ABBAS: An Adaptive Bio-sensors Based Assistive System

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Abstract
Assistive systems have become commercially available to help new workers or workers with cognitive disabilities to learn new tasks. However, continuous feedback systems can make the worker feel patronized or bored, which might influence their performance. We present ABBAS, a novel integration of four different bio-sensors into an assistive system, using in-situ projection for providing feedback and measuring workers' stress levels during assembly work tasks through bio-sensors in real-time. It adjusts work steps according to the worker's state. In two user studies, we assessed the suitability of different bio-sensors to detect the worker's stress level and showed the feasibility of Galvanic Skin Response to create adaptive assistive systems that consider the workers' current physiological state. Finally, we discuss how integrating bio-sensors influences assistive systems and leads to both opportunities and challenges for assistive technology in general.

Author Keywords
Cognitive Workload Measurement; Adaptive Assistive Systems; Biosensors

ACM Classification Keywords
H.5.2 [Information interfaces and presentation (e.g., HCI)]: User Interfaces

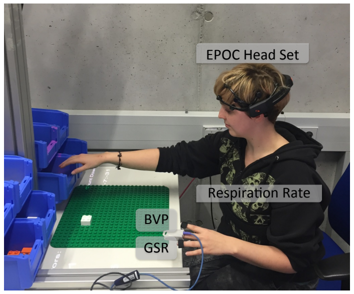

Figure 1: Four different bio sensors to assess a worker's state during an assembly task: Galvanic Skin Response (GSR), Blood Volume Pressure (BVP), Respiration Rate, and Electroencephalography (EEG).

Introduction

Work processes in manual manufacturing are becoming increasingly complex. This is mostly due to a growing number of variants that need to be assembled at a single workplace. Additionally, for reducing storage costs, manufactured products are nowadays produced on demand, *i.e.*, after the customer ordered a product. Frequently changing the product to be assembled at a single workplace leads to a higher cognitive load for the workers. Hence, assistive systems using for instance Augmented Reality (AR) or in-situ projection have been introduced to cognitively support workers at the workplace.

Using head-mounted displays (HMDs) has further been suggested to augment the workplace [22, 25]. Others used in-situ projection to display information directly in the workers' field of view (FoV) [2, 4, 9, 13]. An example for such systems are the Light Guide Systems from OPS solutions[1] or the WERKLICHT system by EXTEND3D[2]. Using such systems during assembly processes was found to increase the workers' performance and reduce the number of errors made during the assembly [9]. However, previous work also showed that presenting too much help at the workplace can result in an increased number of errors and assembly time [6]. Therefore, we should present instructions at the workplace, however the worker should not be overwhelmed with instructions. Thus, we argue to take the current situation and state of the workers into account.

In this paper we present an adaptive assistive assembly system, that takes the cognitive state of the worker in real-time into account. Based on four bio-sensors (see Figure 1), we investigate the feasibility of inferring stress levels in real-time and support the worker according to the current workload during assembly tasks. We conducted two user studies to investigate the usage of commercial bio-sensors to assess workload during assembly tasks. Our findings show that GSR reliably detects cognitive workload in workplace settings and allow instructions to be adapted according to these measured workload levels. Study participants welcomed our approach of using bio-sensors in work environments to enhance assistive systems with adaptive features. The contribution of this work is to show that the GSR is showing reliable results for measuring workers' workload at manual assembly workplaces.

[1] http://www.ops-solutions.com/ - last accessed February 17, 2017
[2] http://www.extend3d.de/werklichtpro.php - last accessed February 17, 2017

Related Work

We review the prior work done in three fields: (1) assistive systems, (2) state assessment and (3) how they have been deployed together to build adaptive and personalized systems.

Assistive Systems

Researchers targeted the development of assistive systems in the workplace using camera-projector systems [2]. Funk et al. [5] evaluated feedback systems for supporting inexperienced workers in an industrial work place. 'The results showed that a contour visualization is a significantly better way to present instructions at the workplace. Funk et al.[7] further evaluated haptic, auditory, and visual error feedback modalities for assistive systems at a manual assembly workplace. Buttner [3] compared HMD with in-situ projection and found that in-situ projection lead to better worker performance.

User's State Assessment

Autonomic Nervous Systems (ANS) controls the organs of our body, such as the heart, stomach, and intestines. It is accountable for activating the glands and organs for defending the body from threats. Its activation might be accompanied by many bodily reactions, such as an increase in the heart rate, rapid blood flow to the muscle, activation of sweat glands, and increase in the respiration rate. These physiological changes can be measured objectively by using sensors [14, 19]. Haak et al. [11] proved that the increase of blinking rate extracted from EEG signals is related to stress levels. However, Yu,et al. [20], explored GSR as indicator of cognitive load. Elise et al. [15] used heart rate, respiration rate and GSR as stress indicator.

Using Bio-Signals to Adapt Systems
Adaptive systems are now deployed in a wide range of systems including cars, games, museums, and work environment. Wang et al. [23] showed that EEG signals can be used to infer the memory workload. Parnandi et al. [17, 18] considered real-time adaptive games introduced two different real-time adaptive biofeedback games.

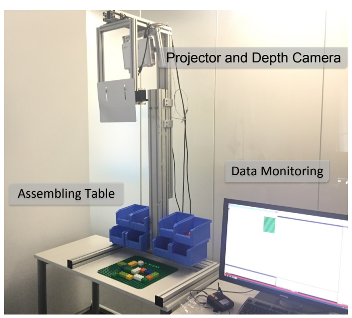

Figure 2: Setup.

Abdelrahman et al. [1] recommended a personalized feedback system that can detect visitor's engagement in the exhibited objects by measuring brain signals. Other researchers were concerned with the work environment. Wang et al. [24] explored how to build an adaptive system that helped workers who heavily use computers on a daily bases by extracting features, such as face pose, eye blinking, yawn frequency and eye gaze from a recorded video. Hernandez et al. [12] integrated bio-sensors, namely: GSR and skin temperature with sensitive keyboard and mouse clicking to be able to discriminate between stressful and relaxing stages in a workplace.

In our work, we aim to evaluate the deployment of four commercially available bio-sensors to monitor the worker's state in a manual assembly environment rather than a stationary or stable environment. When being overwhelmed with a task at hand, workers exhibit symptoms of stress and anxiety. Bio-sensors can detect these symptoms by collecting bio-data, such as GSR, BVP, and respiration rate or by using a Brain Computer Interface (BCI) for the EEG. The system would be able to detect the worker's cognitive state in real-time and adapt the task difficulty accordingly.

The ABBAS-System
In our work we assess the feasibility of using bio data in creating an adaptive assistive system for an assembly workspace. We extended Funk et al.'s [5] assistive system, as shown in Figure 2. The setup consists of a top-mounted projector that provides visual feedback about whether the worker selected the correct part and assembled them correctly using the proper tools.

Based on the survey by Gedon et al. [19], which reviewed bio-sensors, such as EEG, BVP, Heart rate variability (HRV), GSR, and Electromyography (EMG), our system combines the following senors; GSR, blood volume pressure, and respiration sensors using the NeXus[3] device, in addition to the blinking rate and EEG measurements from EMOTIV EPOC [4] headset. Both devices send data via bluetooth. For the EEG measurements, we used the predefined brain stages in the EMOTIV EPOC software namely; frustration, meditation, excitement and engagement.

Pilot Study
To assess the feasibility of our concept and answer the research question "can assistive systems be adaptive using bio-sensors?", we first conducted a pilot study in a controlled lab setting.

The study was designed using a 4-level repeated-measures design with three different tasks and a baseline as the in-

[3] http:http://www.mindmedia.info/CMS2014/
[4] http://emotiv.com

Baseline: Participants were asked to assemble a Lego construct by picking parts out of available Lego picking bins. The top projection indicated which assembly part to pick from one of the Lego bins and where to assemble it on [10]. The baseline did not comprise any tasks in parallel.

Stroop-Test: During the assembly task, names of colors were projected on the assembling table. Participants were asked to say out loud the color [21].

3-back Task: During the assembly task, a sequence of numbers appeared on the assembling table. Participants were asked to say out loud the 3rd number back in that sequence, having to keep track of the numbers projected [16].

Add-3 Task: During the assembly, a number consisting of four digits appeared on the assembling table. Participants were asked to add 3 to each of those digits and tell the experimenter.

dependent variable and the level of cognitive effort as dependent measure. The four conditions with presumably increasing cognitive demand were: Baseline, add-3, 3-back and stroop test (see side column).

As dependent variables, we measured participants' error rate (ER), GSR, BVP, respiration rate, blinking rate, and EEG. We further asked participants to fill in a NASA-TLX survey for mental and physical measurement.

For the data logging we used the NeXus and Emotive Dynamic-Link Libraries(DLLs) to connect and send data between the devices and the assistive system. All data was recorded using time stamps for synchronization. The computerized cognitive load surveys were filled afterwards.

Procedure

To examine the differences in workload, we performed a within-subjects study. All participants performed all tasks during the experiment. The order of the conditions excluding the baseline was counter-balanced using a Latin-square design to avoid any learning effects. The study time was around task 30 (10 x 3 tasks) minutes plus 10 minutes for attaching sensors and ensuring stable connection.

After welcoming the participants, a brief description for the study and its goal was explained to the participant. We attached the sensors to the participant as shown in Figure 1. All participants started with the baseline. The remaining tasks followed in a random order.

Participants

We recruited 12 participants (4 female) with a mean age of 24 years ($SD = 3.51$) using university mailing lists. All participants were students in different majors. Two of the participants were left-handed.

Data grouping: We present the data by getting mean value for each 50 readings. Data was then grouped into data packets from the NeXus and EPOC using time stamps.

Results

We statistically compared the GSR, BVP, Respiration rate, blinking rate, and the EEG as well as NASA-TLX and the cognitive survey responses between for all four conditions. For sensors' data and NASA-TLX analysis we used a one-way repeated measures ANOVA. For the cognitive survey questions we applied a Friedman test.

Using a one-way ANOVA test, Mauchly's test showed that the sphericity assumption was violated for GSR ($X^2(5) = 15.088, p < .010$). We used the Greenhouse-Geisser correction to adjust the degrees of freedom ($F(1.613, 16.128) = 11.795, p < 0.001$) and $\epsilon = 0.538$). The post-hoc test revealed a large effect ($\eta^2 = .541$) and a significant difference ($p < 0.05$) between baseline task and all other tasks. As shown in Table 1, the baseline has the lowest score , following the add-3 , stroop and then the 3-back with the highest score. However for both BVP, and Respiration rate measurements no significant differences could be detected.

Engagement measurements: the baseline had the highest values, followed by the 3-back , the add-3, and finally the stroop task. There was large effect ($\eta^2 = .593$) and a statistically significant difference among approaches ($F(3, 33) = 3.284, p < 0.001$). The post-hoc test revealed a significant difference between baseline task and the rest of the tasks ($p < 0.001$).

Excitement measurements were also considered. The baseline yielded the least excitements measurements, then add-3 task, followed by 3-back, and finally the stroop. There was a large effect ($\eta^2 = .292$) and a statistically significant difference between approaches ($F(3, 33) = 4.538, p <$

	Mean	SD	Significant
Baseline	5.3	1.9	All Tasks
Stroop	7.9	3.9	Baseline
3-Back	7.9	3.2	Baseline
Add-3	7.9	3.5	Baseline

Table 1: GSR Data.

	Mean	SD	Significant
Baseline	0.73	0.10	All Tasks
3-Back	0.62	0.62	Baseline
Add-3	0.61	0.67	Baseline
Stroop	0.59	0.49	Baseline

Table 2: EPOC Engagement Data.

	Mean	SD	Significant
Baseline	0.49	0.17	All Tasks
Add-3	0.52	0.18	Baseline
3-Back	0.58	0.14	Baseline
Stroop	0.69	0.14	Baseline

Table 3: EPOC Excitement Data.

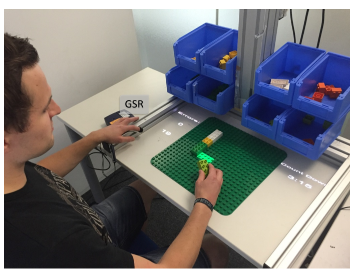

Figure 3: A participant during the second user study with the GSR attached on his fingers.

0.05). The post-hoc test revealed a significant difference between add-3 task and the color task ($p < 0.05$). However, the blinking rate, meditation, and frustration measurements were not significant among the tasks.

NASA-TLX The post-hoc test revealed a significant difference ($p < 0.013$) and a large effect ($\eta^2 = .361$) between the Stroop and the 3-back. Stroop had the lowest score ($M = 53.75, SD = 15.2$) followed by the add-3 ($M = 62.58, SD = 17.9$) and 3-back with the highest perceived cognitive load ($M = 73.0, SD = 17.09$).

Threshold In order to identify the different states, we needed to compute a threshold for the GSR values. We systematically tested the threshold values and computed the false positives and negatives from the normalized graph as shown in Figure 4. Finally, we calculated a general ratio of 1.3 relative to the user's baseline value.

Our findings imply that the BVP sensor was not significant and very sensitive to minimal movements and respiration. EEG values were not significant either. However, the GSR data was significant. Based on the tasks comparison, 3-back challenge has significantly reported the highest challenging task. Therefore, it was used in the second user study for system validation.

Validation Study

To validate the computed threshold and investigate the behavior of the adaptive system based on the threshold we conducted a second user study.

Measuring work load via the GSR sensor, participants were asked to perform the baseline task consisting of the assembly of the Lego parts with the help of the projection as described in the pilot study. The baseline data collected was used to compute the workload threshold (1.3 $\times$ baseline).

Adaptive task: The second task required participants to perform the 3-back task while assembling the Lego parts. The study took 20 minutes in total. The 3-back task duration was longer this time to guarantee efficient evaluation by recording more readings.

The NeXus sensor provided the GSR readings to the system. These values were compared to the calculated threshold. If the GSR values exceeded the threshold, the user was considered to be overwhelmed. Hence, the 3-back challenge was removed and participants were asked to continue assembly without any distractions for 20 seconds. When the GSR values dropped below the threshold, the user was considered to be comfortable again and so the 3-back task would be shown again.

We recruited 8 participants (2 female) with an average age of 22 years ($SD = 1.9$) who had not previously taken part in our pilot study.

After the study we conducted interviews with the participants to evaluate the introduced system.

Results and Observation

After analyzing the data from the 3-back task the following result was observed. The participants' GSR values varied according to their workload state. When the 3-back was displayed, the GSR readings kept rising. When the readings exceeded the threshold, the 3-back was removed and the GSR readings started decreasing. When the GSR values dropped below the threshold the 3-back was added once more to the task and as a result GSR values started increasing again. Figure 5 shown how participants' GSR values varied throughout the task. According to the post tasks interviews, one participant stated that the task was challenging and likable. However, he was relieved when it was removed as a sort of a break. It was noticed that only

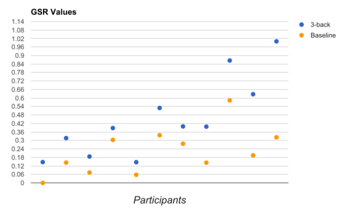

Figure 4: Relation between the baseline and 3-back GSR values.

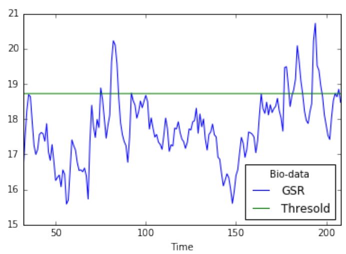

Figure 5: GSR values varying according to the task.

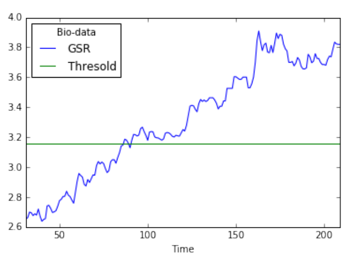

Figure 6: GSR values increasing during the task.

one participant whose GSR values kept increasing during the entire study. Even after the task was adapted to their workload level, as seen in Figure 6. According to the post task interviews, he was stressed and worried that the 3-back would be shown again. Hence, they kept stressing out through the whole task.

Participants	Group	Number of Peaks	Time Up	Time Down
P1	1	7	1.76	0.10
P2	1	3	0.42	0.52
P3	1	2	1.72	0.76
P4	1	2	2.59	0.20
P5	1	2	2.19	0.60
P6	1	7	1.3	0.27
P7	2	1	3.76	-
P8	1	4	2.73	0.49

Table 4: Time taken for frustration and relaxing.

Additionally, to have insights about the behavior of the cognitive workload and the sensor reading, we analyzed the cognitive workload over time. The time it took participants to exceed the threshold was $M = 1.82$sec ($SD = 0.79$), however the mean time taken for them to relax again was $M = 0.42$sec ($SD = 0.24$). This reflects the usability and real time responsiveness of using such a sensor in the assembly working environment.

All participants recommended the adaptive assistive system using bio-sensors in real industrial life in order to monitor workers behavior and offer help when needed. Participants' only concern was the privacy issues as they do not want their bio-data to be public to everyone.

Limitations

During the assembly task, participants were able to complete the task using their dominant hand only. Additionally we should explore different contact-less sensors that will allow participants to use both hands without distraction.

CONCLUSION AND FUTURE WORK

This work explored the feasibility of using bio-data to create an adaptive assistive system. User's cognitive workload level was first measured using different bio-data: EEG, blinking rate, GSR, BVP, and respiration rate. Results indicated GSR to be the most significant measure, NASA-TLX and another cognitive surveys were used to validate this conclusion. Based on our findings we derived a threshold for adapting our assistive system in order to accommodate for when users were overwhelmed with a task. We validated this threshold by conducting a second user study. Post-tasks interviews revealed that participants accepted working in an adaptive environment. By detecting and acting on overly demanding tasks, such systems could eventually prevent burnouts due to high stress levels and at the same time increase productivity in phases of low task engagement by adding work steps. Considering future work, we want to deploy our system in a real-world work environment to study the effects of an adaptive assistive system in an everyday workplace.

Acknowledgments

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