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ABSTRACT

Contact-free camera-based measurement of cognitive stress opens up new possibilities for human-computer interaction with applications in remote learning, stress monitoring, and optimization of workload for user experience. The autonomic nervous system controls the inter-beat intervals of the heart and breathing patterns, and these signals change under cognitive stress. We built a participant-independent cognitive stress recognition model based on photoplethysmographic signals measured remotely at a distance of 3 meters. We tested the model on naturalistic responses from 10 individuals completing randomized-order computer-based tasks (ball control and card sorting). The system successfully detected increased stress during the tasks, which were consistent with self-report measures. Changes in heart rate variability were more discriminative indicators of cognitive stress than were heart rate and breathing rate.

Author Keywords

Physiology; photoplethysmography; heart rate; breathing rate; heart rate variability; cognitive stress; remote; camera.

ACM Classification Keywords

H.5.2. Information interfaces and presentation: User Interfaces – Input devices and strategies, Interaction styles.

INTRODUCTION

The measurement of cognitive stress and performance on cognitive tasks has huge potential for human-computer interaction and affective computing applications, including remote learning, automated tutor systems, workload optimization [10] or "flow" understanding [4], and stress monitoring. Physiological responses contain rich affective information [7, 18] even when a subject is not expressing any signs outwardly. Additionally, they are less visible, and are not as susceptible to manipulation from social display
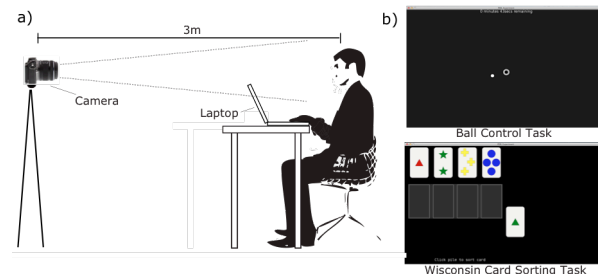
Figure. 1. a) Experimental set-up. Participants completed tasks on a laptop and were recorded with a camera 3m away. b) Screenshots of the Ball Control Task (top) and the Berg Card Sorting Task (bottom) used to induce cognitive stress. Prior to, and between tasks, participants rested.

rules or influences. While people may manipulate themselves to smile and look happy when they are stressed, the underlying physiology may still reveal that they have high stress. The autonomic nervous system (ANS) has three branches: the sympathetic nervous system (SNS), the parasympathetic nervous system (PNS), and the enteric nervous system. This work focuses on the SNS and the PNS. The SNS mobilizes the body's resources in response to a challenge or a threat, the PNS works antagonistically to control this process and is most active during rest and digestion. Inter-beat intervals (IBI) of the heart and breathing patterns are controlled by both the SNS and the PNS, enabling different types of stress responses to be captured by measuring each heartbeat. In particular, the heart rate variability (HRV) low frequency (LF) component is modulated by both sympathetic and parasympathetic activity and the high frequency (HF) component reflects parasympathetic influence on the heart. An estimate of sympathetic modulation (the sympatho/vagal balance) can be made by considering the LF/HF power ratio. During cognitive stress, we expect to see the HRV LF become elevated relative to the HRV HF. During rest we expect the HRV HF to be highest.

Typically, physiological responses are measured using contact sensors on the body (e.g. the torso or finger tips). However, contact sensors require hardware that can be uncomfortable or unnatural to wear and can limit the motion or dexterity of the user, especially when interacting with technology. Recent work has shown that physiological measurements of heart rate and respiration can be accurately captured remotely, via photoplethysmography

(PPG) using a low-cost camera and ambient light [14, 19]. However, in that work, participants were seated in front of a camera and asked to hold still, and the focus was on demonstrating the accuracy of measurement of the underlying cardiorespiratory parameters.

This paper examines a different set of conditions that are appropriate to HCI. We propose a new measure, which aims to extract an estimate of cognitive stress from the non-contact physiology.

BACKGROUND

Experiments using contact sensors have shown that cognitive tasks have an impact on HRV [3, 9, 16]. People under mental load show reduced HF HRV components compared to a control group [9]. During high-attention tasks absolute measures of LF and HF HRV power have been observed to decrease when compared to a baseline [16]. Measureable changes in heart rate (HR) were also observed; however, the increases or decreases were task dependent. With methods such as spectral analysis of HRV, it may be possible to predict such things as the optimal work time under mental load [11]. Other applications of our approach include emotion tracking [8, 12] and health monitoring. The method we present has the advantage of not requiring the user to be in contact with a device. Furthermore, it has the potential of being much more scalable due to the ubiquitous nature of cameras.

Remote measurement of physiology [6, 21] and stress [20, 22] has been demonstrated using expensive thermal cameras and Dopplar radar. However, these methods require hardware that is not available ubiquitously. Recent work has shown that HR, breathing rate (BR) and HRV LF and HF components can be measured from PPG signals recovered from the human face via a low-cost ordinary webcam [14, 19]. However, in that work, it was not examined whether these measurements would be sensitive enough to capture subtle changes due to increases in cognitive stress whilst a person interacts with a computer. Bousefsaf *et al*. [3] found that remote measurements could be used to capture changes in physiological parameters when participants completed a Stroop task. However, they did not capture measurement whilst people engaged in active computer tasks nor did they show a generalizable predictive model for stress level. Physiological signals have been useful in a number of scenarios when measuring the impact of computer and cognitive tasks [1, 8, 12]. Recently, contact PPG measurements have been found to be sensitive and reliable indicators of cognitive stress during computer tasks [12]. Our work contributes a new way to capture similar signals using just a camera.

EXPERIMENT

Ten healthy adult participants of both genders (five females), different ages (18 to 28) and multiple skin colors (Caucasian, Asian) were seated in front of a computer. All data were recorded on another computer (Toshiba running Windows 7). Six participants were wearing glasses and one

had a beard. During the experiment participants were seated approximately 3 meters from the camera, an Olympus DSLR (see Figure 1(a)). The participants were each recorded for 10 minutes while they completed two three-minute computer tasks, each preceded by a two-minute rest period. The tasks were designed to test whether the impact of cognitive tasks could be captured using remotely measured physiological responses and were presented in a randomized order. Both tasks were programmed using the Psychology Experiment Building Language (PEBL) [17], which contains validated cognitive tests. Figure 1 (b) shows screenshots of the tasks. During the rest period before each of the tasks, participants were asked to relax while viewing a pleasant image on the computer for two minutes.

The **ball control task** involved controlling a ball on a computer screen. The ball was drawn to the edges of the screen and the participant's aim was to keep the ball in the center. The participants used the laptop computer touchpad to control the ball during the task. If the ball reached the edge of the screen, there was a loud audio buzzer that sounded. Participants were also told that their performance was being logged and compared to that of others. The task lasted three minutes (one minute at three different randomized difficulty levels). In a number of cases the participants could not keep the ball from hitting the side of the screen and the buzzer sounded. This provides evidence that the task was sufficiently challenging.

The **Berg Card Sorting Task** (BCST) [2] is a problem solving exercise in which participants are required to sort cards into one of four piles according to a rule that has not been revealed to them. During the exercise the rule can change, again without an indication to the subject. The card-sorting task involved completing a shortened 64 card task version of the BCST [5]. If the participants had not completed the task after three minutes it was ended automatically. Again, not all participants were able to finish the task showing that it was sufficiently challenging.

Stress Questionnaire

In order to capture the self-reported levels of stress that participants experienced during the task, they were asked to complete a short questionnaire after finishing the tasks. We used a shortened version of the Dundee Stress State Questionnaire [13]. Of most relevance in this analysis the participants were asked to report their stress during the tasks: "During the task I felt" on a five-point Likert scale with end points "very stressed" (1) and "no stress at all" (5).

REMOTE COGNITIVE STRESS MEASUREMENT

Physiological Measurement

We recover the PPG signals from each video using the approach presented by McDuff *et al.* [14]. From the PPG signal a 120 sec. moving window (step size=1s) was used to quantify the following parameters. The HR was calculated as the average of the IBIs. The BR was determined from the center frequency of the highest peak (f_{HFpeak}) between 0.15
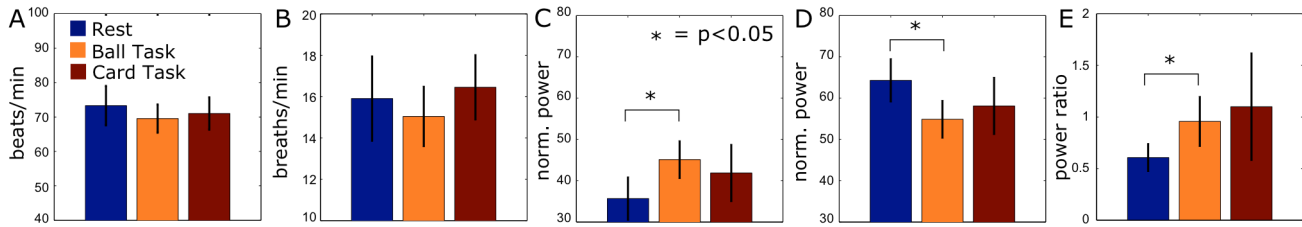
Figure 2. Mean physiological parameters (and 95% confidence) during each task. A) Heart rate, B) Breathing Rate, C) HRV LF normalized power, D) HRV HF normalized power, E) HRV LF/HF. Rest task, N=20; Ball task, N=30; Card task, N=30.

and 0.4Hz of the HRV power spectrum. For the frequency domain HRV parameters LF and HF powers of the HRV were calculated as the area under the PSD curve corresponding to 0.04-0.15Hz and 0.15-0.4Hz respectively. LF and HF were quantified in normalized units in order to minimize the impact of difference in total power. We also computed the unnormalized LF and HF powers of the HRV for use as features in the cognitive stress recognition model. The accuracy of this method for measuring HR, BR and HRV parameters was characterized in [14] and [19] and compared to FDA-approved contact sensor measurements. Therefore, we do not repeat this validation here.

Cognitive Stress Classification

We used the following seven physiological parameters for classification: i) heart rate, ii) breathing rate, iii) HRV LF normalized power, iv) HRV HF normalized power, v) HRV LF/HF ratio, vi) HRV LF total power, and vii) HRV HF total power. We used independent remote physiological measurements from a more controlled preliminary study featuring 10 subjects to train a cognitive stress recognition model. In the preliminary study participants completed two minute rest and two minute mental arithmetic tasks while remaining still and looking directly at the camera. The physiological features were extracted from the two-minute videos. A Naive Bayes classifier was trained and validated using a leave-one-participant-out procedure. The accuracy of rest vs. cognitive load classification was 86% on the holdout examples. The training sets and testing sets were participant independent, so that nobody in the testing set was also in the training set. The BR, HRV HF and LF features were the best single features for discriminating between the restful and stress states. For more details about the training data and classification see [15]. The computer task data we collected and analyze below was independent of the training data used for the predictive model and, in all but two cases (P1 and P3), the participants were different. Furthermore, the tasks considered in this work represent more realistic everyday computer activities that require cognitive processing and dexterity. Activities such as looking at the computer screen and using the computer track-pad introduced motion artifacts that can negatively influence the quality of the remote physiological readings as well as introduce physiological changes associated with body motions. Furthermore, the participants showed more spontaneous facial expressions, such as smiling, during the computer tasks. All of these aspects make this situation much harder than prior work addressed.

RESULTS

Using the method described above we extracted physiological parameters from the videos of individuals completing the 10 minute computer tasks. We divided the signals into two-minute segments (one-minute overlap) yielding a total of 20 segments of rest data, 30 segments of ball task data and 30 segments of card task data. We applied the NB model, defined earlier for predicting cognitive stress, to the data to determine whether the changes in activities were associated with changes in predicted levels of cognitive stress. Figure 2 shows the mean values of HR, BR, HRV LF, HRV HF and HRV LF/HF for all of the participants during each of the tasks. The average heart rates and breathing rates were not significantly different in any case, showing that heart rate and breathing rate alone may not be a very discriminative indicator of cognitive stress. In our preliminary work we found breathing rate to be significantly different during cognitive tasks than rest periods. However, perhaps breathing rates are dependent on the type of task and less generalizable. The changes in HRV power seem more generalizable and did allow us to discriminate between the rest periods and tasks. The HRV was impacted the most by the ball task and changes in LF (p<0.05), HF (p<0.05) and LF/HF (p<0.05) power were all significant (based on two-sample t-tests) compared to the rest periods. This in turn impacted the cognitive stress predictions the most. There was higher HRV LF power and lower HRV HF power in the card task than the rest task (mean LF/HF ratio was 0.61 in rest and 1.10 during the card task) suggesting considerably greater sympathetic activation and cognitive stress; however, the variability was higher explaining why the differences were not significant at a 95% confidence.
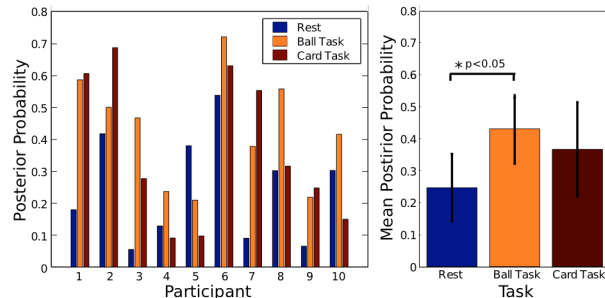

Figure 3. Cognitive stress posterior probability predictions. A) For each participant and task. B) Average probability (and 95% confidence intervals) for each task across all participants. The predicted stress was significantly higher (p<0.05) during the ball task compared to the rest period. Rest task, N=20; Ball task, N=30; Card task, N=30.

Figure 3 (a) shows the mean posterior probability of the stress model for each participant during each task. For 80% of the cognitive tasks the mean predicted stress was higher than during the rest periods. For 70% of the participants the mean predicted stress was higher during both cognitive tasks compared to the rest periods. This result did not appear to be due to the ordering of the tasks. The mean predictions across all participants during the rest periods were significantly lower when compared to the predicted cognitive stress levels of the ball control task (p<0.05). All the participants reported that their attention was directed toward the task and that they were determined to succeed. Furthermore, all reported feeling stress during the tasks.

Figure 4 shows the predicted cognitive stress model posterior probability output for two individuals, based on the non-contact physiological measures. Broken vertical lines indicate transitions between activities. These participants exemplify those who said that they felt high levels of stress during the tasks. We noticed high LF power in the HRV spectra during the computer tasks for both participants. The decrease in parasympathetic activity (lower HF HRV power) was indeed associated with an increase in predicted cognitive stress. Changes in HRV activity are often subtle and require highly accurate PPG peak detection; however, the model captures the changes during both of the computer tasks, with particularly high levels of stress during the ball control task. Similar findings were observed for the other participants. Different cognitive and dexterity-related tasks are likely to cause different levels of cognitive stress. The ball task did induce a higher level of cognitive load overall compared to the card task. This may result from the fact that the participants could not control the pace of the task.

The cognitive stress predictions were consistent with the self-report measures. Mean posterior probability from the
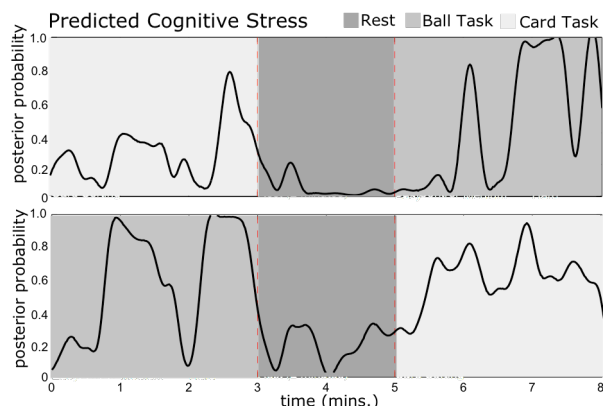

Figure 4. Predicted cognitive stress from the NB model. The tasks are highlighted by the shaded areas. In the examples the mean and peak predicted stress was much higher for the ball control and card sorting tasks compared to the rest period. These participants reported they felt high levels of stress during the tasks but not during rest periods. A two minute moving window was used.

stress model was 0.48 for a rating of 2 out of 5 (high stress), 0.37 for a rating of 3 out of 5 (moderate stress) and 0.36 for a rating of 4 out of 5 (low stress). No participants reported stress as 1 or 5. P1 and P6 reported two of the highest stress levels during the task (2 out of 5, where 1="very stressed") in the post survey and also showed the highest predicted stress based on their physiological responses. Conversely, P9 and P10 had lower predicted stress levels and they both reported two of the lowest stress levels during the task (4 out of 5, where 5="no stress at all"). It must be noted that there is a high amount of variability in the baselines between individuals, which is a well-known challenge associated with physiological parameters. However, our model also identifies the changes in stress due to the different tasks well. In all but two cases (P1 and P3), the participants did not have any data in the training set; thus, our model demonstrates the ability to capture differences in cognitive stress, which generalize across people, during the different computer interactions, a very valuable property.

CONCLUSION

This work demonstrates that remotely measured physiology parameters of HR, BR and HRV captured at a distance of 3 meters from a digital camera allow for automatic recognition of the cognitive stress of individuals during computerized tasks. Remotely measured physiological signals showed HRV does change significantly between tasks, and can be measured without contact. As expected, HR and BR alone were not very discriminative indicators of cognitive stress. A person-independent predictive model was evaluated in our experiment during which participants completed two computer tasks (a ball control task and a card sorting task). We show that periods of cognitive stress or engagement can be differentiated from periods of rest using our model. We found that the recognized stress levels were significantly higher during tasks than rest periods, this matched with the participants' reports of stress experienced during the tasks. The analysis was performed offline using MATLAB and required a windowing procedure. The computational cost of the procedure was small.

Overall, this work shows that remote measurement of physiology can be used to capture changes in cognitive stress using only a digital camera. This work opens up the possibility of interactive tools modulating workload without the participant having to wear anything or take any special actions. It has always been our hope that cameras will not be turned on without the user's prior informed consent. Our work adds a new reason why this should not happen: information that is usually private can now be sensed from a computer-user's face remotely during natural interaction. We must note that the participants in our study were filmed under relatively constant ambient lighting and did not move their heads much. Future work will consider other naturalistic activities that incorporate greater head and body motions and changes of ambient light that may impact the accuracy of the proposed methods.

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