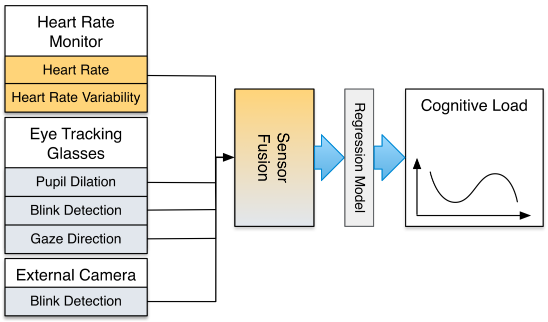

Sidebar 1: Concept Overview: For a system non-intrusive Measurements for Mental Load

Integrated real-time, non-intrusive Measurements for Mental Load

Muneeb Imtiaz Ahmad
Ingo Keller*
Katrin Lohan†
m.ahmad@hw.ac.uk
ijk1@hw.ac.uk
k.lohan@hw.ac.uk
Social Robotics Group, School for Mathematical and Computer Sciences, Heriot-Watt University
Edinburgh, United Kingdom

ABSTRACT

In this position paper, we propose to develop a system that takes input data from different sensors on physiological behaviors such as Pupil Diameter, Blinking Rate, Heart Rate, Heart Rate Variability, and Galvanic Skin Response to estimate users' mental load (see Sidebar 1). We firstly aim to collect data on these behaviours and then intend to understand the correlation between them and later want to predict an estimate of cognitive load in real-time. We hope to use this measure during Human-Computer Interaction and Human-Robot Interaction to personalize our interfaces or robots' behaviour according to user mental load in the real-time.

CCS CONCEPTS

• **Computer systems organization** → **Embedded systems**; *Redundancy*; Robotics; • **Networks** → Network reliability.

KEYWORDS

Cognitive load, Physiological Sensor, Human-Computer Interaction, Human-Robot Interaction

Workshop proceedings *Everyday Automation Experience'19*
In conjunction with CHI'19, May 5th, 2019, Glasgow, UK
Website: http://everyday-automation.tech-experience.at

INTRODUCTION

With the advancements in the field of Machine Learning and Artificial Intelligence, there lies a huge interest in the Human-Computer Interaction (HCI) and Human-Robot Interaction (HRI) communities to implement ways in which user interfaces or robots can adapt to users characteristics [1]. One of the user traits rests in the amount of cognitive load faced during the HCI. The amount of cognitive load has been identified to influence the users' performance during different tasks in an HCI scenario [15].

Cognitive load refers to the amount of effort placed on the working memory during a task. According to the Cognitive Load Theory [21], there are three different types of load produced during problem-solving or learning: 1) intrinsic load, 2) the extraneous load and 3) the germane load.

(1) Intrinsic load depends on the complexity of the structure of the material and its association with the learner.
(2) The extraneous load is caused by the way this material is presented to the learner.
(3) The germane load is a result of the learner's ability to assimilate the material.

On the other hand, cognitive load is also defined as a construct that can be measured in three dimensions: 1) mental load, 2) mental effort and 3) performance [22]. In other words, past research indicates that cognitive load and mental load are related to each other in terms of the working memory. Therefore, we will be using them interchangeably. It is also interesting to note that the amount of workload varies between individuals [2]. This suggests that the amount of working memory is different for each individual. Thus, it highlights the significance of measuring the amount of the mental load in real-time in order to adapt the Interface during the HRI or HCI. Consequently, we are also involved in creating the technology that can adapt to the user's mental load in real-time. More specifically, we want to personalize the behaviour of the robot or adjust the information on the user interface to adjust humans mental overload.

Past research has indicated that it remains an open challenge to best estimate the individual's mental load in real-time [4, 14]. It suggests that mental load can be measured in three different ways: through subjective rating questionnaires (NASA Task Load Index[1]), through physiological sensors, or through performance-based objective measures (Mathematical Equations). However, subjective rating-based and performance-based objective measures are limited and cannot be utilized in real-time during HCI or HRI to adjust the interface or the behaviour of the robot. On the contrary, existing literature has highlighted different physiological measures that are continuous and can be used estimate mental load in real-time [14]. These measures include Pupil Diameter (PD), Blinking Rate (BR), Heart Rate (HR), Heart Rate Variability (HRV), Electroencephalography (EEG) and Galvanic Skin Response (GSR). Each of these methods have been shown to measure mental load during various tasks however each of them has their limitations. For instance: Eye activity (PD, BR) may not be suitable

[1] NASA Task Load Index - https://humansystems.arc.nasa.gov/groups/TLX/downloads/TLXScale.pdf

for tasks requiring continuous reading. Similarly, the sensitivity of pupil changes in cognitive load diminishes with age [25]. Additionally, the HRV may depend on the physical fitness of the individuals [10]. It is, therefore, significant to understand the relation between these physiological behaviors under different tasks or circumstances with each other and also onto each other. As our long-term goal is to estimate user's mental load in real-time to personalize interfaces or robot's behaviour, therefore, we believe that understanding the relationship between different physiological behaviour is vital and will help us in achieving our long-term goal of creating a model that takes various physiological behaviours as input to estimate mental overload or cognitive load in an efficient manner.

To achieve our long-term goal, we are currently collecting data from various physiological sensors to understand the relationship between aforementioned physiological behaviours under various task during HCI and HRI respectively [11, 17, 26]. Building on the prior work, this position paper proposes a system that could estimate a user's mental load during HCI and HRI in real-time. Our system will take various physiological features such as PD, HRV, HR, BR, and GSR as inputs and later these inputs will be used to implement a linear mixed-effects regression model to estimate the amount of user's cognitive load or mental load in real-time. We believe that such a system would help in adapting user interface and robot's behaviour during HCI or HRI and will in term improve user task performance.

RELATED WORK

In the past, empirical findings have highlighted a relationship between mental load or cognitive load and various physiological behavior (PD, HRV, HR, BR, GSR and EEG). It has been shown that the HRV reduces with an increase in the amount of cognitive load during a range of computerized tasks [13]. Similarly, another study observed an increase in HR with an increase in the difficulty level of the task or in other words in a situation demanding higher cognitive load [5]. In addition, we find a body of literature that suggests that pupil diameter increases with an increase in the number of mental load [16, 18]. Moreover, research suggests that the average number of blinks per minute in normal healthy adults varies according to the task. A study conducted with 150 adults showed that individuals on average blink four to five times per minute during a reading activity. Similarly, the rate of blinking per minute is higher during resting (17) and during conversation (26) [3]. Later, it has been shown that the blinking rate is minimized in the case of higher mental overload [6].

In summary, we find enough empirical evidence from past research implying that the change in the physiological behavior can be attributed to cognitive load or mental load and it also refers to various levels of mental processing. It is also important to note that the data collected on physiological behaviors through the various state of the art sensors is not only continuous but is also a robust and accurate representation of the particular behavior [7, 24]. It has been highlighted that users are required to wear cumbersome equipment, however, with the advancement of design and technology, existing solutions have been devised to collect such data in non-invasive ways.

In relation to our long-term goal, we currently find empirical evidence that few of the physiological behaviors are correlated with each other. For instance, both pupil dilation and blink-eye rate were seen to be correlating with each other in a digit-sorting task [19]. However, to the best of our knowledge, the relationship between all these behaviors have not been explored and is necessary to efficiently create an estimation for cognitive load or mental load. As highlighted we need to understand the relationships between different behaviors because this can help in creating a linear mixed-effect regression model that may estimate mental load in real-time during HCI or HRI. Consequently, We are currently conducting studies in order to collect data on these behaviours and also analyzing the relationships between different physiological behaviors.

System Description

We propose to develop a system that takes input based on different physiological behaviors grounded in the literature to estimate mental load or cognitive load. In this section, we describe our method to collect data from different sensors on various physiological behaviours.

To get data on blinking, we used a real-time algorithm that uses facial landmarks [20]. We firstly trained our Convolutional Neural Network (CNN) on the existing closed eyes in the wild dataset [23]. We later take each frame from the camera and crop the eyes and process the cropped images using the trained CNN. We then take the mean of the predictions and count the consecutive close predictions. If they meet the threshold, we count it as a blink.

To get data on pupil diameter in real-time, our system connects the Tobii Pro 2 eye-tracking glasses using the Tobii Pro Glasses 2 Python controller [24] library over Wifi with a computer. The system provides information on the cognitive load of the participant at 17 fps. After an elementary calibration phase that takes advantage of the pupillar light reflex [9], the system is able to track the user's cognitive load, based on an empirically set threshold. Our system provides a running average ζ, of pupil diameter:

$$\zeta(d) = \frac{\sum_{t=1}^{N} d_t}{N}$$

where d_t is the current pupil diameter and N the number of frames. It further provides a windowed average:

$$\zeta(d) = \frac{\sum_{t=1}^{15} d_t}{15}$$

where the average is calculated based on the past 15 frames only. Furthermore, our system provides a running peak estimation where we assume that when the size of the pupil is larger than 70% of the maximum the cognitive load is high [12].

To collect data on HR and HRV, we used the EliteHRV coreSense device [8]. The device comes with an API and works in the following manner. The HRV is calculated through receiving the R-R intervals directly from the device. R-R intervals refers to the small changes (milliseconds) in the intervals between successive heartbeats. After performing necessary data cleaning, a Root Mean Square of Successive Differences (RMSSD) calculation is applied to the R-R intervals. Later, a natural log (ln) is applied to RMSSD. The ln(RMSSD) is expanded to generate a useful 0 to 100 score to give a value of HRV [7].

To collect data on the galvanic skin response, we used GSR device from ProComp Infiniti of Thought Technology Ltd.

In the current setup, we are collecting data simultaneously from all the sensors and trying to understand the relationship between them. Upon successful collection of data, we hope to analyze the data through running Pearson's correlation to understand the relationship between these behaviours. We later intend to device a linear mixed-effect regression model to index cognitive load in real-time.

Conclusion and Future Work

In the paper, we proposed an idea of a system that could potentially provide a robust non-intrusive measurement of mental workload in real-time during HCI. Our future work is focused on the implementation of our model and later testing it during various HCI and HRI scenarios.

REFERENCES

[1] Muneeb Ahmad, Omar Mubin, and Joanne Orlando. 2017. A systematic review of adaptivity in human-robot interaction. *Multimodal Technologies and Interaction* 1, 3 (2017), 14.

[2] Alan Baddeley. 1992. Working memory. *Science* 255, 5044 (1992), 556–559.

[3] Anna Rita Bentivoglio, Susan B Bressman, Emanuele Cassetta, Donatella Carretta, Pietro Tonali, and Alberto Albanese. 1997. Analysis of blink rate patterns in normal subjects. *Movement Disorders* 12, 6 (1997), 1028–1034.

[4] Fang Chen, Natalie Ruiz, Eric Choi, Julien Epps, M Asif Khawaja, Ronnie Taib, Bo Yin, and Yang Wang. 2012. Multimodal behavior and interaction as indicators of cognitive load. *ACM Transactions on Interactive Intelligent Systems (TiiS)* 2, 4 (2012), 22.

[5] Kristen N Cranford, Jessica M Tiettmeyer, Bryan C Chuprinko, Sophia Jordan, and Nathaniel P Grove. 2014. Measuring load on working memory: the use of heart rate as a means of measuring chemistry studentsâĂŹ cognitive load. *Journal of Chemical Education* 91, 5 (2014), 641–647.

[6] Morris K Holland and Gerald Tarlow. 1972. Blinking and mental load. *Psychological Reports* 31, 1 (1972), 119–127.

[7] Elite HRV. 2018. How do you calculate the HRV score? Webpage. https://help.elitehrv.com/article/54-how-do-you-calculate-the-hrv-score

[8] Elite HRV. 2019. CorSense Heart Rate Variability. Webpage. https://elitehrv.com/corsense

[9] Andrew L Kun, Oskar Palinko, and Ivan Razumenić. 2012. Exploring the effects of size and luminance of visual targets on the pupillary light reflex. In *Proceedings of the 4th International Conference on Automotive User Interfaces and Interactive Vehicular Applications*. ACM, 183–186.

[10] Antonio Luque-Casado, Mikel Zabala, Esther Morales, Manuel Mateo-March, and Daniel Sanabria. 2013. Cognitive performance and heart rate variability: the influence of fitness level. *PloS one* 8, 2 (2013), e56935.

[11] Georgios Minadakis and Katrin Lohan. 2018. Using Pupil Diameter to Measure Cognitive Load. *arXiv preprint arXiv:1810.07593* (2018).

[12] Georgios Minadakis and Katrin Lohan. 2018. Using Pupil Diameter to Measure Cognitive Load. *arXiv preprint arXiv:1812.07653* (2018).

[13] Shalini Mukherjee, Rajeev Yadav, Iris Yung, Daniel P Zajdel, and Barry S Oken. 2011. Sensitivity to mental effort and test–retest reliability of heart rate variability measures in healthy seniors. *Clinical Neurophysiology* 122, 10 (2011), 2059–2066.

[14] Fred Paas, Juhani E Tuovinen, Huib Tabbers, and Pascal WM Van Gerven. 2003. Cognitive load measurement as a means to advance cognitive load theory. *Educational psychologist* 38, 1 (2003), 63–71.

[15] Leah M Reeves, Jennifer Lai, James A Larson, Sharon Oviatt, TS Balaji, Stéphanie Buisine, Penny Collings, Phil Cohen, Ben Kraal, Jean-Claude Martin, et al. 2004. Guidelines for multimodal user interface design. *Commun. ACM* 47, 1 (2004), 57–59.

[16] Jamie Reilly, Alexandra Kelly, Seung Hwan Kim, Savannah Jett, and Bonnie Zuckerman. 2018. The human task-evoked pupillary response function is linear: Implications for baseline response scaling in pupillometry. *Behavior research methods* (2018), 1–14.

[17] Yerlikzhan Sabyruly, Frank Broz, Ingo Keller, and Katrin Solveig Lohan. 2015. Gaze and Attention During an HRI Storytelling Task. Artificial Intelligence for Human-Robot Interaction : AAAI 2015 Fall Symposium Series, AI-HRI 2015 ; Conference date: 12-11-2015 Through 14-11-2015.

[18] Yerlikzhan Sabyruly, Frank Broz, Ingo Keller, and Katrin Solveig Lohan. 2015. Gaze and Attention During an HRI Storytelling Task. In *2015 AAAI Fall Symposium Series*.

[19] Greg J Siegle, Naho Ichikawa, and Stuart Steinhauer. 2008. Blink before and after you think: blinks occur prior to and following cognitive load indexed by pupillary responses. *Psychophysiology* 45, 5 (2008), 679–687.

[20] Tereza Soukupová and Jan Cech. 2016. Real-time eye blink detection using facial landmarks. In *21st Computer Vision Winter Workshop*.

[21] John Sweller. 1994. Cognitive load theory, learning difficulty, and instructional design. *Learning and instruction* 4, 4 (1994), 295–312.

[22] John Sweller, Jeroen JG Van Merrienboer, and Fred GWC Paas. 1998. Cognitive architecture and instructional design. *Educational psychology review* 10, 3 (1998), 251–296.

[23] Xiaoyang Tan. 2019. Closed Eyes In The Wild (CEW). Webpage. http://parnec.nuaa.edu.cn/xtan/data/ClosedEyeDatabases.html

[24] Davide De Tommaso. 2018. Tobii Pro Glasses 2 Python controller. Webpage. https://github.com/ddetommaso/TobiiProGlasses2_PyCtrl

[25] Pascal WM Van Gerven, Fred Paas, Jeroen JG Van Merriënboer, and Henk G Schmidt. 2004. Memory load and the cognitive pupillary response in aging. *Psychophysiology* 41, 2 (2004), 167–174.

[26] Abdelrahman Yaseen and Katrin Lohan. 2018. Playing Pairs with Pepper. *arXiv preprint arXiv:1810.07593* (2018).