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Arbitration of Authority in Physical Human-Robot Collaboration with Combined Preventive and Reactive Fatigue Management

Álvaro Gil Andrés, Niek Beckers, David A. Abbink, and Luka Peternel*

***Abstract*— We present a method for arbitration between human and robot involvement in a collaborative physical task execution based on ergonomic metrics. The existing methods for ergonomic control of physical human-robot collaboration perform the real-time arbitration primarily based on a single type of ergonomic metric. The novelty of our approach is twofold. First, the system enables real-time arbitration based on combining two types of ergonomic metrics: preventive and reactive. Second, we use a preventive metric to prevent worker fatigue and discomfort due to overexertion in the future and a reactive metric to avoid immediate fatigue and discomfort. To this end, we considered two metrics respectively: human arm manipulability and muscle fatigue. The developed multi-metric arbitration method translates the human multi-metric state to a robot control level over a collaborative task execution using a finite state machine. We demonstrate the proposed method on a Kuka LWR iiwa robotic arm in a collaborative human-robot polishing task that requires a specific force production.**

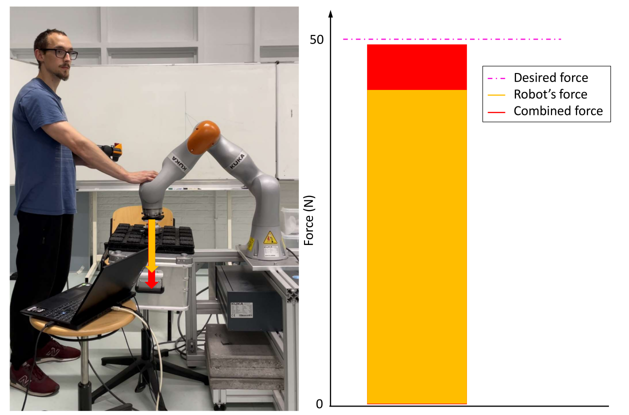

Fig. 1: Illustration of the task: the human and the robot collaboratively exert a desired force against a horizontal surface. The graph on the right represents the desired force level of the task (pink), the robot's end-point force (orange), and the combined measured exerted force (red). This graph is also used for real-time visual feedback to the human operator.

I. Introduction

In physical human-robot collaboration (pHRC), the human and the robot contribute to a common goal depending on their skill set. Typically, humans are good at adapting to unknown/changing environments and task requirements, and have manual dexterity skills that robots lack. On the other hand, robots are able to perform tasks with higher speed, precision and consistency, while not being impacted by muscle fatigue. When deciding, or arbitrating, who does what in pHRC, the arbitration system should take these strengths and weaknesses into account. Arbitration is defined as the mechanism that assigns control over the task or moderates the level of engagement between the human and the robot [1], [2]. It determines the interaction strategies between the human and the robot, such as teacher-student, supervisor-subordinate, or leader-follower, to fit their skills and the task [1], [3]. Generally, arbitration can be on the process level–to allocate and schedule multiple sub-tasks [4], [5]–or on the task level, where the aim is to share a portion of effort over the same shared task [6]–[8]. This paper focuses on the latter.

Arbitration in pHRC for industrial applications is often driven by the human worker's ergonomy to ensure a safe and efficient production process [9]. Typical ergonomic metrics are arm manipulability and muscle fatigue. Arm manipulability derives from the classic velocity and force manipulability ellipsoids, which represent a quantitative metric of how well an arm end-effector can produce velocity/force in different directions in a given arm configuration with given joint velocities/torques [10]. Studies in pHRC showed the importance of manipulability on collaborative task performance [11], [12]. Besides benefits to task performance, the study in [13] revealed that arm muscle activation and consequent muscle fatigue are strongly related to human arm manipulability; having to exert force with a low arm manipulability results in muscle fatigue. Moreover, research concluded that a fatigued muscle is more likely to get injured [14]–[16]. Therefore, to ensure that human arm manipulability is ergonomic, an arbitration system can provide a preventative way to avoid muscle fatigue and minimise the risk of injury.

Manipulability has also been used in robot control to actively improve the working conditions of the human worker during the collaboration. The study in [11] developed a control method for a physical human-robot co-manipulation and handover scenarios that integrates a human body model for ergonomic optimisation, where human arm manipulability is one of the constraints. For example, the manipulability limits were set so that the algorithm would find arm configurations that keep the manipulability isometric while optimising for minimum joint torques. As a result, the robot ensured that the human co-worker had equal force/velocity production capacity in all directions of Cartesian space, thus improving the effectiveness of co-manipulation. An extended version of classic manipulability also incorporates human muscle properties [17], [18]. For example, this extended manipulability was used as a supervisor-subordinate arbitration metric in a control of an arm exoskeleton for human power augmentation, where the robot compensated for the minor ellipsoid axes and formed an isometric manipulability ellipsoid in

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any arm configuration [17]. However, these studies did not explicitly consider the effect of preventing human fatigue by ensuring that arm manipulability is acceptable.

While arm manipulability provides only an indirect way to prevent fatigue, fatigue can be estimated and acted upon directly using computational models. Some models use an external force (e.g., on an object by the human) as input to calculate a fatigue-related measure [15]. Others developed fatigue models that infer the force generated by human muscles based on physiological muscle motor unit behaviour [19]. Others used computational models that assessed whether exerted torques were overloading the human joints by including each joint's torque capacity [16], [20]. While the fatigue estimations based on an external force or joint torques give a convenient overall estimation, they do not provide a detailed insight into the fatigue of individual muscles that actuate each joint and consequently the end-effector.

The method in [7] measured muscle activities through electromyography (EMG) signals in order to estimate individual muscle fatigue. The algorithm used fatigue to arbitrate control between human and robot; the robot took over the task whenever human muscle fatigue reached a predetermined threshold. In [21] the robot adapted the working configuration to relieve the fatigued muscles and involve the fresh ones. However, in this case, the muscle activity was modelled instead of measured. While modelling the individual muscle effort eliminates the need and complexity of physiological measurements, the estimation is limited to the accuracy of the model. On the other hand, while measuring the end-effector force or joint torque simplifies the measurement system, they do not give muscle-specific fatigue estimation. In that respect, using a fatigue model with measured EMG signals gives an edge over the other methods, at expense of some extra complexity.

We classify the ergonomic metrics used in human-robot collaboration control into two main categories based on their function regarding fatigue management: reactive and preventive. Since fatigue is essentially integrated effort over time and the robot acts to reduce fatigue once a certain level of fatigue is reached, it falls into the reactive category. On the other hand, optimising for manipulability will improve the arm effectiveness in terms of force production and thus reduce the effort, which in turn reduces the fatigue that will be accumulated over time in subsequent task execution. Thus, manipulability falls into the preventive category. Nevertheless, both preventive and reactive approaches on their own have significant limitations.

Combining arm manipulability and muscle fatigue estimations to arbitrate control between the human and the robot has advantages over existing methodologies. Previous methods only *reactively* adjust the arbitration between human worker and robot when the human is already fatigued (e.g., [7]) and thus have a higher risk of injury. We aim to *prevent* muscle fatigue in the first place by taking a two-pronged approach. First, given that better arm manipulability leads to lower fatigue in the long run, we propose to arbitrate control in pHRC such that the robot enables the human to optimise their arm manipulability. The limitation of using only arm manipulability is that it only indirectly affects muscle fatigue and therefore the exact level of fatigue at any given moment is unknown. Thus, to account for unpreventable or unforeseen fatigue, we also infer muscle fatigue directly through EMG measurements to immediately react and adjust the arbitration such that the robot takes over when the human is tired. The challenge is that arm manipulability and muscle fatigue are interdependent, which requires an arbitration method that can successfully incorporate both metrics, while resulting in stable arbitration in which both the human and the robot are actively involved.

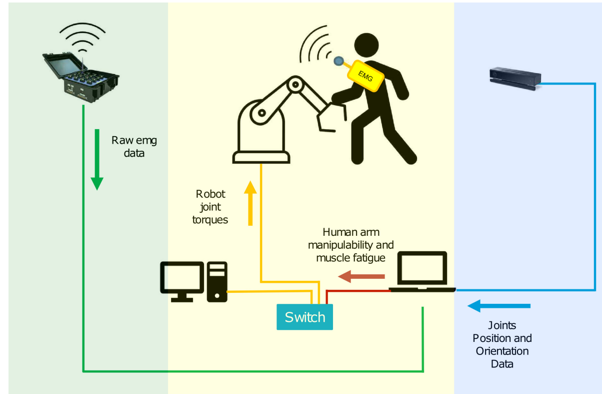

Fig. 2: The proposed system consists of three main components, which communicate through UDP. (Yellow) The arbitration module incorporates the method based on a finite state machine that translates the fatigue and manipulability values into a percentage of the total force exerted by the robot. (Green) The fatigue module models fatigue values based on the measured and processed EMG. (Blue) The Manipulability module captures the pose of joints and calculates the manipulability value in the direction of the exerted force.

Here, we propose a multi-metric arbitration method that combines human arm force manipulability and muscle fatigue to achieve preventive and reactive pHRC. The proposed method includes a finite state machine with four states and assistance levels that provide smooth transitions between the states. The main contribution of this work is a novel arbitration approach for physical human-robot collaboration that can simultaneously account for metrics related to both preventive and reactive behaviour. The proposed method is demonstrated with experiments on a collaborative human-robot polishing task (see Fig. 1).

II. METHODS

The proposed method consists of three main modules (see Fig. 2): 1) the multi-metric arbitration module, 2) the manipulability estimation module, and 3) the fatigue estimation module. The multi-metric arbitration module is based on a finite state machine (FSM). Depending on a normalised value of human arm force manipulability and muscle fatigue, the FSM smoothly converges towards an arbitration value $a \in [0, 1]$ that represents the ratio of the robot's contribution to the task execution ($a = 0$: the human produces all the force, $a = 1$: the robot produces all the force). The normalised human arm force manipulability value follows from an estimate of the force manipulability ellipsoid, which is measured through human arm pose estimation. Finally, the fatigue estimate module computes a normalised fatigue level based on muscle activity through EMG measurements. The fatigue module distinguishes between two modes: fatigue mode when the estimated fatigue slowly converges to 1, and recovery mode when it is slowly converging to 0.

The proposed method is demonstrated on a collaborative task that requires the human and robot team to physically collaborate and apply a constant force for an extended period and requires the human to control the position of the applied force. Polishing and drilling a workpiece are typical applicable industrial tasks. The human and the robot provide a portion of the total desired force based on how the force production sharing is arbitrated (e.g., more by the human $a \rightarrow 0$, or more by the robot $a \rightarrow 1$). The force production arbitration is assigned online depending on the human muscle fatigue and arm force manipulability in the direction of the desired force. For example, in collaborative human-robot polishing of a surface, the robot and the human hold the polisher against the surface. The human swipes the polisher through the part of the surface that needs polishing while exerting a percentage of the force. Depending on the human arm pose and fatigue of the involved muscles, the robot adapts by exerting different force contributions. The human can monitor the measured and desired forces through visual feedback (see Fig. 1, right side).

The method results in a human-robot arbitration in which the robot reactively assists the human depending on the human fatigue, allowing the human to rest when needed, while still keeping the human in the loop to control the position of the polishing and supervise the task. The assistance that depends on force manipulability constitutes a preventive approach; the robot increases assistance when the human is in a posture that is less effective, thereby allowing the human to re-position and prevent fatigue in the long term. At the same time, the robot keeps track of the fatigue level even though it actively assists to prevent it, and acts based on fatigue when it cannot be prevented from happening.

A. Arbitration Method

Manipulability and fatigue need to be translated into an arbitration variable a, which is subsequently integrated into an impedance control scheme of the robot. The arbitration algorithm is a finite state machine (FSM) composed of five states (see Fig. 3): four states (s1, s2, s4, s5) for a multi-metric arbitration mode, and a fifth (s3) that substitutes the two middle states (s2 and s4) in case a single-metric arbitration mode is desired. Thus, the method also offers modularity in terms of including or excluding a specific metric. For example, if the system is to be used for a quick task such as drilling a few holes in places that are not in a comfortable arm configuration, then setting up the EMG sensors might be inconvenient, and only manipulability-based assistance would suffice. Three states are relevant in this scenario: s1, s3 and s5. On the other hand, when the task takes a long time and fatigue becomes relevant (e.g., as in our experiment task), combining preventive and reactive

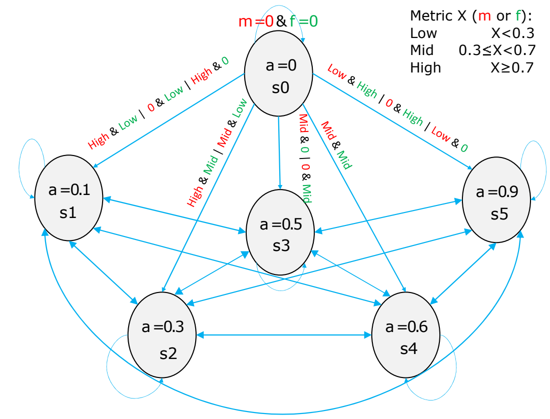

Fig. 3: Schematic representation of arbitration with the finite state machine (FSM). On the top right corner, we can see a legend explaining the intervals for the variables: manipulability m and fatigue f. By the arrows pointing out the top state, we can see the conditionals that lead to each of the states. In red we can see the values or intervals referring to manipulability m. In green we can see the values or intervals referring to fatigue f.

assistance is preferable. Four states are relevant for this scenario: s1, s2, s4 and s5.

The initial state is $a = 0$, when manipulability $m = 0$ and fatigue $f = 0$. The five other states depend on values of m and f: $[0, 0.3)$, $[0.3, 0.7)$ or $[0.7, 1]$. When m is in the low interval or f is in the high interval, arbitration is $a = 0.9$ and the robot exerts 90% of the desired force and thus provides maximum assistance. When m and f are in the middle interval, arbitration is $a = 0.6$ and the robot provides a high-intermediate level of assistance. When m is in the high interval and f in the middle interval, or f is in the low interval and m is in the middle interval, arbitration is $a = 0.3$ and the robot provides a low-intermediate level of assistance. When m is high and f is low, or in single-metric arbitration mode when the metrics is in a good condition, arbitration is $a = 0.1$ and the robot provides minimum assistance. Finally, in single-metric arbitration mode, when the metric is in the middle interval, arbitration is $a = 0.5$ and the robot provides intermediate assistance. State transitions between arbitration values are smoothed using a sigmoid function as

$$a(t+dt) = \begin{cases} a_t + (a_0 - a_t) \cdot \left(1 - \frac{1}{1+e^{E(t)}}\right) & \text{if } a(t) > a_t \\ a_0 + (a_t - a_0) \cdot \left(1 - \frac{1}{1+e^{E(t)}}\right) & \text{if } a(t) < a_t \\ a(t) & \text{if } a(t) = a_t \end{cases} \tag{1}$$

$$E(t) = -\frac{\frac{a_0+a_t}{2} - (a(t) + \frac{(a_t-a_0)t_s}{T})}{t_s} \tag{2}$$

where a_0 and a_t are the current and the target state (i.e., arbitration value), respectively. The expanded exponential term E is shown in (2), where t_s is sampling time and T determines minimum time in each state after a transition. T was set to 5 seconds to avoid fast state transitions and to allow the human to adapt to the new state.

B. Human Arm Manipulability

The manipulability calculation requires measuring the human arm configuration in the joint space and the arm Jacobian. We used a Kinect V2 to acquire human arm

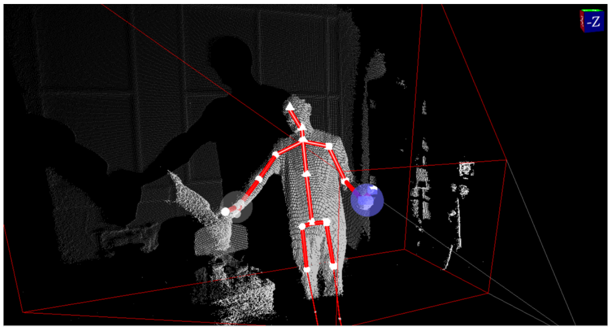

Fig. 4: Collaborative human-robot setup with human body segment skeleton, as extracted by Kinect V2 camera using the Kinect Studio v2.0 software.

joints angle in real-time (see Fig. 4). From the measured joint angles, we obtained the Jacobian by using the method based on human arm triangle space projection [22]. The force manipulability ellipsoid for a redundant arm can be calculated by a singular value decomposition as

$$\boldsymbol{M} = (\boldsymbol{J}(\boldsymbol{q})\boldsymbol{J}(\boldsymbol{q})^T)^{-1} = \boldsymbol{U}\boldsymbol{\Sigma}\boldsymbol{V}^T, \quad (3)$$

where $\boldsymbol{\Sigma} \in R^{m\times n}$ is a diagonal matrix composed of the singular values $\sigma_n \geq 0$, and $\boldsymbol{U} \in \mathbb{R}^{m\times m}$ and $V \in \mathbb{R}^{n\times n}$ are orthogonal matrices containing singular vectors. Each entry of $\boldsymbol{U} \in \mathbb{R}^{m\times m}$ is an unit vector $\boldsymbol{u}_i$ that defines a direction of one of the principal axes of manipulability ellipsoid, while the corresponding singular value σ_i defines the size of the principal axis. The principal axis $\sigma_1\boldsymbol{u}_1$ represent the direction in which the end-effector can exert the highest force with the given joint torques. Similarly, $\sigma_m\boldsymbol{u}_m$ represents the direction of the lowest force production capacity.

In the task examined in this study, orientation was not relevant and therefore we only used the three values/vectors related to position. We were interested in the direction where the polishing force has to be exerted on the surface, which was aligned with robot base frame z-axis, thus manipulability metric was defined as

$$m = u_{1,z}\sqrt{\sigma_1} + u_{2,z}\sqrt{\sigma_2} + u_{3,z}\sqrt{\sigma_3}, \quad (4)$$

where the m value was then normalised using a sigmoid function with 0.5 value on m = 1.0283.

C. Fatigue model

We used the fatigue model from [7] that operates with measured EMG and is based on a first-order system:

$$\frac{df_i(t)}{dt} = \begin{cases} (1 - f_i(t))\frac{A_i(t)}{C_i} & \text{if} \quad A_i(t) \geq A_{th1} \\ -f_i(t)\frac{R}{C_i} & \text{if} \quad A_i(t) < A_{th2} \end{cases}, \quad (5)$$

where the top equation represents the fatigue induction phase and the bottom one the recovery phase. The fatigue index of the muscle i $f_i(t)$ increases when the muscle activation level $A_i(t)$ is above an activation threshold A_{th}. Similarly, the muscle fatigue index decreases when the mentioned muscle activation is below a threshold at a recovery rate R. Different thresholds A_{th1} and A_{th2} for passing up and passing down between effort and relaxation modes can be used in order to form a hysteresis and prevent the states from switching rapidly back and forth. The speed with which the fatigue induction or recovery happens also depends on the fatigue-related capacity C_i of muscle i. The parameters C_i and R were calibrated in the same way as in [7]. The muscle activation signals are defined as

$$0 \leq A_i(t) = \frac{EMG_i(t)}{MVC_i} \leq 1, \quad (6)$$

where $A_i(t)$ is the activation level of muscle i, $EMG_i(t)$ is the processed EMG signal and MVC_i is the EMG at the maximum voluntary contraction. The raw EMG signal was processed by high pass filtering, by rectification and finally by low-pass filtering. We used wireless Delsys Trigno System to collect the raw EMG signal.

III. Proof-of-concept demonstrations

To demonstrate the functionality of the developed FSM, we first conducted six simulations with different variations in the values of ergonomic metrics and two simulations with variations of only one metric. Figure. 5 shows that for different combinations of manipulability m and fatigue f, the arbitration value is adapted according to the FSM in Fig. 3.

To validate the proposed method as a whole we performed a test on a Kuka LWR iiwa robotic arm (see Fig. 1). The task of the human user and the robot was to collaboratively exert a vertical force of 50N against a horizontal surface. While keeping the desired combined force, the human had to change the arm posture to test the robot's adaptability to the manipulability value and fatigue accumulation. The arbitration value and forces were displayed to the human in real-time by a monitor (see Fig. 1). We examined four different arm configurations with different manipulability values; Fig 6 shows the sequence of configurations. Because the task mainly involved pushing the arm down on the surface, the Latissimus Dorsi muscle had a major contribution to this action. We placed the EMG sensor on the Latissimus Dorsi of the subject and calibrated the fatigue model parameters. We tuned the model to be more sensitive than usual in order to achieve a faster system response and to check the state transitions quicker online. We set the recovery rate $R = 0.5$. The thresholds between the induction and recovery modes were set to $A_{th1} = A_{th2} = 0.3$, which were intentionally relatively high for the purpose of demonstration.

Figure 6 shows the results of the test. The top graph displays the fatigue value, the manipulability value, and the arbitration value. We can see how manipulability changes with the different arm configurations of the human operator. The second graph displays the calculated robot force and the measured combined force. When the manipulability was low in the first configuration, the robot took over the majority of the effort to produce the desired combined force. In accordance with that, human effort was very low as can be seen from the muscle activity signal in the bottom graph. Note that for the first part of this stage (around 13 seconds) the arbitration is still at a lower value $a = 0.3$ (state s2), which is a result of (2) that prevents rapid switching between states. Thus, it took some time for the arbitration value to switch to $a = 0.9$ (state s5).

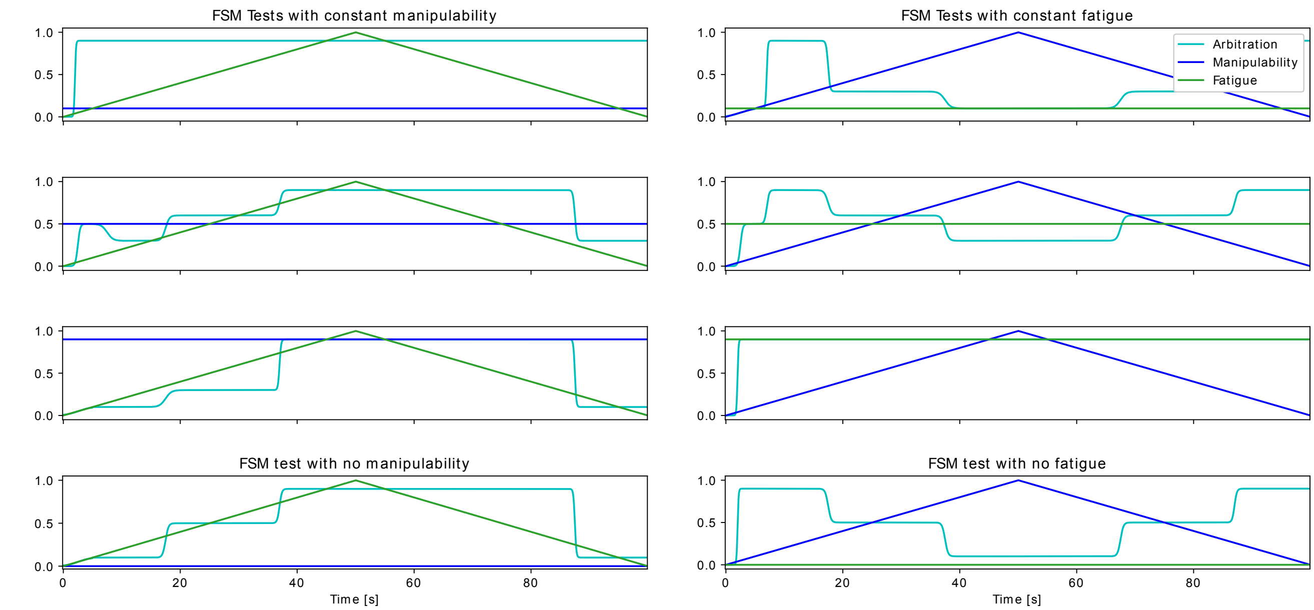

Fig. 5: Results of FSM simulation. The graphs show an arbitration value a (i.e., robot contribution to the task) for different combinations of manipulability m and fatigue f, which are normalised values. The graphs in the left column show different constant manipulability values against uniformly increasing and decreasing fatigue. The graphs in the right column show different constant fatigue values against uniformly increasing and decreasing manipulability.

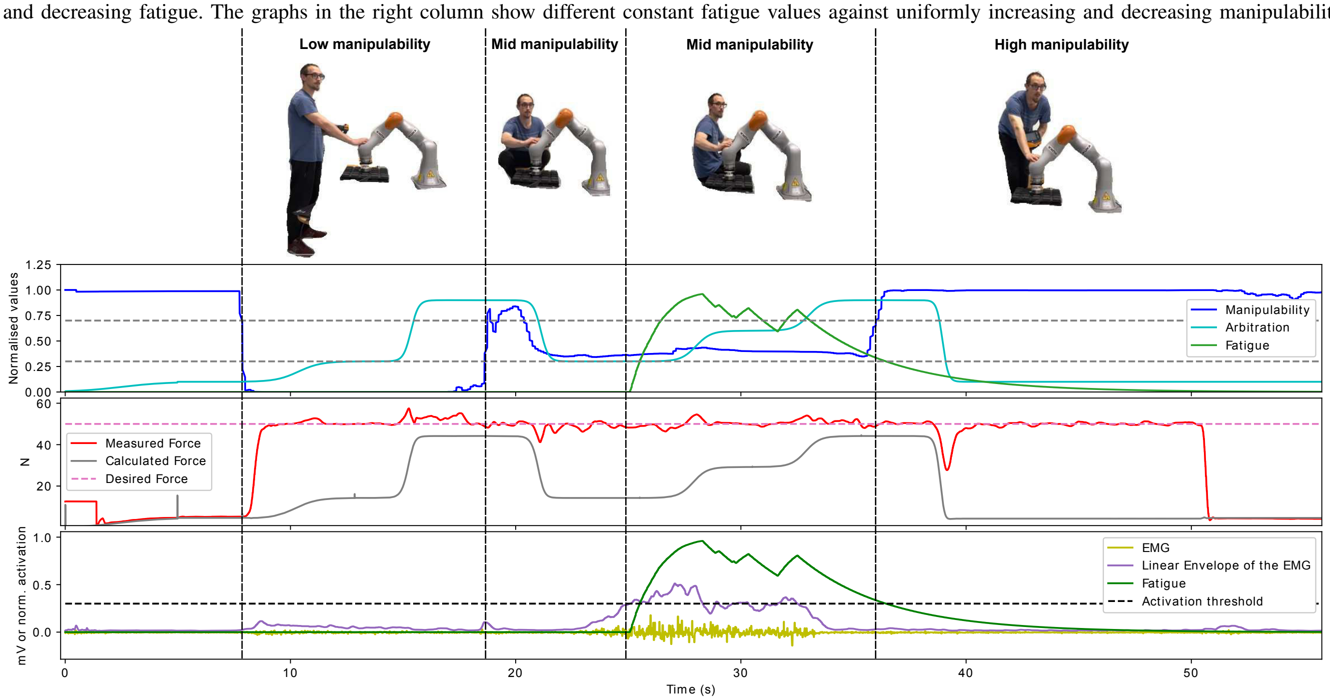

Fig. 6: Results of the experiment. The top row shows photos of different human arm configurations. The top graph shows fatigue, manipulability and arbitration values throughout the experiment. The middle graph shows the calculated robot force and measured exerted force (note: the human force contribution is the difference between the two). The measured force was obtained from the sensors on the robot, while the calculated force is the desired robot force from the impedance controller. The bottom graph shows the raw EMG signal, the normalised EMG's linear envelope and estimated fatigue.

The second arm configuration improved human manipulability and the arbitration shifted more effort to the human. In the third arm configuration, the human muscle activity reached above the predefined relaxation threshold, thus fatigue gradually increased. When the fatigue increased beyond the predefined level, the state was transitioned and the arbitration shifted more effort to the robot. After that, the human effort was reduced and fatigue gradually reduced as a result. In the last configuration, the manipulability was extremely high since the human arm was in a singular configuration. That meant that very little muscle effort was required for the human to produce most of the desired combined force. Accordingly, the arbitration shifted the effort predominantly to the human. However, even though the produced force was high, the muscle effort was low due to high manipulability, thus fatigue did not occur.

IV. Discussion

Collaborative robots aim to decrease human workload, prevent injuries in the workplace, and increase task performance. Nevertheless, decreasing the cognitive load below the individual skill of the user could lead to boredom [23]. Boredom is highly related to a detriment in vigilance [24], which can be problematic in terms of safety and quality of work. The proposed method keeps the human engaged in the task most of the time with various levels of involvement.

Existing methods exploit the manipulability and fatigue metrics separately and achieve either only the preventive or only the reactive robot behaviour. The method in [7] employed fatigue for binary single-metric arbitration. The robot takes over the task only when a certain level of muscle fatigue is reached. The approach in [17] used manipulability for single-metric arbitration in a power-augmentation exoskeleton. This way, the exoskeleton provided assistance based on the difficulty of exerting force in every possible position. The approach reduced the effort and thus reduced the induced fatigue, however, it did not actually monitor or react to it. We filled this gap by successfully developing a multi-metric arbitration method, which combines both preventive and reactive strategies to manage human fatigue. The manipulability metric is exploited to reduce the probability of getting fatigued, while the muscle fatigue metric is used to react when fatigue cannot be prevented.

There are two main approaches to arbitrate the percentage of human and robot involvement in a common task: the binary arbitration [6], [7], and the continuous arbitration [8], [25]. The main advantage of binary arbitration is clear attribution of task performance, i.e., either fully robot or fully human, and we know exactly who is responsible for good or bad task execution [26]. However, changes between the states can be too significant for the user to adapt to them quickly. On the other hand, continuous arbitration provides smooth transitions between the percentage of human and robot involvement. However, human has to constantly adapt the effort according to the arbitration, leading to an unnecessary additional workload. Thus, the proposed arbitration method tries to strike a middle ground by considering a trade-off between the binary approach and the continuous approach.

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