What's on your mind? Mental Task Awareness Using Single Electrode Brain Computer Interfaces

Alireza Sahami Shirazi, Mariam Hassib, Niels Henze, Albrecht Schmidt
VIS, University of Stuttgart, Stuttgart, Germany
firstname.lastname@vis.uni-stuttgart.de

Kai Kunze
Osaka Prefecture University, Osaka, Japan
kunze@m.cs.osakafu-u.ac.jp

ABSTRACT
Recognizing and summarizing persons' activities have proven to be effective for increasing self-awareness and enable to improve habits. Reading improves one's language skills and periodic relaxing improves one's health. Recognizing these activities and conveying the time spent would enable to ensure that users read and relax for an adequate time. Most previous attempts in activity recognition deduce mental activities by requiring expensive/bulky hardware or by monitoring behavior from the outside. Not all mental activities can, however, be recognized from the outside. If a person is sleeping, relaxing, or intensively thinks about a problem can hardly be differentiated by observing carried-out reactions. In contrast, we use simple wearable off-the-shelf single electrode brain computer interfaces. These devices have the potential to directly recognize user's mental activities. Through a study with 20 participants, we collect data for five representative activities. We describe the dataset collected and derive potential features. Using a Bayesian classifier we show that reading and relaxing can be recognized with 97% and 79% accuracy. We discuss how sensory tasks associated with different brain lobes can be classified using a single dry electrode BCI.

ACM Classification Keywords
H5.2 [Information interfaces and presentation]: User Interfaces. - Graphical user interfaces.

Author Keywords
EEG, BCI, reading, general knowledge, wearable computing

INTRODUCTION
Determining the user's activities is central for ubiquitous computing. Being able to determine what a user is doing enables numerous use cases. The recent quantified self movement, for example, shows that there is an increasing interest in self-monitoring what we are doing. Certain mental activities, however, cannot easily be recognized from the outside. Differentiating between sleeping, relaxing, listening to music or thinking hard about a problem can look exactly the same from the outside. Therefore, recognizing and monitoring cognitive processes has gained momentum as a novel source for contextual information [8, 21].

Recognizing mental activities usually requires expensive and bulky hardware (functional magnetic resonance imaging, eye trackers) with few notable exceptions [2, 8]. Still most of the systems can just monitor the user for 1-2 hours due to battery constraints and are cumbersome to wear. In this paper, we explore to what extent an off-the-shelf, single electrode Brain Computer Interface (BCI) system can be used to recognize mental activities. The system itself is relatively unobtrusive, lightweight (a head band and a mobile phone) and can be used for long term deployments (battery life of 6-8 hours).

We are particularly interested in cognitive processes related to learning, especially reading, because the amount we read directly influences the size of our vocabulary and language skills [4]. Additionally, the more people read throughout the day the higher are their general knowledge and critical thinking skills [4, 19]. Being able to just count the minutes we daily read would help to assess the general knowledge of a person, as there are strong correlations between the two [19]. In addition, regular relaxation, breaks and naps are correlated with more effective skill acquisition and learning [6, 20]. Relaxing sufficiently often and long enough can improve ones health, mood and fitness [16]. Thus, recognizing when a user reads and relaxes would enable and extend applications that help to improve users' life.

The contributions of this paper can be summarized as follows: (1) we present a feasibility study of a wearable, unobtrusive brain computer interface system (BCI) capable of running up to 6-8 hours for the purpose of mental task recognition. (2) We are able to recognize reading and relaxing tasks out of 4 other activities with up to 97.2% and 73.2% respectively (user dependent) and with an accuracy of 70-100 % for 8 out of 15 users (user independent). (3) We provide a dataset to other researchers for reproducing and building on our results.

RELATED WORK
Previously Brain Computer Interface (BCI) systems have been mostly used in medical and clinical research. They are mainly used for enhancing the lives of patients with motor disabilities and brain disorders such as Alzheimer and Amyotrophic lateral sclerosis (ALS). For example, there is a semi-autonomous wheelchair that uses a BCI to retrieve certain mental signals to move the chair [7]. Furthermore, researchers have investigated task classification using EEG signals. Hosni et al. used the Kerin & Aunon dataset [11] and compared three different feature extraction techniques using

AH'14, March 07–09 2014, Kobe, Japan.

http://dx.doi.org/10.1145/2582051.2582096

Radial Basic Function and Support Vector Machine classification [10]. The best accuracy classification reported was 70%. Del R Millan et al. proposed a user-dependent neural classifier to recognize three mental tasks from online spontaneous EEG signals with 70% accuracy [5]. The tasks were relax, left/right movement, cube rotation, and subtraction.

Researchers also utilized EEG signals or eye movements to classify text comprehension, reading skills, and reading techniques. Mostow and Beck used neuro-feedback to discover reading problems in children [12], being able to discriminate between reading easy and hard sentences. Bulling et. al proposed a method for reading segmentation recognizing eye movement by electrooculography [2]. In contrast to previous research, in this work we investigate the feasibility of classifying reading and relaxing tasks based on EEG signals retrieved from a single electrode BCI.

With the advances in technology off-the-shelf BCIs are available which can be used in other research domains. The Epoc BCI by Emotiv and NeuroSky devices (MindSet, MindWave, BrainBand) are the two most popular BCI sets. The EPOC has 14 saline sensors and two reference electrodes. Whereas the NeuroSky BCIs have a single dry electrode. Both devices have been used in various researches. Sahami et al. use the EPOC to annotate movies based on excitement levels [15]. NeuroPhone [3] and ThinkContacts [13] are mobile phone BCI applications designed to help users with motor disabilities to dial numbers without navigating to their contact list. Petersen et al.[14] used the EPOC and attempted to distinguish among emotional responses reflected in different scalp potentials when viewing pleasant and unpleasant pictures compared to neutral content.

DATA ACQUISITION

To evaluate the feasibility of classifying reading and relaxing using a single electrode BCI, we chose simple tasks that contain auditory and visual stimuli as well as thinking.

Task set

Apart from reading and relaxing tasks we chose three other common mental tasks for classification: listening, watching a movie, and a problem solving task. For reading we had a short story and for problem solving we used a Sudoku game in the medium level. We recorded an audio from a popular radio station for the listening task. Finally, a short documentary video was used for the watching task. The task set includes auditory and visual sensory tasks which occur in different brain lobes.

Apparatus & User Study

We developed an application to collect data from the NeuroSky BrainBand device. The device is a commercial BCI equipped with a single dry electrode placed on the subject's forehead. It has one reference electrode on the left ear. The device includes a chip which filters and preprocesses the EEG signal and transmits it via Bluetooth to the application(1 Hz). The EEG processing protocols are not open source. As stated in the NeuroSky white papers [1], an FFT is done on the raw signal giving the band powers which are then scaled using a proprietary algorithm to produce outputs which are only relative to each other.

Figure 1. A participant playing the Sudoko task during the user study

We recruited 20 participants (8 female) with an average age of 23.3 years (SD=2.2). The study consisted of the five aforementioned tasks. All content used during the user study was in Arabic. Arabic was the mother-tongue of all participants which was particularly important to ensure that no extra mental effort was exerted during the tasks. After a short introduction, the participants was asked to fill in a demographic questionnaire. Then, they performed the five tasks one after the other. We counterbalanced the order of the tasks to reduce sequence effects. The study was conducted in a quite university laboratory with normal lighting conditions and minimal noise from other electronics equipment (Figure1). Each session took approximately 35 minutes. Only three participants had experience using a BCI device prior to the study.

Dataset

We collected following data during the user study:

eSense Values: Attention and Mediation values ranging from 1 to 100, at a sampling rate of 1 Hz. These values are determined via Neurosky proprietary algorithms. Values between 40 and 60 are considered 'neutral' or baseline, between 60 and 80 mean slightly elevated eSense levels, and between 80 to 100 refer to strongly elevated attention/meditation levels. Values below 40 are interpreted as (slightly/strongly) lowered levels. A zero eSense value means the signal cannot be calculated reliably due to background noise.

Neurosky Power Values: A series of eight 3-byte long values ranging from 0 to 224 provided at 1 Hz. These values are: delta (0.5–2.75Hz), theta (3.5–6.75Hz), low-alpha (7.5–9.25Hz), high-alpha (10–11.75Hz), low-beta (13–16.75Hz), high-beta (18–29.75Hz), low-gamma (31–39.75Hz), and mid-gamma (41–49.75Hz). These values have no units, therefore can only be interpreted by comparing them with each other and to themselves, to consider relative quantity and temporal fluctuations.

Blink: A one byte value ranging between 1 and 255 provided whenever a blink is detected. The value has no unit and only indicates the relative strength of the blink.

[1] **`www.neurosky.com/AcademicPapers.aspx`**(accessed 21.02.14)

Raw Wave: A 16-bit value provided at 512 Hz sampling rate. Values for the communications protocol lie in the interval between -/+2048. Typically in EEGs, time-frequency transforms are used to change the raw signal to the frequency domain, to extract the EEG power values.

The initial analysis revealed that data collected from five participants was corrupted. Thus, the data from these five participants was removed. Further, the power values were clipped for some seconds due to reaching the maximum value for some of the subjects. Since this noise was minimal it was rectified by taking the average of surrounding signals to compensate for the clipped signal at particular points.

TASK CLASSIFICATION

We used the annotated data collected from the 15 participants to derive features. These features were used to train classifiers for recognizing relaxing and reading. We developed a user-independent classifier that determines the mental activity without prior training and user-dependent classifier specific for individual participants. In the following, we describe the features derived from the data and outline the results.

Feature Set

We derived spectral and time-domain features from the collected data. In addition, we use the signals preprocessed by the NeuroSky development kit. The features are determined for one second jumping windows using Matlab.

Spectral features are computed by applying a fast Fourier transform (FFT) on the raw signal and bandpassing the delta, theta, alpha, beta and gamma frequency bands, the average of each band is used as the feature. In addition, the ratios between all pairs of frequency bands are calculated. The mean FFT value and the variance of the FFT are also used. In total, 17 spectral features are computed. Seven time-domain features are extracted from the raw time-domain EEG signal. These include the maximum positive, minimum negative and average amplitude of the raw signal per segment, and the Root Mean Squared (RMS) value of the raw signal. Four features are extracted from the NeuroSky signals: the average attention and meditation values as well as the average NeuroSky power band values for the five frequency bands.

Classification and Results

We used the features as input to train Bayesian networks that recognize relaxing and reading versus the respective other tasks. The experimental results reported in the following are obtained using WEKA [9]. All learning parameters use the default values in WEKA unless otherwise stated.

We trained user independent classifiers using the leave-one-out cross-validation to train a classifier and test its performance. That means we trained the classifier with data from 14 participants and evaluated the performance using the data from the remaining participant. The process was repeated for all participants resulting in 15 runs that were aggregated afterwards. In addition, we trained user dependent classifiers. Four minutes of each activity were used to train the Bayesian networks leaving 1 minute for evaluation. For both classifiers we used the feature selection option Weka provides.

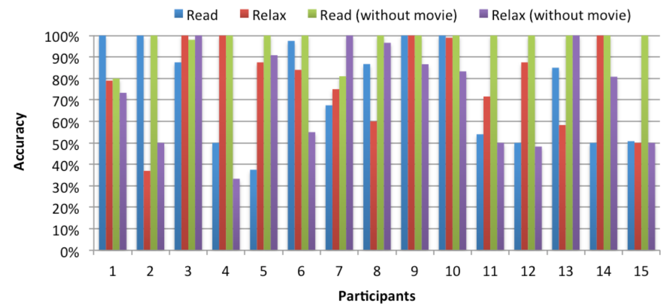

Figure 2. The result of the user-dependent classification

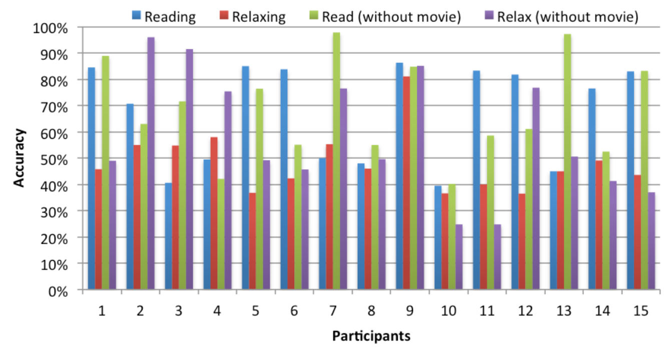

Figure 3. The result of the user-independent classification

The result revealed that the user independent classification between reading and the other tasks was on average 68.2% and between relaxing and others was 53.5% of all cases. The user dependent classification determined reading vs. other tasks with 74.4% and relax vs. others with 79% on average.

Since the classification performance left room for improvement, we pairwise classified reading and relaxing with other tasks using the same classifiers. The result revealed that the classification performance between the reading or relaxing and all other tasks on average were more than 75% except for the reading vs. watching movie tasks (64%). Therefore, we excluded the movie task and repeated the classification using the same classifiers. The result showed that the user independent classification between reading and the other tasks excluding the watching movie was on average 68.5% and between relaxing and others was 58.2% of all cases. The user dependent classification determined reading vs. other tasks with 97.2% and relax vs, others with 73.2% on average. As expected, excluding the data from the watching task increased the performance of the classifications in total. Figures 2 and 3 depict the results of user dependent and independent classification for all 15 participants.

DISCUSSION

The results show that the mental task classification has a higher accuracy if it is preformed subject dependent. With independent reading classification we achieve between 80 % to 100 % for 8 of the 15 participants. Although the single electrode BCIs have a crude spatial and temporal resolution, the results interestingly show that user-independent classification could be possible. Qualitative feedback revealed that all participants can imagine carrying the BCI for a longer period of time during everyday life.

Furthermore, the results reveals that the EEG signals from the front side of the brain seem similar for the reading and watching movie tasks. Although there is no one-to-one mapping between different mental tasks and certain brain lobes, certain sensory tasks can be majorly associated to particular brain lobes. For example, listening, as a auditory sensory task, is associated with temporal lobe activity. In contrast, listening to speech involves language understanding which is associated with frontal lobe activity [18]. During mediating/relaxing the concentration in the relaxation process itself leads to high frontal lobe activity [1]. Brain puzzles such as Sudoko require memory, concentration and high cognitive load which are all functions of the frontal lobe [17]. Watching movies and reading are associated with different parts of the brain. While the occipital lobe is responsible for vision which is in the rear part of the brain, the frontal lobe is responsible for interpreting. As watching a movie is mainly a visual task, the mental activity is also in the rear lobe. Since the BrainBrand's electrode is placed on front part of the brain, it mainly retrieves EEG signals from the frontal lobe. Hence, it is assumed that the BrainBrand BCI is suitable for classifying the activities mainly happen in the front side of the brain.

CONCLUSION

In this paper, we show that it is feasible to determine reading and relaxing activities using single electrode off-the-shelf BCI systems. The findings suggest that such BCIs can be used to determine activities that mainly occur in the frontal lobe of the brain. The distinction of reading with 97.2% and relaxing with 73.2% in the user-dependent cases is a first step to implement an application that can count the minutes read/relaxed during the day. Such an application helps in assessing one's language skills, general knowledge and learning progress [4]. Next step is a larger study to evaluate reading and relaxing activities during everyday living with more diverse activities.

The results also reveal that user independent classification is possible, whereas all computer brain interfaces needed dependent training. Regarding the importance of reading as knowledge acquisition task, this is an important insight. For future work, we plan to investigate how to increase the recognition accuracy of the subject independent classification for the users with low accuracy. The collected dataset is available to other researchers for other potential work.

ACKNOWLEDGMENT

This work is funded by the DFG within the SimTech Cluster of Excellence (EXC 310/1) and the EU within the Recall project (No. 612933).

REFERENCES

1. J. Banquet. Spectral analysis of the eeg in meditation. *Electroencephalography and clinical neurophysiology*, 1973.
2. A. Bulling, J. A. Ward, H. Gellersen, and G. Tröster. Robust recognition of reading activity in transit using wearable electrooculography. In *Proc. of Pervasive*, 2008.
3. A. Campbell, T. Choudhury, S. Hu, H. Lu, M. Mukerjee, M. Rabbi, and R. Raizada. Neurophone: brain-mobile phone interface using a wireless eeg headset. In *Proc. of SIGCOMM workshop*, 2010.
4. A. Cunningham and K. Stanovich. What reading does for the mind. *Journal of Direct Instruction*, 2001.
5. J. del R Millan, J. Mouriño, M. Franzé, F. Cincotti, M. Varsta, J. Heikkonen, and F. Babiloni. A local neural classifier for the recognition of eeg patterns associated to mental tasks. *IEEE Trans. on Neural Networks*, 2002.
6. N. K. Duke and P. D. Pearson. Effective practices for developing reading comprehension. *Journal of education*, 2008.
7. B. Graimann, B. Allison, and G. Pfurtscheller. *Brain-Computer Interfaces: Revolutionizing Human-Computer Interaction*. 2011.
8. E. Haapalainen, S. Kim, J. F. Forlizzi, and A. K. Dey. Psycho-physiological measures for assessing cognitive load. In *Proc. of Ubicomp*, 2010.
9. M. Hall and E. e. a. Frank. The weka data mining software: an update. *ACM SIGKDD Explorations Newsletter*, 2009.
10. S. Hosni, M. Gadallah, S. Bahgat, and M. AbdelWahab. Classification of eeg signals using different feature extraction techniques for mental-task bci. In *Proc. of ICCES*, 2007.
11. Z. Keirn and J. Aunon. A new mode of communication between man and his surroundings. *IEEE Transactions on Biomedical Engineering*, 1990.
12. J. Mostow, K. Chang, and J. Nelson. Toward exploiting eeg input in a reading tutor. In *Artificial Intelligence in Education*, 2011.
13. M. Perkusich, T. Rached, and A. Perkusich. Thinkcontacts: Use your mind to dial your phone. In *Proc. of ICCE*, 2011.
14. M. Petersen, C. Stahlhut, A. Stopczynski, J. Larsen, and L. Hansen. Smartphones get emotional: mind reading images and reconstructing the neural sources. *Affective Computing and Intelligent Interaction*, 2011.
15. A. Sahami Shirazi, M. Funk, F. Pfleiderer, H. Glück, and A. Schmidt. *MediaBrain: Annotating Videos based on Brain-Computer Interaction*. 2012.
16. C. Smith, H. Hancock, J. Blake-Mortimer, and K. Eckert. A randomised comparative trial of yoga and relaxation to reduce stress and anxiety. *Complementary Therapies in Medicine*, 2007.
17. R. Sobolewski, R. Reilly, S. Finnigan, P. Dockree, K. O'Sullivan, and I. Robertson. Monitoring of cognitive processes in older persons. In *Proc. of NER*, 2009.
18. L. Stewart, K. Von Kriegstein, J. Warren, and T. Griffiths. Music and the brain: disorders of musical listening. *Brain*, 2006.
19. P. Terenzini, L. Springer, E. Pascarella, and A. Nora. Influences affecting the development of students' critical thinking skills. *Research in higher education*, 1995.
20. P. Ward, N. J. Hodges, A. M. Williams, and J. L. Starkes. Deliberate practice and expert performance. *Skill acquisition: Research, theory and practice*, 2004.
21. Z. Ye, Y. Li, A. Fathi, Y. Han, A. Rozga, G. D. Abowd, and J. M. Rehg. Detecting eye contact using wearable eye-tracking glasses. In *Proc. of Ubicomp*, 2012.