Towards a Robot-Based Multimodal Framework to Assess the Impact of Fatigue on User Behavior and Performance: A Pilot Study

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ABSTRACT

Objective: In this paper, we present a multimodal robot-based framework to investigate how physical and mental fatigue affect task performance, and how it relates to subjective self-reports.
Methodology: In this pilot study, seven healthy participants underwent the robot-based assessment. In each session, the participants performed a series of reaching tasks, including a task with cognitive demands, by moving the end effector of the Barrett WAM arm in the direction of the virtual targets displayed on a computer screen. Multimodal data, including EEG, EMG and user performance data like reaction time, number of targets, trajectory of the robot path, were recorded for further analysis.
Results: Based on the analysis of subjective user self-report and objective task performance metrics, we observe that the user's perceived level of task difficulty increased over time while objective task performance also improved over time. We speculate that this might be due to the effect of fatigue on the user's perception of task difficulty.
Conclusion: Further studies are required, with a more diverse population, to understand the impact of fatigue on the user's cognitive and physical ability. We must also evaluate how contextual parameters may affect task performance and fatigue.

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CCS CONCEPTS

• **Human-centered computing → HCI theory, concepts and models**; **Empirical studies in HCI**; • **Applied computing → Health informatics**.

KEYWORDS

robot-assisted training, user skill assessment, cognitive assessment, fatigue, multi-modal dataset

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1 INTRODUCTION

Efficiency, high productivity and accuracy, and reduction in costs have made several industries adopt heavy machinery and automated robots in their workplace which can do repetitive, mundane and jobs that are dangerous for humans with high accuracy and efficiency [13]. It is also important to note that these machines and autonomous robots with high-end sensors and control units require human-robot collaboration [30]. That is, a human collaborator must always be present to work with the system either side-by-side or as a supervisor. Increasing demand for products makes manufacturing industries adapt round-the-clock production, putting further demands on the human workers who attend these machines for long hours and in shifts. This practice affects the sleep cycle and rest time of employees and may in turn result in fatigue which is a very unsafe workplace condition [22]. Fatigue is defined as a lack of energy, or a constant feeling of tiredness, and adversely affects performance [10]. It may be physical or cognitive/mental in nature. Physical fatigue can be peripheral, where fatigue mainly acts on muscles/muscle groups, or central, which manifests as an overall sense of exhaustion [7, 34]. Whereas, cognitive fatigue may manifest as a loss in cognitive control, high level information processing and attention [6]. It is essential that a human collaborator is highly attentive and efficient with proper executive function in a human-robot collaborative environment. Fatigue in the workplace due to working long hours or in shifts may lead to several health and safety issues, with economic implications for both employees and their employers [13].

Fatigue is also a prevalent symptom in several medical conditions like Multiple Sclerosis (MS) [20], Traumatic Brain Injury [4] and Parkinson Disease [16], to name a few. It is one of the most disabling symptoms and often affects the quality of life of the patients and may also lead to depression [29]. Yet it is poorly understood, principally because it is subjective and its etiology varies both across individuals and across different stages of disease progression. Surveys and clinical tests are most commonly used to assess fatigue and are based on patient self-report and clinical observation. Because of the subjective nature of these tests, they are always susceptible to human error, such as bias, from both the patient and the clinicians [31]. Hence, there is a need for objective assessment of fatigue. Similarly, in an industrial environment, being able to detect that a person's performance is affected due to fatigue would be a great asset to an employer in avoiding any workplace-related injuries or fatalities.

In a previous work, we have proposed a task-driven framework for multi-modal fatigue analysis [37]. Based on this framework, the goal is to build an assessment and training system to collect multi-sensing data during both physical and cognitive tasks, specifically designed to extract behavioral and physiological patterns related to fatigue. There is a need to understand the extent to which cognitive and physical fatigue affects a user's behavior and task performance.

Game-based experimental paradigms have been used to show better user engagement, and have aided in user training and assessment [2, 36]. In this work, we propose a multimodal robot-based framework to simulate and assess the impact of cognitive and physical fatigue on user performance using serious games. The primary objective of this study is to make a preliminary evaluation of our proposed robot-based system, with a longer-term goal of developing a framework that com- bines physiological, behavioral, and user self-report data to assess the impact of fatigue on user performance, and to understand how different individuals perceive fatigue. Serious games usually refer to virtual games used for training, simulation, or education and can engage users in cognitive and physical tasks. The design of serious games may offer insights into the user's cognitive and physical behaviors while they try to accomplish structured tasks. In this study, the participants performed a reaching task, which we call "The Fruits and Fox Game" (Frox), in which a user has to perform both physical and cognitive tasks in a multisensing environment, while the system collects physiological and task performance data. In order to gain insight into how users perceive and experience both physical and mental fatigue, we developed a questionnaire based on a Visual Analog Scale.

2 BACKGROUND AND RELATED WORK

Physical activity monitoring systems have been proposed towards assessing physical fatigue, either based on task-based physical performance using motion and physiological sensors [14] or by evaluating user performance in activities of daily living (ADLs) using both objective and self-reporting methods [28]. There has been an increasing use of multiple wearable devices for analyzing and quantifying physical performance and fatigue, associated with specific chronic diseases and their expected behavioral patterns [1, 9, 15, 24].

Towards this end, different sensing modalities have been explored using various types of sensors such as camera-based approaches, electromyography (EMG), heart rate and galvanic skin response (GSR). On the other hand, electroencephalography (EEG) analysis has been the major instrument of assessing cognitive fatigue and related research has shown that it is highly correlated with various neurological impairments like MS [5, 12, 23]. Such approaches have been also exploited to better understand learning abilities and cognitive workload patterns, towards designing adaptive and user-centric assessment tools [8, 25]. Some studies have also employed multimodal approaches toward assessing cognitive task performances [3].

Research aimed at associating subjective and objective measures to analyze both physical and cognitive fatigue to develop reliable fatigue measurement tools is still in its very early stages [38]. Our work is motivated by the current need to understand the extent to which mental and physical fatigue is perceived by different individuals, as well as the extent to which it affects user performance. In the next section, we present our robot-based serious game, designed as a reaching task with cognitive demands. The user study in this paper aims to better understand the relationship between task performance and both physical and cognitive fatigue through the analysis of physiological, behavioral and self-reports.

3 METHODS AND MATERIALS USED

3.1 Experimental Setup

Our experimental setup consists of three main devices, a Barrett WAM arm [35], a Delsys EMG sensor [17], and an OpenBCI EEG headset [26] as shown in Figure 1. The Barrett WAM arm is a 4-DOF (degree of freedom) robot with a round handle as an end-effector. The subjects held this end-effector while playing a cognitive game (see section 3.2.1). This robot is capable of providing resistive forces to the subject to induce physical fatigue as explained in section 3.2.3. The Delsys EMG sensor was used to capture EMG data from the subject's muscles while they played the game. We recorded data from subjects' deltoids, biceps, and triceps using three sensors, one in each location, to get a representation of their muscle activity during the game. OpenBCI EEG headset is a 3D printed headset to record EEG data using dry electrodes. This setup is highly configurable and can record data from up to 16 sensors. The system consists of the main board dubbed the "Cyton board" which interfaces with all the electrodes and transfers the data over Bluetooth. The system was configured to record data at 250Hz and store it on a PC paired with the EEG headset. We recorded data from the prefrontal and the parietal cortex, using eight dry electrodes mounted on the 3D headset, to study the effect of fatigue on the brain [11, 27].

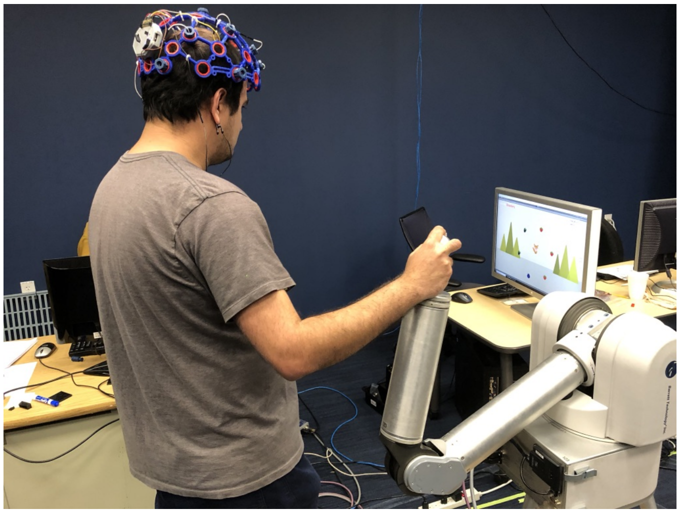


Figure 1: A user playing the Fruits and Fox game.

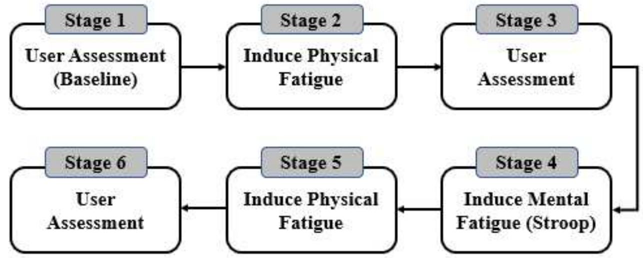


Figure 2: Flowchart showing the study's design.

3.2 Experimental Protocol and Tasks

In this study, subjects worked through six sequential stages. Figure 2 shows a flowchart of the study design. Before and after each stage, the participants were asked to fill a Visual Analog Scale of Fatigue (VAS-F) to evaluate fatigue severity (see section 3.2.4), with questions about their current level of cognitive and mental fatigue and related symptoms like drowsiness and tiredness. This survey This survey provided a measure of both physical and cognitive 'state' fatigue, or the fatigue they experienced 'in the moment'. During stage one, the participants played the Fruits and Fox game which provided a measure of user performance in an unfatigued state. During stage two, the participants performed a robot-assisted shoulder flexion task where the robot applied a resistive force of up to 20 N to induce physical fatigue. During stage three, the participants played the Fruits and Fox game again. Because this stage followed the induction of physical fatigue in Stage 2, this allowed us to assess the effect of physical fatigue on cognitive performance. In Stage 4, cognitive fatigue was induced using a modified version of the Fruits and Fox game which employed the Stroop effect to make the game more cognitively challenging. This was implemented by providing three possible targets, one of which was presented in an incongruent color. A detailed explanation of this method is provided in section 3.2.2. Figure 4 shows a screenshot of this game. In stage five, we induced physical fatigue again (with the robot arm) before moving on to the final Stage. Finally, in Stage six the participants played the original Fruits and Fox game again, and performance was assessed while they were physically and cognitively fatigued. During all stages, data recorded included physiological data from EEG, EMG sensors and task performance metrics: completion time, number of targets captured (score), errors and the trajectories of the robotic arm.

3.2.1 The Fruits and Fox Game. The Fruits and Fox Game is a combination of cognitive and physical tasks which the participant plays through his interaction with the robot. This task simulates a reaching task, which is commonly used to assess reaching skills both for rehabilitation and assessment in post-stroke patients [32] and to simulate an industry worker's day-to-day activity which would involve reaching and grasping [19]. In this game, the participants were required to hold the end-effector of the Barrett WAM arm to control a fox and help it catch berries (targets) displayed to the participants on a monitor. The game started with the fox at the start position surrounded by different colored berries, as shown in Figure 3a.

Figure 3: The Fruits and Fox cognitive game developed for user performance assessment. The left image (a) shows the start screen of the game. The right image (b) shows the screen after a participant catches a target.

The task was to move the fox to capture as many berries (targets) as possible within five minutes, based on the instruction displayed at the top-left corner of the computer screen. The possible targets included three different berries with a font color associated with them like strawberry (red), blueberry (blue) and blackberry (black). Figure 3a shows a screenshot of this game. After the user captures one of the targets, as shown in Figure 3b, the participant had to return to the home position, and only then will the next round's instruction be displayed. In each round, task performance parameters are recorded. These parameters include reaction time, errors, the trajectory of the robotic arm, and physiological sensor data. Prior to the beginning of each round, the experimenter was able to modify task parameters like the number of targets to be displayed and the distance between the targets and the fox's start position, enabling the complexity of the task to be increased or decreased.

3.2.2 Stroop Effect based Game Variation to Induce Cognitive Fatigue. An alternate version of the original game was developed to induce cognitive fatigue. In this version, the task was made more difficult by presenting one of the berry names in an incongruent color (the Stroop effect [33]). Unlike in the baseline version of the game, in which all of the berry names were presented in congruent

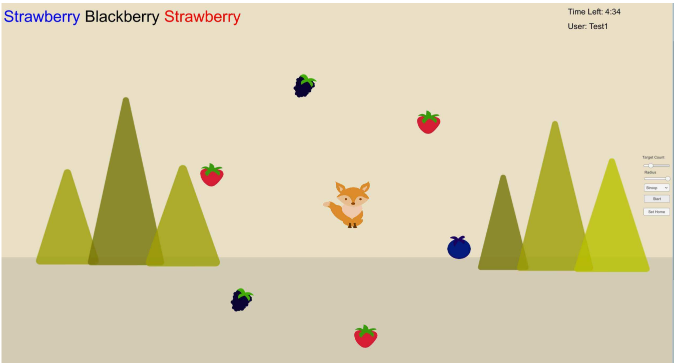
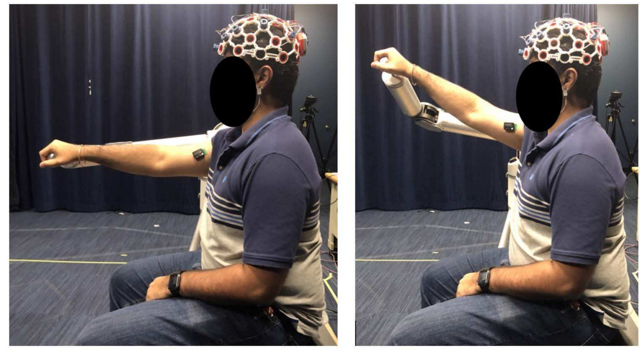


Figure 4: Variation of the Fruits and Fox game to induce cognitive fatigue through Stroop effect



a b

Figure 5: Shows a user performing shoulder flexion. The left image (a) shows the start position which is at shoulder level. The right image (b) shows the end position which is slightly above the eye-level.

colors (e.g., strawberry presented in red), in this version the color of the text of one of the berries was incongruent (e.g., strawberry in blue; see Figure 4). This modification to the original version of the game increased the difficulty of the task, thereby inducing cognitive fatigue. The participants had to identify which of the three words had the wrong color association and then identify the correct target according to the font color of the mismatched option (i.e., choose the blue berry).

3.2.3 Shoulder Flexion to Induce Physical Fatigue. One of our main goals of this study was to implement a system to investigate the effect of both cognitive and physical fatigue. This was done to simulate a real-world scenario where a task may be both cognitively and physically challenging. To this end, physical fatigue was induced by asking the subject to perform an exercise with the robotic arm. The arm's capability of providing resistive forces was leveraged to simulate an exercise with weights. The subjects were asked to perform shoulder flexion, where they would start the exercise with their hand in front of them holding the end-effector (Figure 5), extended at the shoulder level. When instructed they would raise their arm. To be consistent, they were asked to raise their arm just above their eye level. This movement utilizes the deltoid and the trapezius muscle among others [18, 39]. The exercise was designed to induce isometric contractions in the muscle by asking the subjects to hold the final position until they started to feel fatigued. During the exercise, we recorded the EMG data from the deltoid and EEG data.

3.2.4 The Visual Analog Scale to Evaluate Fatigue Severity (VAS-F). The VAS has been used in several studies to measure the severity of pain or fatigue [21]. The subject is presented with a 100 mm horizontal line and is told that one extreme (0 mm) is, for example, "not fatigued at all" and the another extreme (100 mm) represents "extremely fatigued." This scale provides a measure of the level of fatigue a patient is experiencing at a given point in time. A Visual Analog Scale to Evaluate Fatigue Severity (VAS-F) was developed to evaluate different types of fatigue experienced during the study. The VAS-F consisted of 6 questions:

- How tired do you feel?
- Do you feel sleepy or drowsy?
- Do you feel mentally fatigued?
- Do you feel physically fatigued?
- Do you feel active and energetic?
- How difficult was the task?

4 DATA COLLECTION AND ANALYSIS

For this study, we recruited seven (six male, one female) participants, with a mean age of 27 ± 1. Each session lasted for 45 minutes to an hour, during which participants were given an introduction to the study and its design, completed the consent form, (IRB: 2019-0224), worked on the six stages of the study and completed the questionnaires.

We present our preliminary results from the analysis of self-reports (subjective) and task performance (objective) data. More specifically, we were interested in how the users perceived task difficulty, mental and physical fatigue and how these self-reported measures were related to task performance, e.g., score (number of targets captured) and delay (completion time). It should be noted that the analyses were confined to task blocks during which subjects performed the simple version of the game. Therefore, the difficulty of tasks was held constant. We present the data in two ways: the average performance metrics across stages, and also the values from each individual (Figures 6 and 7).

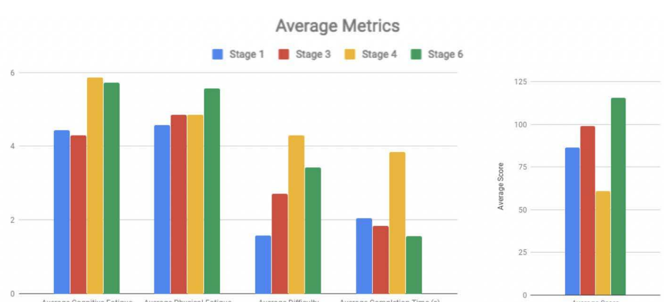


Figure 6: Average metrics for each task

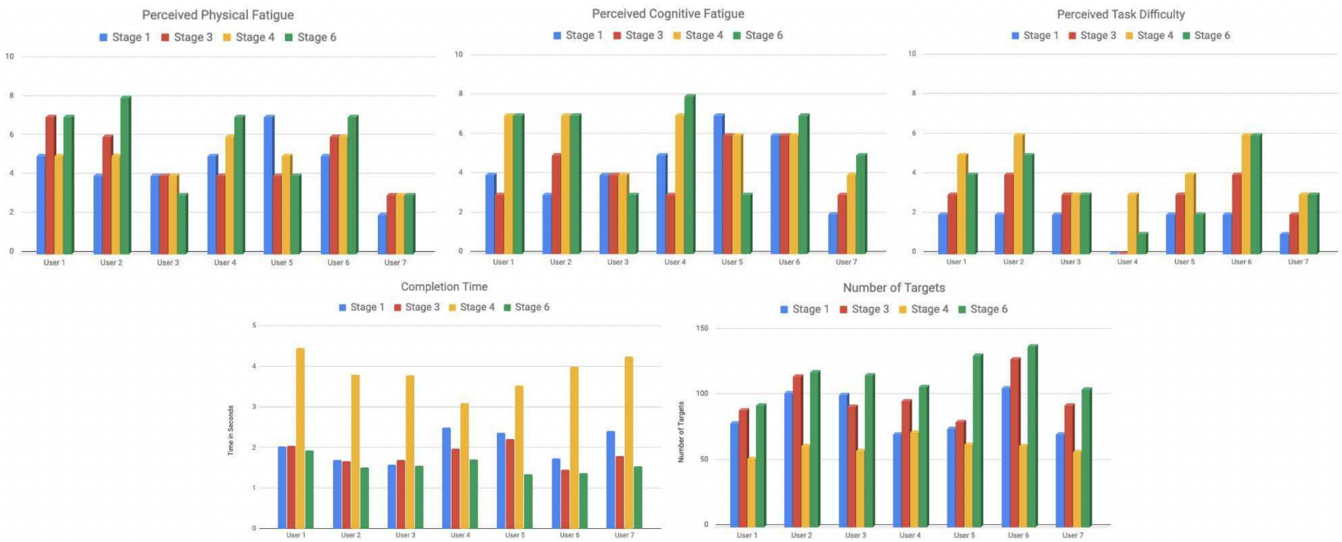


Figure 7: User survey and performance results. Visualization of self-report on (a) physical fatigue, (b) cognitive fatigue and (c) task difficulty, for all users. We also visualize the objective measures of (d) completion time and (e) task performance (number of targets reached).

In both the figures, it can be seen that most users reported that task difficulty increased over time (Stage 1, Stage 3 and Stage 6). However, task performance (targets, delay) nevertheless improved over time. This discrepancy between subjects' objective performance and subjective assessment of task difficulty could be possibly due to cognitive and physical fatigue. That is, while repeated performance of the task undoubtedly led to improvements in the number of targets captured due to practice, the induction of fatigue may have led subjects to a belief that the task was getting harder. More participants and analysis of the multimodal data (EEG and EMG) are required to test this hypothesis.

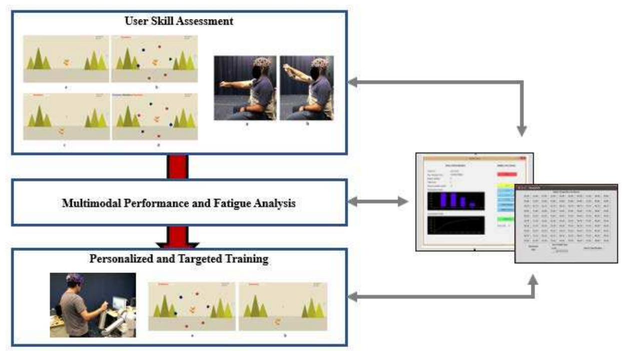


Figure 8: Proposed Framework

5 DISCUSSION

In this paper, we employed a multimodal robot-based framework to assess the impact of physical and cognitive fatigue on user performance. We presented pilot data with a serious game which can be used for physical and cognitive assessment and training. Preliminary data analysis indicated a difference between subjective and objective measures: while participants reported task difficulty to be increasing across successive task blocks, their performance nevertheless improved. This discrepancy may be due to mental and/or physical fatigue. Our ongoing work includes data collection from more participants. As the population increases, we also plan to conduct comparative studies under different conditions (e.g., order of tasks), in order to evaluate how contextual parameters affect task performance and fatigue.

Our long-term goal is to develop a personalized robot-based assessment and training system. This system will utilize the different parameters of the Frox game, including task parameters (target locations), haptic feedback (assistive or resistive forces), cognitive demands (different variations can assess different skills, e.g., working memory) and others, in order to collect information about the user's physical and cognitive skills, identify their weaknesses and strengths, and provide a personalized and targeted training, through the analysis of the collected multisensing data. By selectively focusing on different cognitive or physical parameters of the task and by focusing on either physical or cognitive skills based on the user's performance, we will be able to achieve personalization.

An important part of such a framework is to include the human in the loop, through self-reports and expert recommendations, considering physical and mental fatigue. Physiological, behavioral and human feedback can be used for performance and fatigue analysis, providing an expert user with data s/he can use to make recommendations for training. Graphical User Interfaces can be used to enable a human expert to monitor the different phases of the system (assessment, recommendation, training) and to intervene when needed. Figure 8 shows the assessment-recommendation-training architecture.

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