Assessment of Physical Fatigue in Robot Teleoperation during Complex Motion Coordination Tasks

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I. Introduction

Teleoperated robotic systems are widely used for extending and augmenting the physical and cognitive capabilities of humans in various tasks [1]. This combination of robot power and precision with human dexterity and decision-making enables performance of complex tasks in unstructured environments [2, 3], while maintaining a greater degree of safety than using human agents [4] and a higher success rate than purely autonomous robots [5, 6]. Teleoperation also lends itself to robot learning from human teachers, permitting simultaneous task performance and learning [7]. Through teleoperation interfaces, operators can demonstrate high-level task structure, human preference, and low-level motion primitives for robot motion coordination (refer to [8] for a review).

Many teleoperation interfaces have been developed for robotic systems, and are summarized in [9]. Common examples include hand-held game pads and joysticks, exoskeletons, and motion capture systems. High degree-of-freedom humanoid robots may require a multi-modal combination of interface components for full control. While these systems are often ideal for performing a wide range of motion coordination tasks in cluttered human environment, controlling and/or teaching humanoid robots can be both cognitively and physically demanding [8]. Despite a large field of study in ergonomic factors in the workplace [10], little research has investigated the fatigue in humanoid robot teleoperation.

In this paper, we propose a study to evaluate teleoperation interfaces in the performance of complex motion coordination tasks on the basis of *operator physical fatigue*. We present a methodology to investigate physical fatigue while using different teleoperation interfaces to perform tasks using a humanoid robot, and compare the estimation of fatigue with the overall performance across interfaces and tasks. We aim to use the results of the fatigue analysis to inform the design of efficient user interfaces and teleoperation strategies that complement the physical limitations of the operator.

II. Related Work

Human Performance in Teleoperation — Research on human performance in robot teleoperation has investigated the workload that leads to physical and mental fatigue [11–13]. The assessment of physical and cognitive workload has been used to inform the design of user interfaces [14], and to compare effectiveness of different levels of autonomy [13]. Thus far, the evaluation of operator workload has relied heavily on subjective ratings. Self-reported ratings (such as the NASA-Task Load Index) are used to investigate the effects of operator expertise, task familiarity, task structure, and other factors on the perceived workload of the operator (e.g., [15]). Recently developed interfaces enable robot teleoperation through a variety of input devices, including motion capture systems. As the human body becomes more involved in robot teleoperation interfaces, the increased physical workload and fatigue needs to be evaluated to appraise the teleoperation interface usability. Previous research efforts (see [16]) assessed the usability of different interfaces (voice control, motion tracking) on the Robonaut to minimize operator workload using subjective ratings. However, the fatigue measurement approach was intrusive, requiring the operator to break away from the task implementation to respond to the survey. In addition, objective and quantitative assessment of the teleoperator's physiological states are necessary for understanding the development of fatigue in the teleoperation of complex motion coordination.

Physical fatigue measurement — Researchers have proposed means of evaluating and estimating physical fatigue through non-invasive sensors such as surface electromyography (sEMG) sensors [17]. This is based on the established finding that certain changes in the temporal and spectral characteristics of the EMG signal from a muscle correlate with fatigue build-up within the muscle [17, 18]. In this context, physical fatigue relates to the transient inability of the muscle to sustain optimal performance. Existing methods for estimation of physical fatigue from sEMG include spectral analysis, which is assumed to be limited to isometric contraction scenarios [19], and time-frequency analysis, which is more robust in dynamic tasks [20]. In occupational ergonomics, accurate estimation of physical fatigue has motivated the improved design of operator workspaces and tools [21]. [22] proposed a method to assess physical fatigue during robot-assisted rehabilitative therapies using sEMG. They found that accurate fatigue estimation can advance the design of safer rehabilitative devices.

III. Proposed Methodology

We propose a study in which novice human operators complete complex motion coordination tasks through three distinct teleoperation interfaces, while biofeedback, kinematic, and self-reported data is recorded. The resulting data will be

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analyzed using three fatigue models proposed in literature to describe the evolution of fatigue in tasks with different motion features and using different teleoperation interfaces.

The study will be performed using the TRINA (Tele-Robotic Intelligent Nursing Assistant) platform as the robot agent, described in section III-A. The tasks to be performed by the operator-agent team are enumerated in section III-B, and the data analysis pipeline is presented in section III-D.

A. System Setup

We have prepared the teleoperation system architecture for the study as shown in Fig. 1. The TRINA robot hardware includes a bimanual humanoid robot torso with two, seven-DOF manipulators (Rethink Robotics' Baxter) mounted on an omnidirectional mobile base (HStar AMP-I). A three-fingered hand (Righthand Robotics' Reflex Hand) is fitted onto both robot arms for complex object manipulation. For perception, two cameras (Intel RealSense SR300) are fitted to the wrists of the robot, accompanied by the built-in head camera on the Baxter robot, and a third-view camera looking at the robot and the workspace. In our operator console, the following teleoperation interfaces have been set up for our experiment: (1) marker-based motion capture (Vicon Motion Capture System), (2) haptic control device (OMNI Geomagic Touch), (3) gamepad (Logitech F710). The operator console also supports voice control for switching camera views.

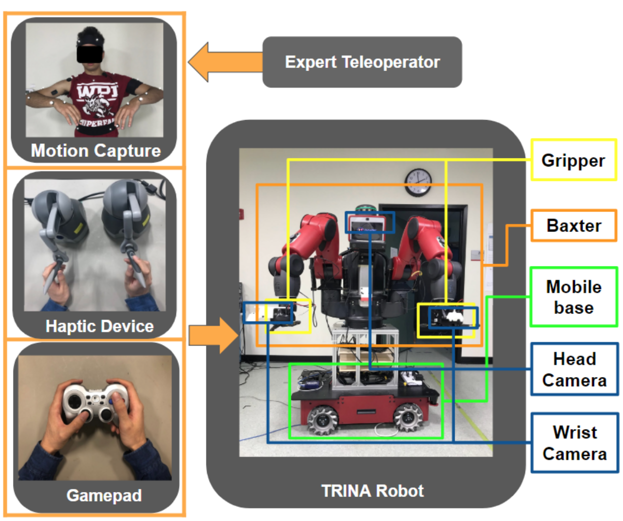

Fig. 1: TRINA robot with three teleoperation interfaces: direct motion mapping using motion capture, haptic device and gamepad

B. Experiments

To assess the progression of fatigue in humanoid robot teleoperation, we propose a human motion study involving 10 subjects performing teleoperation task sets that demonstrate a range of motion features. Specifically, we focus on the level of motion precision, the requirement for locomotion, and the need for bimanual coordination. These features describe a broad set of motor skills that may be necessary in any teleoperated task. We classify the motions as fine (**F**) if the grasp, motion trajectory, or placement is highly constrained, otherwise the motion is gross (**G**). If the task requires moving the robot base during execution, it is a locomotion task (**L**), otherwise it is stationary (**S**). Finally, if the task requires moving or coordinating two hands simultaneously, it is bimanual (**B**), otherwise it is unimanual (**U**). For this study, we select two task sets that are common in home-care, although the skills are broadly applicable to many teleoperation roles. The tasks are described in Table I.

Laundry Task	
Collect "dirty" laundry	GSU
Move laundry hamper (2 handles)	GLB
Move towel basket (1 handle)	GLU
Fold towels	FSB
Move towel stack to shelf	FLB
Grocery Task	
Unpack grocery bag	FSU
Store items on shelf	GLU
Retrieve items from fridge	GLB
Set the table	FSB
Hand over cooking tools	FSU

TABLE I: Teleoperation task sets and motion features

C. Procedure

Each subject will be asked to complete six sessions in this experiment. A session includes completing one of two tasks sets (see Table I) using one of three teleoperation interfaces (see section III-A). We will attach EMG and IMU sensors (Trigno EMG, Delsys, Inc) to the active muscle groups in the upper limbs of the subject to record both EMG signal data and motion data during the sessions. Sensor placement will be consistent with SENIAMs (Surface ElectroMyoGraphy for the Non-Invasive Assessment of Muscles) recommendation [23]. Sufficient rest times will be provided between sessions to prevent cumulative fatigue over the study. Subjects will also provide a self-assessment of fatigue using the local perceived discomfort (LPD) survey [24].

D. Data Analysis

We will analyze the EMG and motion data recorded across each session using multiple fatigue analysis methods, as well as the subject's self-reported fatigue evaluation. The EMG data collected will be band-pass filtered at 5-100Hz, rectified and low-pass filtered (with cut-off frequency of 20Hz) to eliminate noise and transients. This preprocessed EMG data is then used in our fatigue analysis. Existing methods proposed in literature for fatigue analysis include time-domain analysis, spectral analysis and time-frequency analysis. In this study, we employ three different methods as follows:

a) Spectral fatigue index: Spectral analysis method evaluates the effects of fatigue on the EMG signal by computing the ratio of different spectral moments of the power spectral distribution. Dimitrov *et al* has shown that best results are obtained when a ratio between the spectral moments of order -1 and 5 is used [25]. This is because the moment of order -1 reflects the increments in low frequencies in the signal whereas moments of order 5 emphasize the decrements in the high frequencies. This index has been shown to have higher sensitivity to mapping fatigue than traditional metrics such as the median and mean frequencies.

b) Instantaneous mean frequency (IMF): Bonato *et al* proposed an index calculated over time-frequency distributions of the EMG signal [26]. Time-frequency analysis were introduced because the assumption of stationarity may not hold when recording EMG signals in dynamic contractions. The continuous wavelet transform has been shown to have the best accuracy in mapping changes in EMG signals to fatigue [19, 20]. In IMF, the mean frequency of the signal over the time-frequency spectrum is computed at each instant of time. A decrease in the IMF over time would reflect build up of fatigue in the muscle.

c) Dynamic fatigue model: The fatigue model proposed in [27] is inspired by the first-order dynamics of an RC circuit. One limitation of the model is that it may not possess high bio-fidelity in its computation, however, it lends itself to real-time fatigue estimation which has very promising applications in human-robot interaction. The fatigue in the muscle is modeled to increase based on the current effort exerted by the muscle, which is estimated from the RMS of the EMG signal. Other parameters such as the muscle capacity and recovery rate are subject specific and, hence, computed experimentally [27].

We will compare the resulting fatigue estimations across teleoperation interfaces and task features to identify trends in operator fatigue.

IV. Future Work

This paper proposes a study to investigate the development of fatigue in robot teleoperation for a range of complex motion coordination tasks, and a method to inform the selection or design of teleoperation interfaces to support the needs of a teleoperator in a particular task procedure. Given the assessment of physical fatigue in teleoperation, our future work will consider (1) shifting the control in the range from direct human teleoperation to robot autonomy, (2) distinguishing good and bad demonstrations in the robot teaching through teleoperation interfaces, and (3) adjusting the level of cognitive assistance for teleoperators.

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