Measuring Cognitive Load Through Event Camera Based Human-Pose Estimation

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Measuring Cognitive Load Through Event Camera Based Human-Pose Estimation

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Abstract. The cognitive load is related to the effort associated with performing a specific task. It can affect learning efficiency, problem-solving abilities, and overall performance. In human-robot collaboration, the capability of a robot to assess cognitive load of humans during a joint task execution can positively affect performance, as robots can adapt its behaviour and mitigate cognitive demands. In this study, we measured behavioural responses to cognitive load, to assess how varying levels of cognitive load affects human body pose and movement. To this aim, we used low-latency, high temporal resolution, compressive event cameras and a lightweight human pose estimation network that can work in real-time at high frequency. Our results demonstrate that participants exhibit stiffer body movements under high cognitive load and more relaxed movements when cognitive load is low. Also, the reaction time is affected by the level of cognitive load. These findings suggest that cognitive load can be effectively inferred from event-driven pose estimation data, offering a non-invasive real-time method to monitor cognitive states and implement online adaptive responses in collaborative tasks.

Keywords: cognitive load, human pose estimation, event camera, HRI

1 Introduction

Cognitive load refers to the mental effort required to process information and is crucial to understand how people learn, perform tasks, and make decisions [13]. An effective assessment of cognitive load can significantly improve performance in various settings, such as education [25], workplace environments [18], and human-robot interaction [2]. In human-robot collaboration, recognizing and responding to a human partner's cognitive load is particularly important. Robots that detect high cognitive load in humans can adapt their assistance to alleviate mental strain, thereby improving overall task performance and collaboration efficiency.

Cognitive load theory posits that conscious thinking processes require working memory, making the cognitive load a critical factor in cognitive science [13].

It affects learning efficiency, problem-solving abilities, and overall performance. Cognitive load significantly affects human performance, especially in tasks requiring complex decision-making and multitasking [21]. High cognitive load can lead to errors, decreased efficiency, and mental fatigue [20]. In human-robot interaction, cognitive overload can impair effective interaction with robotic systems [1]. Therefore, effective assessment and management of cognitive load can enhance performance and safety in collaborative environments, allowing robots to provide the appropriate support and reduce human mental strain [7, 19].

Human Pose Estimation (HPE), which involves detecting and tracking body postures, has emerged as a valuable tool for assessing cognitive load. Research indicates that body movements and postures change in response to varying cognitive demands. By analyzing these changes, it becomes possible to infer an individual's current cognitive load and gain insight about their mental state during a task [14, 23]. Human pose can be an indicator of cognitive load [27]. People tend to behave differently at various levels of cognitive load, exhibiting specific movements such as rubbing their forehead, moving their legs, or shifting their shoulders more frequently, or becoming stiffer as cognitive load increases [8]. Human pose can be detected using an RGB camera and popular libraries such as OpenCV, MediaPipe [6], and OpenFace [5] and is a well-established field of research. However, standard RGB cameras have limitations, as they operate synchronously at a certain frequency, missing events occurring between frames. This restricts their ability to detect fast movements or subtle changes in the environment.

Event cameras address these challenges by capturing changes in the visual scene asynchronously with high temporal resolution. This allows them to detect rapid and subtle movements that standard cameras might miss due to lower frame rates and motion blur [29]. Event cameras are particularly beneficial in dynamic environments, where capturing every subtle change in body pose is crucial [4]. They are also an effective choice for robotic applications due to lower power and computational requirements. While extensive research has focused on assessing cognitive load using physiological metrics such as pupil dilation, eye tracking [11], and heart rate variability [17], there is a notable gap in studies quantifying changes in human pose under different cognitive load conditions. Despite evidence suggesting that body posture and movements are influenced by cognitive load, few studies have systematically measured and analyzed these changes [3, 26]. This study aims to fill this gap by using event camera technology to quantify and analyze how human pose varies with cognitive load, providing a new dimension to cognitive load assessment that complements existing behavioural measures.

In this study, we investigated behavioral responses to cognitive load using event camera-based human pose estimation. The purpose was to assess how varying levels of cognitive load (manipulated in the context of a Stroop task) affect human body pose and movement. We also considered subjective measures by using a questionnaire to evaluate users' perceptions of various tasks. Figure

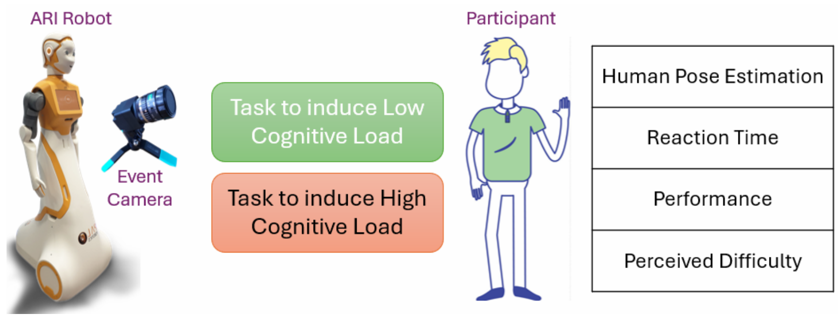

Fig. 1. Study design to measure behavioural responses to different levels of cognitive load: the human subject is asked to perform a Stroop task with high or low cognitive load. Event-cameras recorded the human behaviour were used to measure pose, task difficulty was assessed using reaction time, accuracy, and perceived difficulty (through a questionnaire).

1 shows an overview of the study. Cognitive load is induced through tasks, and human pose, reaction time, performance, and perceived difficulty are measured.

The goal of the present study is to confirm whether cognitive load impacts human movements and poses, and, in doing so, to demonstrate the efficacy of event camera-based HPE as a tool to assess this effect. To achieve this, we manipulated cognitive load (high vs. low) during a Stroop task [15] and tested the following hypotheses:

- H1 Self-reported cognitive load will be higher in the high cognitive load condition than in the low cognitive load condition.
- H2 The average reaction time of participants in the Stroop task will be higher in the high cognitive load condition than in the low cognitive load condition.
- H3 The accuracy of participants in the Stroop task will be lower in the high cognitive load condition than in the low cognitive load condition.
- H4 The amplitude of participants' movements will differ between the high cognitive load condition and the low cognitive load condition.
- H5 The frequency of participants' movements will differ between the high cognitive load condition and the low cognitive load condition.

2 Methods

2.1 Human Pose Estimation with Event Camera

Human Pose Estimation (HPE) is essential for accurately understanding human position, pose, and movements. The accuracy and efficiency of HPE significantly influence the performance of these systems, necessitating methods that can operate quickly and effectively in real-time scenarios. Traditional HPE methods using mainstream sensors, such as RGB cameras, have made considerable advances in recent years [24]. These methods typically rely on frame-based data, which can be limited by issues such as motion blur and low temporal resolution [16]. In contrast, event cameras mitigate those challenges and offer several other advantages over conventional frame-based cameras.

Event cameras are bio-inspired visual sensors that capture the change of intensity in the scene at very high temporal rate. They are not affected by the absolute intensity of light and thus remain effective in various lighting conditions. Event cameras only capture the movements in the scene, thus only the relevant components are capture and need to be processed, thus using lower amount of computation and requiring less power than their frame-based counterparts while capturing data with lower latency and high temporal resolution. Robots are constrained in the computation resources they have available onboard and power they can provide the various modules that are online at any given time. Additionally, in order to interact effectively with a human, a robot should be able to decipher the non-verbal cues of the human agent in real-time, and modify its behaviour accordingly. For these reasons, event cameras are very effective in robotics applications. And any choice of algorithm should ideally follow the same paradigm.

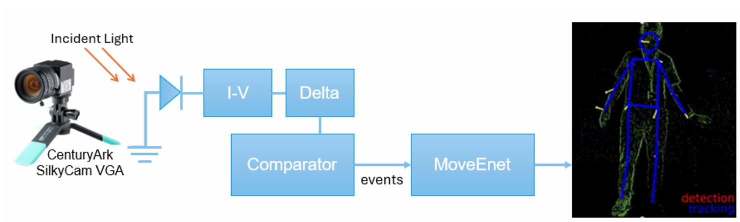

Fig. 2. CenturyArk SilkyCam VGA (event camera) and its basic circuit. When light strikes individual pixels, it converts into an electrical voltage. When this voltage exceeds a predefined threshold within a comparator, it triggers the generation of an event. These events are feed to MovEnet model to get human pose estimation.

Despite these advantages, event camera-based HPE is still an emerging field. While there are several solutions available, each has its own limitations. EventCap [30] and EventHPE [31] rely on hybrid approaches that combine event cameras with traditional frame-based images, thus leveraging the strengths of both technologies but also inherit the limitations of frame-based data, such as increased data redundancy, potential latency, and additional potential errors can be caused due to asynchronousity between the two modalities. LiftMonoHPE [22] is based only on event-based data, but requires high computation and has high latency in online implementation, taking away form the advantages of the event-based approach.

MoveEnet [9] stands out as a notable exception in the realm of event-based HPE. Unlike hybrid systems, MoveEnet operates directly on the event stream from event cameras. This lightweight system is designed to update high-frequency and high-accuracy human pose estimates in real-time, fully utilizing the unique capabilities of event cameras. By processing the event stream without relying on additional frame-based data, MoveEnet achieves superior performance in terms of speed and accuracy, making it an ideal choice for applications that demand rapid and precise pose estimation. This is why we used MoveEnet in our experiments. Figure 2 shows the basic circuit diagram of the event camera and an example of human pose estimation with MoveEnet.

2.2 Experimental Design

We designed a within-subject experiment where the level of cognitive load while performing a task is manipulated (i.e., low vs. high cognitive load). This experiment has been preregistered using aspredicted.org ($https://aspredicted.org/4ZY\_H4F$) and approved by the Bielefeld University Ethics Review Board (application no. 2024-126 of 06.04.2024). The study utilized the Stroop task [15], a well-known psychological test designed to measure cognitive load and interference [10]. The Stroop task involves presenting participants with colour words (e.g., "red," "blue," "green," "yellow") written in congruent or incongruent ink colors (e.g., the word "red" printed in blue ink) and asking them to name the color of the ink rather than the word itself. This task is relevant to the study of cognitive load, especially when it creates a conflict between the automatic process of reading the word and the controlled process of identifying the ink colour [15]. The study has been designed using PsychoPy [28]. The study begins with a practice phase that aims to familiarise participants with the format and procedures of the Stroop task. This phase ensures that participants understand the task requirements and can perform the task accurately and efficiently. PsychoPy then randomly selects which condition between low cognitive load (LL) and high cognitive load (HL) will be the first assigned to a participant.

For the low cognitive load task, participants performed the Stroop task by identifying the colors of the words displayed on the screen and pressing the corresponding keys on the keyboard. Each key was labeled with a color sticker to facilitate accurate responses. For the high cognitive load task, participants engaged in another round of the Stroop task, similar to the low cognitive load task, but were additionally required to memorize a string of six digits that they had to repeat at the end of the task. This secondary memorisation task was meant to occupy participants' working memory during the Stroop task, hence increasing cognitive load. After completing each task, participants completed the NASA Task Load Index (TLX), adapted as a seven-point Likert scale to provide feedback on their experience and perceived difficulty.

Participants were recruited during the CapoCaccia Neuromorphic Workshop (CCNW) 2024. Participation in the study was entirely voluntary, with participants free to withdraw at any time without any disadvantage. Each participant was brought to a room where the experiment was set up, and they stood in front of a projector screen. An information sheet was provided to participants, and they signed a consent form at the start of the experiment. For sake of simplicity and to avoid novelty effect we didn't use a robot here. Participants could visualise all instructions on the screen and use a keyboard, placed on the left or right side according to their preference, to select the answer (a: red, s: green, d: yellow, f: blue). On average, the entire process took around 15 minutes. Throughout the study, an event camera was placed in front of the participant to capture their body pose. All personal data collected during this study were handled with strict confidentiality and in compliance with GDPR. Only movement tracking data were retained. Figure 3 shows the experimental setting.

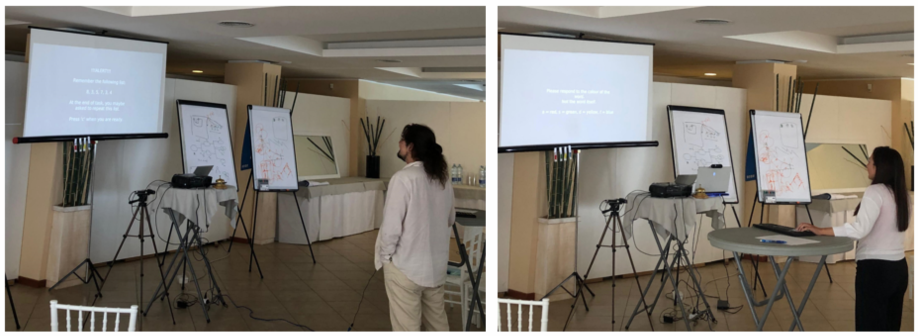

Fig. 3. Participants performing the study. The task, along with the instructions, is displayed on the projector screen.

3 Results and Discussion

At the end of the study, we had body pose data for each timestamp, performance, and reaction time of the participant for the Stroop task in both conditions (LL, HL). Additionally, we had performance and reaction time data for congruent and incongruent trials in the Stroop tasks. From the participant's information form, we obtained the age, gender, English proficiency, and education level of each participant. Filled questionnaires provided information on the user's experience and perceived difficulty for each condition.

The study had a total of N=34 participants, of which 25 identify as male and 9 as female. The average age of the participants was 31.56 years. Among them, there were 1 Master's student, 22 Ph.D. students, and 11 participants who had completed their Ph.D. Regarding English proficiency, 2 participants were at the B2 level, 16 were at the C1 level, 14 were at the C2 level, and 2 were native speakers. Table 1 summarizes these results.

Through the analysis of data from the NASA TLX questionnaire, we confirmed that our tasks induced distinguishable cognitive load in the users. The NASA TLX scores for mental demand, physical demand, temporal demand, performance, effort, and frustration were averaged to compute an overall score for each condition. We employed the Wilcoxon signed-rank test to compare the

Metric	**Value**
Avg. Reaction Time of Males (Low CL, High CL)	1.320 sec
Avg. Reaction Time of Females (Low CL, High CL)	1.461 sec
Avg. Reaction Time (Low CL)	1.344 sec
Avg. Reaction Time (High CL)	1.367 sec
Percentage Correct (Low CL)	93.202%
Percentage Correct (High CL)	92.630%
Avg. Reaction Time (Low CL, Congruent)	1.341 sec
Avg. Reaction Time (Low CL, Incongruent)	1.347 sec
Avg. Reaction Time (High CL, Congruent)	1.366 sec
Avg. Reaction Time (High CL, Incongruent)	1.367 sec

Table 1. Summary of Cognitive Load (CL) Experiment Results

overall scores between the high and low cognitive load conditions. This non-parametric test is appropriate for our study as it compares paired samples, which in our case are the same participants under different cognitive load conditions. The Wilcoxon signed rank test does not assume a normal distribution of the differences, making it suitable for ordinal data collected from the Likert scale. The results of the Wilcoxon signed rank test indicated a statistically significant difference between the overall scores for high (M=3.22, SD=0.66) and low (M=3.02, SD=0.64) cognitive load conditions ($W = 48.5$, $p < .001$, $r = 0.47$). Figure 4(a) is the box plot that shows the NASA TLX scores under both conditions. This finding supports hypothesis H1. This suggests that cognitive load significantly affects participants' perceived workload, validating the effectiveness of our task design in inducing varying levels of cognitive load.

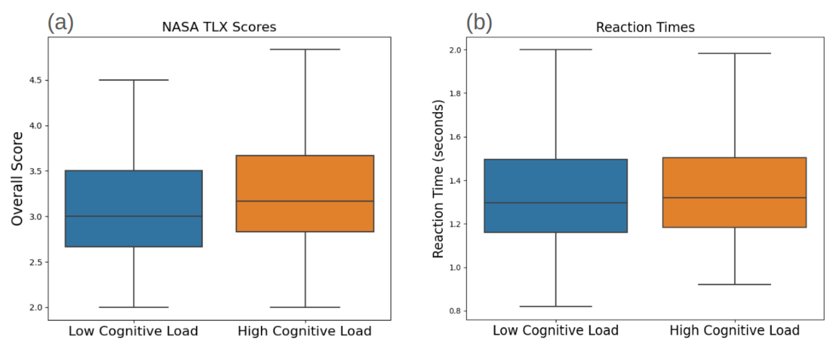

Fig. 4. NASA TLX score and Reaction time under low and high cognitive load conditions.

When examining reaction times, it was found that participants took slightly longer to respond under high cognitive load (M=1.37, SD=0.26) conditions compared to low cognitive load (M=1.34, SD=0.25) conditions. This trend was consistent for both congruent and incongruent stimuli. Aditya et al. [12] demonstrated that there is a difference in reaction times between genders. For both conditions (LL-HL), the average reaction time for male participants was 1.32 seconds, while for female participants it was 1.46 seconds. A Wilcoxon signed rank test was conducted to compare reaction times between the two cognitive load conditions (W=573102.5, p=.009, r=0.46). We found a significant difference in terms of reaction times between low and high cognitive load conditions, which supports hypothesis H2. Figure 4(b) shows the box plot of reaction times under both conditions. Therefore, the results suggest that an increase in cognitive load leads to a measurable and statistically significant increase in reaction times, implying that higher cognitive load impairs performance by slowing down the participants' response times.

In terms of the correctness of answers, the percentage of correct responses was slightly higher under low cognitive load conditions (93.20%) compared to high cognitive load conditions (92.63%). Despite this difference, the Wilcoxon signed-rank test for correctness yielded a W=2646.0, p=0.3843 and r=0.02. Thus, the cognitive load did not significantly impact the accuracy of participants' responses. This finding does not support our hypothesis H3. The results demonstrate that while an increase in cognitive load significantly slows down reaction times, it does not significantly affect the accuracy of responses.

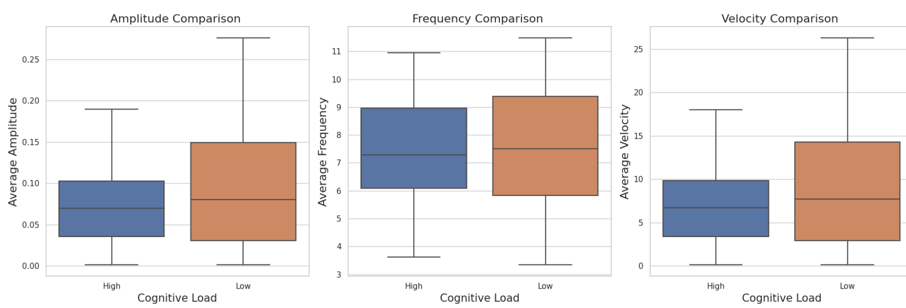

Fig. 5. the average amplitude, frequency, and velocity of movements under high and low cognitive load conditions. The Wilcoxon signed-rank tests confirmed that these differences are significant.

Measure	**W**	**p-value**	**r**
Reaction Time	573102	.009*	0.46
Correctness	2646.0	0.384	0.02
Amplitude	10542	<.001*	0.24
Frequency	11789	.007*	0.29
Velocity	10544	<.001*	0.29

Table 2. Wilcoxon Signed-Rank Test Results. * represents a significant p-value.

The Wilcoxon signed-rank tests on human pose data with an event camera also revealed significant differences in the amplitude, frequency, and velocity of movements between high and low cognitive load conditions. Specifically, average amplitude (W=10542, $p < .001$, r=0.24), frequency (W=11789, $p = .007$, r=0.29), and velocity (W=10544, $p < .001$, r=0.29) were all significantly higher under low cognitive load compared to high cognitive load. These findings suggest that physical indicators of cognitive load, such as movement characteristics, are notably affected by the level of cognitive load, supporting hypotheses H4 and H5. Figure 5 shows the box plots of the results. Table 2 shows all the results of Wilcoxon signed-rank tests. These findings suggest that users tend to move more when cognitive load is low and become stiffer when cognitive load is high.

4 Conclusion

Our study highlights how cognitive load affects human behavior and performance, as observed through event camera-based human pose estimation. High cognitive load results in stiffer and less frequent movements, while low cognitive load leads to more relaxed and frequent movements. Reaction times are longer under high cognitive load. This research confirms that data collected using HPE present convergent validity with other indicators of cognitive load, such as pupil dilation, heart rate variability, and skin conductance.

Acknowledgment

This work is funded by MSCA Horizon 2020 for the project PERSEO (Grant agreement No. 955778) and PRIMI. The study was conducted during the CapoCaccia Neuromorphic Workshop (CCNW). For open access, the author has applied a Creative Commons Attribution (CC BY) license to any Author Accepted Manuscript version arising from this submission.

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