Task-Consistent Signaling Motions for Improved Understanding in Human-Robot Interaction and Workspace Sharing

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***Abstract*—In this paper, the concept of signaling motions of a robot interacting with a human is presented. These motions consist in using the redundant degrees of freedom of a robot performing a task as new means of meaningful robot-human communication. They are generated through quasi-static torque control, in consistency with the main robot task. A double within-subject (N=16) study is conducted to evaluate the effects of two signaling motions on the performance of a task by participants and on their behavior towards the robot. Our results show a positive effect on both the task execution and the participants behavior. Additionally, both signaling motions seem to improve the situation awareness of the participants by fueling their mental model throughout the interaction.**

***Index Terms*—Situation Awareness ; Human-Robot Interaction ; Industrial Robotics ; Collaborative robots ; Signaling Motions**

I. Introduction

With the emergence of collaborative robotics [1], the use of robots is envisioned out of their cage and in direct interaction with operators. This raises performance and safety issues, which are some of the main challenges of human-robot interaction [2].

The three necessary conditions for the safety and efficiency of an operator whilst interacting with a complex system are i) the correct perception of the elements present in the environment within a volume of time and space, ii) the comprehension of the current state of the situation and iii) the ability to make a relevant projection of that state in the near future. Endsley defines these conditions as *situation awareness* (SA) [3]. SA plays a major role in the process of decision making and thus in the performance and safety of an action. Consequently, decisions made under poor SA may result in human errors and lead to accidents. Several factors degrading SA have been defined by Endsley [4] and have been grouped in eight so-called *SA demons*. In the domain of industrial robotics, these demons have been identified as the key factors leading to accidents [5]. For example, the false belief that "a motionless robot is a powerless robot" [6] is typically linked to the *errant mental model* SA demon. Indeed, in this situation the motionless robot may just be in a waiting mode and a bad understanding of this situation is a major source of danger as operators may feel safe while actually being potentially under threat. Considering SA demons in human-robot interaction is therefore relevant and SA oriented design [7] should aim at undermining their manifestation.

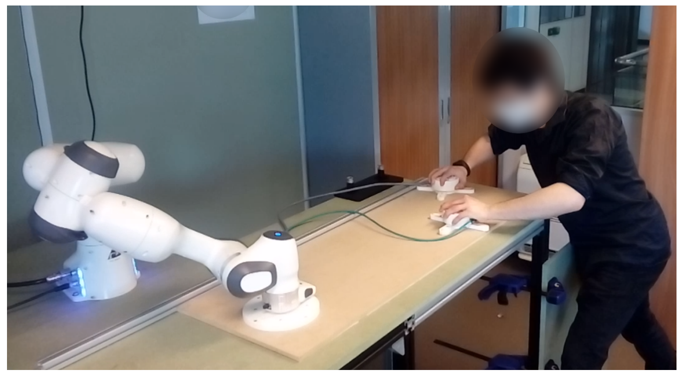

Fig. 1. Subject performing an experiment of a milling task in carpentry using a physically realistic mock-up. The wooden part is being pushed through handles incorporating 6-axis F/T sensors. A 7-DOF collaborative robot is attached to the wooden part and reproduces the cutting forces based on a wood cutting model

Finding a meaningful, yet minimally intrusive, way of alerting about the state of the robot or giving information about its actions is thus of major importance [8]. The most commonly used robot-to-human communication channels are sound, text, or light signals [9] and previous works have shown the effectiveness of using social cues and non-verbal communication for robot perception [10]. While these research works demonstrate the relevance of these communication systems for an increased awareness of the robot presence, they actually do not explicitly address the SA of the users themselves but rather their overall social perception of the robot.

In [2], it is recommended to develop intuitive interfaces to facilitate and increase human-robot communication. This can be done by using screen based interfaces that provide explicit real-time information to the operator. While such interfaces may help in maintaining a high level of SA, there exists a risk of displaying too much information or misleading information (*data overload* or *misplaced salience* demons according to Endsley). Alternatively, sound alarm signals have been suggested [11].

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Nevertheless, the use of alarms may be impaired by the ambient noise in industrial environments and can also be detrimental to SA [12].

Another way to favour proper SA is to use the robot motion itself as a vector of information. This may be a way to give access to important intangible information and/or reinforce information that is already provided without overloading the existing communication channels. While expert operators may be able to interpret functional motions of the robot to some extent, these motions are overall poorly understandable. The use of explicitly legible robot motions [13] follows the principle of transparency [14]. At the cognitive level, transparency is part of the SA-oriented design principles [4], [15]. For a system, it can be defined as the observability ("what is the system doing?"), the understandability ("why is it doing this?") and the predictability ("what will it do next?") of its behavior [16]. Based on these ideas of transparency and legibility, the use of robot motions has been envisioned as a non-verbal communication channel to communicate its states and actions [8] and help the operator while performing its task [17]. Yet, these works have been mostly focused on toy-like robots with interactivity rather than safety or performance in mind. Using the robot's motions can be considered as a way to feed the mental model of the human interacting with the robot.

In this work, we consider the context of an industrial environment where task complexities and variabilities may lead to accidental or hazardous situations for the operator. To address these potential problems, we superimpose signaling motions to the main, task-oriented, motion. These task-compatible motions are envisioned as a new means of communication supporting the individual's SA while accompanying his or her decision making.

In Section 2, the concept of signaling motion is introduced. Next we present our solutions for implementing them in Section 3. In Section 4, an experimentation demonstrating the relevance of signaling motions in a human-robot collaboration framework is described. We then proceed to analyze the results and discuss them in Section 5 and 6. Finally, in the last section, the main conclusions are presented.

II. USING ROBOT MOTIONS TO SUPPORT SITUATION AWARENESS

It has been revealed that an *errant mental model* is the most prevalent SA demons occurring in industrial robotics [5]. This one acts as a trigger for other demons like *out-of-the-loop*, *attentional tunneling* or *misplaced salience* and can also be a result of it depending on the situation. These SA demons can be directly related to uncontrolled and/or undesired physical interactions with a robot. Therefore, the challenge is to find solutions to reduce the frequency of their occurrence. In this work, the use of signaling motions of the robot is explored as a minimally intrusive way to support operators' SA. More specifically, the signaling motions contribute to improve the mental model of the involved operator regarding the current working context and task.

Several granularity levels can be addressed when trying to support SA. At the macroscopic level, it appears important to deal with the false belief that a stationary robot is a powerless robot. This problem is application independent and the retained motion has to be general enough to cover a wide range of contexts as well as a wide range of expertise of potential human users. To address these two characteristics, the robot should default to the chosen motion whenever a confusion may exist regarding its on/off state. The chosen motion should be explicit and universal enough to avoid ambiguity. This type of motion can be defined as a **diffuse signaling motion**.

In this work, it is proposed to exhibit a *breathing motion* with the robot to signal its idle moments. Breathing motions exploit anthropomorphism, which has been shown to be a favourable feature for human robot coexistence and interaction [8], [18]–[20]. Implicit bonding among the individuals of a group is also related to spontaneous synchronization of respiratory rhythms [21]. This type of diffuse motion has already been studied in the framework of the toy robot Nao [22], [23] as well as in that of more standard serial manipulators [10]. Nevertheless, in these works, these effects are only analyzed according to the social acceptance level, while, in this paper, the breathing effect is examined through situation awareness issues, trying to support the mental model of the individual.

Beyond the high-level aspects of safety related to the four aforementioned SA demons, the knowledge of both the current state of the task and the robot can improve SA. It can also improve safety in phases where the robot is not idle but actually active. The second studied motion is thus one that keeps the operator informed. We propose to superimpose an **explicit signaling motion** to the task related motion of the robot. This signaling motion aims at keeping the human involved in the task and help his/her decision making and action taking. Especially, variations in the process and tuning of the robot are information of primal interest both for safety and performance. Motion superimposition can be achieved in several ways. One of them consists in exploiting the fact that robots are more and more kinematically redundant with respect to their tasks. Redundancy allows to generate postural variations while performing the very same task. In this work, these variations are explored as a way to reactively encode information to be transmitted seamlessly to the human operator.

In the next section, the generic implementation of both diffuse and explicit signaling motions at the robot control level is explained.

III. GENERATION OF SIGNALING MOTIONS

Both diffuse and explicit signaling motions have to be implemented without drastically modifying the control architecture of the considered robot. Collaborative robots require a fine level of access to the control layer in order for integrators to endow these robots with advanced behaviours in specific industrial contexts. This requirement is more and more often met with "open control" APIs, allowing access to joint level velocity (e.g. UR robots) or even torque control (e.g. KUKA IIWA, Franka Emika Panda).

The state-of-the-art in robot control includes several methodologies for the computation of control inputs leading to the simultaneous and hierarchical achievement of several tasks [24] [25]. These methods exploit the redundancy of the robot with respect to the main task to be performed to achieve secondary control objectives. With serial manipulators, redundancy is usually limited and these secondary objectives mostly aim at improving general performance indicators such as manipulability [26] or apparent mass minimization [27]. More recently, these multi-tasks control approaches have been expressed as Quadratic Programming (QP) problems [28] [29]. This endows control design with the capability of explicitly accounting for constraints at the control computation level rather than at the planning one. It opens the door to truly reactive control approaches where part of the environment dynamics can be accommodated for through the online updates of the constraints included in the control problem [30] [31]. Beyond well described theoretical foundations, the formulation of control problems as QPs is accompanied by the development of several dedicated software libraries [32] [33] [34].

Building on these general control frameworks, the proposed signaling motions are generated, through quasi-static torque control, in concordance with the main robot task through the solving of the following control problem at each control instant

$$\boldsymbol{\tau}^* = \underset{\boldsymbol{\tau}}{\arg\min} \quad f_{task}(\boldsymbol{\tau}) + f_{sig}(\boldsymbol{\tau}) \tag{1}$$

$$\text{s.t.} \quad \boldsymbol{c}\left(\boldsymbol{\tau}, \underline{\boldsymbol{\tau}}, \overline{\boldsymbol{\tau}}, \boldsymbol{q}, \underline{\boldsymbol{q}}, \overline{\boldsymbol{q}}, \dot{\boldsymbol{q}}, \underline{\dot{\boldsymbol{q}}}, \overline{\dot{\boldsymbol{q}}}, \dots\right) \leq \boldsymbol{0} \tag{2}$$

In equation (1), $f_{task}(\boldsymbol{\tau})$ and $f_{sig}(\boldsymbol{\tau})$ are cost functions respectively associated to the achievement of the main robot task, generally expressed at the end-effector level, and to the signaling motion. These cost functions are expressed as a function of the joint torque $\boldsymbol{\tau}$ and this problem is solved at each control instant (typically at $1kHz$). Equation (2) expresses the constraints under which the control problem is solved. These constraints are related to the robot lower (_) and upper (¯) limits on joint position $\boldsymbol{q}$, velocity $\dot{\boldsymbol{q}}$ and torque but can also express environment related constraints.

In the quasi-static control paradigm, end-effector related tasks are expressed as a desired wrench $\boldsymbol{w}^\star_{task}$ coming from an higher-level loop either related to some explicit force control or position/orientation control objectives [35], chap. 11. $f_{task}(\boldsymbol{\tau})$ can thus be written

$$f_{task}(\boldsymbol{\tau}) = \left\| \boldsymbol{J}^T(\boldsymbol{q})\boldsymbol{w}^\star_{task} + \boldsymbol{g}(\boldsymbol{q}) - \boldsymbol{\tau} \right\|_2^2 \tag{3}$$

where $\boldsymbol{J}(\boldsymbol{q})$ is the end-effector Jacobian and $(\boldsymbol{q})$ are the gravity induced joint torques which have to compensated for.

Independently from its nature, the signaling motion should not induce any error on the performance of the main task. This can be achieved by projecting $\boldsymbol{\tau}^\star_{sig}$, the torque related to the realization of this signaling motion, onto the nullspace of the linear application related to the main task. This leads to

$$f_{sig}(\boldsymbol{\tau}) = \left\| \left(\boldsymbol{I} - \boldsymbol{J}^T \boldsymbol{J}^{T+} \right) \boldsymbol{\tau}^\star_{sig} + \boldsymbol{g}(\boldsymbol{q}) - \boldsymbol{\tau} \right\|_2^2 \tag{4}$$

In the following, possible expressions of the diffuse and explicit signaling motions considered in this work are provided.

A. Diffuse signaling motion: breathing

As introduced in section III, the retained diffuse signaling motion is a breathing like motion. Such a motion can be generated at the joint level through a rather straightforward PD controller written for joint i

$$\tau^\star_{sig,i} = k_{p_i}\left(\left(\sin\left(\sigma^\star t\right) q^\star_{i,max}\right) + q^\star_{i,0} - q_i\right) - k_{d_i}\dot{q}_i \tag{5}$$

where k_{p_i} and k_{d_i} are respectively the strictly positive proportional and derivative gains. σ is the desired period of the breathing motion, $q_{i,max}$ is the desired breathing motion amplitude and $q_{i,o}$ the neutral breathing configuration.

B. Explicit signaling motion: postural encoding

The encoding of task related information through robot posture is also straightforward and can, similarly to (5), be expressed for joint i as

$$\tau^\star_{sig,i} = k'_{p_i}\left(q_i^{\star j} - q_i\right) - k'_{d_i}\dot{q}_i \tag{6}$$

where k'_{p_i} and k'_{d_i} are respectively the strictly positive proportional and derivative gains related to the posture task. $q_i^{\star j}$ is the posture retained to encode information j.

It is important to note that, given the retained hierarchical controller structure, the absence of redundancy leads, through equation (4), to an absence of signaling motion. Thus, redundancy appears to be a required robot feature so that nonverbal communication channels can be intrinsically available for the robot.

IV. EXPERIMENTATION

To evaluate the effects of signaling motions on the situation awareness, a double within-subject study with 3 conditions each is proposed. This study is based on an experiment involving both the use of explicit (postural encoding) and diffuse (breathing) signaling motions implemented on two Franka Emika Panda robots.

A. Participants

We recruited 17 participants for our experimentation from a university campus thanks to email lists and networking. They had to register beforehand on an event planning tool[1]. They were aged between 20 and 32 (M = 23.06, SD = 2.91) and were not familiar with the task. One participant was removed due to technical and material problems during the experiment. The results were analysed on the remaining 16 participants. Additionally, two sensor failures led to missing data for 2 trials of 2 participants (2 of 90 data for one measured variable in the first case, 2 of 21 data for one measured variable in the second case). Given the limited number of missing data, we chose to keep these two participants and accordingly adapt the data analysis so that the difference would not be troublesome.

[1]https://evento.renater.fr/

B. Experimental set-up

The mock up described in fig. 2 reproduces the process of a wood shaping task, where a 7 degree of freedom collaborative robot reproduces the cutting forces applied by the machine tool on the wooden piece accordingly to the model developed in [36] and to the implementation proposed in [37].

In the performed experiment, subjects achieve a simulation of a woodworking task. They are asked to push a wooden board on a work-desk along a rail at constant speed, using handles equipped with force sensors. The board is connected to a Panda robot (Cobot 1) which reproduces the resistance of three different types of wood against the motion direction of the participant. The Panda robot can be torque controlled with a control sampling frequency of $1kHz$. The reproduction of the cutting wrench can be obtained by choosing the control torque $\boldsymbol{\tau}^c$ as:

$$\boldsymbol{\tau}^c = \boldsymbol{g}(\boldsymbol{q}) - \boldsymbol{J}(\boldsymbol{q})^T \boldsymbol{w}_s(\boldsymbol{p}_w) \tag{7}$$

where $\boldsymbol{w}_s(\boldsymbol{p}_w)$ is the modeled cutting wrench, which depends on several parameters $\boldsymbol{p}_w$ related to the wood type (density, wood grain...) and the cutting extension (number of teeth, diameter of the tool...). It is assumed that the denser the wood plank, the greater the resistance during shaping. The three resistances for wood are set at 30.41N (30N on x-axis and 5N on y-axis), 46.10N (45N on x-axis and 10N on y-axis) and 61.85N (60N on x-axis and 15N on y-axis). Those three resistances are respectively denoted as: **low**, **mean** and **high**. The experiment consists in three phases of 30 trials each. Every tenth trial, the participant is asked to answer a diversion question on a computer about its perceived effort. A second Panda robot (Cobot 2) is located in the experimental room to simulate an industrial working environment. More precisely it is placed on the walkway to a computer used for the diversion question. Additionally, participants are asked to complete a questionnaire between each phase about their own perceived SA during the task.

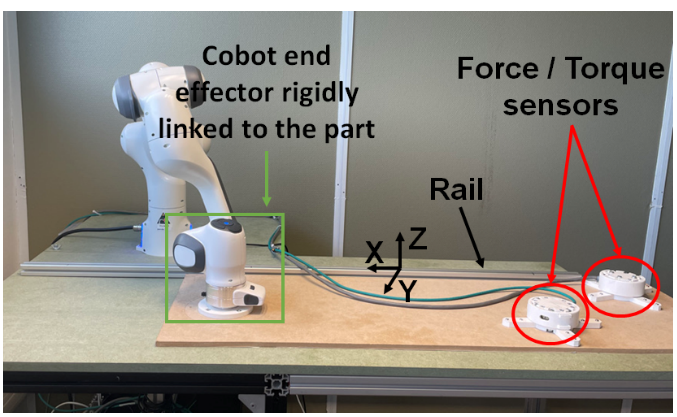

Fig. 2. Experimental set up to simulate a milling task in carpentry using a physically realistic mock-up. The wooden part is being pushed through handles incorporating 6-axis F/T sensors. A 7-DOF collaborative robot is attached to the wooden part and reproduces the cutting forces based on a wood cutting model.

1) Cobot 1: This robot is in charge of implementing the resistances when the participant performs the task. The resistances are presented in a controlled random order which is the same for all three phases. Beyond its role of emulating the task, the first robot is also used to evaluate the efficiency of the postural encoding motion. This could typically be the case for a robot used to train apprentices. Two distinct behaviors are considered: postural encoding **OFF** and postural encoding **ON**. If the signaling motion is **ON**, the robot tilts its elbow more or less depending on whether the resistance is stronger or weaker. The **ON** modality is also splitted in two experimental sub-modalities: in the first case the experimenter does not explain to the participant the meaning of the motion (**ON_¬E**) and in the other he does (**ON_E**).

2) Cobot 2: The second robot is used to evaluate the impact of the breathing motion on the path chosen by the participant to pass by it. It has three distinct behaviors: **motionless**, **active** and **breathing**. Even if this robot is not involved in the wood shaping task, the behavior of the participants towards it is observed as they share the same workspace. By default, the robot is performing a task (the robot in that case is said to be **active**) while the participant performs his/her trials. It changes (or not) its behavior between the last trial of one series and the first one of the next series, *i.e.* when the subject passes along it to go answer the diversion question. The robot is positioned in such a way that the participant is forced to walk in front of it. This allows to check whether the participant moves more or less away from the robot depending on its behavior (immobile, active or breathing).

C. Procedure

The experimenter starts with a presentation of the experimental set-up to the participant and performs two demonstration trials. Then the participant goes to the computer to answer the demographic questionnaire and sign the participation agreement. Following this, the participant performs 9 training trials to familiarise itself with the task and the three resistances. In this training phase, it is chosen to present the resistances three times in ascending order so that the participant is able to grasp the differences between them. Once training is performed, the participant answers the diversion question about its perceived physical effort on a computer in order to walk past Cobot 2 for the first time. In total, the participant will walk past the robot 21 times, i.e. 7 times per behavior during the experiment. The behavior of the Cobot 2 changes automatically during the trials of the task and is presented in a controlled random order.

Once this is done, the experimentation begins and the participant performs its first 30 trials while Cobot 1 is under condition **OFF** of the postural encoding motion. Every tenth trial, he/she is asked to answer the diversion question about its perceived physical effort. At the end of the first series, the participant is asked to fill in a questionnaire asking about its subjective perception of SA. In the second phase, Cobot 1 is now set to postural encoding motion **ON** but the participant is not informed about its meaning (condition **ON_¬E**). As in the first series, he/she performs 3 times 10 trials and fills in the questionnaire

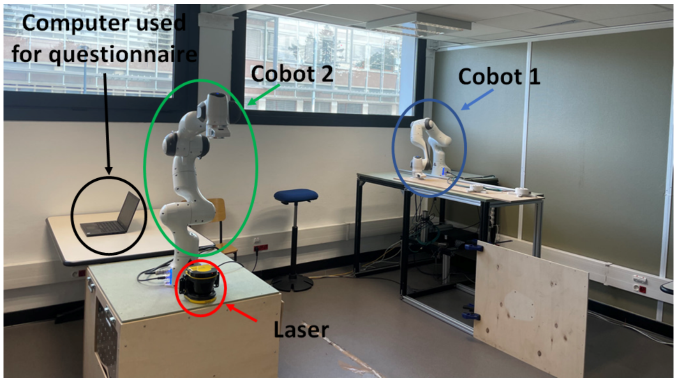

Fig. 3. View of the room used for the experiments. Participants perform their trials on the left side of the board close to the work table of Cobot 1. To reach the computer, they have to walk in front of the Cobot 2.

to pass by Cobot 2. After the 30 trials, he/she fills in the questionnaire about his/her subjective perception of SA. Before starting the third round, the experimenter asks the participant if he/she have noticed the three tilts of Cobot 1 and if he/she has any intuition about their meaning. After the explanation (if necessary), the last series begins. The latter is conducted similarly to the previous one, except that the participant now knows the meaning of Cobot 1 signaling motions (condition **ON_E**). The experiment stops once he/she has completed a third questionnaire about its perceived SA. Overall, the experimentation takes between 30 and 45 minutes.

D. Measures

Objective and subjective measures are collected during an experiment to evaluate the effects of both signaling motions on the participants SA. Objective measures are obtained with i) data time stamps for time ii) handles equipped with force sensors attached to the wooden part for interaction forces and iii) a 2D laser range sensor for human-robot distance. Subjective measures are collected through questionnaires completed during the task.

1) Objective measures: In order to assess the SA of the participants during the experiment, different measurements are proposed. They are linked to the performance of the task with Cobot 1 and to a correct understanding of safety issues regarding the state of Cobot 2. The following measurements are made across the three modalities of the Cobot 1 postural encoding motion for each resistance.

Time - A faster trial is indicative of better performance on the task and therefore a better SA. A participant takes longer to complete the trial if it is jerky due to resistance. The more appropriate his/her initial strength, the faster and more smoothly he/she performs the task. Adding information on the resistance produced by the robot should reduce the jerk and the time required to perform a trial.

Force on x-axis - This measure refers to the average force during a trial. Producing adequate force on the x-axis (along the rail) corresponds to better SA. Without a priori information about the resistance, it is expected that the force of the participant may be higher than necessary for low resistances and lower than needed for high resistances. Thus, supporting the participant's SA using the signaling motion should allow him to adjust his starting strength.

For the robot breathing modality, an additional objective information is measured for each behavior of Cobot 2.

Distance to Cobot 2 - The distance from Cobot 2 allows to verify the effect of the breathing motion. A participant who feels safe near the robot tends to pass close to it as this is the shortest path to the computer used for the diversion question. Conversely, if the participant sees a risk to pass in front of the robot, he/she avoids it, leading to a longer path to reach the computer.

2) Subjective measures: During the experiment, subjective measures are collected through questionnaires. The **SART questionnaire** is proposed to assess the participants SA [38]. It focuses on the attentional demand (instability, variability and complexity of the situation), the supply (arousal, spare mental capacity, concentration and division of attention) and the understanding (information quantity and quality and familiarity) of the situation. Participants have to rate each dimension on a seven point rating scale (1 for low and 7 for high). Once the questionnaire is completed, an SA score is calculated based on [38].

E. Hypothesis

Through this experiment several hypotheses are tested.

H0 – *The robot's signaling motions improve the SA of the individual interacting with the robot.* This hypothesis is tested with both signaling motions.

Following this, two additional hypotheses are proposed to consider H0 valid:

H1 – *Postural encoding motions improve the SA of the individual.* This requires that a better SA of the participants is measured when the postural encoding motion is **ON** (with or without explanation) than when the encoding motion is not performed (**OFF**). This results in a consistent improvement in our objective and subjective measures related to the wood milling task. Concerning time, participants are expected to be faster in the last modality. Regarding the force, they should produce an adequate one for the resistance informed by the robot. Finally the SA scores of the questionnaires should be better after the third modality.

H2 – *Breathing motions improve the SA of the individual.* This requires that a better SA of the participants is measured when the robot performs the breathing motion rather than when it is motionless. This translates into a greater distance to the robot if it is performing motions (i.e. active or breathing). Thus, the participant's mental model is fed by seeing the robot in motion even if it is idle.

V. RESULTS

Statistical analyses were performed using the Jamovi[2] data processing software and Rstudio. Repeated measures ANOVAs have been performed to explore the effect of both signaling motion on the participants SA.

[2]The jamovi project (2021). jamovi. (Version 2.0) [Computer Software]. Retrieved from https://www.jamovi.org.

A. Time

A two-factor repeated measures ANOVA is performed to evaluate the effect of the postural encoding motion (OFF, ON_¬E and ON_E) and resistances (low, mean and high) on time. It shows a global and statistically significant effect on the time ($F(4, 636) = 11$; $p < .001$). Repeated measures ANOVAs also shows differences along modalities of the postural encoding motion only ($F(2, 318) = 454.1$; $p < .001$) and resistances only ($F(2, 318) = 74.1$; $p < .001$). Posthoc paired-tests using Tukey correction reveal that participants needed less time to achieve one trial in ON_E modality (M = 1.52, SD = 0.43) than in ON_¬E modality (M = 1.86, SD = 0.42) and in OFF modality (M = 2.18, SD = 0.52). Posthoc paired-tests also show that participants needed more time to achieve one trial when the resistance was set to high (M = 1.96, SD = 0.56) than when the resistance was set to mean (M = 1.86 , SD = 0.53) and low (M = 1.74, SD = 0.49). If we focus on the interactions between the modalities of the signaling motion for a same resistance, we can observe a decrease in the time performed to carry out trials as illustrated in Figure 4 (See Appendix 1 p. 1-3 for more details).

B. Force on x-axis

A two-factor repeated measures ANOVA is performed to evaluate the effect of the postural encoding motion (OFF, ON_¬E and ON_E) and resistances (low, mean and high) on the force. It shows a global effect of the postural encoding motion and resistances on the force applied by participants ($F(4, 632) = 97$; $p < .001$). Statistical differences along modalities of the motion only ($F(2, 316) = 68.2$; $p < .001$) and the resistances ($F(2, 316) = 1381.5$; $p < .001$) only are also found.

As for the time, post-hoc paired-tests using Tukey correction reveals that participants needed to push less hard to achieve trials in ON_E modality (M = 58.83, SD = 18.47) than in ON_¬E modality (M = 62.38, SD = 14.11) and in OFF modality (M = 63.73, SD = 11.73). Regarding the resistances, posthoc tests show that the participants needed to push with less force when the resistance was set to low (M = 49.62, SD = 9.81) than when it was set to mean (M = 57.53, SD = 9.58) or high (M = 77.81, SD = 8.89).

Concerning the interactions between the modalities of the signaling motions for a same resistance, the results are varied. For the low resistance, the participants produced more force to push the plank in the OFF modality (M = 56.3, SD = 9.29) than in the ON_¬E (M = 51.27, SD = 7.28) and ON_E (M = 41.29, SD = 5.77) modalities. An additional difference is observed between the ON_¬E and ON_E modalities. For the mean resistance, the participants produced a similar force between the OFF (M = 60.02, SD = 9.46) and the ON_¬E modalities (M = 58.56, SD = 9.94) and a smaller one for the ON_E modality (M = 54.02, SD = 8.29). Also, the participants needed less force for the ON_E than the ON_¬E modality. For the high resistance, they applied more force in the ON_E modality (M = 81.17, SD = 9.53) than in the ON_¬E (M = 77.38, SD = 9.1) and OFF (M = 74.87, SE = 6.65) modalities. A smaller force can also be observed between the OFF and the ON_¬E modalities as illustrated in Figure 5 (See Appendix 1 p. 4-6 for more details).

C. Distance to Cobot 2

For the distance to Cobot 2, a repeated measures ANOVA has been computed to assess the impact of the breathing action (ac-

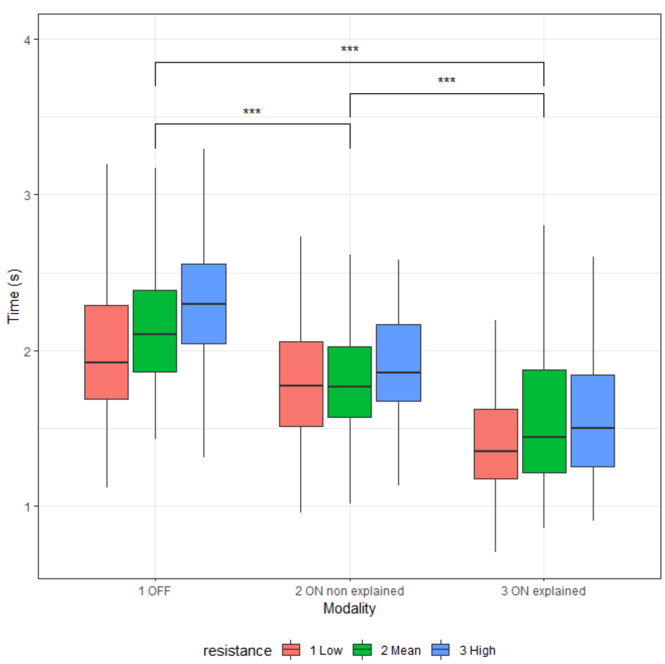

Fig. 4. Boxplot of the measured time for each modality of the postural encoding motion and for each resistance.

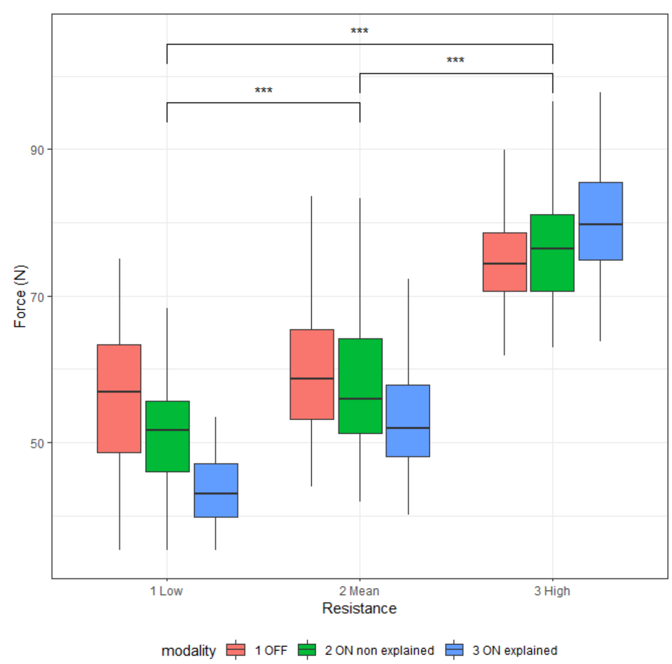

Fig. 5. Boxplot of the measured force for each modality of the postural encoding motion and for each resistance.

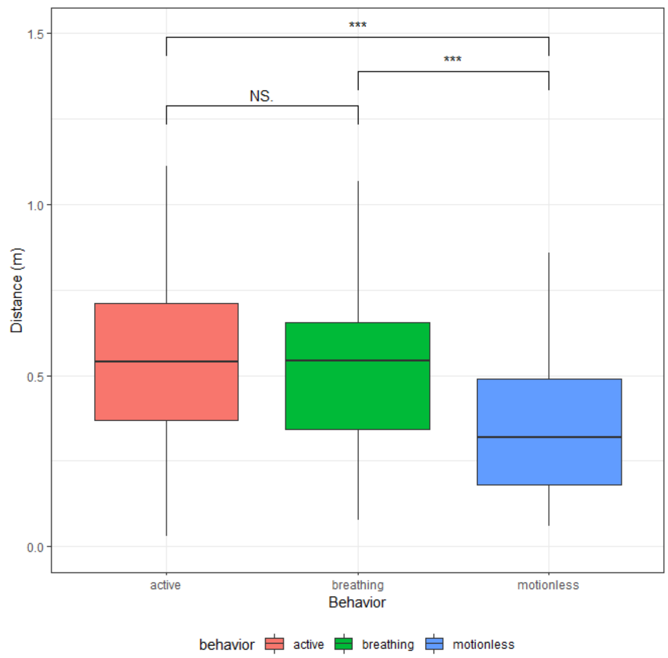

Fig. 6. Boxplot of the measured distance for each modality of the breathing motion.

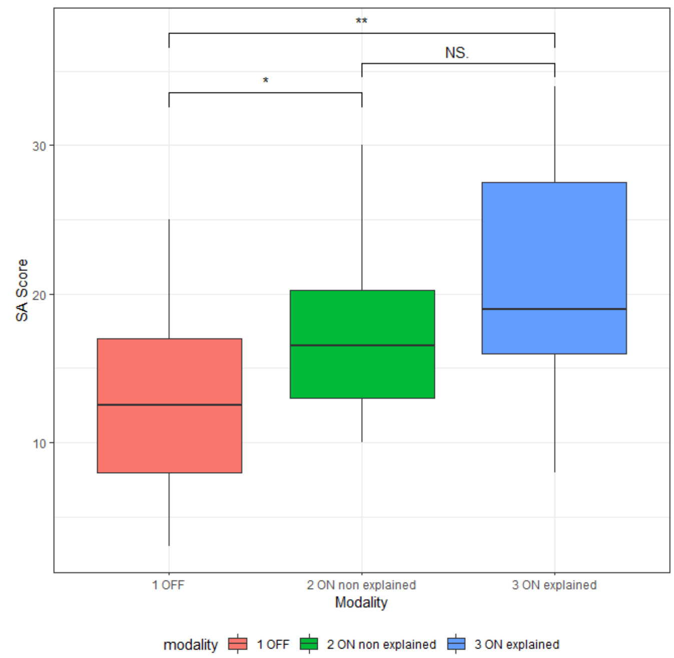

Fig. 7. Boxplot of the computed SA score for each modality of the postural encoding motion

tive, breathing, motionless) on human behaviors. The analysis reveals a statistically significant global effect on the distance to Cobot 2 ($F(2,218) = 37$; $p < .001$).

Post-hoc tests using Tukey correction reveals that participants walked closer to Cobot 2 when it was motionless (M = 0.34, SD = 0.19) rather than when it was active (M = 0.54, SD = 0.29) or breathing (M = 0.53, SD = 0.23). On the other hand, there were no significant differences between the active and breathing behaviors ($p = .564$). These results are illustrated in Figure 6 (See Appendix 1 p. 7 for more details).

D. SART questionnaire

We performed a repeated measures ANOVA to evaluate the effect of the postural encoding motion on the participants SA.

We find a global effect of the postural encoding motion on the participants answers to SART questionnaires ($F(2,30) = 8.19$; $p < .001$). Post-hoc test using Tukey correction reveals that participant had a worst SA when the postural encoding motion was OFF (M = 13.31, SD = 6.14) than when the modality was ON_¬E (M = 17.62, SD = 5.95) or ON_E (M = 20.81, SD = 7.35). Finally, the ON_¬E and ON_E modality cannot be shown to be significantly different ($p = .130$). These results are illustrated in Figure 7 (See Appendix 1 p. 8 for more details).

VI. DISCUSSION

The goal of this study is to evaluate the effects of signaling motions on the situation awareness of humans sharing tasks and workspace with robots. More specifically, we implement two signaling motions using two collaborative robots or cobots: one performing a postural encoding motion as an explicit one and the other a breathing motion as a diffuse one. These motions are intended to support operators' SA.

A. Explicit signaling motion as a support to SA

Both objective and subjective results confirm hypothesis **H1** which suggest that postural encoding motion improves the SA of the individual interacting with the robot. The activation of the explicit signaling motion reduces the task completion time, which indicates that it has a positive impact on the user's performance. This impact is more pronounced when the assistance behavior is explained. In the context of the use case this is explained by a better knowledge of the task (improvement of the mental model). This enhancement is illustrated by the evolution of the force applied by the subjects according to the three modalities. When participants had no indication about the resistance, they did not estimate in advance how much force was needed. Conversely, once its meaning was known, participants were more successful in managing their efforts to complete the task. More precisely, the participant applies globally more forces when the robot indicates a high resistance and, oppositely, he/she applies less forces when a low resistance is expected. This illustrates the positive impact of the proposed assistance, indeed the participant adapts his/her handling strategy according to the resistance which illustrates an improvement of the mental model of the task. Finally, regarding postural encoding motion, the SA scores obtained from the SART questionnaire confirm our objective results. The results show an improvement in SA when participants knew the meaning of the explicit signaling motion. Although the SART questionnaire is a subjective measure, the physical performance seems to be consistent with the obtained results.

It should be noted that the explicit motion performed by the robot influences unconsciously the task performance as its effect is significant even without explanation. This is an encouraging result which should be confirmed when trying to convey more complex information about the task through postural encoding.

B. Diffuse signaling motion as a support to SA

The measured passing distances to the robot confirm hypothesis **H2** which suggest that breathing motion improves the SA of the individual interacting with the robot. Indeed, the purpose of the breathing motion is to raise someone's awareness of the robot's state. Even if a robot is motionless, it is not necessarily turned off and it is therefore important to be alert to its presence and, potentially, activation. Through breathing motion, the person knows that the robot is in an idle state but can resume its task at any time. This is especially important since the robot does not interact directly with the human but only shares its workspace. The fact that there is no significant difference between the crossing distance of the subjects close to the robot when it performs a breathing motion and an active behavioral motion suggests that the two are perceived and interpreted similarly. People are then more alert to the robot when it makes a diffuse motion that signals its state. Although in both cases (motionless and breathing) the robot is in a waiting state, subjects tend to enter the robot's workspace when it is motionless, while they tend to move away from it when it is breathing, indicating that the diffuse movement transmits activity information to the user and increases its vigilance. The breathing motion therefore helps to improve the mental model of the individual. As for the postural encoding motion, the breathing one acts as a support of SA. Specifically, the mental model is supplied in such a way that knowledge of the robot's state is no longer unclear for the person.

C. General discussion

Based on the approval of **H1** and **H2**, our initial hypothesis **H0** is supported. By proving the positive effect of postural encoding and breathing motions we show the positive effect of signaling motions on SA. The addition of the two signaling motions to the robots contribute positively to the improvement of the mental model of the person interacting with the two robots. Being performed in the nullspace of the main robot task, these motions do not affect it. This is a critical feature in the industry and a clear advantage of the proposed approach. They act as a postural complement of information through an indirect communication channel which does not affect the overall performance.

D. Limits

The potential limitation of this work is that we chose to not randomize the trials. The first two modalities could have been randomised to ensure that the learning effects of the task did not influence the results for Cobot 1. However, the last one could not be randomised because it was preceded by a verbal explanation given after the first two modalities. In practice, if we look at the completion time for each trial, we can see a slight intra-modality learning effect. However, if we look at inter-modality differences, large drops in completion times can be observed when switching from one modality to the next (see fig 8).

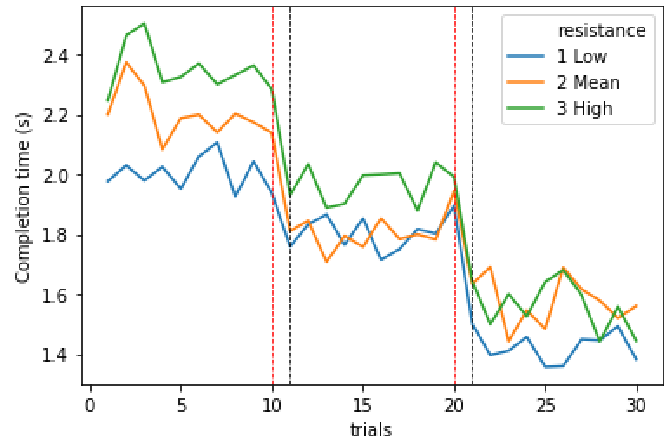

Fig. 8. Inter-difference for each resistance between each modalities. Red dashed line corresponds to the last trial of OFF and ON_¬E modality. Black dashed line corresponds to the first trial of ON_¬E and ON_E modality.

Theses abrupt changes are clearly not an effect of continuous task learning solely and can quite logically be interpreted as a consequence of the postural encoding motion (and associated explanations in third modality). This is confirmed by the SA questionnaires filled in by each participant.

VII. CONCLUSION

Signaling motions have been set up to improve a person SA. We have implemented two distinct motions: diffuse (breathing) and explicit (postural encoding) signaling motion. They both lead to the improvement of the mental model related to the environment and to the task (respectively). Thus, they contribute to the improvement of SA. The breathing motion made people more aware of their workspace and the postural encoding motion informed them during the evolution of their task.

While this work provides evidences of the feasibility and utility of signaling motions, our long term goal is to understand the link between the task to be achieved (nature, complexity, context) and the potential effects on SA given specific characteristics of the operator (fatigue, level of expertise, level of stress,...). This could allow to generate SA supporting mechanisms, such as signaling motions, that could be convoked in an automatic, seamless and appropriate way by a supervision control layer given a mental model of the operator and an online prediction of its potential weaknesses and failures.

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