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Shared Autonomous Interface for Reducing Physical Effort in Robot Teleoperation via Human Motion Mapping

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***Abstract*— Motion mapping is an intuitive method of teleoperation with a low learning curve. Our previous study investigates the physical fatigue caused by teleoperating a robot to perform general-purpose assistive tasks and this fatigue affects the operator's performance. The results from that study indicate that physical fatigue happens more in the tasks which involve more precise manipulation and steady posture maintenance. In this paper, we investigate how teleoperation assistance in terms of shared autonomy can reduce the physical workload in robot teleoperation via motion mapping. Specifically, we conduct a user study to compare the muscle effort in teleoperating a mobile humanoid robot to (1) reach and grasp an individual object and (2) collect objects in a cluttered workspace with and without an autonomous grasping function that can be triggered manually by the teleoperator. We also compare the participants' task performance, subjective user experience, and change in attitude towards the usage of teleoperation assistance in the future based on their experience using the assistance function. Our results show that: (1) teleoperation assistance like autonomous grasping can effectively reduce the physical effort, task completion time and number of errors; (2) based on their experience performing the tasks with and without assistance, the teleoperators reported that they would prefer to use automated functions for future teleoperation interfaces.**

I. Introduction

Tele-nursing robots are expected to perform a wide range of patient-caring tasks. The objects manipulated in tele-nursing tasks range from large, bulky, heavy objects (e.g., blankets, linens, patient transfer bed, etc) to small, light objects (e.g., medicine containers, used syringes), which vary greatly in their physical properties (see Fig. 1). In such an intricate and hazardous environment, teleoperation is a practical way for tackling the complexity of tele-nursing tasks and protecting the safety of both the patients and healthcare workers. Compared to other teleoperation interfaces (e.g., joysticks [1], a stylus based device with haptic feedback [2], graphical user interface [3], etc), mapping human motion is more intuitive and effective to control the multiple degrees of freedom of the humanoid robot simultaneously. Furthermore, it is suitable for freeform teleoperation which can perform unstructured tasks, like collecting a mixture of deformable and rigid objects in a cluttered workspace. Such tasks are challenging for fully automated systems. However the physical fatigue caused due to robot teleoperation via a motion mapping interface is not trivial, particularly when teleoperation lasts for extended durations. Such physical workload not only influences the teleoperator's task performance, but may also negatively influence the worker's perception and attitude towards the usage of teleoperation interface as well as nursing robot technologies.

This paper will investigate how shared autonomy reduces the physical fatigue incurred while using the motion mapping teleoperation interface. Shared autonomy for teleoperation assistance has been used to enhance the functionality of the slave platform [4] and improve the accuracy of robot teleoperation [5]. The design and evaluation of the teleoperation assistance mostly focuses on how it can influence the task performance and fluency of human-robot teaming [6], the cognitive workload [7], situational awareness [8] and trust of the operators. However, limited work has been done to design shared autonomy which considers the effects of physical fatigue in teleoperation and thus improve the "ergonomics of teleoperation assistance". To fill this gap, we will explore how to use shared autonomy to manage the physical workload in freeform teleoperation. Based on our prior work on assessing the physical fatigue in robot teleoperation using the motion mapping [9], we will evaluate the benefits of teleoperation assistance on reducing muscle effort while improving accuracy and efficiency of freeform teleoepration.

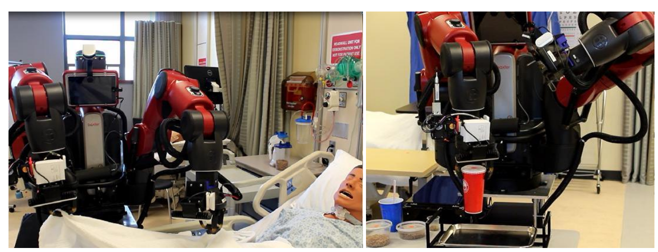

Fig. 1: Tele-nursing robots perform a variety of patient-caring tasks including cleaning and food delivery.

Our prior research [9] identified the fatigue causing actions by assessing the muscle effort while using the whole-body motion mapping teleoperation interface to perform general assistive tasks. Precise manipulation and steady posture maintenance were identified as actions that caused physical fatigue. Our prior work identified the Deltoids, Biceps and Trapezius muscles as the most used and fatigued muscles during these precise teleoperation tasks. Based on our findings, we hypothesize that automating the fatigue-causing task components will reduce the physical effort of teleoperation via motion mapping. We evaluate our hypothesis with the implementation of a manually triggered autonomous grasping function to assist object grasping during teleoperation. Our

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user study (N=8) helped us conclude that, (1) this simple autonomous grasping function can effectively reduce the user's physical and cognitive workload; (2) the proposed teleoperation assistance is more effective and less error-prone for both the dominant and non-dominant hands; (3) the comparison of robot teleoperation with and without assistance shapes the user's preference towards the usage of teleoepration assistance and improves their acceptance of using teleoperated robot technologies.

II. Related Work

A. Tele-action Assistance for Motion Mapping Interface

Various motion mapping interfaces have been proposed for real-time and offline teleoperation, particularly for the teleoperation of humanoid robots, bimanual and mobile manipulators (e.g., [10]–[12]). The interfaces range from the more expensive but accurate systems (e.g., Vicon motion capture systems [13]) to more affordable and portable options like Microsoft Kinect and other RGB-D cameras [14], Inertial Measurement Unit (IMU) sensors [15], whole body motion capture suits [16] and virtual reality headsets and controllers [17]. The motion mapping interface promises to be the future of intuitive and effective teleoperation for complex robot systems in various domains. However, it is necessary to develop appropriate teleoperation assistance for such teleoperation interfaces to mitigate the risk of work-related musculoskeletal disorders caused by the non-trivial physical workload that occurs due to extended robot teleoperation.

Within the spectrum of automation ranging from fully manual to fully automated, *action support* and *shared control* are often used to assist freeform teleoperation using motion mapping interfaces (for a review of levels of robot autonomy, see [18]). *Action support* like tremor filtering [19], obstacle avoidance [20] and precise orientation assistance [21], usually assists the execution of a selected action. Shared control is mostly used to assist the operator in actions towards a goal or generating motion along certain trajectories. Rakita et. al. have recently developed teleoperaion assistance for a motion mapping interface which uses a predict-then-act strategy where the implementation infers an action based on a bimanual action library and engages an appropriate assistance mode to enhance efficiency [22]. This implementation blends the suboptimal user translational and rotation control inputs with known translation and rotation paths in space in which the user can easily guide the robot. Laghi et al [23] combined arm motion tracking, impedance control and hand gesture recognition for using a single arm of the operator to perform bimanual manipulation. In this paper we propose to use a manually-triggered autonomous function to assist precise grasping such that the teleoperators will not be constrained to follow a specific task structure or trajectory.

As workload is an essential factor in robot teleoperation, both subjective and objective methods have been proposed to comprehensively evaluate the mental and physical workload. Most of the subjective measurement for both mental and physical workload relies on user surveys [7] like NASA Task Load Index [24] and customized questionnaires. The commonly used objective metrics for mental workload is heart rate measurement which increases with increase in cognitive workload [25]. Limited work have used quantitative and objective metrices to assess and monitor the physical workload in robot teleoperation via motion mapping.

B. Physical Workload Assessment and Management

Over the years, several methods have been utilized to identify fatigue. Physical fatigue has been analyzed by observing jerk in human motion [26], changes in joint torque patterns [27] and human model simulations [28]. Surface based EMG (sEMG) sensors are a common tool used to identify muscle effort by monitoring the chemical changes in the muscle during motion [29]. sEMG based measurement is a non-intrusive and real-time method that can help identify the muscle activity of a particular muscle group, thereby helping segregate muscle activity during teleoperation.

A study by Liu et al [30] shows that physical fatigue negatively affects the quality of teleoperation. Hubert et al [31] report higher workload and physical strain in teleoperation without robot assistance than with robot assistance based on electromyography measurement. Regarding physical fatigue management, Peternel et al [32] have developed a co-manipulation interface that varies the support provided by the robot based on the user's EMG muscle activity and force exerted during operation. When muscle activity goes beyond a pre-defined threshold the robot will take actions to reduce fatigue by increasing support. This interface ensures that the robot performs almost autonomously when the user is fatigued giving time for the operator to recover. Nevertheless, limited work has been done to manage the physical fatigue in teleoperation, especially for a whole-body motion mapping teleoperation interface. Our previous work has used sEMG-based measurement and analysis to assess muscle effort in motion mapping teleoperation and identified that actions involving precise manipulation and steady postures caused the most fatigue [9]. In this paper, we further assess whether the user's muscle effort will be reduced if the motion mapping teleoperation is implemented with an autonomous grasping function.

III. Platform and Teleoperation Assistance

Here we describe the robot platform, the design of the whole-body motion mapping interface and the autonomous function for teleoperation assistance. The Tele-Robotic Intelligent Nursing Assistant (TRINA) (Fig. 2) consists of a dual-armed humanoid torso (Rethink Robotics Baxter), an omnidirectional mobile base (HStar AMP-I) and two three-fingered grippers (Righthand Robotics ReFlex grippers). The visual sensor suite of this nursing robot includes a 180° fisheye camera on the head, a Microsoft Kinect 2 attached to the robot's chest and two Intel RealSense D435 depth cameras attached to the robot's wrists. Table I defines the controls for the motion mapping interface. Motion capture of the teleoperator is done using the Vicon motion capture system (10 Vero cameras). This system captures passive

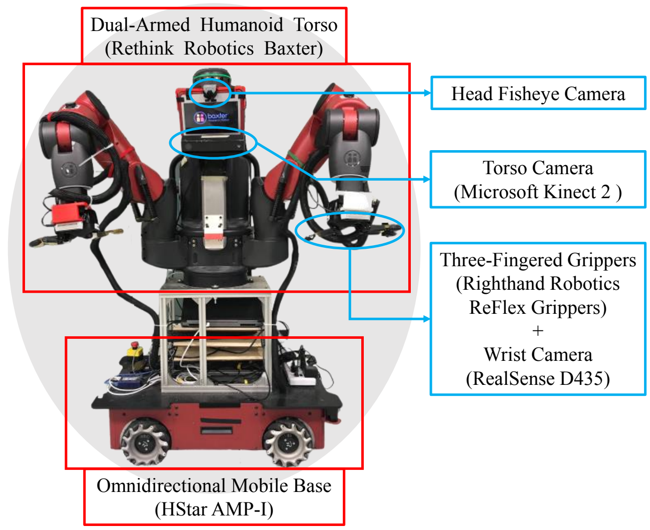


Fig. 2: Tele-robotic Intelligent Nursing Assistant (TRINA) system.

reflective makers attached to the human torso, arms and legs. The users thus control actions like reaching, grasping, locomotion of the mobile humanoid robot, the selection of cameras and the movement of these cameras. Human motion was captured at 100 Hz and streamed at 50 Hz for robot control. The proportions of the subjects (height, limb lengths, etc) do not affect the end-effector positions of the robot. This is because the position and orientation of the wrist and the swivel angle of the teloperator is mapped to the robot during teleoperation. The swivel angle is defined as the rotation of the position of the elbow of the operator with respect to the axis connecting the centers of the shoulder and wrist joints [33], which indicates the operator's arm posture.

Teleoperation Input	**Robot Function**
Robot's Upper Body	
Hand position & orientation	End-effector position & orientation
Arm posture & orientation	Manipulator arm posture
Rotate upper body	Rotate mobile base orientation
Hand open/close	Gripper opens/closes
Angle between feet $\geq 60^o$	Gripper preshape pinch grasp
Angle between feet $< 60^o$	Gripper preshape power grasp
Right shank flexion	Activate teleoperation assistance
Robot's Lower Body	
Squat	Engage/Disengage teleoperation
Lift left leg	Switch primary camera view
Lift right leg	Switch secondary camera view
Leg steps forward/backward	Mobile base moves front/back
Left (right) leg steps left (right)	Mobile base moves left (right)

TABLE I: Motion Mapping Teleoperation Interface.

The flowchart in Fig. 3 describes the design of the autonomous grasping function for teleoperation assistance. The Kinect camera detected all the objects to grasp in the workspace using Mask-RCNN [34], [35]. As the teleoperator controls the robot hand to reach into the Teleoperation Assistance Zone (TAZ) — a bounding box of $(2 \times height) \times (3 \times thickness) \times (5 \times width)$ (cm^3) around the center of an object, the object will be locked as the "target", and an autonomous reaching-to-grasp motion will be planned for this object. Based on the bounding box created by the computer vision module, points on the mid-point of the left and right sides of the box were identified as the target grasping points. According to which robot arm is in the TAZ, the corresponding nearest target point is selected. If both the arms are in the TAZ, the right hand is selected by default to move to the target point on the right side of the bounding box. The inverse kinematics for this target location is solved and the joints of the selected robot arm are moved to these desired joint angles. The user is informed that the autonomous grasp function is ready to be triggered based on auditory and visual cues (Fig. 4).

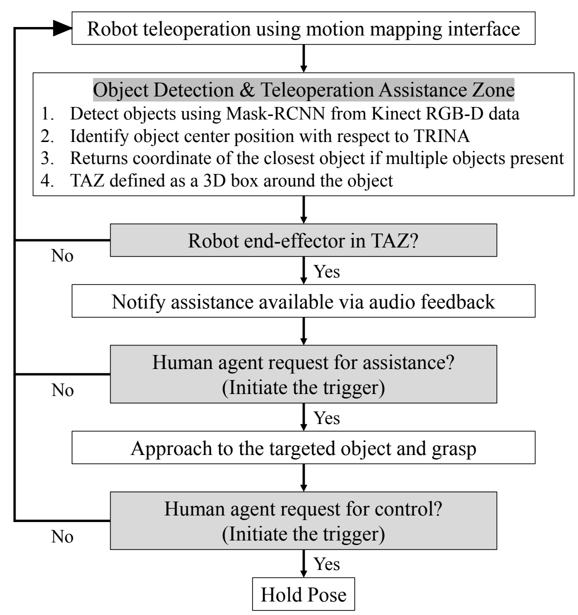


Fig. 3: Autonomous Grasping Function for Teleoperation Assistance.

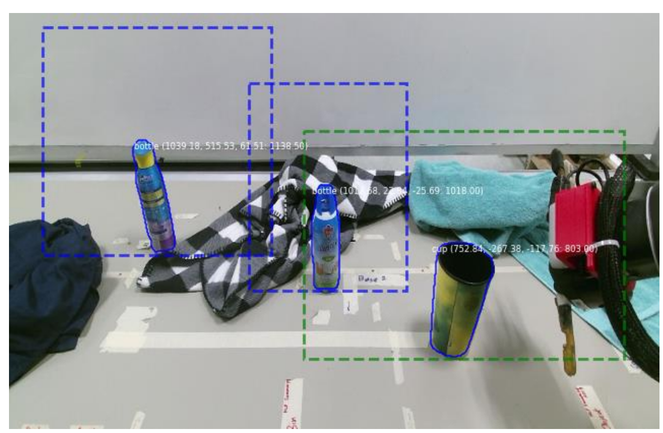


Fig. 4: Demonstration of object detection in cluttered environment.

IV. Experiment

Our user study aims to evaluate if the teleoperation assistance will reduce the physical workload and improve the task performance of robot teleoperation via whole-body motion mapping interface. The hypotheses we evaluate include:

Hypothesis 1: *The proposed teleoperation assistance will reduce the teleoperator's task completion time, number of* *errors, physical workload in terms of muscle effort and cognitive workload.*

Hypothesis 2: *Teleoperators will prefer to use the teleoperation assistance based on their experience performing the tasks with and without teleoperation assistance. With teleoperation assistance, users will prefer to work more with the teleoperated robots in the future.*

A. Participants and Tasks

We recruited N=8 participants (6 male and 2 female, all right-handed) to use the teleoperated robot system described in Section III to perform the following tasks: (1) reaching to grasp an individual object, and (2) grasping multiple objects in a cluttered workspace (see Fig. 5). We choose these tasks because precise orientation control in reaching-to-grasp has been demonstrated to be challenging for teleoperation and requires careful design of teleoperation interface assistance (e.g., [36]). Our prior work has indicated the teleoperation of precise manipulation is one of the most fatigue-causing factors.

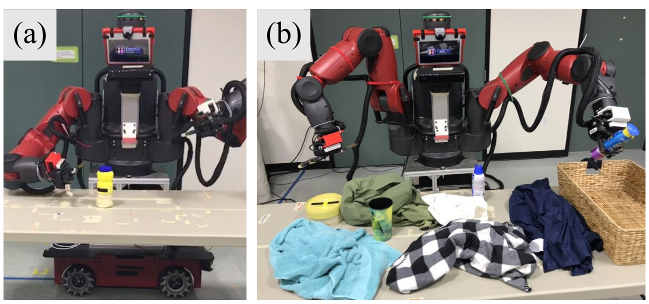


Fig. 5: Teleoperation tasks: (a) reaching-to-grasp an individual object; (b) collecting multiple objects in a cluttered counter workspace.

B. Experiment Procedure

a) Preparation: Our experiment uses EMG-measured muscle effort to assess the physical workload. Before the experiment, each participant performs a maximum voluntary contraction (MVC) test for each muscle. The collected data is used for normalizing the EMG signal with respect to the maximum force generated by each muscle [37]. Each participant undergoes a training session to get familiar with the teleoperation interface, the autonomous grasping function and the robot. The training task is to pick up a bottle on the counter and place it in a basket. The participants are allowed to practice in this traning session until they feel confident and comfortable to use the teleoperation interface and assistive function.

b) Session 1 — Object Grasping: In this session, a participant was instructed to reach and grab a bottle placed on the counter (Fig. 5). The participants were asked to grab the objects for five repetitions, using their dominant and non-dominant arms, with and without the teleoperation assistance (Total number of trials = 5 repetitions $\times$ 2 arms $\times$ 2 modes). The order of arms and modes were randomized. All the repetitions of the object grasping task were set to have the same initial robot arm configuration, initial and final location of the object. The participants were required to pick up and place the object in a stable manner. During each trial, we record the time for completing the task, the number of times the object was knocked down and the EMG signal of the muscle groups for muscle effort analysis (described in Section IV-C). The participants also answered survey questions about their teleoperation experience, in the NASA Task Load Index (NASA-TLX) format on a 1-7 Likert scale.

c) Session 2 — Cleaning the Workspace: In this session, the user has to pick up three cylindrical objects in a cluttered workspace and place it in a basket (see Fig. 5(b)). This task was to simulate a real-world scenario in which a nursing robot needs to clean and organize a workspace with medical supplies, patient room debris and laundry (as the tasks identified in [38]). The participant was allowed to choose between picking up the object manually or using teleoperation assistance. If the object was dropped they are allowed to pick it up unless the object falls off the counter. We counted the number of times that the user uses teleoperation assistance. We also scored the participant's task performance in the following way: (1) +10 points for picking up each object and placing it in the basket; (2) -20 points for knocking an object down or dropping an object when moving it to the basket.

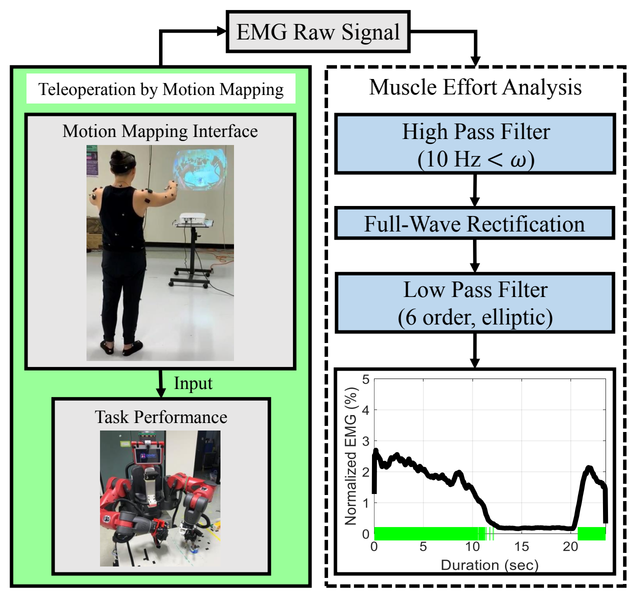
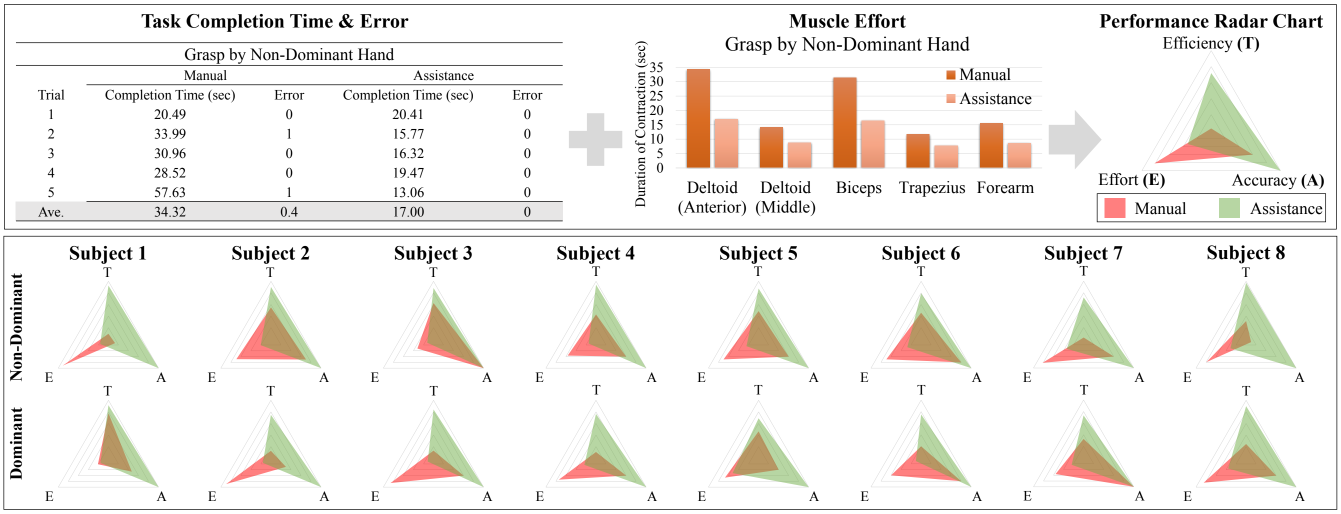


Fig. 6: Muscle efforts analysis process.

C. Muscle Efforts: Data Collection and Analysis

We used Wireless sEMG sensors (Trigno^{TM} from Delsys Inc.) to record the EMG signals at 1,000 Hz for 10 individual muscles, namely the Anterior and Middle fibers of the Deltoid, the Biceps, the Brachioradialis and the Trapezius of the left and right sides of the body. These muscles were selected as they are the most involved in controlling human upper body motion.

Our analysis of the sEMG data aims to evaluate individual muscle effort during teleoperation using motion mapping



Task Completion Time & Error

	Grasp by Non-Dominant Hand			
	Manual		Assistance	
Trial	Completion Time (sec)	Error	Completion Time (sec)	Error
1	20.49	0	20.41	0
2	33.99	1	15.77	0
3	30.96	0	16.32	0
4	28.52	0	19.47	0
5	57.63	1	13.06	0
Ave.	34.32	0.4	17.00	0

Fig. 7: Performance evaluation procedure and summary for object grasping across all subjects.

with and without the assistance feature. Fig. 6 illustrates our data analysis process where we have determined individual muscle contraction levels and contraction duration. In the graph on the bottom right the black line represents the muscle contraction and the green bars collectively represent the contraction duration.

The recorded EMG signals are within the 40 Hz-700 Hz range in the spectrum domain. In the muscle effort analysis, the raw EMG data was pre-processed using a high pass filter (cutoff frequency 10 Hz), to remove the soft tissue artifact and offset the frequency baseline. The processed signal further went through a full wave rectification and then a sixth order elliptical low pass filter (cutoff frequency 50 Hz), to remove noise and transients and develop a linear envelope of the EMG signal [29]. Using the method in [29], we determine the appropriate threshold for muscle contraction to be the signal baseline offset by thrice the standard deviation of the muscle static contraction obtained from the first 200 frames of the EMG signal in the MVC test.

V. Results and Discussion

We compared the muscle efforts, task completion time and numbers of errors in Session 1 (object grasping task), to objectively and quantitatively assess the teleoperators' physical workload reduction when using teleoperation assistance. We further use the results from the NASA-TLX survey and customized questionnaires in Session 1 and 2 to assess their perception of workload, preference of teleoperation assistance and their change of attitude toward teleoperated robot technologies.

A. *Performance and Efforts of the Object Grasping Task*

*a) **Objective Indices**:* Fig. 7 illustrates how we computed the indices for rating the teleoperator's efficiency, accuracy and effort in Experiment Session 1 (object grasping task). For *Efficiency* (T) and *Accuracy* (A), we averaged task completion time and the number of errors across all five repetitions in the four discrete conditions (with and without assistance, and for both the dominant and non-dominant hands). The *Effort* (E) is measured by the mean contraction duration for all the muscle groups. For each participant, these three indices were then normalized to range between 0 and 1, with respect to the the difference between maximum and minimum values across all the conditions. Fig. 7 also compares the performance Radar Charts across participants. Overall, the teleoperation assistance improves the task *Efficiency* and *Accuracy* for all the participants and for teleoperation using both the non-dominant and dominant arms. The reduction of **Effort** is more prominent and consistent for the non-dominant arm across the teleoperators.

Our ANOVA analysis further reveals the improvement in task Efficiency and Accuracy when using teleoperation assistance for the object grasping task. This can be seen by the recorded task completion times (non-dominant arm: $F(1,12)= 33.87$, $P< 0.01$; dominant arm: $F(1,12)= 52.35$, $P< 0.01$), number of errors (non-dominant arm: $F(1,12)= 6.02$, $P< 0.05$; dominant arm: $F(1,12)= 9.85$, $P< 0.01$) and duration of muscle contraction (non-dominant arm: $F(1,12)= 5.93$, $P< 0.05$; dominant arm: $F(1,12)= 7.93$, $P< 0.05$). Overall, grasping without teleoperation assistance took 13.3 seconds longer for the non-dominant arm and 11.9 seconds longer for the dominant arm on average. This is mostly because the teleoperation assistance reduced the risk of knocking down the object during grasping and the effort for precise manipulation.

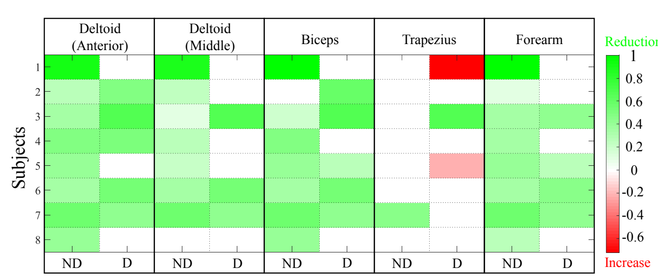


Fig. 8: Comparison of physical effort across all muscles with dominant (D) and non-dominant (ND) hand.

We further compared the muscle efforts between teleoperation with and without the assistance across all muscle groups for each participant. As shown in Fig. 8, most of the muscles had a significant reduction in physical effort (marked as green) with a higher level of relaxation for the deltoids and biceps of the dominant/non-dominant hand. The different levels of muscle effort was calculated using the Kullback-Leibler (KL) divergence measurement and all the results were normalized by the maximum value. It is noted that the Trapezius muscle however has reduced reduction (marked as white) or increased physical effort as shown by the red marks for 2 subjects. Overall, the assistance function performed equally effectively on both arms for all subjects thus validating **Hypothesis 1**. Even if there was a variation between the subjects (the second half of Fig. 7), most of them still performed better using teleoperation assistance and we believe that a greater sample space of users would reinforce this conclusion.

		Mental		Physical		Temporal		Performance		Effort		Frustration	
		Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
ND	Manual	3.25	1.713	3.75	1.391	2.875	1.268	3.875	1.615	3.5	1.5	2.375	1.727
	Assistance	1.625	0.856	1.75	0.433	2	1.322	2	1	1.75	1.089	1.375	0.484
D	Manual	3.5	1.870	3.625	1.727	2.75	1.47	3	1.118	3	1.5	2.25	1.479
	Assistance	1.875	0.780	1.75	0.661	1.875	0.927	2.125	0.927	1.75	0.829	1.625	0.695

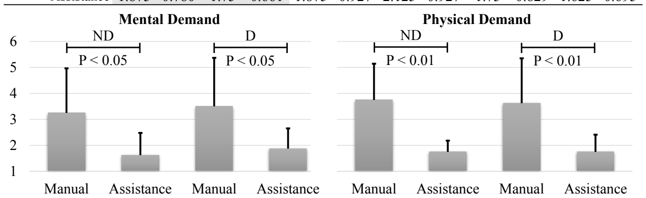


Fig. 9: Results of subjective survey from NASA-TLX.

*b) **Subjective Indices**:* We also used NASA-TLX survey with 1-7 Likert scale to evaluate the teleoperators' perception of task performance and workload. Shown in Fig. 9, the teleoperators have answered the survey in support of the usability of the assistance function. Without assistance the operators rated the mental demand to be 3.25 ± 1.713 and 3.5 ± 1.87 for the non-dominant and dominant hands respectively. With assistance the users rated the mental demand to be 1.625 ± 0.856 and 1.875 ± 0.78 for the non-dominant and dominant hands respectively. The lower mental demand rating for the assistance function is understandable as there was no errors during operation and the need to manually execute the precise manipulation to perform grasping is eliminated. Thus, we have validated the reduction of cognitive workload in **Hypothesis 1**. Additionally, as the assistance function reduces the duration of muscle contraction the mental fatigue incurred due to teleoperation also reduces. As a result the operation times are reduced as there are no errors and user motion is more efficient. The users may have reported reduced physical workload in their surveys as a result of these advantages.

B. Preference of the Teleoperation Assistance

In Experiment Session 2, participants were allowed to choose whether or not to use the teleoperation assistance to pick and place objects. Table II compares the teleoperators by the number of instrances they used teleoperation

	Performance of Collecting Task									
	Objects Picked		Points-Pick up		Points-Drop in bin		Penalty-Drop Object		Total	
Subject	Manual	Assistance	Manual	Assistance	Manual	Assistance	Manual	Assistance	Manual	Assistance
1	0	3	0	30	0	30	0	0	0	60
2	2	1	30	10	20	10	-20	0	30	20
3	0	3	0	30	0	30	0	0	0	60
4	2	1	10	10	10	10	-20	0	0	20
5	1	2	10	20	10	20	0	0	20	40
6	2	1	20	10	10	10	-40	0	-10	20
7	1	2	10	20	0	20	0	0	10	40
8	0	3	0	30	0	30	0	0	0	60
Sum	**8**	**16**	**80**	**160**	**50**	**160**	**-80**	**0**	**50**	**320**

TABLE II: Performance of score system for collecting three objects.

assistance with their task scores. Overall, we found (1) more participants prefer to use teleoperation assistance, and (2) with the teleoperation assistance their task scores are much higher than the participants who performed the tasks more manually.

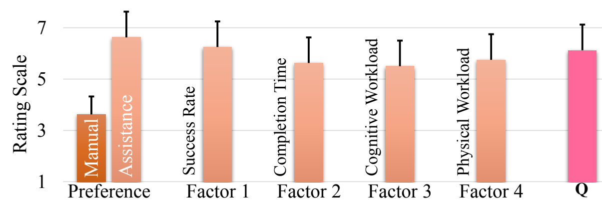


Fig. 10: Rating of preference.

After Experiment Session 2, participants rated in hindsight their preference for teleoperation assistance and manual control during robot teleoperation. As there was a greater preference for the assistive function, the users were questioned on what factors made them favor teleoperation assistance more. They were asked to state to what extent the teleoperation assistance can (1) increase the success rate; (2) reduce the task completion time; (3) reduce the cognitive workload; and (4) reduce the physical workload based on their experience on a 1-7 Likert scale with 1 being the least and 7 being the most in terms of agreement. Finally, we evaluate their acceptance of using teleoperated robot technologies by asking the question (Q): "With the teleoperation assistance, do you prefer to work more with teleoperated robots?". The results represented in Fig. 10 highlight the participant's belief that teleoperation assistance improves performance. This further supports **Hypothesis 2**.

VI. Conclusion and Future Work

This paper has demonstrated that with a simple manually-triggered autonomous grasping function teleoperation assistance can effectively reduce the physical workload and improve the efficiency and accuracy of the motion mapping teleoperation interface. This increases the users' preference for using teleoperation assistance and the acceptance for teleoperated robot technology. The work in this paper is limited to a specific robot platform and motion mapping interface design. Our future work will evaluate more advanced shared autonomy for teleoperation assistance and alternate motion mapping teleoperation interfaces focused on reducing physical workload. We will also test the teleoperation assistance technology in a more realistic patient-caring and home-caring tasks with nursing workers and students as the users.

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