A Computer Mouse for Stress Identification of Older Adults at Work

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ABSTRACT

Stress is an unpleasant condition that entails negative emotions such as fear, worry and nervousness. Motivated by existing research that accompanies stress with physical reactions like increased heart rate, blood volume, pupil dilation and skin conductance, this work builds on the premise that measuring such reactions in real-time could implicitly identify stress of older adults at work while interacting with a system. For this purpose, an in-house computer mouse was built with embedded sensors for measuring the users' heart rate, skin conductance, skin temperature, and grip force. We have developed a probabilistic classification algorithm that receives as input these physiological measurements, and accordingly identifies emotional stress events. This work contributes to a large body of research in user modeling, aiming to identify when computer users are stressed, and accordingly provide intelligent interventions and personalized solutions to help reduce their frustration and prevent negative health conditions.

CCS Concepts

• **Human-centered computing → Interaction devices**

Keywords

Computer Mouse; Physiological Sensors; Older Adults.

1. INTRODUCTION

As the population ages, risks of cognitive decline threaten independence and quality of life for older adults, also presenting challenges to the health care systems and their close relatives. Early signs of cognitive decline are already present for some individuals during midlife. The rate of severity of cognitive decline has been proven to be in association with a variety of notably modifiable factors such as emotional stress [1, 2]. However, if risks in emotional stress are identified and modified early on, it will be possible to help detect and prevent the progression of cognitive deficits later in life.

Several research studies have shown that psychological stress can be modifiable to a significant extent, and proactive identification of this factor combined with appropriate ICT-based interventions can decrease the rate of intellectual decay. However, traditional approaches of identifying psychological stress require older adults to take continuous sessions with doctors and psychologists which can be time consuming, frustrating, and worse, might intensify existing stress levels of the individuals. In this context, several works have focused on implicitly identifying stress by utilizing information and communication technologies (ICT) (e.g., [4, 8]).

In contrast to recent works, our efforts have been focused on the seamless identification of psychological stress of older adults that are still active at work, by leveraging sensors that are embedded in a computer mouse. For the purpose of this research an in-house computer mouse was built that entails sensors for the real-time measurement of heart rate, skin conductance, temperature, and grip force. The computer mouse, coined CogniMouse [3], has been implemented in the context of the CogniWin project [20, 22], which is a personalization system for assisting and motivating older adults to stay for longer active in the workplace.

The paper is organized as follows: we next present a brief overview of traditional approaches for stress measurement, followed by a state-of-the-art analysis of approaches that leverage physiological sensors for measuring stress. Subsequently, we present the conceptual design of CogniMouse, focusing on the stress identification algorithm. Then, we present a use case scenario that shows how the proposed mouse is integrated in an intelligent interactive system for personalizing content and functionality based on the users' affective states that are triggered by the stress identification algorithm. We finally conclude the paper with future directions of this work.

2. TRADITIONAL STRESS MEASUREMENT

Measuring stress has been the focus of attention for researchers and practitioners for many years. One of the most common and early approaches of stress measurement is based on analyzing stress hormones (e.g., adrenaline) through blood samples [4]. Less intrusive methods are based on self-report questionnaires. Popular examples include the Daily Stress Inventory (DSI) [5] which is designed to measure the number and relative impact of common minor stressors (interpersonal problems, personal competency, cognitive stressors, environmental hassles) frequently experienced in everyday life. The Depression Anxiety and Stress Scale (DASS) [6] consists of three scales, measuring the negative emotional states of depression, anxiety and stress. The stress scale assesses relaxing difficulty, nervous arousal, and being easily upset/agitated, irritable/over-reactive and impatient. Alternative approaches explore mechanistic and behavioral links between stress, anxiety, resilience, and human behavior, and accordingly leverage such interaction effects aiming to implicitly measure stress [7].

3. PHYSIOLOGICAL-BASED STRESS MEASUREMENT

A vast amount of works leverage ICT for the implicit measurement of stress. Popular examples include interaction analysis of users with the computer keyboard and mouse [4, 8], and the use of physiological sensors. The most commonly used physiological sensors are those measuring galvanic skin response (also referred as skin conductance or electrodermal activity - EDA), pupil dilation, skin temperature, heart rate, and blood volume pulse. The literature reveals works utilizing these sensors that are *attached to the users*, or embedded in *computer devices*. In this section, we present an analysis of state-of-the-art research works of each category.

3.1 Sensors Attached to Users

Popular approaches include exploiting physiological sensors attached directly to the users or to instruments that are in direct contact with the users while interacting with a system (e.g., sensors attached to the chair). Ward and Marsden [9] have examined users' physiological responses to different Web-pages by leveraging sensor data of skin conductance, heart rate, pupil dilation, and blood volume pulse. Other works [10, 11, 12] have also used such physiological measurements for eliciting valence and emotional arousal. While these works have shown a correlation between physiological measurements and human emotions, they share a common barrier of practical applicability since these require additional intrusive hardware to be attached to the user. To alleviate such issues, research works have focused on embedding sensors within computer devices (and wearable devices) since these are equipment that users continuously come in contact with while interacting with a system.

3.2 Sensors Embedded in Computer Devices

Prior works have embedded sensors in computer mouse devices for measuring and identifying stress. Popular and early examples include SenticMouse [13], a computer mouse that contains a pressure sensor that collects finger pressure. Results of an experimental study investigating users' finger pressure signals while browsing affective images revealed a correlation between finger pressure and positive vs. negative valence states. In [14], a computer mouse was built, embedding a grip and click force sensor. A study entailing a stressor task, revealed that click force was significantly higher during stressor tasks, but with no observable main effects in the case of grip force. In [15], a computer mouse was proposed that acquires physiological signals (skin conductance and heart rate) from a computer user for the detection of psychosomatic state, affect and emotional responses. In a follow up study [16], the same computer mouse was used for deducing user states of engagement utilizing the same physiological measurements. The work reported in [17] investigated the effects of physiological or behavioral data on stress, by making use of a wrist sensor that measures acceleration and skin conductance, and mobile phone usage, combined with a survey (eliciting stress, mood, general health, beverage intake, etc.). Based on a machine learning approach, the system achieved over 75% accuracy in a binary classification. Another stream of research focused on leveraging sensor data from wearable devices (e.g., smart watches). Fletcher et al. [18] presented a wireless sensor platform and the design of wearable sensors for long-term measurement of electrodermal activity, temperature, motor activity, and photo plethysmography. Based on this work, Embrace Watch [19] was announced recently which is a smart watch that monitors stress, arousal, sleep and physical activity based on physiological sensors.

Fig. 1. Mockup Design of CogniMouse.

4. A COMPUTER MOUSE FOR STRESS MEASUREMENT – THE CASE OF COGNIMOUSE

4.1 Overview

CogniMouse is an advanced human interface device built around a standard computer mouse. The main innovative goal behind this smart device is to detect *older adults'* emotional states and any stress occurring whilst performing tasks in a personal computer. Hence, its user-friendly design illustrated in Figure 1, has been chosen so that older adults feel acquainted, making it more likely to accept CogniMouse when carrying out their work. Currently supporting Windows 7, 8 and 10, the software developed is able to run on the background without interfering with user actions, while at the same time acquiring multi-sensory information in real time.

The design of the mouse consists of a suite of physiological sensors that include: an inertial measurement unit (IMU), temperature, heart rate, grip force, and galvanic skin response sensors. Figure 2 illustrates the CogniMouse hardware architecture. A custom PCB (Printed Circuit Board) has been developed to integrate all sensors, the corresponding signal conditioning electronics and a microcontroller. The microcontroller is responsible for reading and preprocessing of raw data coming from the sensors, transmitting it over USB. The PCB also has an embedded USB hub in order to allow the transmission of the sensor data and mouse motion over USB to the computer.

Besides this, the device leverages valuable information such as mouse movement and click streams provided by low-level OS calls, *a priori* knowledge of the user health profile and history of sensor data. Through the combination of all these components, it is possible to assess the user's conditions. More particularly, this device focuses on the detection of symptoms associated to stress episodes, such as: indecisiveness, lack of focus, impaired decision-making, fearful anticipation, agitation, feeling tense, general unhappiness, stiffness, rapid heartbeat, sweating hands, etc.

4.2 Stress Classification Algorithm

A classification algorithm is currently under development and testing, which is grounded on probabilistic theory, and continuously provides a level of certainty at which the user might be experiencing stress. A Bayesian-based formalism inspired on conditional probability distributions is employed to solve the problem due to its flexibility of incorporating new variables/inputs. The inputs used for the classification algorithm are: *i)* grip force; *ii)* heart rate; *iii)* skin conductance; *iv)* hand temperature variations; *v)* a hand trembling indicator given by mouse motion and accelerations; and *vi)* click stream frequency.

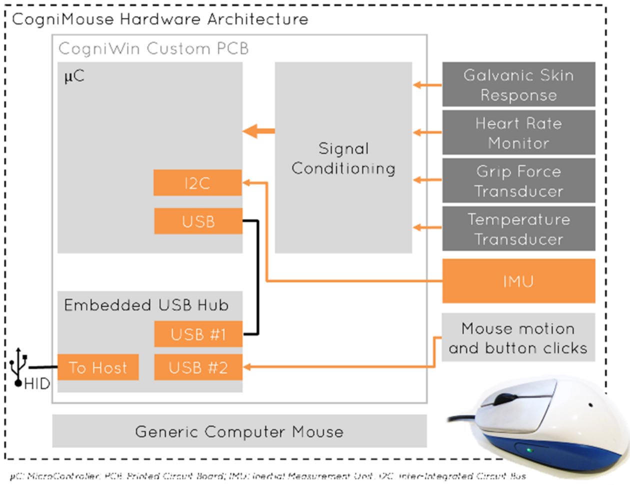

Fig. 2. CogniMouse Hardware Architecture.

A prior distribution is modeled using typical intervals of the user sensory parameters extracted previously from the mouse in a relaxed environment during a long period of time. Likelihood functions for each input have been derived heuristically by defining increasing influence to high deviations or abnormal input levels. An independent stress measurement is obtained by applying Bayes formula at each step considering prior and likelihood distributions, paired with a normalization factor that scales the result to a [0, 1] interval. Finally, the output of the classification algorithm results from applying a smoothing filter to the measurement obtained, which gives recursively decreasing weights to past measurements of stress, which have been obtained using the same probabilistic method.

A validation of the algorithm proposed is currently planned, which will allow to conduct further tests, and eventually adjust the approach developed. Preliminary trials with a small group of distinct senior users are envisioned so as to verify whether the algorithm adapts to each person's specific profile and provides valid outputs concerning user's stress levels. These outputs should then be cross-verified by annotations from psychologists and experts which will be witnessing the trials attentively. These preliminary trials will allow adjustments of the approach so as to adapt to all kinds of users, and the final validation will be conducted within the time frame of the CogniWin project [20, 22], in which a large group of older adults will test the system at the end-users' premises of ArgYou in Bern, Switzerland; and Zuyderland Care Center in Sittard, the Netherlands.

4.3 Scope and Innovation

CogniMouse [3, 21] has been implemented in the context of the CogniWin project [20, 22], which is a personalization system for assisting and motivating older adults to stay for longer active in the workplace. The CogniWin system architecture is generically presented in Figure 3. Accordingly, CogniMouse is supplied with two applications. The first is a background worker responsible for parsing the incoming messages. This application is also responsible for distributing the incoming messages for other applications with interest on the data. The second application intends to be an easy way to visually verify the incoming data. This application will provide user-friendly charts displaying the classification of the emotional state of the user, a histogram with the last measurements from the CogniWin mouse sensors, and the possibility to record and export data.

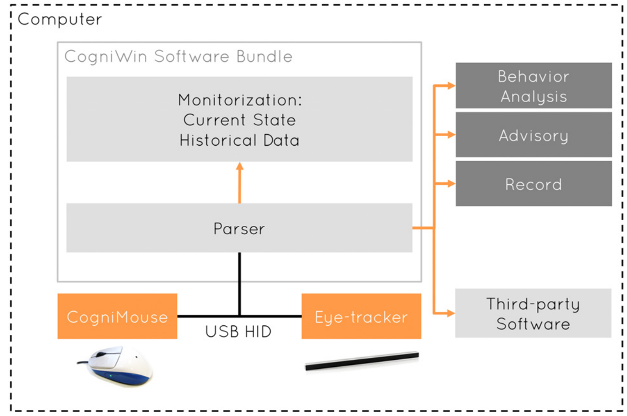

Fig. 3. CogniWin System General Architecture.

In this context, CogniMouse measures and analyzes data from the aforementioned physiological sensors that have been seamlessly embedded in the mouse, and provides personalized information to the users and caregivers, such as an indication of the emotional state of the user, whether the user is hesitating or having problems while performing a task [3], whether the user is frustrated [21] or is feeling sleepy. Apart from displaying this information to the user, any third-party software can use this information for providing personalized services, e.g., in case user hesitation is detected within a given task, the system may infer that the user is having difficulties completing the task and thus might provide support to the user.

To the best of our knowledge, the main innovative goal behind this smart device is three-fold: *i)* the seamless detection of older adults' emotional states and any stress occurring whilst performing tasks in a computerized working environment; *ii)* the combination and fusion of different types of sensor data developed for measuring and identifying unpleasant situations of older adults in their work environment (e.g., stress, frustration), detecting difficulties in completing a particular task [3] and/or user frustration [21]; and *iii)* the application of the computer mouse in the CogniWin system for supporting older adults at work by leveraging their emotional states through real-time sensor signal analysis.

5. USE CASE SCENARIO

Rolf is 61 years old and has been working for 15 years as senior consultant at AOK, a German health insurance company. He gained a long experience on AOK's customer relationship management system and he is responsible for vital operations of the company. As he still feels young, and is active, his intention is to stay for three more years working in the company in a paid mode. Recently the company undertook a lot of changes which resulted in several upgrades to the system that he has been using, triggering negative emotions such as stress and lack of confidence in staying longer at work. His director recognized his concerns and provided him with an innovative computer mouse called CogniMouse that will assist him to adapt his process' operations to fit into the new environment. He was told that the mouse will monitor his computer tasks' activities and adapt the workload to his performance in order to avoid overloading him and all the stress and performance loss that could be generated. In this respect, Rolf was trying to carry out a transaction, but was hesitating as he was not sure if he was doing it correctly. CogniMouse realized this hesitation by analyzing the data collected from the intelligent mouse (imprecise movement, increased stress levels), and a contextual recorder. Accordingly, the system presents a graphical help wizard of how to further proceed by guiding Rolf's mouse and keyboard actions to the graphical system area that contains the next step of his process. Rolf was very surprised as he felt that CogniMouse is refreshing his memory and assisting him to complete the tasks. Rolf starts feeling less stressed and happy that he can manage all the new technological changes in his work.

6. CONCLUSIONS AND FUTURE WORK

This work-in-progress paper presents a research effort towards the design and development of an intelligent computer mouse for implicitly measuring users' stress levels. For this purpose, an existing off-the-shelf computer mouse was redesigned and developed embedding physiological sensors for measuring in real-time the users' heart rate signal, skin conductance, skin temperature, and grip force. Based on the raw input of these measurements, a novel probabilistic classification algorithm has been developed for identifying stress raising events. A study with older adults at work is currently in progress aiming to investigate the accuracy of the classification algorithm in specific stress triggering events. Future work includes the integration of CogniMouse in the CogniWin system [20, 22], and in combination with other sensor data (e.g., eye tracker) and contextual task information, personalized assistance and support will be provided to users in raising events of difficulty, frustration and uneasiness.

7. ACKNOWLEDGMENTS

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