

Safety and health of operators in a manufacturing environment are severely influenced by human factors. To date, only limited research has been conducted to understand the psychological influence on humans cooperating daily with a robot. To ensure the efficiency and productivity of the HRC system, the human teammate must feel comfortable when working with a robot (Rajavenkatanarayanan et al. 2020). The term 'good feeling' encapsulates the concept of developing healthy and safe HRC operations in which quantifying the level of fatigue is crucial. Besides being a physiological response of the human body to prevent overwork, fatigue is a symptom associated with various diseases and health conditions. Fatigue impairs cognitive and/or motor performance, reducing work efficiency, productivity and product quality, as well as increasing the risk of injury and death (Martin et al., 2021). Fatigue is often defined as a decline in mental and/or physical performance caused by cognitive overload, physical exertion, sleep deprivation, alteration of the circadian phase/rhythm, or illness (International Civil Aviation Organization, 2012). According to the classification proposed by (Giannakakis et al., 2022), fatigue can be divided into four types:

- Mental fatigue: decreased mental performance because of cognitive overload (due to task duration and/or workload), independent of sleepiness (Borragan et al., 2017).
- Sleepiness: fatigue resulting from factors related to sleep and circadian rhythm (e.g. sleep deprivation, disruption of circadian rhythm), monotony or low workload (Hu and Lodewijks, 2020).
- Physical fatigue: decline in overall physical performance caused by physical exertion (Zhang et al., 2019).
- Muscle fatigue: decrease in isolated muscle performance due to reduced contractile activity (Allen et al., 2008).

Due to the multidimensional and subjective nature of fatigue there is no golden standard method of measurement, however, there exist non-invasive methods that are mainly based on five principles of measurement: *subjective measures*, that consist of assessing self-reported fatigue through questionnaires and scales, *performance-based methods*, based on the fact that subjects' cognitive and consequently motor performance on specific tasks reflect their level of fatigue, *biomathematical models*, that predict subjects' level of fatigue based on information on sleep-wake times work-rest pattern and circadian cycle, *behaviour-based methods*, that follow an observational approach to detect fatigue and include external signs, such as yawning, sighing, closing the eyes or nodding the head and *methods based on physiological signals*, detecting the onset of fatigue based on changes in subjects' physiological responses, such as brain activity and heart rate (Giannakakis et al., 2022). As presented in (Kunasegaran and al., 2023) stress and mental fatigue can be differentiated according to their inducers. This distinction is introduced with a view to contextualising the use of similar biosignal-based metrics to assess the state of stress or mental fatigue.

The multidimensional nature of stress can be broken down into three main components: the psychological, the behavioural and the physiological. The subjective assessment of stress is influenced by systemic errors, such as providing the expected response of the examiner. Furthermore, although some bodily behaviours, as facial expressions and body gestures, occur in response to stress, they may be subject to intentional or even partially conscious control. Conversely, the physiological component to stress refers to bodily changes brought about by environmental events or conditions, known as stressors. The mechanisms underlying stress and mental fatigue are different and produce bio-behavioural states that are distinguishable. The experience of stress is accompanied by the activity of two main pathways, one involving the hypothalamus, pituitary gland and adrenal cortex, known as the hypothalamus-pituitary-adrenal (HPA) axis, and the other the sympathetic component of the autonomic nervous system and the adrenal medullary, known as the sympathetic-adrenal system (SAM). The first pathway is responsible for the release of hormones such as cortisol and adrenaline, which help the body to cope with the perceived threat by increasing glucose levels and immediately supplying energy to muscles and nerve cells in order to adapt to stressors (Giannakakis, 2022). The main physiological effects of SAM activation are increased heart rate, respiratory rate, blood pressure, muscle tension, diversion of blood flow from internal organs to the brain and muscles, sweating and dilation of the pupils.

In order to propose some new algorithms and protocols to improve safety and mental fatigue monitoring in human robot cooperation INAIL, the Italian national institute for insurance against work injuries, in cooperation with Politecnico di Torino, University of Bologna and University of Cassino, is developing the ISACOB project which intends to develop a test rig to implement and test the complete set of algorithms and to evaluate the effectiveness of sensors existing in the market.

In the following it is described the aims of the research, the layout of the test facility under development and the basis of the algorithms to be developed.

2. Aims of the research

The adoption of collaborative robots working closely with human operators requires ensuring safety from human-machine interaction risks. Technical standards currently do not account for adjusting robot operations based on the operator's changing conditions, such as posture or cognitive fatigue. To address this, the introduction of control algorithms and informative systems is suggested to make interactions more intuitive and reduce accident risks, especially due to operator fatigue or overconfidence. This paper suggests a monitoring system for collaborative workspaces that combines sensors and safety protocols on robots to improve operator awareness and robot adaptability to human behaviours. This system aims to monitor cognitive fatigue, assess musculoskeletal stress, and adjust tasks to prevent operator overexertion, including measures for collision avoidance tailored to be psychologically comfortable for the operator. The system is particularly designed for tasks requiring significant force and visual interaction and includes mechanisms for slowing or stopping the robot during extreme fatigue and planning safe interaction trajectories.

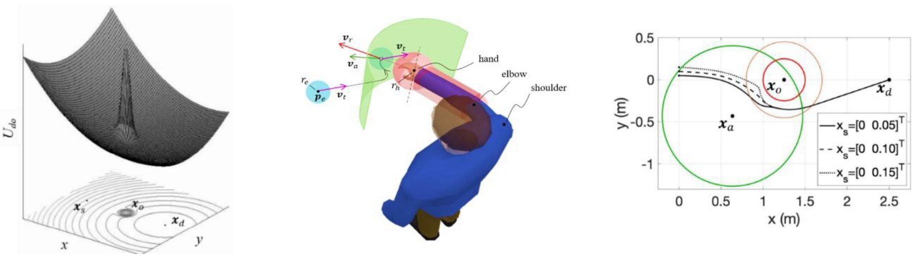
3. Anti-collision algorithms

In the considered case study, the robotic platform will perform tasks belonging to the cooperation and the collaboration modalities, as defined in (Malik and Bilberg, 2019). In both cases the human operator and the robot share part of their workspaces and operate in the common area at the same time, but in cooperation they work on different components, while in collaboration they work on the same components and physically interact with each other. In such scenarios, collision avoidance strategies must be enforced to ensure safety and, at the same time, to let the human operator perform his/her activity with more ease. The developed algorithms consider path conditioning methods to modify the trajectory of the robot (cooperation), and null space methods that allow to avoid collision between the kinematic chain of the robot and the human without interfering with the movement of the end effector, which is manually guided by the operator (collaboration).

3.1. Path conditioning methods

Collision avoidance poses a formidable challenge in robot control, requiring an efficient and reliable means for path definition and conditioning. Among the widely employed methods, the artificial potential field (APF) stands out for its efficiency, effectiveness, and ease of implementation. The fundamental concept behind APF involves designating high-potential areas around obstacles and low-potential areas near the goals. This way, the robot or its end effector is guided toward the goal position while circumventing obstacles. The negative gradient of the potential field serves as the command vector, representing virtual forces.

As a local planner, APF offers the advantage of real-time adaptability, adjusting the trajectory as the robot approaches obstacles. Various functions can be employed to model potential fields corresponding to obstacles and goal positions. Examples include the superquadratic potential function (Volpe et al., 1990), navigation function (Rimon et al., 1992), and evolutionary APF (Vadakkepat et al., 2000). In Figure 1a, an illustrative example of APF is presented. In particular, $\boldsymbol{x}_s$ is the starting point of the trajectory of the robot, $\boldsymbol{x}_d$ is the goal position and $\boldsymbol{x}_o$ is the position of the obstacle. In corrispondence of the obstacle a high potential field is placed, while in corrispondence of the goal a low potential one. However, the simple application of APF does not allow to predict the path the robot will follow to reach a goal position. When the obstacle is represented by a physical object, this aspect may not be relevant. When the obstacle is a person, the possibility to predict robot motion can be crucial aspect of the motion planning.



(a) (b) (c)

Fig. 1. (a) Example of APF. The obstacle is modelled as the pick in the potential field, while the goal position is the minimum of the potential function;
(b) Application of APF with local attractor on a human operator;
(c) Application of APF with local attractor to a mobile robot.

This study explores a collision avoidance algorithm that utilizes an APF approach with the incorporation of local attractors to address the challenges associated with unpredictable path planning. The introduction of local attractors serves as a mechanism to modify the potential field within which the robot operates, influencing its motion predictably. Placing a local attractor compels the robot to navigate in proximity to the attractor itself.
Figure 1b illustrates the application of an APF-based method that combines repulsive volumes with local attractors (Melchiorre et al., 2022a). In this scenario, the human operator is considered as the obstacle to be avoided by the end-effector of a robotic arm, which is represented by a sphere with radius r_h, centered in position $\boldsymbol{p}_e$. To simplify the example, a repulsive potential field is strategically placed only on the operator's arm, represented by the red cylinder on the arm and the red sphere on the hand, with radius r_h.

A similar approach can be extended to other parts of the operator's body. Conversely, the local attractor is depicted as the green half-cylinder positioned in front of the arm. Its location is fixed relative to the operator's wrist, ensuring it moves in tandem with the operator. The presence of the local attractor translates into an attractive velocity $\boldsymbol{v}_a$ on the robot, which sums with the repulsive action $\boldsymbol{v}_r$ and with the velocity component related to the task $\boldsymbol{v}_t$. When the robot is far from attractive and repulsive regions, it undergoes $\boldsymbol{v}_t$ only; when it approaches the human hand, $\boldsymbol{v}_r$ and $\boldsymbol{v}_a$ combines so that the robot consistently maneuvers in front of the person's hand during collision avoidance operations (Melchiorre et al., 2022a).

A similar approach can be applied to a mobile robot, in order to force the robot to move on a predefined side of the operator (Melchiorre et al., 2022b, 2023). The efficacy of the proposed collision avoidance algorithm can be got from Figure 1c. Here, the local attractor is modeled as the green disk, centered in $\boldsymbol{x}_a$, the obstacle is modeled as the red disk, centered in $\boldsymbol{x}_o$, and the goal position is the point $\boldsymbol{x}_d$. The robot task begins from the starting position $\boldsymbol{x}_s$ and terminates at the goal position $\boldsymbol{x}_d$. The three black lines with different line-style indicates the robot path obtained with three different starting positions. As can be seen, the robot is forced by the local attractor to turn on the right side of the obstacle, even when the shortest path would be on the other side. For more details, it is suggested to refer to (Melchiorre et al., 2022b, 2023).

3.2. Null space methods

Repulsive and attractive actions of the mentioned collision avoidance algorithms are expressed in the operational space $\boldsymbol{v}_e$. To convert this into robot commands, it is required to compute joint space velocity $\dot{\boldsymbol{q}}$. One of the most common ways to implement null space commands is to use the Gradient Projection method (GPM), initially introduced by Liegeois, 1977. This strategy is based on the following solution of the inverse differential kinematics of a redundant manipulator:

$$\dot{\boldsymbol{q}} = \boldsymbol{J}^{\dagger}\boldsymbol{v}_e - k\left(\boldsymbol{I} - \boldsymbol{J}^{\dagger}\boldsymbol{J}\right)\frac{\partial w(\boldsymbol{q})}{\partial \boldsymbol{q}} \qquad (1)$$

where $\boldsymbol{J}$ is the geometric Jacobian, $\boldsymbol{v}_e$ is the vector of desired end effector linear and angular velocities and w is a cost function that ought to be minimized (in the case under consideration, the distance from the human body). The main shortcoming of GPM is the choice of the gain k. In fact, in some joint configurations, a high value of k might generate low joint velocities (and therefore an insufficient distancing from the obstacle), and vice versa, making it hard to properly tune and modify online the value of the gain.

To solve this drawback, following (Monari et al. 2023), two innovative null space control techniques will be applied to the considered case study. Both these strategies rely on the solution of a constrained optimization problem, where the constraints are the maximum positions, velocities, accelerations, and jerks that are allowed by the joint velocity command interface of the robot, and an additional constraint on the null space velocity term that allows to gradually activate and deactivate the null space command. In fact, if an obstacle is farther than a certain safety distance, it is not desirable to keep trying to decrease the cost function.

The first method, called Optimized Gradient Projection Method (OGPM) simply finds the largest k that is allowed by the constraints, since the larger is the gain the greater is the decrease of the cost function. This method is efficient and computationally very light, but it does not search all the directions of the null space, and therefore does not necessarily provide the solution that guarantees the greatest possible decrease of the cost function.

The Null Space Basis Optimal Linear Combination Method (NSBM), instead, is based on the following solution of the inverse differential kinematics:

$$\dot{\boldsymbol{q}} = \boldsymbol{J}^{\dagger}\boldsymbol{v}_e + \boldsymbol{B}\boldsymbol{a} \qquad (2)$$

where $\boldsymbol{B}$ is a matrix whose columns are the elements of a basis of the null space of the Jacobian, and $\boldsymbol{a}$ is the vector of the coefficients of the basis. NSBM, then, solves an optimization problem where the constraints are the same as in OGPM, but the optimization variables are the components of $\boldsymbol{a}$, and the objective function is the distance at the next iteration for a certain choice of $\boldsymbol{a}$. As a result, the inverse kinematics solution that is obtained is the one providing the maximum possible distancing from the obstacle for the current iteration. The computational cost is slightly higher, because the cost function is nonlinear, but was shown to be compatible with the real time constraints of most robotic platforms.

Both these methods will be applied to the collaborative application, and their results and feasibility will be assessed and compared.

4. Mental fatigue measurement: sensors review

Among measurement methods, only those based on behaviour (BM) and physiological signals (PSM) allow a real-time assessment of mental fatigue. On one side, BM metrics related to eye movements (EYE), head movement and facial expression taken via vision systems and/or eye trackers are the most frequently used, although they are susceptible to environmental factors (e.g. light). On the other side, the use of PSM allows for objective and real-time monitoring of fatigue at the individual level; despite changes in physiological variables in response to stressors and fatigue vary both within and between individuals, which complicates the detection of abnormal conditions. Although individuals have little control over their physiological signals, these are susceptible to many other factors, such as environmental conditions, emotions and pathophysiological problems (Giannakakis, 2022).

With a view to developing HRC operations where the physical load is placed on the robot while the direction is left to the operator intellect, mental fatigue is the component, in the first instance, to be monitored. In particular, it is essential to measure mental fatigue in real-time, in order to preserve the health and safety of the operator by intercepting the occurrence of a predetermined threshold level (e.g. high, medium or low).

The following measurement systems have been used in the literature for the real-time assessment of mental fatigue in different contexts:

- EEG (electroencephalogram) - PSM: is a widely used technique for estimating changes in neurophysiological activity associated with external stimuli and/or the performance of specific tasks (Giannakakis et al, 2022). Mental fatigue can be measured using EEG spectral changes in theta, alpha and beta waves, as presented in (Cheng et al., 2011). In a recent study, theta-wave activity was found to be the primary biomarker and alpha-wave activity was considered a second-line biomarker (Tran et al., 2020). Another study proposed a model capable of estimating users' mental fatigue based on the fusion of relevant features extracted from the Positive 300 (P300) and steady-state visual evoked potentials (SSVEPs). The major limitations in the use of EEG for mental fatigue assessment lie in the contrast and noise reduction that are difficult to achieve in real working settings and the reduced comfort in wearing overhead EEG detection systems that are not suitable for everyday use in manufacturing environments. Furthermore, the study developed in (Mitchell et al., 2019) showed that this method may not be able to accurately detect changes occurring in the brain while a mentally fatigued individual is performing a cognitively demanding task or an action with significant motion exertion, which would limit the use of this detection tool for HRC applications.

- ECG (Electrocardiogram) - PSM: is the signal of the heart's electrical activity manifesting its contractile activity. The highest peaks in the ECG are named R points and the interval between two successive maximum peaks is called the RR interval. Several metrics can be derived from the ECG. Among them, the HRV (heart rate variability), which is the distribution of RR intervals over an interval of time, has been used in (Kunasegaran et al, 2023; Zhikang et al, 2020) as a method to intercept mental fatigue. HRV is due to the synergy of the two branches of the autonomic nervous system (ANS): the sympathetic and the parasympathetic. The sympathetic nerve accelerates HR, while the parasympathetic nerve slows it down. The sympathetic and parasympathetic nerves work together to maintain cardiovascular activity and respond appropriately to external and internal stimuli. This makes HRV a good holistic indicator that reflects the level of psychological and physiological stress. However, ECG signal and related metrics extracted in both time and frequency domains are influenced by several disturbing variables such as the individual's movement, heart disease, pathologies and habits such as coffee drinking and smoking, which may complicate its adoption.
- Cortisol level - PSM: As indicated in (Kunasegaran, 2023), there is conflicting evidence on the correlation between cortisol level and mental fatigue. While some study (Moreira et al, 2018; Kirschbaum and Hellhammer, 2007) proposes that mental fatigue modulates autonomic and endocrine responses in the body (Moreira et al, 2018), including the salivary cortisol level which is deemed to increase when an individual is stressed, other works (Assis et al, 2018) instead report a lack of evidence that salivary cortisol correlates with stress and fatigue, suggesting that the relationship between mental fatigue and cortisol levels remains inconclusive. Besides, saliva is easily contaminated by blood and food, thus generating inaccurate measures of cortisol levels (Kunasegaran, 2023), and gender influences temporal changes in salivary cortisol levels, which requires different calibration procedures based on sex (Nakajima, 2012). These considerations make this metric highly unreliable.
- Saccadic eye movements - BM: Saccadic eye movements can be described as the rapid movement of the eyes from one point to another. Saccadic eye movements are related to neural activity in the frontal lobe, the area of the brain most affected by mental fatigue (Ishii et al., 2012; Guo et al., 2018), which suggests that they can be used for the assessment of mental fatigue. To monitor saccadic eye movements, the gold standard is the OEG (electrooculogram), which measures the positive steady-state potential of the cornea in relation to the back of the eye with electrodes placed on the patient's face. Thanks to this measurement, it is possible to detect which muscles are active and the consequent change in eye orientation. Eye-trackers can be used as alternative systems to track saccadic eye movements. In this context, research has shown that people suffering from mental fatigue exhibit specific patterns of eye movement (Kunasegaran, 2023). In particular, a specific study (Jue at ql, 2020) demonstrated the feasibility of applying wearable eye-tracking technology to identify and classify mental fatigue in construction machine operators using measures like blink frequency, blink duration, pupil diameter and gaze position.

In addition to these systems, mostly employed in stan-a-lone configuration, the following sensors have instead been used in multimodal configurations:

- GSR (galvanic skin response) or EDA (electrodermal activity) - PSM: GSR refers to changes in sweat gland activity that reflect the intensity of our emotional state through changes in the electrical properties of the skin. GSR signals provide information on sympathetic nervous system activity, but are also influenced by other factors, such as sweating due to aerobic exercise (Zhikang et al., 2020). As mental fatigue worsens, the sympathetic nervous system becomes weaker in response to stimuli, resulting in a decline of the GSR (Zhikang et al., 2020). Usually, GRS sensors with dual electrodes conveniently attached to the skin are used. In (Lan-lan, 2017) it is shown that metrics such as the sum of peak numbers (number of peaks in a given segment), the sum of peak magnitude and the sum of peak duration show certain relationships with mental fatigue, together with other characteristic indices extracted from ECG and RES (respiratory) sensors.
- PPG (Photoplethysmography) - PSM: is a non-invasive optical method that measures changes in skin tone associated with concomitant changes in blood volume in subcutaneous blood vessels during the cardiac cycle. PPG sensors use optical pulses generated by a red or near-infrared light source (light-emitting diode)

and receive the reflected light with a photodetector (Giannakakis, 2022). From PPG signals, pulse rate (PR), pulse rate variability (PRV), blood oxygen saturation level BVP (SpO2) and blood pressure (BP) can be extracted (Giannakakis, 2022). In the study conducted in (Choi et al, 2017), PPG in combination with GSR, temperature (TEM), acceleration (ACCEL) and rotation speed (GYRO) were used to monitor abnormal conditions of a driver, including stress, mental fatigue and drowsiness.

- SKT (skin temperature) - PSM: Changes in skin temperature (SKT) are associated with stress and anxiety conditions (McFarland, 1985). Such temperature changes can be detected by placing sensors on the subject skin or, alternatively, through thermal imaging. In (Libawy et al, 2016), a new method of analysing and classifying operator fatigue based on a smartwatch with an integrated temperature sensor was presented. Among other parameters (heart rate and skin conductance), the following metrics were considered: mean pulse temperature over samples and the standard deviation of pulse temperature. These metrics along with four others were used as input datasets for classifying the alertness or fatigue state of the operators.
- RES (respiration) - PSM: Respiration can be measured as the rate or volume with which mammals exchange air in the lungs (Zhikang et al., 2020). Breathing frequency and depth (amplitude) are the most common measures of respiration. Under stressful conditions, respiration rate generally increases (Vinkers et al, 2013) with emotional arousal and decreases with relaxation, while tense situations can cause momentary cessation of breathing. As mentioned in (Zhikang et al., 2020), a suitably designed RES sensor was employed for the detection of breathing rate, which was then used among six other metrics in machine learning algorithms to determine levels of mental fatigue.

Based on the existing literature, it is not possible to state that there is an adequate sensor or set of sensors to detect mental fatigue in an absolute sense, as this phenomenon is strongly conditioned by the task that induces the state of fatigue and is strongly linked to the subject that perceives it. Thus, for HRC applications, it is important to develop a versatile fatigue detection system that can be suitable for the various usage conditions.

5. Experimental layout: description and components selection

The proposed layout aims to evaluate a robotic system to carry out cooperative tasks between man and robot. As a reference it was considered a robotic system to facilitate the disassembly of large electric and electronic waste (WEEE), as could be for example the lithium battery of an electric vehicle, through a collaborative human-robot environment. The workstation will be equipped with a suite of sensors in order to make possible the continuous monitoring of the operator in order to ensure safety in the operation: so it will comprise a working table equipped with advanced vision systems to accurately trace the operator's movements and sensors to measure and monitor mental fatigue. Notably, the decision has been made to forego wearable devices for motion tracking, opting to apply additional sensors on the operator for fatigue monitoring and unforeseen behavior detection. Within this collaborative workspace, a mobile robot featuring an overhead anthropomorphic arm will navigate dynamically. Its primary functions include transporting the robotic arm to the designated work area and facilitating the removal of disassembled materials from the workspace. This mobile robot is equipped to optimize efficiency and flexibility in the disassembly process.

Moreover, the operator's interaction with the workspace will be monitored comprehensively, ensuring a seamless collaboration between the human and robotic elements. This monitoring encompasses not only motion tracking for task synchronization and collision avoidance, but also real-time fatigue assessment and the detection of unexpected operator behaviors, enhancing overall safety and operational efficiency. The entire system will be centralized and controlled through a dedicated PC, providing a centralized interface for overseeing the collaborative operations, adjusting parameters, and ensuring the overall coordination of the disassembly process. This holistic approach to human-robot collaboration in WEEE disassembly underscores the commitment to efficiency, safety, and adaptability in this innovative work environment. The designated cameras for operator motion tracking are two ORBBEC Femto Mega cameras. Leveraging Time-of-Flight (ToF) technology, these cameras can deliver depth data at a frequency of up to 30 Hz (source: Orbbec website). Their selection is based on their capacity to not only generate a point cloud but also provide skeleton tracking data, essential for collision avoidance algorithms. Opting for the deployment of two cameras and data fusion is a strategic choice aimed at addressing potential occlusion challenges that might arise when using a single camera.

The selected mobile robot is a PAL Robotics TIAGo Base with a payload capacity of 100 kg. Equipped with two differential drive wheels, it exhibits the capability to navigate within confined spaces, enabled by its capacity to rotate around its axis. This robot represents a well-balanced choice in terms of cost and functionality. It inherently supports a lidar for Simultaneous Localization and Mapping (SLAM) algorithms, seamlessly integrable with the previously described collision avoidance algorithms. Upon operator identification, the collision avoidance algorithms dictate the robot's movement strategy, ensuring it consistently passes behind or to the right of the operator. This approach is designed to enhance operator awareness of the robot's anticipated movements during encounters. Additionally, the potential integration of an RGB camera on the robot is under consideration for marker detection within the workspace, potentially utilizing marker Aruco, to enhance positional accuracy in proximity to known locations. The anthropomorphic robot utilized is the collaborative robot Franka Emika FR3, characterized by an 855 mm workspace and a payload capacity of 3 kg. Boasting 7 degrees of freedom, the design incorporates joint redundancy to facilitate comprehensive collision avoidance across all robot joints. This redundancy also permits the seamless integration of advanced collision avoidance algorithms, enabling the robot to maintain wrist stability while avoiding the operator. In addition to its hardware features, the entire robotic system is orchestrated and controlled through the Robotic Operating System (ROS). ROS not only provides a standardized and modular framework for controlling the robot but also facilitates the seamless integration of various sensors, algorithms, and components, contributing to the overall versatility and adaptability of the robotic system.

The described system is completed by sensors used to assess operator's mental fatigue. Their selection was performed using three main drivers: provide a reliable correlation with mental fatigue; be comfortable so as not to hinder normal work activities; provide a stable measurement with a moving person. For all the sensors chosen, integration compatibility with the robot's control system was verified, as well as the presence of SDK (software development kit) to access and export physiological signals.

The selected sensors and intended metrics are the following:

- Polar H10 chest brace - ECG: is a heart rate monitoring sensor developed by the Polar company. This sensor allows to access HR and RR ECG data and derive metrics such as HRV in real-time. The device is comfortable and easy to wear and relies on Bluetooth and ANT 2.0 communication with external devices.
- Shimmer 3 - ECG - GSR - PPG: The Shimmer3 unit in the chosen configuration (Shimmer 3,2023) is equipped with a GSR+ module that provides connections and pre-amplification for a galvanic skin response (or EDA) data acquisition channel, as well as capturing an optical PPG pulse signal and converting it into a heart rate (HR) estimate, by means of the Shimmer ear clip or optical pulse probe. The Shimmer GSR+ sensor monitors skin conductivity between two electrodes attached preferably to two fingers of one hand (but also to other locations) and provides real-time collection and streaming of physiological data to a host PC via Bluetooth communication. In addition, the device is equipped with a 9 d.o.f. IMU sensor, which is potentially useful for patient posture analysis and ECG module for recording the pathway of electrical impulses through the heart muscle. This device has long been used in studies involving the detection of physiological signals such as in stress (Betti et al., 2018) or physical fatigue (Zahra Sedighi et al, 2017).
- Neon Pupil-Labs – eye-tracker: is an eye tracking system also equipped with a 9 d.o.f. IMU sensor that allows real-time access to streaming video of scene, gaze and IMU data to any device connected to the same local network via the Pupil Invisible Companion App. In addition, it enables to control the device remotely to start and stop recordings or save events and obtain blink, fixation and gaze metrics. Furthermore, it is possible to define AOI (Area Of interest) within the vision space and on objects, e.g. such as the end-effector of the robot, by means of recognition markers and to detect gaze metrics with respect to the surface delimited by the markers. This latter feature could be used to implement human-robot cooperation strategies to improve the safety of the HRC operation. The same device is widely used in research and in various fields as reported on the manufacturer's website (Neon Pupil Labs, 2023).

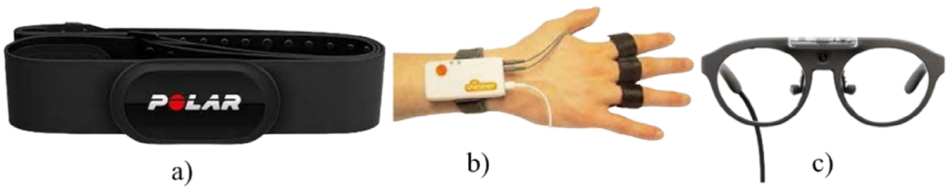


Fig. 2. (a) Polar H10 Chest brace (Polar, 2023); (b) Shimmer 3; (c) Neon Pupil-Labs eye tracker.

We will collect data in real time from selected sensors worn by a human and we extrapolate some metrics related to mental fatigue (e.g. HRV, RR, GSR, blink, metrics extrapolated from gaze data) provided by the operator comparing them to the subjective perception of mental fatigue evaluated by the user in assessment questionnaires.

6. Conclusions

The paper introduces the activities carried out by the partners of the project in order to develop and test a suitable layout to enhance safety and simplicity of use for next generation collaborative robotic systems. The proposed work keeps at its center the wellness of the operator, which is considered the center of the production equipment. The focus is placed on ensuring that the behavior of the robots complies with the expectation of the human operator, avoiding any kind of situation that could cause mental fatigue. This is going to be reached applying new strategies in order to modify the path of the robots according to the motion of the operator and to his/her preferred interaction way. Monitoring of mental fatigue adds a relevant point to the sustainability of the production system: actually, as fatigue increases in time and operators could be exposed to unexpected risks due to an undervaluation of this phenomenon; a continuous fatigue monitoring system makes possible to reduce the working speed when necessary or to impose a pause. Finally, an experimental layout is proposed that can be extended to several kinds of applications. In the next works the algorithms will be fully developed and tested in laboratory conditions.

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References

Adão Martins, N.R., Annaheim, S., Spengler, C.M., Rossi, R.M. 2021. Fatigue Monitoring Through Wearables: A State-of-the-Art Review. Front Physiol. 2021 Dec 15.

Allen, D.G., Lamb, G.D. & Westerblad, H. 2008. Skeletal muscle fatigue: cellular mechanisms. Physiol. Rev. 88, 287-332.

Al-Libawy, H.A. et al. 2016. HRV-based operator fatigue analysis and classification using wearable sensors. 2016 13th International Multi-Conference on Systems, Signals & Devices (SSD): 268-273.

Anandan, T. M. 2019. Fenceless safety methods embrace human-robot interaction. Control Engineering;

Assis. D., Resende. D., Marziale. M. 2018, Association between shift work, salivary cortisol levels, stress and fatigue in nurses: integrative review, vol. 22.

Betti, S. et al. 2018. Evaluation of an Integrated System of Wearable Physiological Sensors for Stress Monitoring in Working Environments by Using Biological Markers, in IEEE Transactions on Biomedical Engineering, vol. 65, no. 8, pp. 1748-1758.

Borragán, G., Slama, H., Bartolomei, M. & Peigneux, P. 2017. Cognitive fatigue: a time-based resource-sharing account. Cortex 89, 71-84;

Breque, M., De Nul, L., Petridis, A. 2021. Industry 5.0: towards a sustainable, human-centric and resilient European industry, European Commission, Directorate-General for Research and Innovation, Breque, M., De Nul, L., Petridis, A. (2021)., Publications Office.

Cheng. S.Y., Hsu H.T. 2011. Mental fatigue measurement using EEG. In: Risk Management Trends. London: IntechOpen.

Choi. M., Koo, G., Seo M. & Kim, S. W. 2017. Wearable Device-Based System to Monitor a Driver's Stress, Fatigue, and Drowsiness. IEEE Transactions on Instrumentation and Measurement. PP. 1-12.

Forster, S., Lavie, N. 2016. High perceptual load makes everybody equal. Sage Journals 18(5):377-381.

Giannakakis, G., Grigoriadis, D., Giannakaki, K., Simantiraki, O., Roniotis, A. & Tsiknakis, M. 2022. Review on Psychological Stress Detection Using Biosignals, in IEEE Transactions on Affective Computing, vol. 13, no. 1, pp. 440-460, 1 Jan.-March 2022.

Guo, Z., Chen, R., Liu X., Zhao, G., Zheng, Y., Gong M. & Zhang J. 2018. The impairing effects of mental fatigue on response inhibition: An ERP study. PLOS ONE. 13. e0198206.

Hu, X., and Lodewijks, G. 2020. Detecting fatigue in car drivers and aircraft. pilots by using non-invasive measures: the value of differentiation of sleepiness and mental fatigue. J. Safety Res. 72, 173-187.

International Civil Aviation Organisation. 2012. Fatigue Risk Management Systems Manual for Regulators. Available online at: www.icao.int (accessed December 20, 2023).

Ishii, A., Tanaka, M. & Watanabe, Y. 2014. Neural mechanisms of mental fatigue. Reviews in the Neurosciences, vol. 25, no. 4, 2014, pp. 469-479.

ISO/TC 299: ISO/TS 15066:2016. Robots and robotic devices – Collaborative robots. International Organisation for Standard-isation, Geneva.

Jue, L., Heng, L., Waleed, U., Hongwei, W., Xuejiao, X., Shukai, Z., Jun, H. 2020. Identification and classification of construction equipment operators' mental fatigue using wearable eye-tracking technology, Automation in Construction, Volume 109.

Kunasegaran K, Ismail, A.M.H., Ramasamy, S., Gnanou, J.V., Caszo, B.A., Chen, P.L. 2023. Understanding mental fatigue and its detection: a comparative analysis of assessments and tools. PeerJ 11:e15744.

Lamti, H.A., Ben Khelifa, M.M. & Hugel, V. 2019. Mental fatigue level detection based on event related and visual evoked potentials features fusion in virtual indoor environment. Cogn Neurodyn 13, 271-285.

Lan-lan, C., Yu, Z., Peng-fei, Y., Jian, Z., Jun-zhong, Z. 2017. Detecting driving stress in physiological signals based on multimodal feature analysis and kernel classifiers, Expert Systems with Applications, Volume 85, Pages 279-291.

Liegeois, A. 1977. Automatic supervisory control of the configuration and behavior of multibody mechanisms, IEEE Trans. Sys., Man and Cyber., vol. 7, no. 12, pp. 868–871.

Malik, A.A. & Bilberg, A. 2019. Developing a reference model for human–robot interaction. In: International Journal on Interactive Design and Manufacturing (IJIDeM) 13, pp. 1541–1547.

Matheson, E., Minto, R., Zampieri, E.G.G., Faccio, M., Rosati, G. 2019. Human–Robot Collaboration in Manufacturing Applications: A Review. Robotics, 8, 100.

McFarland R. A. 1985. Relationship of skin temperature changes to the emotions accompanying music, Applied psychophysiology and biofeedback, 10, pp. 255-267.

Melchiorre, M., Salamina, L., Scimmi, L. S., Mauro, S., & Pastorelli, S. 2023. Experiments on the Artificial Potential Field with Local Attractors for Mobile Robot Navigation. Robotics, 12(3), 81.

Melchiorre, M., Scimmi, L.S., Mauro, S. & Pastorelli, S. 2022a. A Novel Constrained Trajectory Planner for Safe Human-robot Collaboration. In Proceedings of the ICINCO.

Melchiorre, M., Scimmi, L.S., Mauro, S., & Pastorelli, S.P. 2021. Vision‐ based control architecture for human–robot hand‐ over applications. Asian Journal of Control, 23(1), 105-117.

Melchiorre, M., Scimmi, L.S., Salamina, L., Mauro, S., & Pastorelli, S. 2022b). Robot collision avoidance based on artificial potential field with local attractors. In Proceedings of the ICINCO.

Melchiorre, M., Scimmi, L.S., Pastorelli, S.P., & Mauro, S. 2019. Collison Avoidance using Point Cloud Data Fusion from Multiple Depth Sensors: A Practical Approach, 23rd International Conference on Mechatronics Technology (ICMT), Salerno, Italy, pp. 1-6.

Mitchell, R., Smith, R., Chai, H.T., Nguyen, S.M. & Coutts, A.J. 2019. Comparing the Effects of Three Cognitive Tasks on Indicators of Mental Fatigue, The Journal of Psychology, 153:8, 759-783.

Monari, E., Chen, Y. & Vertechy, R. 2023. On locally optimal redundancy resolution using the basis of the null space, in Proc. IEEE Int. Conf. Robot. Autom., 2023, pp. 9665–9671.

Moreira, A., Saldanha, A.M., Franchini, E., Gomes da Silva, M.D., Paludo, A.C., Hideki, O.A. 2018. Mental fatigue impairs technical performance and alters neuroendocrine and autonomic responses in elite young basketball players, Physiology & Behavior, Volume 196, Pages 112-118, ISSN 0031-9384.

Nakajima, Y., Takahashi, T., Shetty, V. et al. 2012. Patterns of salivary cortisol levels can manifest work stress in emergency care providers. J Physiol Sci 62, 191-197.

Neon Pupil Labs Blog. 2023, Online: https://pupil-labs.com/blog/research, accessed 30 December 2023.

Palmieri, P., Gaidano, M., Ruggeri, A., Salamina, L., Troise, M., & Mauro, S. 2021. An inflatable robotic assistant for onboard applications. In Proceedings of the International Astronautical Congress, IAC. International Astronautical Federation, IAF.

Palmieri, P., Melchiorre, M. & Mauro, S. 2022. Design of a Lightweight and Deployable Soft Robotic Arm. Robotics, 11(5), 88.

Polar H10 heart rate sensor strap. 2023. Online: https://www.polar.com/it/sensors/h10-heart-rate-sensor , accessed 30 December 2023.

Rajavenkatanarayanan, A., Nambiappan, H. R., Kyrarini, M. & Makedon, F. 2020. Towards a Real-Time Cognitive Load Assessment System for Industrial Human-Robot Cooperation, 29th IEEE International Conference on Robot and Human Interactive Communication (RO-MAN), Naples, Italy, pp. 698-705.

Rimon, E.; Koditschek, D.E. 1992. Exact Robot Navigation using Artificial Potential Functions. IEEE Trans. Robot. Autom. 1992, 8, 501–518.

Salamina, L., Botto, D., Mauro, S., & Pastorelli, S. 2020. Modeling of Flexible Bodies for the Study of Control in the Simulink Environment. Applied Sciences, 10(17), 5861.

Salamina, L.; Melchiorre, M., Gaidano, M., Mauro, S. 2023. Mobile robot with robotic arm: development and validation of a digital twin. In proceeding of IMECE.

Scimmi, L.S., Melchiorre, M., Mauro, S. & Pastorelli, S. P. 2019a. Implementing a Vision-Based Collision Avoidance Algorithm on a UR3 Robot, 2019 23rd International Conference on Mechatronics Technology (ICMT), Salerno, Italy, 2019, pp. 1-6.

Scimmi, L.S., Melchiorre, M., Mauro, S. & Pastorelli, S.P. 2019b. Experimental Real-Time Setup for Vision Driven Hand-Over with a Collaborative Robot, International Conference on Control, Automation and Diagnosis (ICCAD), Grenoble, France, 2019, pp. 1-5.

Sedighi Maman, Z., Alamdar Yazdi, M. A., Cavuoto, L. A., Megahed, F.M. 2017. A data-driven approach to modeling physical fatigue in the workplace using wearable sensors, Applied Ergonomics, Volume 65, Pages 515-529.

Shimmer 3. 2023. Online: https://shimmersensing.com/product/consensys-gsr-development-kits/, accessed 30 December 2023.

Shitong, H., Jia, L., Pengzhu, Z., Weiqiang, Z. 2018. Detection of mental fatigue state with wearable ECG devices, International Journal of Medical Informatics, Volume 119, Pages 39-46, ISSN 1386-5056.

Thompson, C.J., Fransen, J., Skorski, S. et al. 2019. Mental Fatigue in Football: Is it Time to Shift the Goalposts? An Evaluation of the Current Methodology. Sports Med 49, 177-183.

Tran, Y., Craig, A., Craig, R., Chai, R., Nguyen, H. 2020. The influence of mental fatigue on brain activity: evidence from a systematic review with meta-analyses. Psychophysiology 57(5):e13554.

Vadakkepat, P., Tan, K.C., Ming-Liang, W. 2000. Evolutionary artificial potential fields and their application in real time robot path planning. In Proceedings of the 2000 Congress on Evolutionary Computation, CEC 2000, La Jolla, CA, USA, 16–19 July 2000; pp. 256–263.

Van Elburg, A., Danner, U.N., Sternheim, L.C., Lammers, M., Elzakkers, I. 2021. Mental capacity, decision-making and emotion dysregulation in severe enduring anorexia nervosa. Frontiers in Psychiatry 12:147.

Villani, V., Pini, F., Leali, F.; Secchi, C. 2018. Survey on human–robot collaboration in industrial settings: Safety, intuitive inter-faces and applications. Mechatronics, 55, 248-266.

Vinkers, C. H., Penning, R., Hellhammer, J., Verster, J. C., et al. 2013. The effect of stress on core and peripheral body temperature in humans, Stress-the International Journal on the Biology of Stress, 16, pp. 520-530.

Volpe, R., Khosla, P. 1990. Manipulator control with superquadratic artificial potential functions: Theory and experiments. IEEE Trans. Syst. Man. Cybern. 1990, 20, 1423–1436.

Zhang, L., Diraneyya, M. M., Ryu, J., Haas, C. T. & Abdel-Rahman, E.M. 2019. Jerk as an indicator of physical exertion and fatigue.

Zhikang, Z., Zhao, H., Kangmin, L., Wuxiao, H., Hao, N., Yan, Y., Qing, L., Jihong, L., Zhigang, W. & Jianfeng Z. 2020. Nonintrusive Monitoring of Mental Fatigue Status Using Epidermal Electronic Systems and Machine-Learning Algorithms ACS Sensors, 5 (5), 1305-1313.