SENSITIVITY OF EYE-TRACKING MEASURES TO VARIATIONS IN MENTAL WORKLOAD WHILE LEARNING TO OPERATE A PHYSICALLY COUPLED ROBOT

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Collaborative robots are becoming more usable, versatile, and even becoming operable in close proximity with humans in a variety of industrial settings. However, the mental workload and motor-skill learning associated with operating these devices needs to be understood. We are presenting our work in progress whose aim is to investigate the sensitivity of eye-tracking as a potential measure of workload over the course of learning to use a physically-coupled robot for an object-manipulation task. Our hypothesis is that pupil diameter and blink rate will be elevated, and eye-hand span and target-locking score will be reduced, during initial practice of difficult task conditions. This work is also expected to help identify which eye-tracking measures can best characterize individual rates of adaptation to novel motor tasks. In the long-term, this work can facilitate the development of adaptive learning algorithms that modulate task difficulty to maintain a learner in an optimal state of workload and motor-learning.

INTRODUCTION

Recent developments in robotic control algorithms and material design have ushered in a particularly exciting era for collaborative robots (cobots), which have grown much more usable, versatile, and safer to operate in close proximity with humans compared to older industrial robots (Haddadin & Croft, 2016). In fact, robotic exoskeletons, prosthetics, and some types of cobots remain in complete physical contact with the human operator, mimicking the operator's movements, often cooperating in the performance of a task, or augmenting strength, endurance and precision (Chen & Kemp, 2010; Zhu et al., 2020). In this context, it is important to understand the cognitive challenges involved in controlling these complex devices, and the learning/training needs for diverse operators to effectively utilize them. Recent research suggests that although cobots have achieved higher standards of safety and compliance, they can still impose a significant workload on the user's attentional and cognitive-motor resources (Chadwell et al., 2016; Stirling et al., 2020; Wu et al., 2019) and may require time and effort to learn (Cornwall, 2015; Parr et al., 2019). Thus, it is critical to develop metrics to quantify a user's mental workload for the safe and effective implementation of cobots, especially in environments that are inherently hazardous and safety-critical. This study aims to determine the sensitivity of eye-tracking measures to the changing motor-control demands associated with learning to use a physically-coupled robot, and to explore the extent to which eye-tracking can quantify motor learning rates during use of the cobot.

Background and Related Work

Understanding the dynamics of mental workload over the course of motor learning and continuous measurement of these constructs can help in designing learning/training protocols, and help minimize workload for users of cobots. Specifically, continuous measures of operator state can help design algorithms that adapt the behavior of cobots to best suit the operator's mental workload and level of skill at any given point (Brown et al., 2016; Koenig et al., 2011).

Learning a new skill, especially a 'motor' skill, requires a process called "Internal Model Formation" (Wolpert et al., 2011), in which the learner, with practice, gradually develops the ability to predict the sensory consequences or results of the physical actions associated with a skill. An enhanced ability to predict the results of one's own actions is a critical aspect of what formulates expertise in the task. Learning to use novel or complex tools is also characterized by the formation of new internal models for tool behaviors, as well as updating of the internal models for the limb controlling the tool (Wolpert et al., 2011).

Past research has shown that wearable robots such as myoelectric prostheses and powered exoskeletons tend to be difficult to use because the user cannot easily predict the devices' control dynamics (Chadwell et al., 2016; Cornwall, 2015; Kao, 2009). Similar difficulty in predicting robot behavior and an increased reliance on vision have been observed with other types of cobots, e.g. joystick-operated robotic arms (Aronson et al., 2018) and surgical robots (Law et al., 2004; Wu et al., 2019). Thus, we expect a high mental workload to be present during initial stages of learning as the user attempts to build an internal model of the device and movement (Sailer, 2005) and over the course of practice, mental workload is expected to attenuate due to refinement of neural processes and increasing automaticity in the task (Sailer, 2005; White & French, 2017).

Eye-tracking is a promising technique for measuring mental workload since it can provide both physiological measures, (e.g. pupil dilation, saccade velocity, workload indices) which correlate with the involuntary neural response to mental workload (Just et al., 2003), as well as eye-movement measures such as eye-hand span and fixation- and saccade metrics, which reflect voluntary gaze behavior and strategies based on motor task demands (Land, 2009; Srinivasan & Martin, 2010). Since mental workload is a multidimensional construct which is intricately related with attention, task performance, and strategies (Tsang & Vidulich, 2006), the ability of eye tracking to provide different types of information related to mental workload is advantageous. Importantly, eye-tracking measures have also been shown to track changes over the course of cognitive- and motor-skill learning (Sailer, 2005; Tinga et al., 2020; White & French, 2017). The versatility of eye-tracking, coupled with its increasing wearability and ubiquity (Cognolato et al., 2018) make eye-tracking a viable technology to implement in dynamic, real-world environments.

Although eye-tracking has been previously used to measure mental workload and visuomotor performance while using robotic devices, these studies have mainly focused on single-arm tasks, and specifically in the domain of prosthetics or laparoscopic surgery. Our goal here is on quantifying the sensitivity of eye-tracking measures to mental workload in a bi-manual task performed co-operatively using an industrial robot. Secondly, past studies on prosthetics and surgical robots have also only compared eye-gaze behavior between separate practice sessions e.g. (Sobuh et al., 2014) or between experts and novices e.g. (Law et al., 2004). Thus, there is a need for more fine-grained, trial-to-trial quantification of the changes in eye-gaze behavior, in pursuit of a continuous measure of mental workload.

Given this background, we propose a study with the following aims and hypotheses – Aim 1: To quantify the sensitivity of eye-tracking measures to performing a bimanual task at different levels of motor-task difficulty using a physically-coupled industrial robot. Hypothesis 1: Higher task difficulties will be associated with significant increase in pupil diameter and blink rate, and decrease in eye-hand span and target locking score (TLS). Aim 2: To explore and quantify the changes that occur in eye-tracking indices of workload and visuomotor behaviors over the course of learning to perform the same task mentioned in Aim 1. While error-rates in such tasks have been shown to follow exponential decay, we will estimate best-fit functions for specific eye-tracking indices.

This work will help understand which measures, among the many possible measures that can be extracted from eye tracking, can be used in future studies to track the rate at which an individual is learning and adapting to novel tasks. Since individuals have fundamentally different rates at which they learn, our long-term goal is to develop "personalized" indicators of learning adaptations from eye-gaze behaviors, that can then be used in future intelligent adaptive learning frameworks.

METHODS

Study Task

The inspiration for our task environment is a scenario in which a nurse uses a cobot to help with patient lifting (Chen & Kemp, 2010). The nurse may possibly have to re-orient the cobot arms in different ways to best assist the patient, and also maintain precision under dynamically varying forces caused by the moving patient's weight and the cobot's inherent control dynamics. We attempt to replicate these demands of dynamic weight and multi-joint coordination by varying the arm impedances of a bimanual Baxter robot in our study, and asking participants to balance a ball on a plate while avoiding collisions with other objects. Due to the impedance mismatch, the arms move in slightly different ways from each other, requiring participants to learn how to monitor and reposition the arms such that the ball remains balanced and collisions with other objects are minimized. Specific degrees of freedom are also locked in one of the two arms of the robot, thereby requiring users to find a viable path to complete the transfer task.

This task has been designed in virtual reality (VR), since VR affords high freedom over experimental manipulations, particularly in tasks involving physical-object interaction. VR also enables flexible measurement of motor performance and eye-movement behavior, since the position and orientation of all VR objects relative to the user is precisely known (Clay et al., 2019). Moreover, there is great potential for VR to be used in conjunction with cobots, to train operators in a variety of simulated conditions (Matsas & Vosniakos, 2017) or to provide augmented feedback during teleoperation (Zhou et al., 2020). This work will thus also contribute to the growing body of evidence on the potential efficacy of using VR to study and train human motor behaviors.

A schematic of the setup and is shown in Figure 1. Participants perform the task using the Rethink Robotics Baxter Robot, which has two 7-DOF arms that can be manipulated freely by grasping their wrists. The Baxter SDK enables us to adjust impedances on each individual joint. Additionally, we visualize a virtual model of Baxter inside a Unity VR environment by sending Baxter's real-time joint positions to Unity at 140 Hz using the ROS# package (Zhou et al., 2020) We use the HTC Vive Pro Eye VR headset in this study, along with the embedded Tobii eye-tracker which records gaze data at 120 Hz.

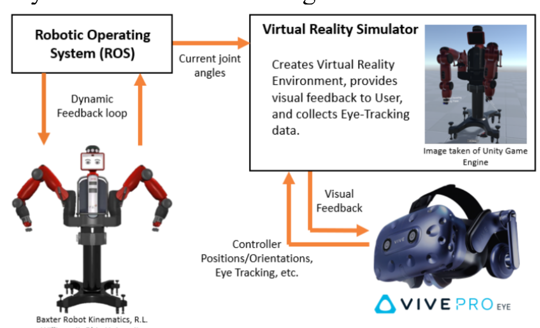
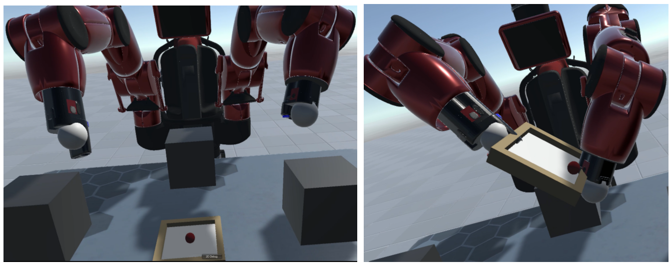


Figure 1. Schematic of communication between Baxter and VR

As shown in Figure 1, participants stand facing the Baxter robot while wearing the VR headset, in a position that allows them to grasp and manipulate the robot's arms. Figure 3 shows the VR environment - a virtual plate along with three target locations in the form of solid blocks are situated on a table between the participant and the virtual Baxter. The plate also contains a virtual ball with simulated physical properties of an actual ball, i.e. it rolls around inside the plate, and if the plate is tilted, the ball will fall out. Participants are asked to pick up the plate from the starting location and transfer it consecutively to three different locations, as fast as possible, while ensuring the plate and the ball do not fall, and that the robot does not collide with any target locations or the table.

Figure 2. Participant wearing the headset and operating the robot



(A) (B)

Figure 3. (A) Participant's view in VR, with robot, plate, and target locations. (B) Ball rolling off due to excessive tilt of the plate

Participants

We are recruiting a gender-balanced sample of 36 participants from the university student pool, by distributing flyers around the university campus. Participants are screened to exclude those with musculoskeletal disorders or injuries. We only recruit participants who are able to read at arm's length without the use of corrective lenses, since lenses or glasses may interfere with the eye-tracking measurement. We also request participants to limit their consumption of caffeine, nicotine, alcohol or sedative drugs prior to the experiment to control for influences on physiology. We exclude individuals with a history of migraine, vertigo and epilepsy, since these conditions can make them susceptible to VR sickness.

Independent Variables

Since internal model formation is a function of both task and tool-manipulation difficulty, two independent variables were chosen for this study: Task difficulty and Robot manipulation difficulty. Task difficulty was set at 3 levels (low, medium, high) by changing the coefficient of friction of the virtual ball. Robot manipulation difficulty was set at 2 levels, matched (easy) and mis-matched (difficult), where the degree of "match" between the two arms of the robot was manipulated. The degree of (mis)match between the two arms of the robot were controlled through varying the joint impedances of the two arms. In the matched (easy) condition, both arms of the robot exhibited identical joint impedances, whereas in the mismatched condition, a subset of joints in one of the arms were set at a higher impedance, and some degrees of freedom were locked. The mismatched condition was expected to increase motor-coordination demands, and consequently, increase the difficulty of balancing the ball on the virtual plate.

Experiment Design and Protocol

The experiment is completed in a single session, and employs a 3 (high, medium, low friction) x 2 (presence/absence of mismatch) repeated measures design. After participants sign their consent, we administer a short test of working memory capacity, record their age, and also their past experience with VR. The experiment begins with a 1-minute familiarization session with Baxter, in which participants are allowed to grasp and move the arms freely while receiving visual feedback in VR. Familiarization is followed by eye-tracker calibration.

Participants begin with a baseline block using only their hands (no robot) and the medium friction condition, followed by 6 learning blocks using the robot to achieve the same task condition. There are 24 consecutive movements (object transfers) in each block. A one-minute break is provided between blocks to minimize physical fatigue, during which participants also provide self-report measures (described later). Additionally, to minimize the transfer of learning between blocks, 12 'wash out' movements are performed after each block, that are identical to the baseline movements (no robot). We progress from the easiest condition (high-friction, matched arms) to the most difficult condition (low-friction, unmatched arms) to provide graded exposure to the task and avoid learning/negative motivational effects of experiencing too high a difficulty early on.

Independent Variables	N/A	Matched Arms			Unmatched Arms		
	Medium Friction	Low Friction	Medium Friction	High Friction	Low Friction	Medium Friction	High Friction
Blocks	**Baseline**	**Block 1**	**Block 2**	**Block 3**	**Block 4**	**Block 5**	**Block 6**

Figure 4. Task description with blocks. Each block except baseline is followed by a 1-minute break and 12 'wash-out' movements

Outcome Measures

Our primary eye-tracking measures are selected based on their ability to provide different types of information about mental workload and visuomotor performance. We will also use NASA-TLX ratings (Hart & Staveland, 1988) as ground truth for mental workload, the Self-Assessment Manikin (SAM) (Bradley & Lang, 1994) as a measure of emotional valence, the Rating of Perceived Exertion (RPE) (Scherr et al., 2013) as a measure of physical workload, and a digit-span test of working memory capacity (WMC) (Woods et al., 2011).

Primary eye-tracking measures: Pupil diameter (PD). PD increases with higher task difficulty and mental workload, and this effect is called the task-evoked pupillary response (TEPR) (Just et al., 2003). *Blink rate.* Blink rate has been shown to increase for high cognitive- and motor-control demands (Marquart et al., 2015; Novak et al., 2015). We expect blink rate to be higher in the initial trials and difficult task conditions. *Eye-hand span*. The eye-hand span is the duration from the start of a fixation on an item until the hand (or another effector) performs the action associated with that item (Land, 2009). In difficult motor tasks or during initial practice of novel tasks, eye-hand span tends to be short, or even negative (i.e. the eyes follow the hands), but can increase with learning (Sailer, 2005). We define the eye-hand span at two different points (Lavoie et al., 2018) – a) Eye-hand span (EHspan) at pick-up, which is the time difference between the moment the plate is lifted and the first fixation on the plate. A positive value of EHspan at pick-up indicates that the eyes reached the plate before it was picked up. b) EHspan at drop-off, which is the time difference between the moment of plate-release and the first fixation on the drop-off location. A positive value of EHspan at drop-off indicates that the eyes reached the target location before the plate was released. *Target-locking-score (TLS)*. While eye-hand span is a temporal measure of eye-hand coordination, TLS is a spatial measure that describes relative attentional focus (Wilson et al., 2010). In our study, TLS is defined as the percentage of eye-fixations on the plate or drop-off location, subtracted by the percentage of eye-fixations on the end-effectors. A positive TLS indicates greater focus on the upcoming targets (higher expertise), whereas a negative TLS indicates greater focus on the end-effector while performing the movement (lower expertise). In this study, the plate itself will be the "target" prior to being picked up, and the drop-off location will be the "target" prior to plate-release. Additionally, we will define a second measure, TLS_{ball}, that considers fixations on the ball instead of the end-effectors. This is because the movement of the ball is a function of the end-effector positions while holding the plate, and participants may adopt a ball-monitoring strategy rather than a hand-monitoring one, or an external focus of attention as opposed to an internal one (Wulf, 2013).

Exploratory eye-tracking measures: In addition, measures such as Index of Pupillary Activity (IPA), peak velocity of saccades, and gaze entropy will be computed as exploratory measures. A few recent studies have shown the IPA to be sensitive and positively correlated to workload since it was first introduced in 2018, albeit in artificial lab-based cognitive tasks, e.g. (Duchowski et al., 2020). *Peak saccadic velocity (PV)* has been found to be negatively correlated with arousal and cognitive workload (Di Stasi et al., 2010; Marchitto et al., 2016). To our knowledge, neither IPA nor PV have been explored in studies involving motor control demands. *Gaze Entropy* quantifies whether an observer's scanning of visual information from the environment is widely dispersed and erratic (high entropy) or confined and ordered (low entropy) (Shiferaw et al., 2019). A study that investigated reaching and grasping tasks using a prosthesis found that the number of gaze transitions between different task-related areas reduced with practice (Sobuh et al., 2014). We expect to observe a similar reduction in gaze transitions over the course of learning, which may also be reflected in a decrease in entropy.

Motor- and task-performance measures: Jerk Index (JI). JI quantifies movement smoothness and will be used as a proxy for movement control. We will calculate JI using the following equation (Hogan & Sternad, 2009):

$$JI = \sqrt{\frac{1}{2}\frac{T^5}{D^2}\int J^2 dt}$$

where T is the movement time (seconds) for each movement cycle, D is the movement distance (meters), and J is the linear jerk (m/s^3). *Movement Time (MT).* MT will be calculated as the duration between when the arms start moving, and the plate is released at the target location. *Accuracy of transfer* will be computed after each plate-release, as the final distance between the center of the plate and that of the target location (D_{acc}), as well as the final angular difference (θ_{acc}) between the horizontal rotation of the plate and the target location. The number of times the participant drops the plate or the ball will be computed as $drops_{plate}$ and $drops_{ball}$ respectively

Statistical Analysis and Expected Results

Aim 1: A repeated measures ANOVA will be used to test the effect of our independent variables on eye-tracking measures, NASA-TLX, kinematic measures and task performance measures. Data for the ANOVA models will be chosen from the middle 8 movements in each block to avoid the potential influence of motor exploration earlier in the block, and potential attenuation due to learning effects later in the block. We will include WMC, SAM, and RPE as covariates in our model to account for individual differences and influence of emotional- and physical-load on mental workload. Post hoc pairwise comparisons will be performed using Tukey's HSD test to test differences between individual conditions. The significance level will be set to $\alpha = 0.05$, and all statistical analyses will be performed in JMP (SAS Institute Inc., USA). We expect to identify the metrics of eye-tracking that are most sensitive to manipulations in task difficulty, with the expectation that in aim 2, these would be the most promising metrics to explore, in terms of how they characterize individual learning rates.

Aim 2: While the change in motor and task performance measures informs the learning rate, to explore how eye-tracking metrics change over the course of learning, we will estimate best-fit regression functions for the primary dependent measures from eye-tracking, in each task condition. In the event of large inter-individual differences in sensitivity to workload or learning, each individual's data will be normalized to their own respective baselines. By comparing the group regression results with individual functions, these models will help understand whether all individuals respond in a similar way to learning. If significantly different individual patterns are discovered, individuals will be classified into groups, and any systematic effects of subjective and individual characteristics on the group classification will be explored.

DISCUSSION

We have presented our research work in progress that investigates the sensitivity of eye-tracking metrics to motor task difficulty. Additionally, we have also proposed to quantify rates of learning, and explore the mathematical functions that can best represent the changes occurring in visuomotor performance over the course of learning. A novel aspect of our research is that it can provide much needed initial evidence on the sensitivity of VR-based eye-tracking to measure mental workload and motor learning rates. Additionally, our work can also provide knowledge on individual-specific visuomotor strategies that operators may employ over the course of learning. We will complete our data analysis and present these results at the conference.

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