Exploring the Recognition of Facial Activities Through Around-the-Ear Electrode Arrays (cEEGrids)

Abstract. NeuroIS scholars increasingly rely on more extensive and diverse sensor data to improve the understanding of information system (IS) use and to develop adaptive IS that foster individual and organizational productivity, growth, and well-being. Collecting such data often requires multiple recording devices, which leads to inflated study cost and decreased external validity due to greater intrusion in natural behavior. To overcome this problem, we investigated the potential of using an around-the-ear electrode array capable of capturing neural and cardiac activity for detecting an additional set of variables, namely facial muscle activity. We find that reading, speaking, chewing, jaw clenching, and six different emotion expressions can be differentiated well by a Random Forest classifier. The results are complemented by the presentation of an open-source signal acquisition system. Thereby, an economical approach for naturalistic NeuroIS research and artefact development is provided.

Keywords: Face Activity • Distal EMG • cEEGrid • OpenBCI • Random Forest

1 Introduction

Observing neurophysiological and behavioral activity offers exciting possibilities like the support of productivity, personal and social growth, and general well-being [1, 2]. This potential is enabled by placing sensors on or near a person, which collect data in high temporal resolution and real-time. NeuroIS researchers leverage these data to (1) develop better understandings of IS use, acceptance and engagement [1]; or (2) for the development of adaptive IS for the regulation of states like mental workload, stress or flow [1, 2]. Despite the substantial advancements in the past decade [1, 2], the observation of such intangible phenomena remains a major challenge due to the lack of one-to-one relationships between physiological and psychological variables [3]. To address these challenges, there is an increasing consensus that data collected from multiple sensors is required [4, 5]. As NeuroIS research requires efficiency, mobility and low intrusiveness to realize externally valid studies, a multi-sensor approach is, however, often difficult to implement.

To overcome this problem, we explore the potential of extending the known feature space of a recently developed wearable sensor called cEEGrid [6]. cEEGrids are placed around the ear and conveniently collect neural and cardiac activity [6, 7]. We argue that they have the additional capability of collecting other variables indicative of mental and physical states, namely facial muscle activity patterns, by capturing the spatio-temporal progressions of electrical activity generated from facial muscles. To assess this potential, we conducted a controlled laboratory experiment in which participants repeatedly posed 12 different facial activities (FA). We find that a random

forest classifier can differentiate these activities to a promising degree with an average F1-score of 0.77. Speaking, jaw clenching, chewing, yawning, and smiling can all be detected with an average F1-score of ~0.85. These results highlight the added potential of using the cEEGrid sensors for the unobtrusive study of neural and behavioral (facial) activities and related phenomena of high interest to NeuroIS scholars. As an additional contribution, we show that the sensor is usable with a low-cost open-source biosignal acquisition system for which the reproduction materials are made available.

2 Related Work

The cEEGrids are flexible, printed Ag/AgCl electrodes arranged in a c-shaped array to fit around the ear [6] (see Figure 1). These sensors have been developed to unobtrusively and comfortably collect EEG data in the field settings, enabling high-quality and multiple hour EEG recordings [6, 8–10]. So far, the cEEGrids have demonstrated their ability to record typical EEG patterns related to visual stimulation [6], auditory stimulation [8, 11–13], sleep stage detection [7, 14, 15] and changes in mental workload [16]. Furthermore, the possibility to extract an ECG trace from the cEEGrid data has been demonstrated [7]. However, the research on cEEGrids has, up to now, focused on answering fundamental EEG methodology questions. The placement close to the face and the numerous dispersed electrodes led us to consider if the activity of muscles in the face can be collected through distal EMG measurement.

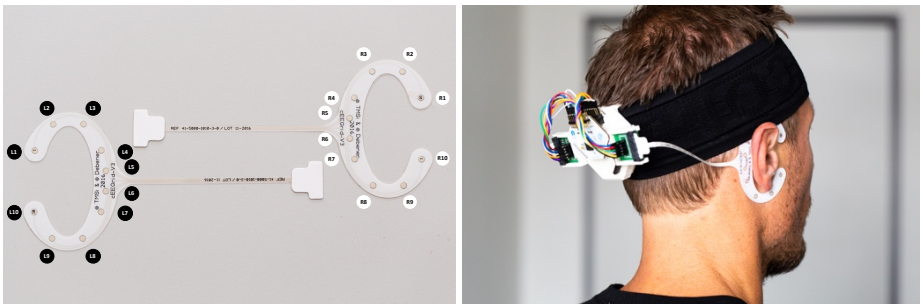

Fig. 1. The cEEGrid recording system. Left: Two cEEGrid electrodes showing the electrode positions. Right: The OpenBCI biosignal acquisition board with cEEGrids.

Distal EMG research has seen increasing interest for various applications due to the benefit of recording a phenomenon of interest from less visible or obtrusive recording sites. These approaches operate by the principle of volume conduction to pick up electrical potentials that propagate through the body. A prime example of distal EMG measurement is the research on affective facial expression recognition. To investigate the detection of emotion expression in real life, researchers have, for instance, employed the placement of electrodes on the side of the head to successfully differentiate real from posed smiles and even related micro-expressions [18]. Comparably, there has been increasing research on the ear-adjacent electrophysiological recording to pick up the heart's electrical activity [7], or to record neural activity from

inside or around the ear [6, 19]. Here, we follow the same distal EMG principles to explore which facial muscle activity patterns can be reliably differentiated from each other using the cEEGrids.

3 Method

A controlled experiment was conducted to collect data for an FA classifier (see Figure 2). Participants completed resting phases, performed maximum voluntary contraction (jaw clenching), read aloud text passages, chewed on gum, yawned, and mimicked one of six discrete emotion expressions shown on screen. Each task was performed multiple times for a few seconds with a three-second break between consecutive trials. The experiment followed the ethical guidelines from the first author's institution. Upon arrival, participants were informed about the recording and signed the consent form. Afterwards, the gelled cEEGrids were attached, and the signal quality assessed. Then, the experimenter left the room, and the experiment was completed autonomously by the participants. Data were collected for five healthy participants (2 female) in the age range of 25 to 37 (mean = 30).

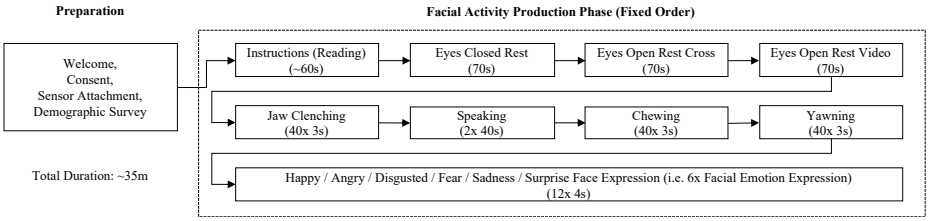

Fig. 2. Visualization of the experiment procedure with phase durations and repetitions

The cEEGrids were connected to an OpenBCI Cyton board with Daisy shield (see Figure 1). This combination enables the low-cost mobile biosignal acquisition on 18 recording channels (two for reference and ground). For this purpose, electronics components and 3D-printed enclosures were designed. While this novel setup means that two electrodes had to be left out from the possible recording sites (here, channel L3 and R3), the use of this open-source platform allows for a much less expensive (~1.500 USD instead of ~10.000 USD) and flexible (i.e., prototyping friendly) recording solution. Both aspects are important when considering NeuroIS research setups and applications that should be usable in various settings and for various levels of scholar's methodological experience.

Each channel signal was first mean-centered, then band-pass (FIR 5-62 Hz) and notch (50 Hz) filtered. Following, the signals were epoched using non-overlapping one-second windows. We extracted a first feature set ($FS_{1\text{-Signal}}$) for each epoch comprising the sum, maximum, Hurst exponent, Petrosian and Higuchi Fractal Dimension, and the Hjorth parameters Activity, Mobility, and Complexity. These features were chosen due to their signal describing properties and their previous use in EEG-based event detection [20, 21]. Two additional feature sets were created that additionally include the same features computed for the first three independent components

(ICs – considered to capture the main muscle activity of interest - $FS_{2\text{-Signal+}}$), and the same features for all ICs together with median and SD statistics of the rectified and smoothed ICs (using a 100ms sliding-window median smoother on the absolute signal – similar to related distal fEMG work [18] – $FS_{3\text{-All}}$).

4 Results

As classifiers, Random Forest, Support Vector Machine, AdaBoost, Logistic Regression, and a Multi-layer Perceptron were tested. Each classifier was trained for a single participant to explore how well FA events can be detected on a subject-specific level through this relatively short data collection period. Overall, Random Forest classifiers with 100 trees showed the best performance. To evaluate the model results, stratified five-fold cross-sampling was used with Synthetic Minority Oversampling (SMOTE) to account for the dataset imbalance [22]. The performance metrics reported in Table 1 represent the average of all folds.

Table 1. Results of the classifier for twelve classes, measured with the F1-score. Values in rows are aggregated across participants. M = Mean, SD = Standard Deviation.

	Read	**Rest**	**Clench**	**Speak**	**Chew**	**Yawn**	**Happy**	**Angry**	**Disgs.**	**Fear**	**Sad**	**Surpr.**	**Mean**
$FS_{1\text{-Signal}}$ *– Per-Subject M Range: .34-.64*													
M	.54	.64	.64	.68	.78	.72	.72	.35	.27	.43	.24	.48	**.54**
SD	.06	.12	0.36	.09	.08	.09	.15	.14	.16	.14	.16	.12	**.14**
$FS_{2\text{-Signal+}}$ *– Per-Subject M Range: .51-.75*													
M	.71	.63	.80	.72	.78	.76	.78	.61	.46	.61	.39	.60	**.65**
SD	.20	.14	.19	.12	.08	.04	.09	.13	.15	.09	.26	.10	**.13**
$FS_{3\text{-All}}$ *– Per-Subject M Range: .70-.80*													
M	.91	.63	.87	.91	.83	.78	.83	.67	.63	.76	.66	.78	**.77**
SD	.06	.07	.05	.08	.04	.04	.04	.05	.08	.06	.18	.03	**.07**

The classification accuracy increases with the inclusion of the additional features with an improvement of the grand mean F1-score from 0.54 to 0.77. The FA events that benefited most from the additional features are reading and emotion expressions. Overall, the $FS_{3\text{-All}}$ classifier can differentiate the 12 different FA to a promising degree with an average F1-score of 0.77 (SD: 0.07). These scores still vary by FA type, with activities involving larger facial muscles strongly (e.g., muscles close to the jaw - masseter and zygomaticus major) showing better prediction scores (e.g., clenching, speaking, chewing, yawning, and smiling). An interesting finding is also, that reading shows high prediction accuracy, a finding that is likely based on the electrical activity generated from eye movements. It has been previously suggested that eye movements might be detectable with cEEGrids [23]. In contrast, FA that involve more and small-

er facial muscles at the center of the face (e.g., corrugator supercilii involved primarily in expressions of anger) shows the weakest prediction scores.

5 Discussion & Outlook

The presented results highlight the added potential of using the cEEGrid sensors for the unobtrusive study of behavioral (facial) activities and related phenomena of high interest to the NeuroIS field. This potential is added to the already useful capabilities of the cEEGrids to capture neural and other physiological phenomena. With an average F1 score of 0.77, the classifier is able to predict one of 12 different FA events well above chance level. Presently, the detection appears most suitable for FA events based on large facial muscles such as chewing, smiling, clenching and yawning. NeuroIS scholars could, for instance, use the cEEGrids to investigate relationships between technostress [2] and bruxism or between flow experiences and IS enjoyment [24]. In contrast, the observation of FA events reliant on smaller muscles and muscles closer to the center of the face will require further investigation. It could be possible to extend the cEEGrid system to include electrodes on the side of the face (e.g., on the temporalis muscle closer to the face). These results are made possible by the novel combination of the OpenBCI biosignal acquisition board with the cEEGrids. The materials needed to reproduce the system are provided online[1]. Altogether, this system offers numerous advantages (flexibility in sensor use, low cost, open-source access to materials and APIs) that enable the development of NeuroIS studies and applications. Importantly, the system can be used in field research and allows for comfortable multi-modal data collection over the whole day [6, 23].

To build on the latter point is considered the next most important step to further evaluate the FA diagnostic potential of the cEEGrids. In natural settings, FA events are likely to occur under the influence of various confounding effects. For a field study evaluation, we propose to leverage an interactive machine learning approach [25] that builds on an initial controlled classifier and asks participants occasionally whether a particular FA was observed correctly or asks about what happened when an unknown FA instance was recognized. Through this approach, classifiers can be iteratively improved without having participants to complete diaries or work with additional sensors. As an incentive, participants could use the detection logs at the end of the study period to reflect on their experiences (e.g. what made them happy or what made them grind their teeth during the day? – see, e.g. [26]) and to evaluate whether or not the interactive process helped becoming more aware of a particular phenomenon (e.g. to avoid clenching their jaw). While the technology can improve further in terms of wearability, miniaturization advancements will make this technology genuinely wearable and usable in real life at some point (e.g. integrated into headphones or simply with less visible amplifier placements). For now, the cEEGrid-OpenBCI system already represents a promising novel approach for NeuroIS scholars to observe neural, physiological and behavioral activity patterns in a highly flexible, convenient, and accessible manner in the lab and the field.

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[1] https://github.com/AnonymousAuthor-2021/openbci-ceegrids - anonymised for the review

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