Cognitive Performance Assessment based on Everyday Activities for Human-Robot Interaction

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ABSTRACT

Human-Robot Interaction often involves a robot assisting or providing feedback to a human partner’s performance or cooperating to complete a task. In such an interaction scenario, the robotic system requires to perceive the human teammate’s cognitive state that might affect task performance. In this pilot study, the focus is on developing a framework that assesses the human’s cognitive performance for human-robot synergetic task, such as an assembly task. Specifically, we explore the correlation between a person’s quality of sleep and performance metric through a standard task for cognitive assessment, the N-back task. To validate our hypothesis, we conducted a study with 25 participants, and our results indicate that there is a moderate correlation between some stages of sleep cycle and performance. Additionally, we present a possible Human-Robot Interaction setup that could benefit from our results.

KEYWORDS

cognitive assessment; human-robot interaction; wearable sensors; human activity

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1 INTRODUCTION

In recent years, humans and robots have started interacting with each other in different fields, such as manufacturing [4], industry [12], surgery [7], assistive care [8], education [2], and others. The primary concern in the design of Human-Robot Interaction (HRI) is the human’s safety and health. Typically, the HRI-design covers issues related to collision avoidance and to ensure that the robot should not cause an immediate injury or harm the human user [13]. However, there is less emphasis on considering the influence of long-term HRI on human health and well-being.

Researchers [3, 13] have focused on Ergonomic HRI in industry, by developing frameworks to improve the human posture and to minimize the risk of developing work-related musculoskeletal diseases and disorders. Moreover, socially assistive robots (SAR) are used as companions or therapists to improve mental health and well-being [5]. It is evident that robots are required to understand human behavior, health, and well-being.

In this work, the focus is on the human’s cognitive state assessment for HRI using data from Fitbit, a non-obtrusive light-weight everyday wrist-worn wearable fitness band, and task performance metrics. Fitness bands provide information about sleep quality, an essential parameter of cognitive state assessment [9]. Prior research has indicated that lack of sleep has a negative impact on cognitive tasks that require working memory [14]. In this study, we present a preliminary analysis of sleep quality data from Fitbit and cognitive performance.

2 EXPERIMENTAL STUDY

We conducted a user study with 30 participants to test our hypothesis, which was approved by the Institutional Review Board at The University of Texas at Arlington. The participant pool consisted of 23 male and 7 female participants with an age range of 19 - 38. Five participants’ data were removed during analysis due to missing sleep data from the sensor. The participants were provided with a Fitbit smartwatch, which was recording the user’s sleep pattern over five days. During two of these five days, the participants were asked to participate in a cognitive assessment task, the N-back task, which is commonly used in cognitive neuroscience to measure working memory and attention, two essential skills in an assembly task [10] . The N-back task is a sequential cognitive task where we present stimuli sequentially one-by-one. For each stimulus, the participant needs to decide if it is the same as the one presented N stimuli back.

Several versions of the N-back task exist, such as the N-back task with alphabets for sequences, visual N-back task where stimuli appear on different positions of the screen. In our version, we present the user with a sequence of shapes one at a time, as shown in Figure 1, from a pool of eight shapes with eight different colors. Figure 1 depicts a 2-back task where, based only on the shape, the

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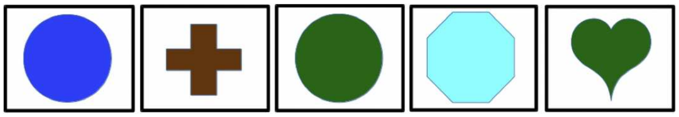

Figure 1: The N-back Task. In this example, a 2-back task, we use a sequence of shapes.

user responds by pressing the space-bar on the keyboard when they see the second circle, which repeats after exactly two stimuli. During the assessment, we record the score, which is measured as the difference between the percent of total correct responses and the percent of total wrong responses.

For this study, we used an easy 0-back task and the 2-back task, which places a higher cognitive load. In the 0-back task, we present the participant with a target shape beforehand. The user presses the space-bar when they identify this shape in the sequence displayed. In each task, we present a total of 64 stimuli, of which 12 were targets. Each stimulus lasted for 2500 ms. The order of each type of task was counterbalanced among participants, whereas each task was presented twice. The study lasted for approximately 45 minutes for all participants.

3 PRELIMINARY RESULTS AND DISCUSSION

In our analysis, we try to find a relationship between data from the cognitive task (the N-back task) and sleep quality data from Fitbit. Sleep quality features extracted from the Fitbit sensor are total duration of sleep, percent of deep, light, Rapid Eye Movement (REM) sleep, and awake time.

Table 1: Summary of correlation analysis between stages of sleep and task performance. (τ/ρ) denotes the degree of correlation while P denotes if the correlation is significant.

	Kendall		Spearman	
Variable	τ	**P**	ρ	**P**
total	-0.0483	0.760	-0.0261	0.901
%deep	0.0933	0.541	0.1169	0.578
%light	**-0.3519**	**0.018**	**-0.4593**	**0.021**
%rem	**0.3409**	**0.021**	**0.4689**	**0.018**
%awake	0.0104	0.962	0.0033	0.988

We performed D'Agostino's K^2 test [6] to determine the normality of the data. The test indicated that the task performance metric does not follow a normal distribution. Hence, we performed the Kendall and Spearman correlation between each of these features and performance metric, which is the average score in each assessment. As shown in Table 1, the light sleep cycle has a moderate negative correlation with task performance, while the REM sleep cycle has a moderate positive correlation with high confidence. The results are in line with related research in sleep and its effect on cognition. According to the description given by Fitbit [11], the light sleep cycle is responsible for processing memory, emotions, and metabolism regulation. The REM sleep cycle, on the other hand, is responsible for emotion regulation, memory, and protein synthesis. Based on this description and the results we present, it gives us a positive indication that sleep affects memory and thereby task performance. Further research may prove worthwhile to learn the appropriate features that help in understanding human cognition in an HRI setup. This could help to create a smartwatch application that provides input to the HRI system based on the sleep quality for personalized robot behavior in application areas like manufacturing, rehabilitation, social interaction or education. Moreover, additional physiological measures, such as daily heart rate and physical activity, could be considered as inputs to the HRI system.

4 HRI, HUMAN COGNITION AND SLEEP

In most cases of HRI, a human user interacts with a robot to achieve a common goal, such as product assembly, rehabilitation therapy, or others. Depending on the task performed, the level of assistance offered by the robot varies from providing hints in a task [1] to providing personalized feedback [15] while a user performs the task. In this section, we propose an HRI framework for cooperative assembly using a lathe assembly set available off the shelf, as shown in Figure 2. In this task, the robot provides a user (human teammate) with parts to assemble while the user assembles it with small nuts, bolts, and screwdriver, which are typically hard for a robot to handle. We propose this task to emulate a real-world assembly

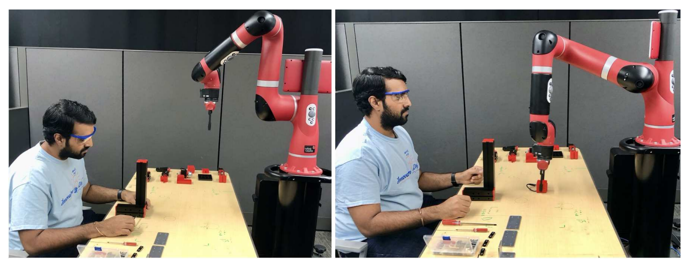

Figure 2: HRI Setup with Baxter Robot: [left] User performs an assembly task. [Right] Robot provides parts for assembly.

environment where the user needs to perform specific sequential tasks, which requires working memory and attention skills similar to the N-back task in our user study. These cognitive abilities are affected positively or negatively based on sleep quality. As a future work, we propose a personalized HRI system by assessing the individual's cognitive state based on their sleep quality along with task performance. To enable personalization, the robot will adapt its speed or provide recommendations based on the human teammate's cognitive assessment.

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