Detecting Daytime Bruxism Through Convenient and Wearable Around-the-Ear Electrodes

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Abstract. Bruxism is associated with multiple health issues and affects millions of people worldwide. To enable effective interventions, precise, easy-to-use and unobtrusive detection systems are required. Unfortunately, especially for daytime bruxism, such systems still rely on electrodes placed on the face, recording diaries, and manual algorithm tuning. In this work, we present a novel approach for bruxing event detection using comfortable and inconspicuous around-the-ear sensors (cEEGrids) as a form of distal EMG-based measurement. Using Random Forest classifiers on laboratory experiment data, promising F1-scores (up to 0.9) are found for the detection of bruxing events in contrast to a variety of other facial muscle activity events. Thereby, a promising new alternative for feasible awake bruxism detection is demonstrated.

Keywords: Bruxism · Distal EMG · cEEGrid · Machine Learning · Classification

1 Introduction

Bruxism, the repetitive clenching or grinding of the teeth, is associated with multiple physiological and psychological health issues, including fractures, erosion of the teeth, headaches, stress, and anxiety [1, 2]. Even though prevalence for awake bruxism (AB) is relatively high among adults (22-30% - compared to sleep bruxism - SB: 1-15%) its detection and intervention have been researched sparsely [1–3]. AB detection challenges are that bruxing events need to be differentiated from a variety of other facial activities, and that daily recordings need to occur inconspicuously and ergonomically. Therefore, to enable daytime interventions, acceptable and effective wearable measurement solutions need to be developed [1, 2]. State-of-the-art wearable systems show increasing sophistication, yet still primarily require either the placement of electrodes directly on the face (e.g. on the masticatory muscles) or the manual tuning of algorithmic thresholds for bruxing detection by experts, still with limited precision for the detection of single bruxing events [4–6]. Thus, there is a major gap in the AB detection literature regarding the convenient, unobtrusive, and automatic detection of AB events. Systems able to integrate these requirements are essential not only for better bruxism research (to, for example, understand which transient factors like stress or arousal might influence the emergence AB periods - see [5]) but also for pragmatic interventions (for example live feedback systems - see [2]). Here, we present an approach for detecting AB events using flexible around-the-ear EEG electrodes, so-called cEEGrids [7]. The conceptual benefit of cEEGrids is that these sensors can be worn inconspicuously and comfortably throughout the day. Furthermore, they provide readings from 20 electrodes spaced out around the ear and close to the jawline. To evaluate the cEEGrid potential for AB event detection, we investigate three research questions in a controlled experiment: (RQ1) to which degree a machine learning classifier can differentiate between jaw clench and facial resting events, (RQ2) to which degree such a classifier can also differentiate jaw clench events from other facial activity, and (RQ3) whether the classification performance is influenced by the amount and position of electrodes in use. Four participants completed a series of repetitive facial activity tasks: jaw clenching (as AB events), chewing, speaking, yawning, and six different facial emotion expressions (typical facial activities to compare the AB events with). For RQ1 similar classification performances as in related in-ear-EEG work on SB detection [8] are found using a Random Forest classifier. For RQ2, an expected drop in classification performance is found, yet still with encouraging values. For RQ3, a strong increase in classifier performance is found with more electrodes and with electrode positions closer to the jaw. These results demonstrate a promising new solution for future AB interventions to build upon.

2 Related Work

Despite the higher prevalence of AB among adult populations, most previous research has focused on examining possible treatments and interventions for SB [1, 2]. A likely reason for this focus is the more feasible bruxism detection during sleep through polysomnographic recordings - the current gold standard for SB diagnosis [4]. Thereby, recordings of electrical potentials from muscle activity (the two main masticatory muscles - temporalis and masseter) are primarily used to detect the occurrence of bruxing events. While the polysomnographic approach allows for a multi-sensoric observation during rest, this approach is not feasible for AB detection which requires mobility, low intrusiveness, sparse data (e.g. fewer sensor types and locations), and methods to cope with the increased variety and frequency of other facial and masticatory muscle activity throughout the day (e.g. eating, speaking or similar facial muscle activity) [4]. Due to these challenges, AB is researched less frequently and less rigorously [5]. Nevertheless, there has been a recent increase in research on approaches that use wearable EMG on masseter or temporalis muscles to detect AB (see [4] with a review). According to such work, it is somewhat possible to identify bruxers or bruxing events, yet, the present state of work comes with a few key limitations. In many cases, the accuracies of the developed systems are not reported and sometimes even questioned by the authors themselves [5, 6]. In other cases, the detection algorithms require subject-dependent adjustment by the researcher [6], or challenging functional EMG activities are omitted from analyses (e.g. meals are excluded [5]). Finally, in most cases, the main caveat of designed systems is that their feasibility and practicability are still very limited. Many systems require the application of electrodes on the face [5, 6]. In many studies subjects must also self-record what they were doing to make sure that the system can be calibrated or used for the correct detection of AB occurrence (frequencies or events). It is for these reasons why we consider in this work to use a less visible electrode array (a form of distal EMG measurement by which EMG electrodes are placed in the proximal vicinity of the region of interest – not in it) and the development of classifiers that can automatically detect AB events.

Distal EMG Research has seen an increasing amount of 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 emotion recognition. While proximal facial EMG has been established to record facial muscle activity (and thereby, the facial expression of emotion) [9], the approach is relatively exclusive to the laboratory environment. Therefore, 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 [9]. Comparably, there has been increasing research on the ear-adjacent electrophysiological recording to pick up the electrical activity of the heart [10], or to record neural activity from inside or around the ear (i.e., distant to the typical EEG recording that is performed on the scalp - see [7, 8]). Altogether these works demonstrate the general potential of using distal EMG measurement to increase convenience and daily applicability of wearable sensors. Regarding the detection of bruxism, only one previous study used distal EMG [8]. In this study, it was found that EEG sensors in the ear canal can well differentiate active vs relaxed facial muscle activity during sleep and therefore identify SB events. However, no work has been conducted using distal EMG for AB detection. Here, we follow the same principles for distal EMG measurement and employ a promising new sensor type called cEEGrid [7]. The conceptual benefit of cEEGrids is that these sensors can be worn inconspicuously and comfortably throughout the day. Furthermore, they provide readings from 20 electrodes spaced out around the ear and close to the jawline. Thereby, this sensor array could detect the particular signature of a bruxing event (the spatio-temporal electrical potential progression) in contrast to other facial muscle activity. Therefore, we consider it a prime candidate for the detection of AB events.

3 Method

To collect data for an AB classifier, a controlled experiment was conducted. Participants wearing cEEGrids completed a series of repetitive facial activity tasks: jaw clenching (as AB events), speaking, chewing, yawning, and six different facial emotion expressions to compare the AB events with. For the jaw clench phase, participants were asked to repeatedly perform maximum voluntary contraction for three seconds (similar to [6]). For the speaking condition, participants were asked to read two passages from a text aloud. For the chewing conditions, participants ingested a chewing gum at the start of this phase and removed it at the phase's end. For the facial emotion expressions, participants were asked to mimic pictures showing six discrete emotions (from the KDEF stimuli database – see [11]). Participants were asked to perform each task multiple times for a few seconds with a three-second break between consecutive trials (see Figure 1). To provide a baseline recording, participants completed eyes-closed and eyes-open resting phases (once with a fixation cross and once watching a video of fish swimming in the ocean).

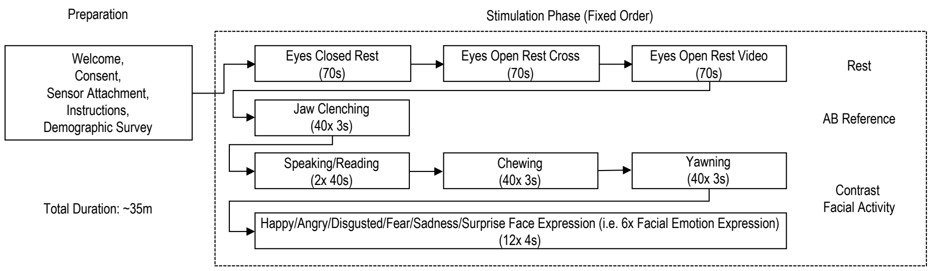

Fig. 1 . The Experiment Procedure Visualized.

The cEEGrids were connected to an OpenBCI Cyton board with Daisy shield (see Figure 2) that enables the low-cost mobile biosignal acquisition on 18 recording channels (two of which are used for reference and ground electrodes). While this setup means that two electrodes had to be left out from the possible recording sites (here, channel L3 and R3 were left out), 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 developing an AB detection setup that should eventually be usable during the day.

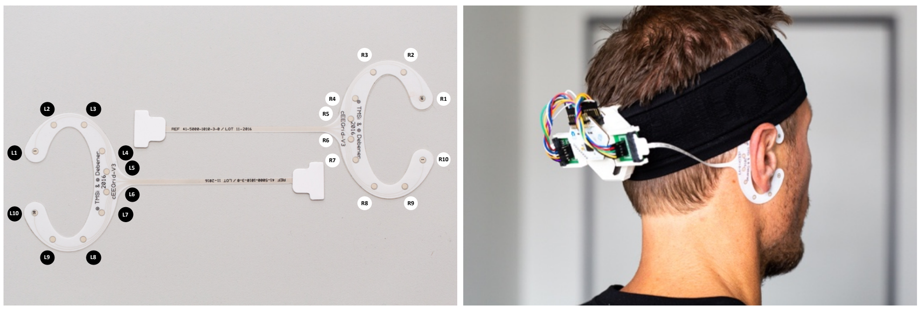

Fig. 2. The cEEGrid Recording System. Left: Two cEEGrid Electrodes Showing the Electrode Positions. Right: The OpenBCI Biosignal Acquisition Board With cEEGrids.

The experiment followed the ethical guidelines from the first author's institution, and participants provided informed consent before their participation. The experiment was conducted in a quiet room. Upon arrival in the recording room, participants were first informed about the type of recording and signed the consent form. Afterwards, the gelled cEEGrids were attached to the participant, and the signal quality was assessed using the OpenBCI GUI software. Afterwards, the experimenter left the room, and the experiment was completed fully autonomously by the participants. Data were collected for four participants (2 female) in the age range of 25 to 37 (mean = 29.5). All participants had full eyesight and were generally healthy.

4 Signal Preprocessing and Inspection

The electrophysiological data were processed by mean centering each channel first. Afterwards, the recorded signals were high pass filtered (FIR 1 Hz) to remove signal drifts (similar to [8]). For one participant, one channel had to be removed due to recording errors. In previous AB detection work, [5] argue that daytime bruxers can be well differentiated from non-bruxers by extracting EMG burst events recorded from the masseter muscle. These authors use a threshold-based algorithm for the burst event extraction where the absolute amplitudes of a high pass filtered and smoothed EMG signal (average values for a sliding 0.1-second window) are searched for bursts of more than three times the average baseline amplitude with a burst duration of 0.08 seconds or more and with an interval of 0.08 seconds or more to the adjacent burst. To develop an understanding of the cEEGrid suitability for AB event detection (considering the distal electrode placement), this EMG burst metric was computed for all participants and experiment phases. Figure 3 shows the counts of such burst events for each cEEGrid electrode. Two interesting observations emerged from this analysis. First, other facial expressions (especially chewing and yawning) also show very high counts of EMG burst events, while speaking and facial expressions do not. This means that it would appear unsuitable to identify bruxing events from sole burst detection from single (distal) electrodes alone. Second, jaw clenching episodes appear to be more pronounced over electrodes closer to the face. Thus, using the information across several electrodes might be useful for the differentiation of the type of facial muscle activity. For this reason, we pursued an AB event classification analysis using all cEEGrid electrodes.

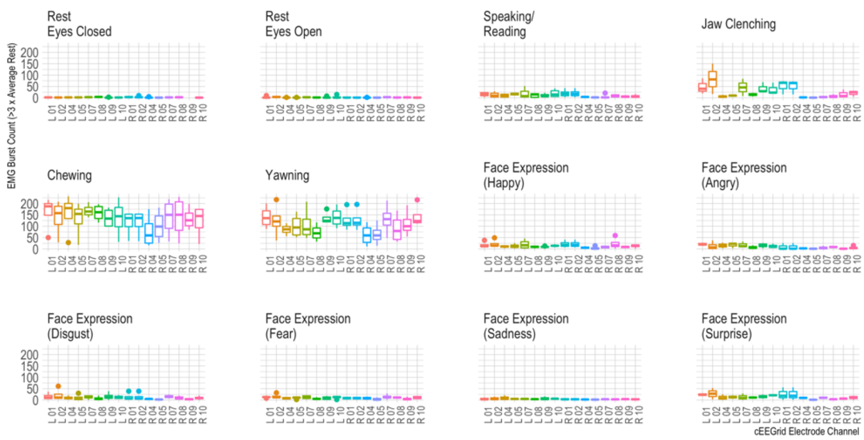

Fig. 3. The Distributions of EMG Burst Events Extracted Using the Threshold Logic from [5].

5 Classification Results

After the pre-processing of the signal, each data point was labeled according to the corresponding experiment phase and trial (with a shift of 350ms for onset/offset of the facial activity per trial). To answer our RQs, two different feature spaces were used. In the first feature space, only the filtered channel values (as described above) were used ($FS_{filtered}$). In the second feature space ($FS_{extended}$), more advanced feature engineering was pursued. For the latter approach, the signals were segmented using sliding windows of one second without overlap. In terms of features, we extracted 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 [12, 13]. Features were computed for each channel resulting in datasets with 128 features and between 349 and 392 samples. Each window containing more than five percent of data points from a clenching trial was labeled as an AB event. Oversampling was used to account for the imbalanced nature of this dataset (about 16 percent of the data contain an AB event). As classifiers, Random Forest, Support Vector Machine, AdaBoost, Logistic Regression, and a Multi-layer Perceptron were tested. Each classifier was trained for a single subject to explore how well AB 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 cross-sampling was used. Five folds and oversampling were used with each training fold. The performance metrics reported below represent the average of all fold's.

For RQ1 (to which degree a classifier can differentiate between jaw clench and facial resting events), similar results ($FS_{filtered}$: F1-scores: 0.68 to 0.89 cross-subject mean = 0.78; $FS_{extended}$: F1-scores: 0.86 to 0.95, cross-subject mean = 0.9) as in related in-ear-EEG work on SB detection [4] are found. For RQ2 (to which degree a classifier can also differentiate jaw clench events from other facial activity), all experiment phases were subsequently entered into the classifiers. An expected drop in classification performance is found, yet still with encouraging values ($FS_{filtered}$: F1-scores: 0.14 to 0.78, cross-subject mean = 0.42; $FS_{extended}$: F1-scores: 0.73 to 0.9, cross-subject mean = 0.8). From both classifications it can be seen that the extended feature space ($FS_{extended}$) showed better classification accuracies. For RQ3 (how the number and position of sensors influence the classification results), a strong increase in classifier performance was found with more electrodes and electrode positions closer to the jaw. To evaluate the impact of the number of sensors, we iteratively increased the number and evaluated the performance using the $FS_{filtered}$ dataset. In particular, we tested the following tuples (L1, L2) and (L1, R1, L2, R2) and (L1, R1, L2, R2, L4, R4). Adding each pair of additional sensors increased the performance of our classifier ((L1, L2) mean = 0.13, (L1, R1, L2, R2) mean = 0.21, (L1, R1, L2, R2, L4, R4). mean = 0.25). To measure the impact of the position of the sensors, we used an ex-post feature importance measurement, SHAP values (SHapley Additive exPlanations) [14]. Strong performing electrodes were, for example, L1, L2, R1, and R2, where features had the highest SHAP values. Figure 4 shows the top twenty most influential features for participant 1 as an example.

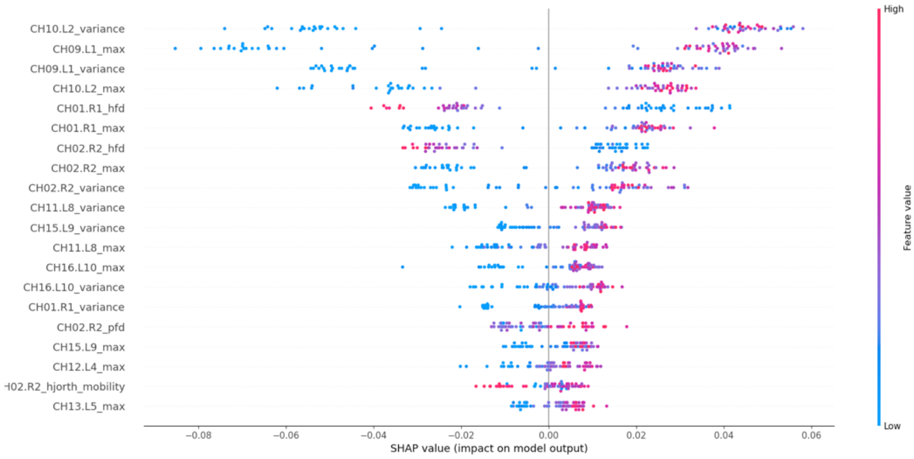

Fig. 4. Examples of Important Features Based on SHAP Values for Participant 1.

6 Discussion & Conclusion

In this work, we investigated the potential of using cEEGrids for AB event detection through a controlled experiment with repetitive facial activity tasks. The results from threshold-based event detection and event type classification demonstrate the potential of detecting AB events to a promising degree (with F1-scores up to 0.9) even in the presence of other facial activity. In this regard, the threshold-based EMG burst detection results suggest a difficulty to differentiate bruxing from other functional EMG burst events (e.g. chewing or yawning), as has been described previously for mandibular muscle EMG [5, 6]. In contrast, the subject-specific classifiers show that AB events could be detected with reasonable certainty from this short data collection (~35 minutes per participant - an acceptable timeframe for system calibration by prospective users). As the reason for these promising results, we consider that the placement and amount of electrodes of the cEEGrids integrate information on the spread of the electrical signals generated from different facial muscles (in particular the mandibular muscles – to which the L1, L2, R1, R2 electrodes are close). Given that the cEEGrids can be placed around the ears in an ergonomic and inconspicuous way (the electrode mediums could even be transparent in the future), they represent a valuable new approach for real-life AB event detection. Nevertheless, future work should integrate EMG data collections from the masseteric muscles to include a direct comparison of the cEEGrid performance to this state-of-the-art approach (see [4]). Also, given that our experiment was conducted in the laboratory and that the sample was very small, future work will have to evaluate practicability and accuracy in naturalistic settings. Notably, the assessment of feature suitability and performance of the herein created classifiers needs more externally valid data. To collect such data while adhering to low system intrusiveness, we propose to adapt our signal processing and feature extraction pipeline to perform on real-time data streams to predict the occurrence of AB events in real-life and continuously refines the classifier accuracy through interactive machine learning. In doing so, participants would not have to complete diaries of their activities. Instead, they could only be prompted occasionally by a simple experience sampling-like survey application that asks whether or not a detected AB event was correctly classified or not. The presented OpenBCI-cEEGrid recording system already provides an adaptable open-source environment for this purpose and thereby represents a valuable new toolkit for advancing this research.

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