HEAR-BRUX: HEARable for handling BRUXism

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Contents

To my lovely and supportive family and friends.

Summary

Bruxism is a parafunctional oral behavior that can occur during sleep (sleep bruxism) or wakefulness (awake bruxism). Bruxism is characterized by teeth grinding and jaw clenching. It can lead to various health consequences such as tooth fracture, tooth wear, and muscle fatigue. Several devices have been developed to treat and detect the symptoms of bruxism. Oral splints are the most widely used device to manage sleep bruxism by eliminating tooth contact. Electromyography (EMG) is used to monitor the activity of the masticatory muscles to detect bruxism. However, mouth guards are passive devices that don't necessarily reduce the occurrence of bruxism, and EMG can be cumbersome to wear while sleeping or wakefulness. Haerables are wearable ear devices that can record signals such as sound. Such devices may be advantageous for the detection of bruxism induced events as they are easy to use and socially acceptable. Therefore, the question is whether ear devices - sometimes called hearables - that use sound as a biomarker can be affordable devices to detect bruxism. In a first study, I investigated the effect of the type of ear occlusion on recording and found that complete occlusion of the ear with a moldable earpiece supported recording of the characteristic feature of jaw clenching. For reasons of practicality and hygiene, I fitted an off-the-shelf earpiece with a transducer as part of an experimental setup in a second study to investigate the effect of transducer placement on the recording. The oral behaviors recorded were: jaw clenching, teeth grinding, reading, eating, and drinking. The transducers were placed on the zygomatic bone, frontal bone, temporal bone, and inside the ear. Finally, I investigated the use of 2D sound representations to classify the different oral behaviors recorded from the ears using deep learning. Three classifiers were tested, 2-Class (Grinding and Pause), 4-Class (Eating, Grinding, Pause, and Eeading), and 6-Class (Clenching, Drinking, Eating, Grinding, Pause, Reading). I observed that sounds of bruxism-induced events can be recorded from different parts of the head. From the experiment, I observed that the ear is an ideal location to record bruxism-induced sounds, because it compensates for head movements due to eating or drinking that may affect the recording. I also successfully classified the sounds recorded from the ear, but - as expected - the overall test accuracy of the classifier decreased as the number of classes increased. This result has good practical implications, as my approach demonstrated that bruxism-induced sounds can be recorded and distinguished from other oral behaviors. Finally, this project focused on bruxism from a biomechanical lens with the goal of developing a method to record and distinguish bruxism events from other oral behaviors. This method could be used to activate bio-feedback. Future research directions would be to investigating the causes of bruxism - which were not addressed in this work - and for this, further research is important to address one of its main causes, chronic emotional stress, which requires viewing bruxism through a biopsychosocial lens.

Preface

Experimental work, evaluation, and writing of this thesis was performed at the Bio-Inspired RObots for MEDicine-Laboratory (BIROMED-Lab), Department of Biomedical Engineering (DBE), University of Basel.

Chapter 1 is a general introduction to the clinical description of bruxism, epidemiology, and risk factors. Also, it contains sections on the instrumental assessment on bruxism and the diagnostic issues. Finally, it holds the research questions and the outline of the thesis.

Chapter 2, is based on journal publication [1]:
M.K. Nahhas, N. Gerig, P. Cattin, E. Wilhelm, J.C. Türp, G. Rauter, "Reviwing the potential of hearables for the assessment of bruxism," *at-Automatisierungstechnik*, vol. 72, no. 5, 2024, pp. 389-398. Permission of reuse has been granted.

Chapter 3, is based on the conference publication [2]:
M.K. Nahhas, N. Gerig, J.C. Türp, P. Cattin, E. Wilhelm, G. Rauter, "Impact of Ear Occlusion on In-Ear Sounds Generated by Intra-oral Behaviors," *in New Trends in Medical and Service Robotics. (MESROB) 2021*. Permission of reuse has been requested.

Chapter 4, is based on a journal publication [3]:
M.K. Nahhas, J.C. Türp, P. Cattin, N. Gerig, E. Wilhelm, G. Rauter, "Towards wearables for bruxism detection: voluntary oral behaviors sound recorded across the head depend on transducer placement," *Clinical and Experimental Dental Research*, 2024. Permission to reuse is under Creative Commons Attribution License.

Chapter 5, is based on the submitted journal publication [4]:
M.K. Nahhas, J.C. Türp, N. Gerig, P. Cattin, E. Wilhelm, G. Rauter, "Experimental classification of accoustic emissions from oral behaviors including bruxism using deep learning," *Submitted for publication in IEEE Transactions on Biomedical Engineering*, 2024. Permission to reuse will be requested once the manuscript is accepted.

Each of these chapters is opened with a "Forward and Overview" that connects the different chapters together and provides the context of the chapter within this thesis. The format of the manuscripts has been adapted to the format of the thesis.

Chapter 6, recaps the achievements reached during this PhD, and reflects on their relevance, limitations, and outlook.

Chapter 1

General Introduction

I have worked during my PhD project on exploring the use of ear devices to detect bruxism-induced sound emisisons. The motivation behind this project stems from the need to develop easy to use and inexpensive devices to detect bruxism which can occur through out the whole day. This chapters starts by explaining what bruxism is from a clinical perspective, followed by three short paragraphs on the epidemiology of bruxism, its risk factors, and how bruxism can be understood through a wider lens than the biomechanical one. Then, a description of the various instrumental devices used to assess bruxism is presented, followed by the limitations of these devices.

1.1 Bruxism, a parfunctional orofacial behavior

The mandible is the only movable bone of the skull. Movements in the temporomandibular joints are achieved by the coordinated work of seven paired muscles on both sides, which attach to the mandible. The neuromuscular interaction allows the mandible to open, close, protrude, retract, and move laterally relative to the maxilla. The mandible has a functional relationship with the maxilla via the teeth or tooth analogs through occlusal contacts. The mandible plays a central role for facilitating functional behaviors such as chewing, speaking, and swallowing. These are distinguished from so-called involuntary parafunctions, which can be divided into dental (jaw clenching and/or teeth grinding, summarized under the term *bruxism*) and non-dental (e.g. tongue pressing, lip biting, cheek sucking). The term *bruxism* refers to all occlusal (i.e. teeth-related) parafunctions that occur during sleep or wakefulness and are accompanied by persistent or rhythmic jaw muscle activity. A distinction is made between sleep and awake bruxism. Jaw clenching and teeth grinding are observed during both sleep and wakefulness. However, there is no reliable data on the frequency of occurrence of either activity during sleep or wakefulness.

In 2013, an international expert commission proposed to expand the definition of bruxism. Accordingly, bruxism has been redefined to be "a repetitive jaw muscle activity characterized by clenching or grinding of the teeth and/or by bracing or thrusting of the mandible" [5]. There is now a consensus in the scientific literature that bruxism is not a peripheral (occlusal or anatomicalmorphological) phenomenon, but a central nervous phenomenon. Contrary to earlier views, bruxism is interpreted less as a disorder or dysfunction and more as an expression of certain physiological and behavioral processes [6]. In some cases, bruxism is even seen as having positive aspects: it plays a role in postural and stability control (jaw clenching when lifting heavy loads), keeps the airway open (teeth grinding during sleep), and stress management.

1.2 Epidemiology

Bruxism is common in the population. In an epidemiological study from the Netherlands (n=1209), 5% of adults reported awake bruxism and 16.5% sleep bruxism [7]. Since the majority of patients do not know whether they are clenching or grinding, it is reasonable to assume that the true, unknown percentage of patients performing these parafunctions is significantly higher. To provide an example, assuming 8% of severely pronounced forms of bruxism (and thus requiring therapy), in Berlin (population approximately 3.7 million [8], of which approximately 3.1 million are 18 years of age or older [9]), the number of adults requiring therapy would be approximately 250,000. In reality however, the number of people receiving appropriate therapy for bruxism is estimated far smaller.

1.3 Risk factors

Many risk factors for bruxism have been identified in recent decades. The most common risk factor is emotional stress, while social phobia has the highest odds ratio [10]. Bruxism, in turn, can be a risk factor for a more frequent occurrence of defined adverse effects than non-bruxing individuals. These may include pain in the area of the masticatory muscles [11, 12]. It may also cause anterior displacement of the articular disc of one or both temporomandibular joints (TMJs), that is often accompanied by clicking in the affected TMJ [11, 13].

1.4 Bruxism beyond a biomechanical assessment

In addition to the above described risk factors, psychological and social factors also play an important role in the development of bruxism [14–16]. The biopsychosocial approach considers biological, psychological and social factors in assessing the health of the individual [17]. The World Health Organization places great importance on the social determinants of health "They are the conditions in which people are born, grow, work, live, and age, and the wider set of forces and systems shaping the conditions of daily life." [18], as research has presented that the "social determinants can be more important than health care or lifestyle choices in influencing health" [18]. We can therefore assume that bruxism is not just an individual issue but rather a behavior that needs to be placed within a broader social analysis of health. Thus, considering the set of causes of bruxism from a biopsychosocial perspective can contribute to the design of public policies and protocols to deal with bruxism.

1.5 Awake and sleep bruxism instrumental assessment

The gold standard for diagnosing sleep bruxism is polysomnography (PSG) with audio and video recording (AV), but this approach is expensive, time-consuming, and cumbersome. Therefore, several research groups conducted several studies to investigate the efficacy of wearable devices that are relatively inexpensive and could allow for real-world assessment. Where real-world assessment refers to the assessment of bruxism in the environment where the user lives. For instance, oral splints have been fitted with a force sensor to detect sleep bruxism [19, 20]. Another sensing modality that has been extensively studied is surface electromyography (sEMG), which monitors the activity of the muscles involved in bruxism and has traditionally been used to study sleep bruxism [21, 22]. Both, oral splints and sEMG have their own limitations as they respond not only to bruxism-induced events but also to other oral (functional and parafunctional) behaviors, which could compromise their effectiveness. Another sensing modality that has received renewed attention is the use of sound to detect bruxism-like events. Tooth-grinding sounds propagate across the skull via bone propagation; muscle activation also produces detectable vibrations. Sound detection is not new to dentistry; it was used for occlusal analysis since the second half of the 20$^{\text{th}}$ century [23].

A gold standard for the assessment of awake bruxism is still lacking. However, as concluded by a panel of experienced researchers, "a comprehensive approach including a combination of self-reported and measurement strategies (...) will likely emerge as the gold standard for evaluating awake bruxism" [24]. Accordingly, researchers are investigating the use of mobile phone applications for Ecological Momentary Assessment (EMA) [25]. EMA is a method of collecting data about the patient's behavior in a real-world environment in real-time [26].

Due to its high prevalence and potential as a risk factor, bruxism is an important public health issue. Therefore, there is a need to develop devices that can detect and monitor bruxism [27]. These devices should be easy to use, as wearing sEMG devices or oral splints may not be the most convenient devices to assess both awake and sleep bruxism. In addition, since various parafunctional behaviors other than bruxism as well as functional intra-oral behaviors, such as eating, drinking, and talking, activate the mastication muscles, produce sounds that propagate throughout the head, and mobilize the lower jaw, the diagnostic devices should be able to differentiate between bruxism and other oral behaviors. In order to be able to monitor bruxism in real-world environment during the user's daily routine, it is necessary to develop classification procedures to distinguish between the different sounds that the assessment device might record.

1.6 Bruxism: diagnostic issues

The clinical diagnosis of bruxism is primarily made by the patient history and clinical examination. Self-report has been widely used to assess the onset of sleep bruxism. Self-report, in this case, refers to the perception of bruxing behavior by the affected person, the sleep partner of in the case of children, the parents. The validity and accuracy of self-report were compared to lab PSG; one of the conclusions was that self-report might not reflect the presence of moderate and severe sleep bruxism [28]. Another research group investigated the diagnostic validity of self-report for measuring sleep bruxism compared to a single-channel EMG device, Grind Care® (Medotech A/S, Denmark). The authors concluded that self-report had a low validity and should be used in combinations with other diagnostic tools [29]. The continuous monitoring of the activity of the masticatory muscles activity during PSG and the presence of audio and video recordings help to categorize different behaviors that might not be related to sleep bruxism, but are still visible on the recording of the masticatory muscles. However, this tool has several disadvantages: the environment in which the individual is sleeping and the multiple sensors and wires attached to the participant may affect the sleep behavior and comfort; in addition, such a tool is cumbersome, time-consuming, and expensive [30]. Approaches to reduce the costs by using portable home PSG devices with no audio and video recording have also been tested. However, it was found that the absence of the additional recordings may lead to an overestimation of sleep bruxism-induced events [31].

Different research groups have used the oral splint to transform it from a passive, harm-reducing tool into a monitoring tool by equipping it with transducers that record the forces on the teeth generated by sleep bruxism [19, 20, 32–43]. A systematic review that included articles on randomized controlled trials published between 2007 and 2017 concluded that several studies supported the effectiveness of oral appliances for sleep bruxism [44]. The authors observed that several studies support the effectiveness of oral appliance therapy for sleep bruxism, but that further studies are needed to investigate the long-term reduction of bruxism with larger samples.

The activity of the masseter muscle and the temporalis muscle were monitored using sEMG, either the masseter or the temporalis muscle, to detect bruxism. To this end, several research groups have investigated the possibility of using portable sEMG sensors to detect bruxism [21, 22, 35, 45–55]. In addition, sEMG devices were used to activate a bio-feedback mechanism after detecting the activity of the masticatory muscles. For example, a headband-like device equipped with an EMG sensor was used to deliver electrical pulses to the temporalis muscle to disrupt its activity during sleep; a reduction in the temporalis muscle activity was observed [56]. The efficacy of GrindCare® in reducing the occurrence of sleep bruxism was studied. GrindCare® is a device that uses sEMG to detect the temporalis muscle activity associated with sleep bruxism. It provides a low-voltage stimulation to interrupt the contraction of the muscle. The investigators observed that more than half of the 19 participants reported a substantial reduction in headaches and masticatory muscle pain after waking up [57]. Other researchers investigated the effectiveness of using EMG biofeedback training for the onset of daytime clenching. To do so, an EMG sensor was incorporated into a hearing aid-like device that monitored the activity of the temporalis muscle. The feedback mechanism was a loudspeaker that produced a tone when a certain threshold of clenching activity was detected [58]. In a follow-up study, the potential of using the portable device developed by [58] to detect daytime clenching episodes was investigated in a group of volunteers with self-reported clenching episodes [59]. Afterward, the device developed by [58] was used to investigate the effect of biofeedback training for daytime clenching on sleep bruxism. The results suggest that such training can have a positive effect on the onset of sleep bruxism [60]. In 2014, a systematic review examined the validity of portable instrumental devices for monitoring sleep bruxism compared to the gold standard, PSG with video and audio recordings. The authors concluded that Bruxoff® - a sEMG and ECG device that records the activity of the masseter muscle activity and the heart rate, respectively - presents a viable option for diagnosing sleep bruxism without PSG [48]. In 2021, a scoping review of ambulatory sEMG recording devices and methods to assess sleep bruxism was published, considering 78 studies published between 1977 and 2020. It was concluded that there is a need for standard reporting of methods and the recording procedures, as well as a need to deviate from only scoring sleep bruxism periods to scoring the full spectrum of masticatory muscle activity [61].

1.7 My research questions and outline of the thesis

The various devices mentioned above for the diagnosis and management of bruxism have their advantages and disadvantages. EMG devices have demonstrated reliable performance in detecting masseter muscle activity associated with the onset of bruxism. However, EMG devices are cumbersome to wear at night because of the cables. Although wireless EMG devices have been tested with promising results, EMG devices are limited by their susceptibility to noise when the user touches the device or sleeps on the side to which the device is attached. Oral splints have been prescribed as a management device that eliminates tooth contact during sleep. Mouthpieces have been equipped with sensors to detect tooth contact using pressure sensors. Researchers have studied the use of these devices to diagnose bruxism and reported that the devices have the potential to detect tooth contact and the amount of force applied. However, sensor-loaded mouth guards have some limitations because they require continuous hygiene protocols, and the wear and tear of mouth guards would make such devices expensive to maintain.

With the advancement of wearable devices used to monitor health over time, the ear presents itself as a location for placement of such devices; such devices are sometimes referred to as hearables. Tooth grinding produces sounds that travel through the head via bone conduction. Jaw clenching alters the blood flow around the ear, and activation of the middle ear muscles would deform the eardrum. The sounds produced by teeth grinding, which propagate through bone, can reach the ear. In addition, occluding the ear creates a medium in which sounds generated by the change in blood flow can be recorded. In addition, the pressure in an occluded ear canal can change as the eardrum deforms. Therefore, recording sounds from the ear to detect bruxism events has promising potential.

Several research questions are important regarding the recording of the sounds produced by a bruxism event. The first question is, when sounds propagate through the bone across the head, is there a location on the head that is optimal to record the sound from? Also, there are different levels of occlusion of the ear. So, the second question is how does the degree of ear occlusion affect the quality of the recording? In addition, bruxism occurs throughout the day, as do other oral behaviors such as eating, drinking, or reading, so it is important to investigate a classification algorithm that is capable of distinguishing the different sounds. Therefore, the third research question is can deep learning be used to classify sounds of voluntarily performed oral behaviors?

To answer the above questions, we developed a study to record sounds of different oral behaviors from different participants. Five oral behaviors were recorded: jaw clenching, teeth grinding, reading, eating, and drinking. The setup consisted of eight transducers recording sound from different locations on the head, zygomatic, frontal, temporal, and ear. To answer the various research questions, a review of the potential of hearables to record bruxism sounds was conducted and presented in Chapter 2. The third chapter presents the results of a pilot study conducted with one participant to investigate the effect of ear occlusion type on the recording of sounds. The fourth chapter presents the results of the study investigating the effect of transducer location on the recorded sound. The fifth chapter presents the results of the experimental classification of sounds recorded from the ear using deep learning.

Chapter 2

Reviewing the potential of hearables for the assessment of bruxism

Foreword and Overview

This chapter contains the publication that reviews the use of ear devices for the possible detection of bruxism. It gives a general introduction before delving into the the study I conducted in chapters 3, 4, and 5. The online search was done using two databases PubMed and Livivo, in additoin to individual complementary searches on Google Scholar.

Abstract

Bruxism is a parafunctional oral behavior that affects a large percentage of the population. Bruxism is a risk factor for temporomandibular disorders. A gold standard is still lacking for assessing bruxism while awake, whereas for sleep bruxism, polysomnography with audio and video recording is the gold standard. Wearable devices, particularly those that detect sound (hearables), are cost-effective and convenient and could fill the gap. With this systematic literature review of Livivo and PubMed, extended by individual Google Scholar searches, we aimed to assess the potential of wearable devices that use sound as a biomarker for detecting bruxism. In summary, sounds originating from oral behaviors can be recorded from the ear, and hearables have the potential to detect bruxism-like events.

Abstract [german]

Bruxismus ist ein parafunktionelles orales Verhalten und ein Risikofaktor für kraniomandibuläre Dysfunktionen. Er betrifft einen großen Teil der Bevölkerung. Für die Beurteilung von Bruxismus

This chapter is based an published manuscript [1] in the journal at-Automatesirungstechnik available online at: https://doi.org/10.1515/auto-2024-0029 (Accessed on 12 July 2024). Copyright and licensing information can be found in the Preface.

im Schlaf gilt eine Diagnose mittels Polysomnographie begleitet von Audio- and Videoaufzeichnung als Goldstandard. Für den Wachzustand existiert noch kein solcher Goldstandard. "Hearables" sind tragbare Geräte, welche Schall als Biomarker nutzen und dabei kostengünstig und bequem zu tragen sind. Solche Hearables könnten die derzeitige Lücke in der Diagnose von Bruxismus im Wachzustand schließen. Ziel dieser systematischen Literaturrecherche in Livivo und PubMed, ergänzt durch eine individuelle Suche in Google Scholar, war es, das Potenzial solcher Hearables für die Erkennung von Bruxismus zu eruieren. Zusammenfassend haben wir festgestellt, dass durch orale Verhaltensweisen entstehende Geräusche im Ohr aufgezeichnet werden können und der Einsatz von Hearables zur Erkennung bruxismusähnlicher Ereignisse möglich ist.

2.1 Introduction

Bruxism is a parafunctional oral behavior defined as "a repetitive jaw muscle activity characterized by clenching or grinding of the teeth and/or by bracing or thrusting of the mandible" [5]. In a Dutch epidemiological study (n=1209), 5% of adults reported awake bruxism, and 16.5% reported sleep bruxism [7]. Since most of patients do not know whether they are clenching or grinding, it is reasonable to assume that the real, unknown percentage of patients performing these parafunctions is significantly higher.

A gold standard for assessing awake bruxism is still lacking. However, as concluded by a panel of experienced researchers, “a comprehensive approach including a combination of self-reported and measurement strategies (...) will likely emerge as the gold standard for evaluating awake bruxism" [24]. Conversely, polysomnography (PSG) with audio and video recording (AV) is the gold standard for diagnosing sleep bruxism. However, this approach is expensive, time-consuming, and cumbersome [30, 31]. Therefore, several studies have been conducted by different research groups to investigate the efficacy of wearable devices for bruxism diagnosis that are relatively inexpensive and allow for real-world assessment. One way to implement this principle is to equip oral splints with a force sensor to detect sleep bruxism [19, 20, 32–44]. Another sensor modality that has been extensively studied is surface electromyography (sEMG), which directly monitors the activity of the muscles involved in bruxism and has therefore been widely used to study sleep bruxism [21, 22, 35, 45–62]. Yet, both oral splints and sEMG have some limitations because they respond not only to bruxism-induced events but also to other oral (functional and parafunctional) behaviors, which could compromise their effectiveness. Recently, the use of sound to detect bruxism-related events –from the ear in particular –has received renewed attention. Such wearable devices are sometimes called hearables. Tooth-grinding sounds propagate through the skull via bone propagation, while muscle activation produces detectable vibrations [63, 64]. Sound detection is not new to dentistry; it has been used for occlusal analysis, called *gnathosonics*, since the second half of the 20th century [23, 65–90]. In addition, temporomandibular joint sounds have been recorded to study the position of the mandibular condyles of the temporomandibular joints [91, 92].

Because of its high prevalence and potential as a risk factor for temporomandibular disorders

(TMDs), tooth fractures, and chipping of ceramic restorations, both awake and sleep bruxism are important public health issues (Figure 2.1). Therefore, there is a need for the development of devices that can detect and monitor bruxism and help prescribe the necessary therapy [14]. Wearable devices that can assist in monitoring and assessing bruxism should be easy to use and less intrusive than wearing sEMG electrodes or an oral splint during daily activities. To monitor bruxism during daily activities, it is necessary to develop sound classification. Therefore, the main objective of this review is to highlight wearable devices that record sound and have the potential to unobtrusively assess bruxism in a real-world setting. First, the electronic search method is explained. Then, wearable devices developed to record sounds are described, followed by the description of classification procedures used to differentiate the sounds. Finally, the discussion and conclusion sections reflect on the search outcome and the possible avenues for future work.

2.2 Method

A systematic literature search was performed using the electronic databases PubMed and Livivo. The specific search strings used in the search are listed in Table 2.1. Publications were identified as relevant to this work and were further described in the results section if they met the inclusion criteria. The inclusion criteria were: (a) wearable devices, (b) use of sound as a biomarker, (c) the detection of bruxism or bruxism-like events, and (d) articles published in English. As a first screening step, the title and the abstract of the retrieved bibliographic references were screened for relevant papers. Further online searches were performed in Google Scholar to identify additional relevant publications available only on Google Scholar but not in PubMed and Livivo. Bramer et al. [93], compared doing a systematic search using only Google Scholar or PubMed. They reported that PubMed was more precise than Google Scholar and recommended using PubMed to get a good and reproducible search outcome [93]. Hence, we have used PubMed and Livio as our main search databases and Google Scholar as our search tool for grey literature.

2.3 Results

2.3.1 Sound of bruxism, a historical perspective

The first relevant publication appeared in 1993 by L'Estrange et al., who reported on detecting masseter muscle sounds [94]. In 2018, Bouserhal et al. published their findings on using an ear device to detect various verbal and nonverbal sounds [95]. Two years later, Prakash et al. presented their experience in repurposing an earpiece to capture tooth contact sounds [96]. In 2021, Alfieri et al. presented a wearable device combining an inertial measurement system and a microphone to detect voluntary bruxism [97]. And in 2022, publications by Nahhas et al. [2] and Christofferson et al. [98] focused on an earpiece to detect voluntary tooth contact sounds, among other oral behaviors.

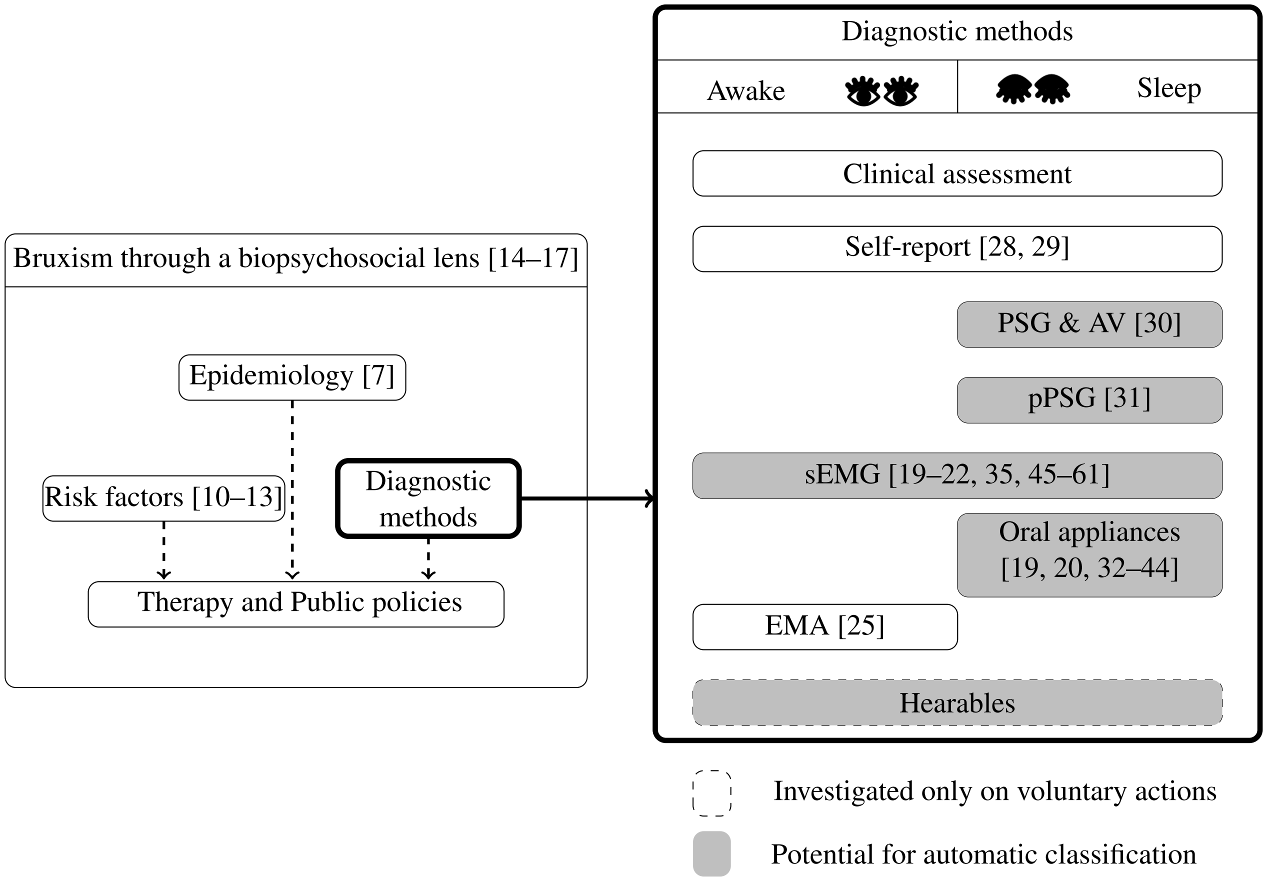

Figure 2.1: Overview of a biopsychosocial perspective of bruxism that considers biological, psychological, and social factors. Developing public policies and therapy requires updated epidemiologic information, which would require reliable diagnostic methods for awake and sleep bruxism (left) and an overview of existing diagnostic methods (right). PSG & AV stand for Polysomnography with Audio and Video recording, pPSG for portable Polysomnography, sEMG for surface Electromyography, and EMA for Ecological Momentary Assessment. Boxes with dashed lines mean that the diagnostic method in the box was tested on voluntary action only. Boxes with a background color mean that the diagnostic method has the potential to be further developed to perform automatic classification.

Database	Search string	Hits	Relevant publications	Accumulated relevant publications
PubMed	bruxism AND hearables	15	0	0
	bruxism AND sound	188	0	0
	bruxism AND sound AND wearable Devices	0	0	0
	tooth grinding AND sound	206	0	0
	tooth grinding AND sound AND wearable device	0	0	0
	jaw clenching AND sound	40	1 [94]	1 [94]
	jaw clenching AND sound AND wearable device	0	0	1
Livivo	bruxism AND hearables	0	0	1
	bruxism AND sound	242	0	1
	bruxism AND sound AND wearable Devices	0	0	1
	tooth grinding AND sound	56	0	1
	tooth grinding AND sound AND wearable device	0	0	1
	jaw clenching AND sound	49	0	1
	jaw clenching AND sound AND wearable device	0	0	1
Google Scholar	[Individual searches]	-	6 [2, 95–99]	7 [2, 94–99]

Table 2.1: List of search terms and databases and the number of publications relevant to this work. The database Google Scholar refers to publications that were relevant for this work and were not found on PubMed or Livivo. As a first screening step, the title and the abstract of the retrieved bibliographic references were screened for relevant papers. References to relevant publications that fulfilled the inclusion criteria are given in parentheses. The inclusion criteria were (a) wearable devices, (b) use of sound as a biomarker, (c) the detection of bruxism or bruxism-like events, and (d) article published in English.

Publication Authors	Publication year
L'Estrange et al [94]	1993
Bouserhal et al. [95]	2018
Prakash et al. [96]	2020
Alfieri et al. [97]	2021
Chabot et al. [99]	2021
Nahhas et al. [2]	2022
Christofferson et al. [98]	2022

Table 2.2: List of relevant publications to this work that fulfilled the inclusion criteria. The inclusion criteria were (a) wearable devices, (b) use of sound as a biomarker, (c) the detection of bruxism or bruxism-like events, and (d) article published in English

2.3.2 Contents of relevant articles

This section is divided into 2 parts. The first section elaborates on the devices described in the publications. The second section describes the classification algorithms used to distinguish the different sounds. In case publications report about a device and according algorithms for sound differentiation, these publications will be mentioned in both sections. The publications included in these sections are listed in Table 2.2.

Sound monitoring and hearables

L'Estrange et al. [94] investigated the possibility of using acoustic myography (AMG) to monitor the activity of the masseter muscles in six participants. The researchers also attached an EMG device to the masseter muscles. They found that the combination of both measurements, EMG and AMG, was promising for electro-mechanical muscle assessment.

Bouserhal et al. [95] used an in-ear device with two microphones, one facing towards the ear canal and one facing the outside of the ear. The aim was to detect and classify various verbal and non-verbal sounds produced by humans. Voluntary tooth grinding and tooth clicking were among the sounds studied. They concluded that an approach with an ensemble of crafted features can improve the accuracy of the classifiers [95].

In another study [96], the speaker of an earphone was repurposed to act as a microphone to capture sounds produced by tooth contact as they traveled across the head to the ear. The goals were to detect the onset of tooth contact, to distinguish between voluntary tooth tapping and tooth slipping, and finally to identify from which side of the head the sound was coming from. The authors demonstrated that their device was capable of identifying different tooth gestures for possible human-machine interface [96].

Alfieri et al. [97] developed a prototype of a portable device that combined acoustic emission measurement with a microphone and a measurement of mandibular movements with an inertial measurement unit (IMUs). The aim was to detect both voluntary jaw clenching and teeth grinding.

The bone conduction microphone was attached to the cheek, while the IMU was attached to the chin and the masseter muscle. They concluded that the prototype can collect the signals required to detect bruxism-induced events [97].

Nahhas et al. [2] investigated the effect of the ear occlusion type on the recording of voluntary tooth grinding and jaw clenching in a case study. These sounds, along with other verbal and non-verbal sounds were recorded in a controlled environment. They observed that the type of ear occlusion affected the strength of the recording and that full occlusion supported the recording of clenching [2].

Christofferson et al. [98] reported using a modified commercially available active noise-canceling earbud to record sounds produced by various intra-oral behaviors. Among the various activities were voluntary tooth grinding and tooth clenching. The commercial earpiece consisted of two microphones: one microphone recorded sounds from the ear canal, and the other microphone recorded sounds from the environment outside the ear. The two microphones were connected to an external data acquisition system, and the participants were asked to voluntarily record various sounds in their homes. They reported that their device could record bruxism-induced sounds [98].

Classification of voluntary oral-behaviors sounds

Bouserhal et al. [95] recorded and classified a variety of voluntarily produced verbal and non-verbal sounds using an earbud. Several temporal and spectral features, such as mel-Frequency cepstral coefficients (MFCC), zero crossing rate, and auditory-inspired amplitude features (AAMF), were used. In addition, factory noise from the NOISEX-92 database was introduced post-hoc into both the training and test data sets. The data sets were then fed to three classifiers: gaussian mixture model (GMM), support vector machine (SVM), and multi-layer perceptron (MLP). The authors reported that the highest average accuracy across all classes was obtained using GMM with values of 75.54% and 73.47% for the clean and noisy data sets, respectively [95].

A follow-up investigation was conducted by Chabot et al. [99], who investigated the effectiveness of using the Bag-of-Features, which is based on the Bag-of-Words method. They also introduced a clustering step in their procedure just before the classification task; the clustering algorithms were GMM and K-Means, and the classification algorithms were SVM and Random Forest. The authors reported that the combination of GMM as the clustering algorithm and SVM as the classifier yielded the highest sensitivity of 81.5% and precision of 83% in a quiet environment. They also investigated the effect of adding noise to the data set, where two types of noise were added separately; factory noise and babble noise. The authors found that the sensitivity dropped to 69.9% and 78.8% for factory noise and babble, respectively. Sensitivity also dropped to 63.4% and 55.5% for factory and babble noise, respectively [99].

In addition to methods that use handcrafted features, deep learning methods that leave the feature extraction to the machine were investigated. The researchers used a 2D convolutional neural network (CNN) with an integrated modified temporal shift module (TSM), which considers

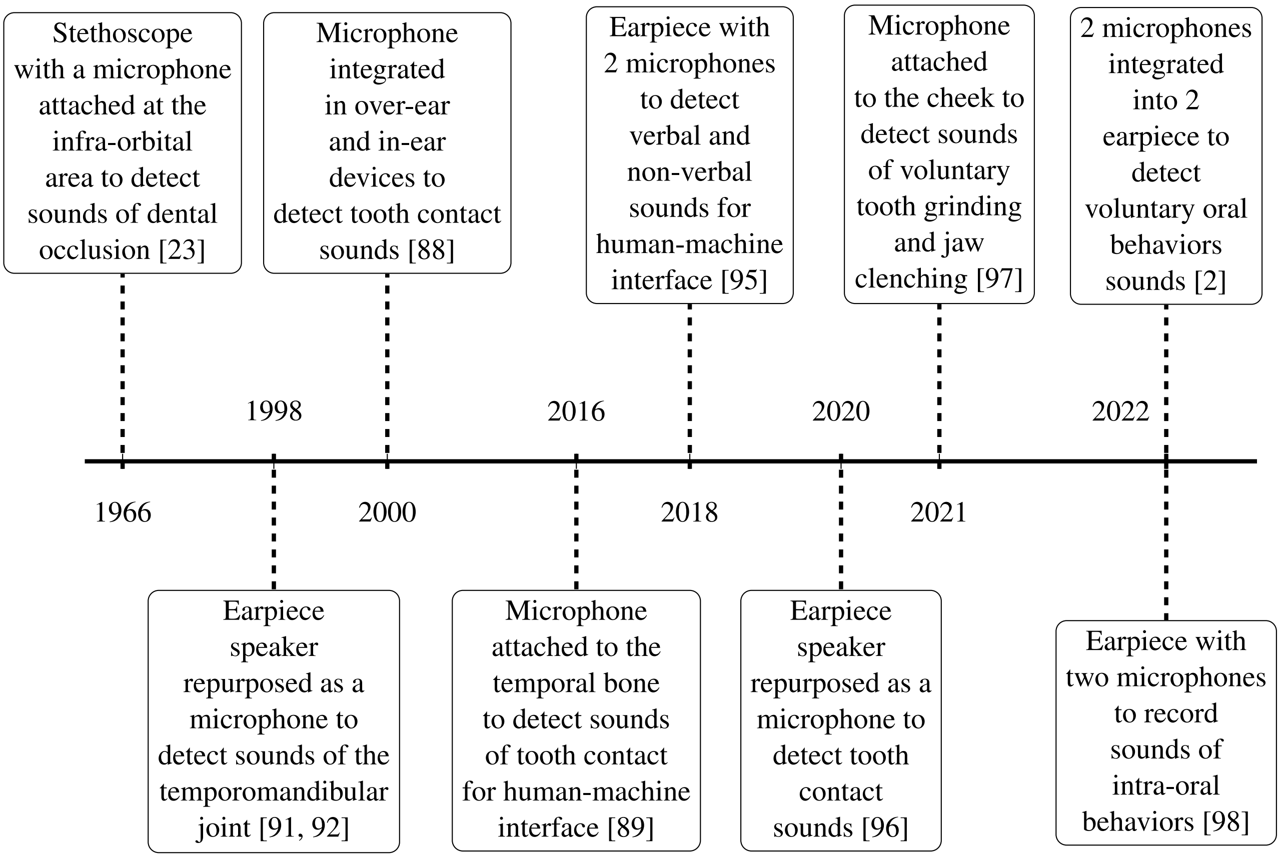

Figure 2.2: Timeline of the milestone publications related to the development of the use of sound for diagnostic purposes in dentistry. Each box lists the transducer reported in the publication and the sounds that were recorded.

the context of a given period within the recording. They transformed the 1D time series into a 2D spectrogram and classified various verbal and non-verbal classes, such as speaking, breathing, and voluntary tooth grinding and jaw clenching. Although they classified voluntary jaw clenching as a subclass of voluntary tooth grinding, the highest accuracy was reported to be 91%, and an F1 score of 0.845 for the multi-class classifier [98].

2.4 Discussion

A reliable diagnosis is necessary for an appropriate and *timely* management of bruxism. An obstacle to a *timely* diagnosis of sleep bruxism is that the gold standard, PSG with AV, is costly and requires the person to sleep in a sleep lab, which may affect sleep patterns. Meanwhile, a gold standard for awake bruxism is still lacking. This has led to the need for the development of special tiny sensors to record bruxism-related activities in the real-world [27].

Although most bruxing-related sounds can be recorded from different locations on the head [2, 89], the ear is a very convenient location for sensor placement. In addition, since bruxism can occur during wakefulness or sleep, the potential wearable device should be comfortable and tolerable, giving ear devices an advantage over EMG devices or oral splints. In fact, we expect that the ear to be less susceptible to external physical perturbations that could interfere with the recording than other locations on the head such the frontal bone or the temporal bone.

The development of in-ear devices has taken a significant leap, creating a new horizon for exploring their suitability for medical assessment in general [100]. Most research on sound as a possible biomarker and in-ear devices has investigated the possibility of recording voluntarily produced sounds, as shown in Figure 2.2. Since bruxism is a parafunctional behavior that occurs involuntarily, there is a need to (a) investigate the use of these devices in real-life situations where involuntary production of the sounds is expected and (b) to compare the device to a gold standard. In addition, there are still other challenges in detecting sounds associated with bruxism. For example, it is important to occlude the ears to increase the signal amplitude [2, 95]. However, complete ear occlusion would again be intrusive and raise safety concerns because it isolates the user from the environment.

As a consequence, a trade-off between the degree of ear occlusion and the classification accuracy of the device is required. It must be considered that additional activities other than bruxism may occur during the recording, such as eating, drinking, swallowing, and other parafunctional behaviors, which would be reflected in the recorded signal regardless of whether the biomarker of interest is sound, force, or EMG. Therefore, it is important to develop classification algorithms that can specifically detect bruxism-induced events.

Several research groups have investigated how to use machine learning to distinguish bruxism-induced events –voluntary tooth grinding and jaw clenching –from other events. Approaches that rely on typical machine learning methods, such as SVM or KNN with handcrafted features, have been investigated to classify voluntary tooth tapping, speaking, and voluntary tooth grinding

[95, 99]. In addition, work has been done on deep learning where a 1D sound signal was converted into a 2D image to be classified [98]. Nonetheless, there are several challenges that need to be addressed in terms of the data storage and power consumption that such techniques would require, as well as the optimal size of a wearable or an in-ear device to be comfortable and convenient. Furthermore, recording sound in real-world environments has both eithical and technical challenges. The ethical challenges are related to the recording of sensitive conversations of people around the user.

2.5 Conclusion

In conclusion, timely diagnosis of bruxism remains a clinical and technical challenge mainly due to the lack of dedicated, small, and easy to use devices. Research on hearables has led to promising developments; dedicated, affordable, and easy-to-use hearables, even outside of controlled environments such as research laboratories have the potential to be effective in detecting bruxism. We also anticipate that ear devices will have an advantage over EMG because they can be conveniently worn through-out the day and are socially acceptable. However, our experience suggests that more work is needed to develop methods to overcome ethical and technical challenges. In addition, the ability of classification algorithms to distinguish between the different sounds produced involuntarily by different oral behaviors and the effectiveness of hearables in real-world settings should be investigated.

Acknowledgement

We are grateful for the generous financial support of the Werner Siemens Foundation and the Department of Biomedical Engineering at the University of Basel.

Appendix I: List of abbreviations

Abbreviation	**Full Term**
sEMG	surface Electromyography
TMDs	Temporomandibular Disorders
AMG	Acoustic Myography
EMA	Ecological Momentary Assessment
PSG & AV	Polysomnography & Audio and Video
pPSG	portable Polysomnography
IMU	Inertial Measurement Unit
MFCC	Mel-Frequency Cepstral Coefficients
AAMF	Auditory-inspired Amplitude Features
GMM	Gaussian Mixture Model
SVM	Support Vector Machine
MLP	Multi-Layer Perceptron
CNN	Convolutional Neural Network
TSM	Temporal Shift Module
KNN	K-Nearest Neighbors

Table 2.1: List of abbreviations found in the paper and the corresponding full term.

Chapter 3

Impact of ear occlusion on in-ear sounds generated by intra-oral behaviors

Foreword and Overview

After showcasing the potential for using hearables to assess bruxism, this chapter presents the results of the pilot study that examined the effect of ear occlusion type on the recorded signal. This work was motivated by the concern that the occlusion type would have an impact on the recording and on the isolation of the user from the environment.

Abstract

We conducted a case study with one volunteer and a recording setup to detect sounds induced by the actions: jaw clenching, tooth grinding, reading, eating, and drinking. The setup consisted of two in-ear microphones, where the left ear was semi-occluded with a commercially available earpiece and the right ear was occluded with a mouldable silicon ear piece. Investigations in the time and frequency domains demonstrated that for behaviors such as eating, tooth grinding, and reading, sounds could be recorded with both sensors. For jaw clenching, however, occluding the ear with a mouldable piece was necessary to enable its detection. This can be attributed to the fact that the mouldable ear piece sealed the ear canal and isolated it from the environment, resulting in a detectable change in pressure. In conclusion, our work suggests that detecting behaviors such as eating, grinding, reading with a semi-occluded ear is possible, whereas, behaviors such as clenching require the complete occlusion of the ear if the activity should be easily detectable.

This chapter is based an accepted manuscript presented at the International Workshop on Medical and Service Robots (MESROB), 2021. It is available online as part of conference proceedings [2] and is available online at: https://doi.org/10.1007/978-3-030-76147-9_16 (Accessed on 12 July 2024). Copyright and licensing information can be found in the Preface.

Nevertheless, the latter approach may limit real-world applicability because it hinders the hearing capabilities.

3.1 Introduction

Our body produces sounds that can act as markers to detect, measure, or asses impaired or abnormal physiological processes. For instance, listening to the heart beat for a relatively short period with a stethoscope is a well established non-invasive method to detect health problems [101]. Wearable devices allow new possibilities for health monitoring [102]. They allow the monitoring of various physiological bio-markers over a longer period. Different research groups used wearable devices to detect health problems with microphones: knee osteoarthritis [103] or irritable bowl syndrome [104]. Wearable devices that are worn in the ear or around the ear which are equipped with various sensors are called: Hearables [100]. They have been utilized by various research groups to monitor sound based bio-markers, for example, sounds made while eating have been monitored from the ear to detect dietary behaviors [105]. Also, breathing rate and heart beat rate monitoring via the earcanal have also been studied [106].

We are interested in detecting the parafunctional orofacial behavior: bruxism. It is defined as “masticatory muscle activities that occur during sleep (characterized as rhythmic or non-rhythmic) and wakefulness (characterized by repetitive or sustained tooth contact and/or by bracing or thrusting of the mandible)” [107]. From the literature, bruxism induces various health implications such as teeth wear, muscles hypertrophy, toothache, and various other complications [108].

Bruxism-induced sounds can be produced by continuous tooth grinding or jaw clenching. They can propagate across the head and reach the earcanal. Therefore, we are firstly, interested in developing a framework to detect sounds generated by various oral behaviors such as bruxism from the ear. One of the important requirements to detect such sounds is to reduce the environmental noise. Various approaches have been explored in the literature, either by adding a microphone directed towards the environment to pick up ambient noise that can be later deducted form the in-ear signal [109]. Alternatively, tightly occluding the ear may reduce environmental noise as well. The aim of this case study is to investigate the possibility to detect various intra-oral behaviors-induced sounds from one semi-occluded and one tightly occluded earcanals.

3.2 Methods

3.2.1 Setup

The setup illustrated in Figure 3.1 consisted of two bone conducting microphones (Sonion, Hoofddorp, Netherlands) to be worn in both ears. For the left ear (L), the microphone was mounted on a commercial solid earpiece positioning the microphone at the entrance of the ear canal. For the right ear (R), the microphone was placed inside the earcanal and was occluded using a mouldable silicon earplug. Thus, the occlusion of the right ear was tighter than that of the left ear. Each microphone was connected to a data acquisition device (Daq-L/R) (MCC,

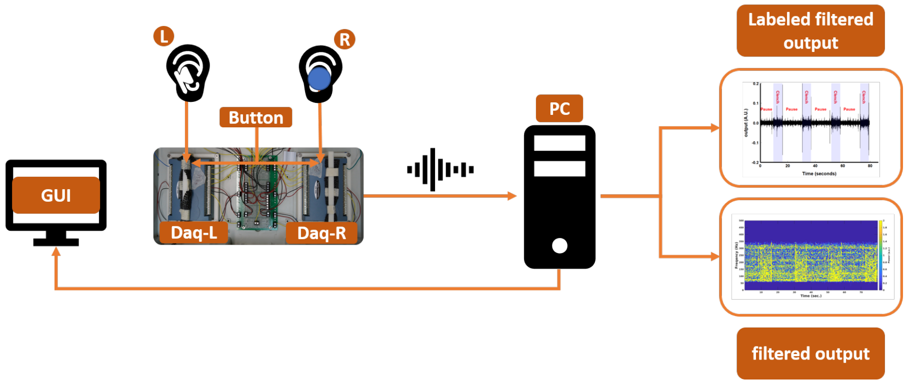

Figure 3.1: Experimental setup: graphical user interface (GUI), left ear sensor (L): semi-occluded with a commercial solid earpiece, right ear sensor (R): occluded with a mouldable silicon earpiece, push button, left data acquisition unit (Daq-L) and right data acquisition unit (Daq-R), a PC to store, label, and filter the data.

Bietigheim-Bissingen, Germany) that was connected to a PC via USB. The Daqs were set to acquire data at a sampling rate of 16 kHz with 18 bit resolution.

In addition, a graphical user interface was developed in-house using the platform Unity (Unity Technologies, California, US) to act as a guide for the participant through the experiment. A push button was handed to the participant to be pressed during certain periods. The Daqs provided the needed voltage for the microphones and the push button, one volt and five volts, respectively. Matlab 2019 (Mathworks, Massachusetts, US) was used to post-process the acquired data.

3.2.2 Protocol

This experiment was performed on one healthy volunteer (male, age = 40 years old), who agreed with the procedure of the study and data publication. The experiment consisted of 6 tasks that were performed in the following order: jaw clenching, tooth grinding, jaw clenching again, reading, eating, and water drinking. The participant was asked to sit in front of the computer screen for instructions through the experiment. The jaw clenching tasks consisted of four clenching periods five seconds each. The participant was asked to clench the jaw with maximum bearable pressure. The tooth grinding task consisted of four grinding periods ten seconds each. Ten seconds pauses were introduced between active periods during the clenching and grinding tasks. The reading task consisted of reciting the paragraph "The North Wind and the Sun" [110]. The eating task consisted of two periods, where the participant was asked to eat a cracker and a fruit. During the final task, the participant had to drink a glass of water.

3.2.3 Data processing

The data from both microphones of the second clenching task were normalized with respect to the maximum data point then were passed first through a low pass - FIR - filter (300 Hz) followed

by a high pass - FIR - filter (55 Hz). In addition, spectral subtraction was introduced to reduce the influence of the test environment noise to a minimum by taking the average of the first three seconds of one of the pause periods as a reference. Also, the spectral flux and the spectrograms were estimated for both sensors. The window size was 50 ms and the overlap was 50%.
To quantify the difference between clenching and pause periods, the energy level for each period was estimated as follows:

$$E_w = \sum_{i=1}^{N_w} |x_i|^2 \tag{3.1}$$

$$E_e = \frac{1}{N} \sum_{w=1}^{N} E_w \tag{3.2}$$

where, E_w is the energy of a window, N_w is the window's number of samples, x_i is the acoustic amplitude at sample i, E_e is the energy of time period e, and N is the total number of windows within the specified period. The energy vector of each sensor was normalized with respect to its maximum value.

3.3 Results

Figure 3.2 illustrates the unfiltered outputs of both microphones for the whole experiment. Both sensors detected grinding, reading, and eating. The drinking task was only detectable from the occluded ear. In addition, both jaw clenching tasks were not visible from either outputs.

Figure 3.3 illustrates the filtered sensors outputs for the second clenching task. The semi-occluded ear output does not show a difference between the clenching and pause periods, whereas, the occluded ear output shows that there is a detectable difference between the different clenching and pause periods.

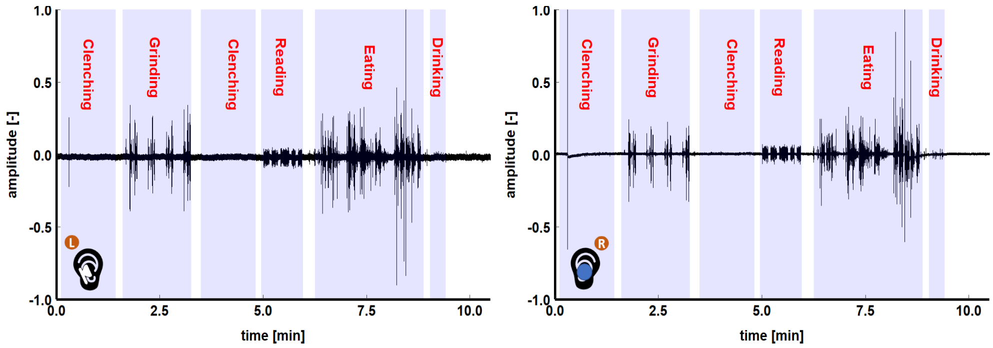

Figure 3.2: Unfiltered normalized acoustic signals of the complete experiment obtained from the semi-occluded left ear (**Left**) and occluded right ear (**Right**). The blue shaded areas depict the tasks, jaw clenching, tooth grinding, jaw clenching, reading, eating, and drinking. While the white sections are pause periods.

Table 3.1: Energy level obtained from Equation 3.2 for each period within the second clenching task. The energy vector of each sensor was normalized with respect to the sensor's maximum value.

Sensor	**Energy [-]**							
	P	**C**	**P**	**C**	**P**	**C**	**P**	**C**
	0.62	0.77	0.66	0.58	0.76	0.78	0.63	1.00
	0.24	0.95	0.28	0.58	0.31	0.73	0.39	1.00

Additionally, the energy levels for the clenching and pausing periods were calculated using Equation 3.2 and listed in Table 3.1. The differences in the energy between the clenching periods and the pausing periods were higher in the recordings obtained from the occluded ear compared to the semi-occluded ear. Figure 3.4 illustrates the spectrograms of the second clenching task filtered outputs. It illustrates that the power of the frequency range 55-300 Hz for the occluded ear was higher during the clenching periods compared to the pause periods. Whereas, the semi-occluded ear produced almost no visible difference. Finally, Figure 3.5 illustrates the spectral flux of the filtered recordings. The amplitudes of the pause periods from the occluded ear were lower than that of the clenching periods. For the semi-occluded ear the amplitudes of the pause and the clenching periods were almost the same.

3.4 Discussion

The variation in the energy levels for the pause periods between the occluded ear and the semi-occluded ear listed in Table 3.1 could be related to the fact that the occluded ear was isolated from

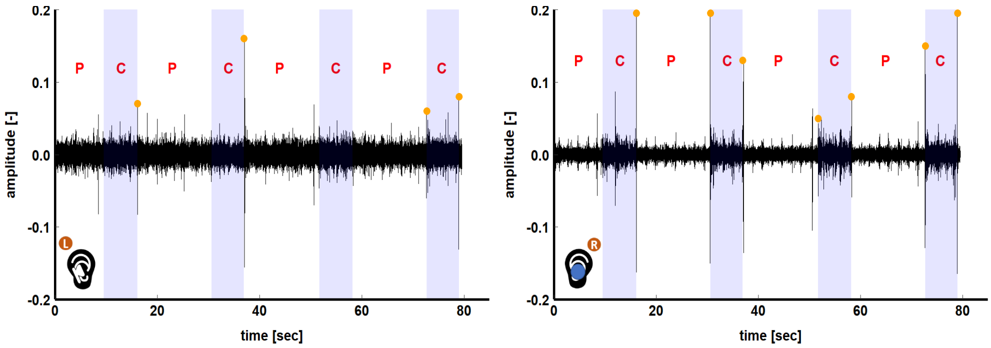

Figure 3.3: Filtered acoustic signals of the second clenching task obtained from the semi-occluded left ear (**Left**) and from the occluded right ear (**Right**). Where, P and C represent the sequence of pause and clenching episodes.

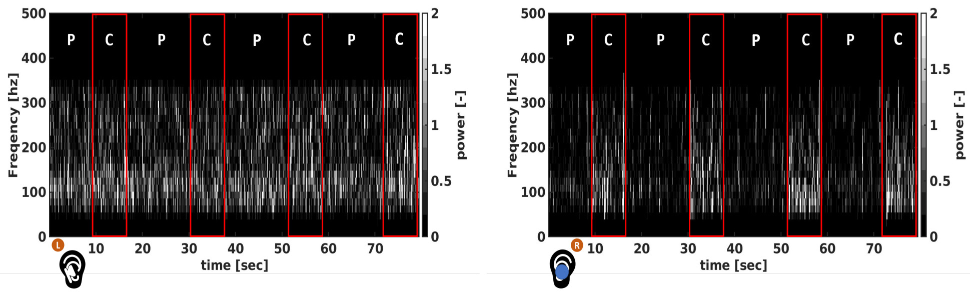

Figure 3.4: Spectrograms of the second clenching task after filtering obtained from the semi-occluded left ear (**Left**) and from the occluded right ear (**Right**). The red rectangles define the clenching periods, whereas, pause periods are outside the rectangles. P and C represent the sequence of pause and clenching episodes.

the environment, thus, reducing the noise level in the occluded earcanal. In addition, from the occluded ear, the clenching periods have had higher energy than that of the pause periods. Three reasons could explain this observation. First, clenching activated the middle ear muscles which deformed the tympanic membrane, thus, changing the pressure inside the sealed earcanal. Also, clenching activates the masticatory muscles that generated sounds. These sounds could propagate to the earcanal via bone conduction. Another plausible reason could be the deformation of the earcanal walls due to clenching-induced movement inside the temporomandibular joint, thus, changing the pressure inside the earcanal.

The jump at the beginning and the end of the clenching periods as illustrated in Figure 3.3 could be attributed to click sounds being generated as the participant brought the upper and lower teeth together or was trying to separate them. The spectral flux illustrated in Figure 3.5 supported the aforementioned explanation as similar jumps at the beginning and the end of certain clenching periods were observed.

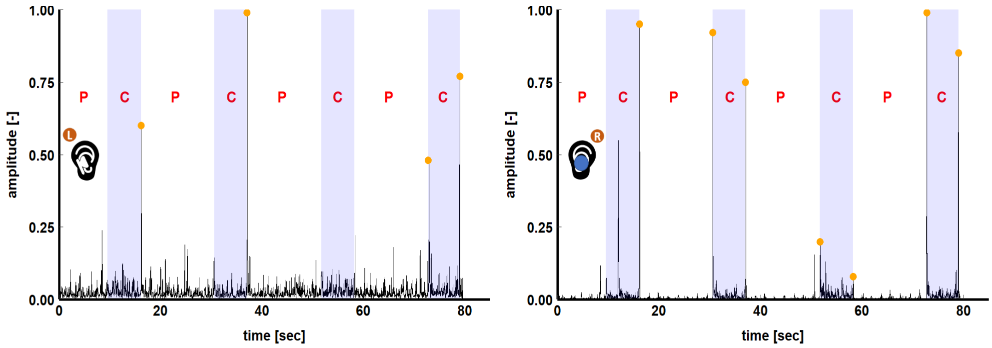

Figure 3.5: Normalized spectral flux for the second clenching task after filtering obtained from the semi-occluded ear (**Left**) and from the occluded right ear (**Right**). Where, P and C represent the sequence of pause and clenching episodes. The orange dots at the beginning and the end of certain clenching periods resemble the jumps that were observed in Figure 3.3.

Also, tightly occluding the ear hindered the hearing capability of the volunteer. Thus, to detect behaviors with low acoustic energy such as jaw clenching in real-world would be challenging. Accordingly, further investigations would be required to implement the optimal occluding approach to detect such low energy signals.

3.5 Conclusion

With this paper, we presented our experimental recording setup that successfully detected intra-oral behaviors such as jaw clenching, teeth grinding, eating, reading, and drinking. We also investigated the effects of either fully occluding or semi-occluding the ear on recording sounds produced by oral behavior. Behaviors such as eating, reading, and tooth grinding were detected from both sensors. However, detecting behaviors such as jaw clenching was not possible at the first glance from either sensors. Eliminating the ambient and electrical noise, revealed that the occluding the ear helped in the detection of jaw clenching. Nevertheless, an occluded ear hinders the user's capabilities in hearing ambient sounds which might be safety relevant in daily life. Therefore, a transfer of the device and task identification from lab environment to the real-world requires further investigations to find the optimal occlusion concept

Acknowledgements

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Chapter 4

Towards wearables for bruxism detection: voluntary oral behaviors sounds recorded across the head depend on transducer placement.

Foreword and Overview

After investigating the impact of the occlusion type on the recording, we have decided to keep the off-the-shelf earpiece as part of the recording setup and further conduct a larger studies. This work was motivated by the fact that sounds can propagate through bone conduction and it is of interest to identify the impact of transducer placement location on the recorded signal.

This chapter is based on a manuscript [3] published in the Journal Clinical and Experimental Dental Research https://onlinelibrary.wiley.com/doi/10.1002/cre2.70001 (Accessed on 06 November 2024). This manuscript was inserted as a file at the moment of submitting this thesis because the manuscript was under the third round of reviews and the journal requested a word file. Copyright and licensing information can be found in the Preface.

Abstract

Objectives: Bruxism is a parafunctional orofacial behavior. For diagnosis, wearable devices that use sounds as bio-markers can be applied to provide the necessary information. Human beings emit various verbal and non-verbal sounds, making it challenging to identify bruxism-induced sounds. We wanted to investigate whether the acoustic emissions of different oral behaviors have distinctive characteristics, and, if the transducer placement has an impact on recorded the sound signals.

Material and Methods: Sounds from five oral behaviors were investigated: jaw clenching, tooth grinding, reading, eating, and drinking. Eight transducers were used; six were attached to the temporal, frontal, and zygomatic bones with the aid of medical tape, and two were integrated into two commercial earphones. Data from 15 participants was analyzed using: time-domain energy, spectral flux, and zero crossing rate (ZCR).

Results: In summary, all oral behaviors showed distinct characteristic features except jaw clenching, however, we were able to observe a peak before its expected onset. For tooth grinding, the transducer placement had no significant impact ($p>0.05$) regardless of the metric of interest. For jaw clenching, the transducer placement had an impact when considering the spectral flux ($p<0.01$). For reading and eating, the transducer placement had a significant impact when considering the three metrics: energy ($p<0.05$ for reading, $p<0.01$ for eating), spectral flux ($p<0.001$ for reading, $p<0.01$ for eating), ZCR ($p<0.001$ for both reading and eating). Whereas, for drinking, the transducer placement had a significant impact when considering the ZCR ($p<0.01$).

Conclusions: Furthermore, recording sounds from the ear was advantageous compared to other locations on the head because we were able to record the onset of almost all behaviors from the ears while providing a stable location for the transducer.

I. Introduction

Bruxism, a parafunctional orofacial behavior, is characterized by tooth grinding or jaw clenching that can happen during sleep or wakefulness [1]. Approximately 8% of the population suffers from severe sleep bruxism, which requires therapy [2, 3]. Bruxism is related to multiple health risks such as emotional stress, drugs, or certain medications [4]. It may lead to many health problems, such as temporomandibular pain, tooth wear, or anterior disc displacement [5, 6]. Polysomnography (PSG) with audio and video recordings is the gold standard to diagnose bruxism [7]. PSG is very resource-intensive and requires an overnight stay in a sleep laboratory. Self-reports are used to indicate the presence of sleep bruxism. However, a shortcoming of self-report is that it does not allow for the determination the severity of sleep bruxism [8]. Consequently, tiny dedicated sensors to monitor bruxism are necessary, not only to monitor sleep bruxism and its severity but also to monitor awake bruxism as well [9].

Development in wearable devices allowed health monitoring in real-world settings for longer duration [10]. The possibility to use such wearable devices for bruxism home monitoring could be a cost-effective alternative to PSG [2, 9, 11, 12]. For instance, monitoring sleep bruxism was investigated in real-world settings using a portable device, Bruxoff (Spes Medica, Battipaglia, Italy). Bruxoff consists of an electromyography (EMG) system to monitor the activity of the masseter muscles and an electrocardiography system to monitor the heart rate [2, 11]. In 2019, a wireless EMG sensor was developed to monitor masseter muscles' activity and to classify different oral tasks such as smiling or chewing gum. Considering the small sample of healthy participants, the research group concluded that their device has the potential to be used for monitoring the activity of masticatory muscles [12]. The former device targeted sleep bruxism and did not monitor awake bruxism. In addition, wearing electrodes on the cheeks during the day may not be tolerated by potential users and is sensitive to non-bruxism-related activities. Consequently, we found current devices limited in their scope - focusing on either sleep or awake bruxism - and there is a lack of real-world testing where non-bruxism activities are present.

Acoustic emissions are used in wearable devices to record or monitor oral behaviors, such as eating [13, 14] or talking [15, 16]. They are also used as biomarkers to detect health problems such as knee osteoarthritis [17] or irritable bowel syndrome [18]. In addition, monitoring heart and breathing rates from the ear has been investigated using an earpiece that is equipped with two microphones, one placed inside the ear canal and another that picks up sounds from the environment [19]. In addition, the possibility of monitoring eye movements from the ear has been investigated using in-ear microphones, leading to the observations that when the eyes moved, the eardrums moved thereby changing the pressure in the occluded ear [20]. Also, tongue movements were detected from the ear using an in-ear barometer for a hands-free interaction [21]. Importantly though, acoustic emissions of tooth contact - extracted from the ear or other locations - have been used in dentistry to assess occlusion properties. In the second half of the 20th century, there were attempts to use stethoscopes to detect the acoustic emissions generated by the temporomandibular joints or the occlusion of teeth during jaw movements, referred to as "gnathosonics" [22]. Later, instead of recording the sounds from the zygoma as described in [22], [23] recorded tooth contact sounds from the ear with transducers built into a portable audio player or over-ear device. In 2016, tooth contact sounds were recorded using bone conduction microphones attached to the temporal bone to realise a hands-free user interface [24]. We inferred from these investigations that acoustic emissions can be used to detect bruxism-induced events. During tooth grinding, sounds are transmitted through bone propagation in the head. Whereas during jaw clenching, detectable signals could be produced via two pathways: (a) middle ear muscles activation that can alter the pressure in an occluded ear [25, 26], (b) vibrations caused by mastication muscles activity that can propagate in the vicinity of the muscle [27–29]. We confirmed the likelihood of this hypothesis in a previous case study [30]. In addition, the possibility of detecting tooth grinding sounds and other non-verbal orally-induced sounds was investigated for telecommunication [31, 32], following up on the work of [19]. The latter investigation successfully classified various verbal and non-oral sounds using an earplug in a controlled environment. Another study recorded the mandibular movement in addition to the acoustic emissions to detect bruxism. The transducers used in their study were two 3-axis inertial measurement units (IMUs) attached to the chin and the masseter muscle and a microphone attached to the cheek to record the sounds [33].

It is important to note that bruxism is a parafunctional behavior that may occur throughout the day, so the location and the type of the detection device should be ergonomically and aesthetically tolerable. Several factors influence the quality of the recording, such as the accurate placement of the transducer, the relative strength

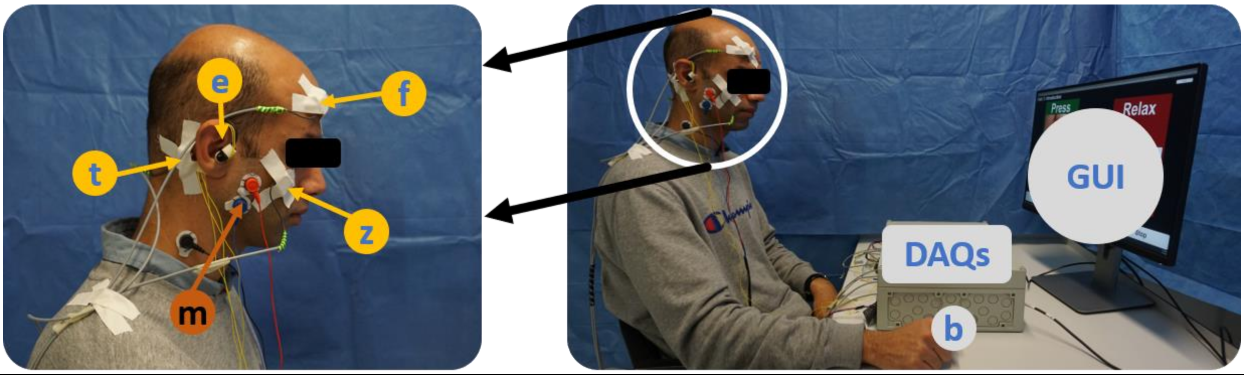


Figure 1: (Left picture) Experimental setup: 8 transducers were distributed symmetrically between the left side and right side of the head: (f) frontal bone, (z) zygomatic bone, and (t) temporal bone, (e) ear. EMG transducer: (m) masseter muscle. (Right picture) a graphical user interface (GUI), push button (b), and two data acquisition units (DAQs).

of the signal when comparing different transducer placements, and the comfort of wearing the transducer for an extended period of time. One of the relevant questions to be answered is: if bruxism-induced acoustic emissions can be recorded from the head, which location on the head is most sensitive to differences in the sounds created by different behaviors? Therefore, in this work we aimed to investigate if the location of the transducer on the head affects the acoustic emissions signal of various oral behaviors including bruxism-like events. And, if there are identifiable characteristics for the different behaviors.

II. Methods

a. Setup

The experimental setup consisted in total of eight bone-conducting transducers: six generic bone conduction transducers (MEAS, Dortmund, Germany) and two voice pick-up bone transducers (Sonion, Hoofddorp, Netherlands), as illustrated in Figure 1. The voice pick-up transducers were integrated into two commercial earpieces that occluded the ear (this type of ear closure will be referred to as 'semi-occluded' in this paper). Using medical tape, the remaining six transducers were attached to the participant's head at the frontal, zygomatic, and temporal bones. The participant was given a push-button to press during active periods of jaw clenching, tooth grinding, reading, eating, and drinking to label data of these activities. Also, two EMG devices (Advancer Technologies, USA), which were not processed for this article, were used to monitor the activity the masseter muscles. The transducers and the push button were directly connected to two data acquisition devices, DAQs (MCC, Bietigheim-Bissingen, Germany). Verbal and non-verbal sounds recorded via bone and tissue conduction have a limited bandwidth, less than 2 kHz [23, 24, 31, 32]. For this study, the highest informative frequency was set at 3 kHz, leading to a sampling rate of 6 kHz. The data acquisition devices were connected to a PC via USB to store the data. Lastly, a graphical user interface realized with Unity, a game development platform, (Unity Technologies, California, US) was used to provide the participant with the cues and timers associated with the tasks. This graphical user interface was developed in-house to guide the participant. It consisted of multiple slides notifying the participant of their task. Also, a timer was displayed on the screen to inform the participant of the time required to perform a certain task.

b. Participants

Fifteen volunteers (seven males and eight females, aged 24 to 40 years, median age: 31 years) participated in this study. They were recruited in Basel, Switzerland. The investigation was conducted after receiving approval by the regional ethics committee (Ethikkommission Nordwest- und Zentralschweiz, application number: 2021-002266). Each participant signed an informed consent.

The inclusion criteria were: ability to speak/read/write in English or German, age between 18 and 50 years, and provision of a signed consent form. Exclusion criteria were: having dental implants (removable full or partial dentures), oro-facial pain, facial beard piercing, pregnancy, not being able to complete the required tasks due to language or psychological obstacles, allergy to silicon or medical tape, ear problems, wearing a hearing aid, Covid-19 symptoms and lastly people involved in the study design, family members, and staff or individuals who are dependent on people involved in the study.

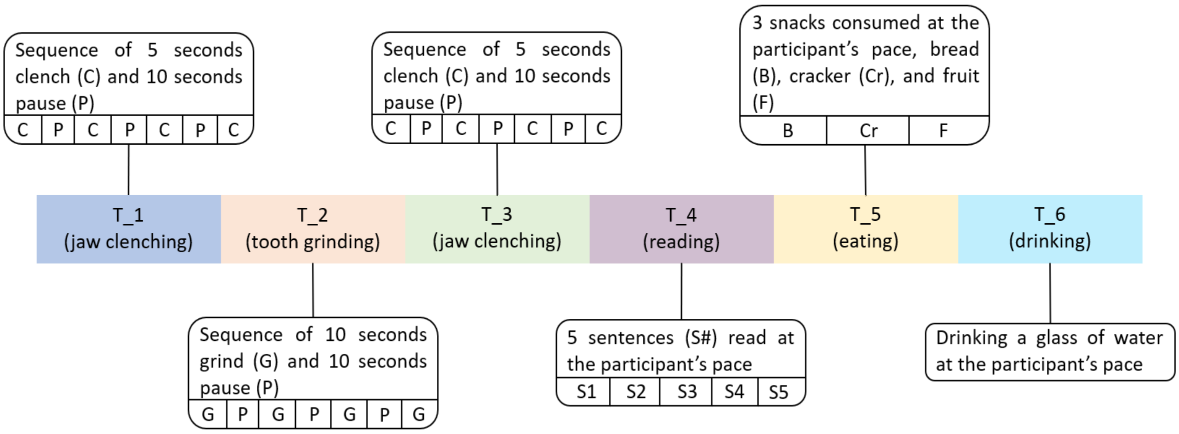


Figure 2: Experimental tasks: T 1 (jaw clenching), T 2 (tooth grinding), T 3 (jaw clenching), T 4 (reading), T 5 (eating), and T 6 (drinking).

c. Experimental protocol

First, the information about the study was discussed with the participant to prevent misunderstandings. Then, the participant was asked to fill out a questionnaire to collect general information on the participant's oral health status, as we wanted to exclude participants that have an oral health status where voluntary oral behaviors could lead to damage. The transducers were then attached to the participant's head, and a condensed version of the main experiment was conducted to familiarize the participant with the setup. The experiment was divided into six tasks: T 1 (jaw clenching), T 2 (tooth grinding), T 3 (jaw clenching), T 4 (reading), T 5 (eating), and T 6 (drinking), between each task, the participants were allowed a one-minute break.

Each participant was asked to sit in front of a computer screen that served as a guide throughout the experiment. The participant was asked to press the push button when performing an activity such as clenching, grinding, reading, eating, and drinking. As illustrated in Figure 2, each task was divided into different periods; for instance, T_1 and T_3 were a sequence of jaw clenching and pausing periods, T_2 was a sequence of tooth grinding and pause periods. During T 4, the participant read the passage "The North Wind and The Sun" divided into five sentences [34]. During T 5, the participant was asked to eat three different snacks: a piece of bread, a cracker, and a fruit. In T 6, the participant was asked to drink at least three sips of water. Finally, the participant was asked to sit quietly for one minute to record a pause period. At the end of the experiment, the participant was asked to fill in a second questionnaire to evaluate his/her experience, with the only goal for us to improve our setup/protocol for future experiments. These answers were not evaluated and therefore not reported. The evaluation of jaw clenching behavior was divided into two tasks (T 1 and T 3) to avoid any unnecessary loads on the participant's joint. In total, the six tasks resulted in recording the five oral behaviors: jaw clenching, tooth grinding, reading, eating, and drinking. The study information and the questionnaires will be provided as supplementary material.

d. Data processing

The data obtained from the study was processed with Matlab 2019b (Mathworks, Massachusetts, US). Recorded data for each transducer was filtered with a least-squares linear-phase FIR low-pass filter (1000 Hz cut-off frequency, order of 20, and 30 % transition window) and a least-squares linear-phase FIR high-pass filter (50 Hz cut-off frequency, order of 15, and a 20 % transition window). Spectral subtraction was applied to the filtered data following the work of Zavarehei [35]. Firstly, we segmented the recording into one-second windows and calculated the energy for each window using equation 1. The window with the lowest energy was assumed to be containing any remaining noise. Then, the completely filtered recording and the one-second window with the lowest energy were converted to the spectral domain. Afterward, the power and the phase spectrums obtained for the one-second window with the lowest energy were removed from the complete filtered recording. Finally, the output of the spectral subtraction was reconstructed from the spectral domain to the time domain.

Afterwards, the processed data was segmented into overlapping windows of 100 ms length and a 50% over- lap with the next window to obtain the following metrics. Three metrics were investigated: energy level in the time domain, flux in the spectral domain [36], and zero-crossing rate (ZCR). The energy level reflects the change between high-energy and low-energy periods, such as reading and drinking. The spectral flux, allows the estimation of the change in spectral power between two consecutive windows. In addition, the ZCR helps distinguish between active periods and inactive periods because the lower the rate, the higher the likelihood that the window contains valuable information [36].

The energy level was estimated using the following equation:

$$E^{w} = \frac{1}{N_w}\sum_{i=1}^{N_w}|x_i|^2 \qquad (1)$$

where E_w is the average energy of a window, N_w is the window's size, and x_i is the data point at time step i obtained from the processed data.

The spectral flux, reflecting the change in spectrum between successive windows, was obtained using Matlab 2019b built-in function: spectralFlux.

The ZCR was obtained for each transducer and for each of the fifteen participants using the following equation:

$$ZCR_w = \frac{1}{N_w}\sum_{i=1}^{N_w-1} f(x_{i+1} * x_i)\,; with\ f(\lambda) = \begin{cases} 1, & if\ (\lambda) < 0 \\ 0, & otherwise \end{cases} \qquad (2)$$

where, ZCR_w is the window's ZCR, N_w is the window's size, x_{i+1} is the post-processed data point at time step $i + 1$, and x_i is the post-processed data point at time step i obtained from the processed data. The data point represents the post-processed transducer's output at each time step.

For each participant and for each transducer output, the periods when the push button was pressed and the pause period at the end were segmented from the full recording after the data was processed. Then, the periods were divided into 100 ms windows with 50% overlap to obtain the energy, flux, and ZCR; the mean value of the total windows per task for each participant and transducer was used to perform the statistical analysis. For the statistical analysis examining the significant difference between the various transducer placements on the energy, flux, and ZCR, a two-way ANOVA was used with a significance level of alpha 0.05. A pairwise comparison t-test between the different locations was performed using the Bonferroni correction. For both examinations, the two-way ANOVA and the pairwise tests, Matlab 2019b built-in functions were used: ANOVA2 and multcompare, respectively. In addition, for some transducers an additional non-parametric test was conducted using matlab's ranksum function. This step was done because from some distributions the normality assumption was strongly violated. We have included in the supplementary material the data (Data.xlsx) that was used for the statistical tests and a script to produce the qqplots for the transducers that have shown significant difference using ANOVA2 and the pairwise test, and to run the statistical tests.

III. Results

The output of the left ear transducer in the time and frequency domains before processing for participant number three is illustrated in Figures 3 (a) and (b). T 5 (eating) has the largest peak-to-peak range of [0.38 0.53] compared to [0.41 0.48], [0.43 0.46], and [0.42 0.46] for T 2 (tooth grinding), T 4 (reading), and T 6 (drinking), respectively, whereas the clenching tasks, T 1 (jaw clenching) and T 3 (jaw clenching), were not observed as illustrated in Figure 3 (a). Figures 9 (a) and (b) in the supplementary material illustrate the output of the transducer after processing the data as described in section II. In Figure 9 (a) of the supplementary material, the signal range was reduced by a factor of ten. Similarly, T 5 has the largest peak-to-peak range of [-0.06 0.08] compared to [-0.03 0.02], [-0.01 0.01], and [-0.02 0.01] for T 2, T 4, and T 6, respectively. The clenching tasks, T 1 and T 3, did not result in a change in audio recording in the time domain. As illustrated in Figure 3 (b) and Figure 9(b) of the supplementary material, T 2, T 4, T 5, and T 6 were below 1 kHz. The spectrograms obtained from the rest of the transducers are illustrated in Figures 2-8 of the supplementary material.

Figures 4 (a) - (g) illustrate the signal's energy in the time domain obtained using equation 1 for the third participant's left ear transducer with a magnified view of the six tasks. The shaded areas represent the active periods, where the participant was asked to intentionally perform one of the tasks listed in Figure 2 while pressing the push-button input. The peak amplitude for tasks T 2, T 4, T 5, and T 6 are listed in Table 1 of the supplementary material. T 5 had the highest energy (arbitrary unit), which is 7-times higher than tasks T 2 and T 4 and 30-times higher than T 6. Figures 4 (b) and (d) show that the clenching tasks had a relatively negligible amount of energy within the shaded areas. However, a peak can be seen just before some of the shaded areas in both figures. Figures 10 (a) - (h) of the supplementary material illustrate the energy of the signal for T 2 obtained from the eight transducer placements for the third participant. As illustrated in Figures 10 (a) - (d) of the supplementary material, the left ear transducer has the highest energy that is approximately 8 times higher than that of the right ear transducer and 30% higher than that of the right temporal transducer illustrated in Figures 10 (e) and (h) of the supplementary material, respectively. The recording amplitude of the remaining transducers was almost negligible, as illustrated in Figures 10 (c), (f) - (g), and (b)-(d) of the supplementary material.

Different transducer placements are analyzed for each behavior, and the *p*-values are displayed in Table 1, obtained for each metric using the mean values of the behavior periods of each participant. A significant effect can be found for the pause period when examining energy and flux. For the clenching behavior, a significant difference can be found among the different transducer placements for flux and ZCR. Regardless of the metric used, the placement of the transducer did not have a significant effect when examining the tooth grinding behavior. However, the transducer placement significantly impacted the recording quality for both reading and eating regardless of the metric under investigation. Finally, only when

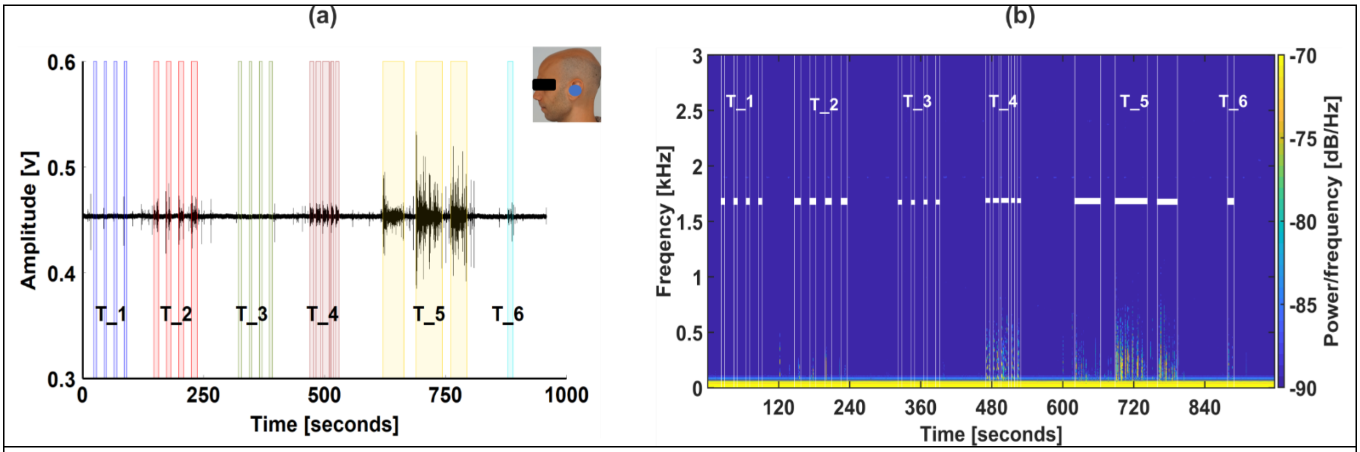


Figure 3: Plot of the time and frequency domains of the left ear transducer for participant number three, before processing). The shaded areas in (a) represent the periods during which the participant was active as recorded by push button input. The active periods were represented in the frequency domain plot in (b) as the area between the white lines. The experimental tasks were as follows: T 1: jaw clenching, T 2: tooth grinding, T 3: jaw clenching, T 4: reading, T 5: eating, and T 6: drinking.

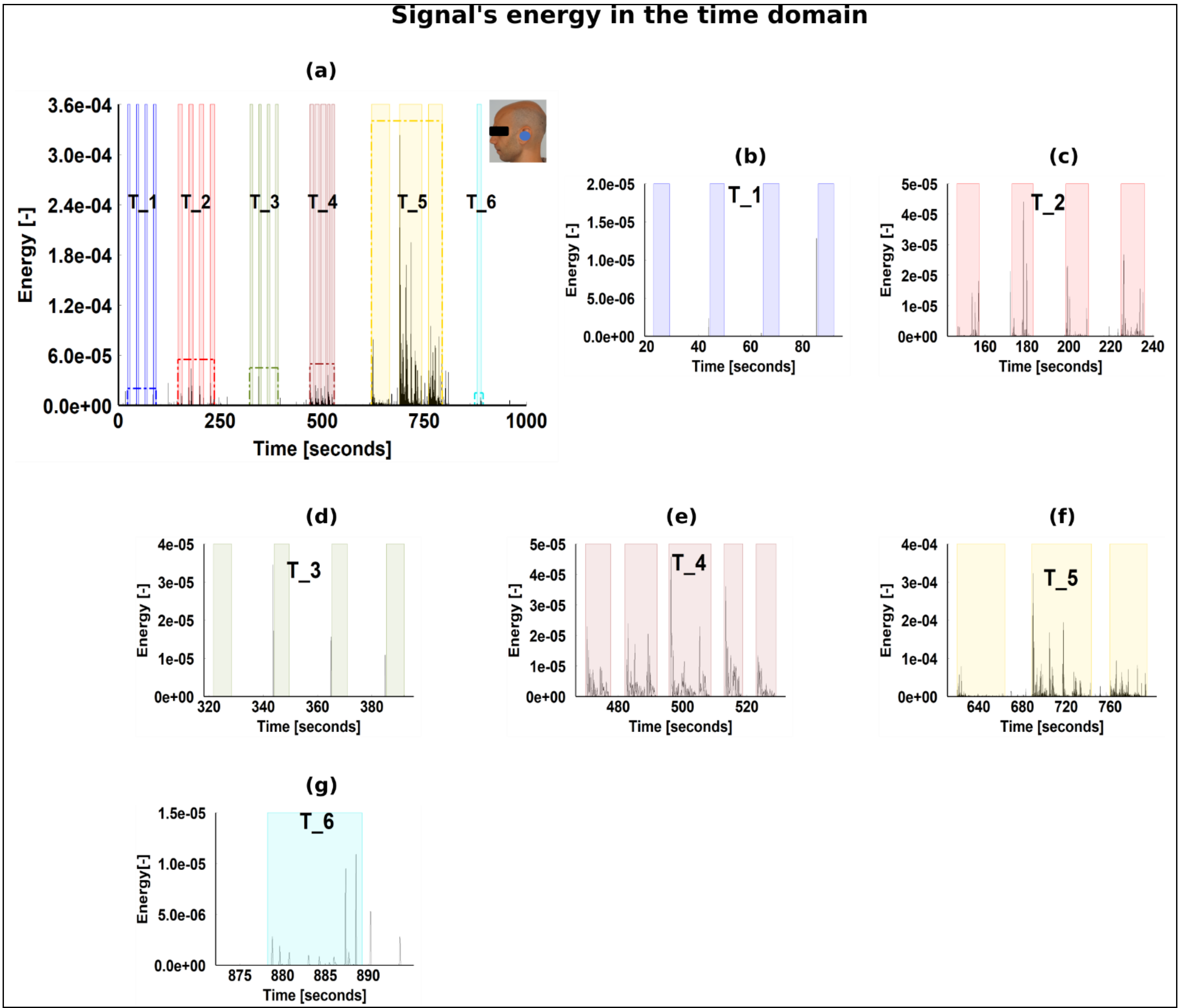


Figure 4: The energy of the signal in the time domain. (a): represents the energy obtained from the left ear of one participant (in this case participant number three). (b) - (g): magnification of the various tasks illustrated in (a). The experimental tasks were as follows, T 1: jaw clenching, T 2: tooth grinding, T 3: jaw clenching, T 4: reading, T 5: eating, T 6: drinking.

Table 1: The p-value of a two-way ANOVA test for the different behaviors using: energy, spectral flux, and ZCR. Here, F, is the F-statistic and the value 7 represents the degrees of freedom (the different transducer placements).

Metric	Behavior					
	Clenching	**Grinding**	**Reading**	**Eating**	**Drinking**	**Pause**
Energy	$F(7) = 1.15$ $p > 0.05$	$F(7) = 1.34$ $p > 0.05$	$\mathbf{F(7) = 2.5}$ $\mathbf{p < 0.05}$	$\mathbf{F(7) = 3.6}$ $\mathbf{p < 0.01}$	$F(7) = 1.42$ $p > 0.05$	$\mathbf{F(7) = 2.55}$ $\mathbf{p < 0.05}$
Flux	$\mathbf{F(7) = 3.06}$ $\mathbf{p < 0.01}$	$F(7) = 0.85$ $p > 0.05$	$\mathbf{F(7) = 6.77}$ $\mathbf{p < 0.001}$	$\mathbf{F(7) = 3.39}$ $\mathbf{p < 0.01}$	$F(7) = 1.28$ $p > 0.05$	$\mathbf{F(7) = 3.16}$ $\mathbf{p < 0.01}$
ZCR	$\mathbf{F(7) = 2.39}$ $\mathbf{p < 0.05}$	$F(7) = 0.48$ $p > 0.05$	$\mathbf{F(7) = 5.24}$ $\mathbf{p < 0.001}$	$\mathbf{F(7) = 8.4}$ $\mathbf{p < 0.001}$	$\mathbf{F(7) = 3.34}$ $\mathbf{p < 0.01}$	$F(7) = 1.4$ $p > 0.05$

investigating ZCR output of drinking did the transducer placement show a significant influence.

Figure 5 presents the box plots of every behavior for each of the three metrics: energy, flux, and ZCR, obtained from the mean values of each behavior for the 15 participants. Superimposed on top of the box plots are the results of the pairwise tests for each behavior and each metric that already yielded a significant difference ($p < 0.05$), as shown in Table 1. The p-values of each pairwise test are listed in Table 2 of the supplementary material. Notably, reading and eating behaviors had the highest medians for energy and flux. In addition, the placement of the transducer had a significant influence on the spectral flux, and the ZCR for both eating and reading as illustrated in Figures 5 (g) - (l). Also, the transducer's location affected the energy of the eating task and the pause period.

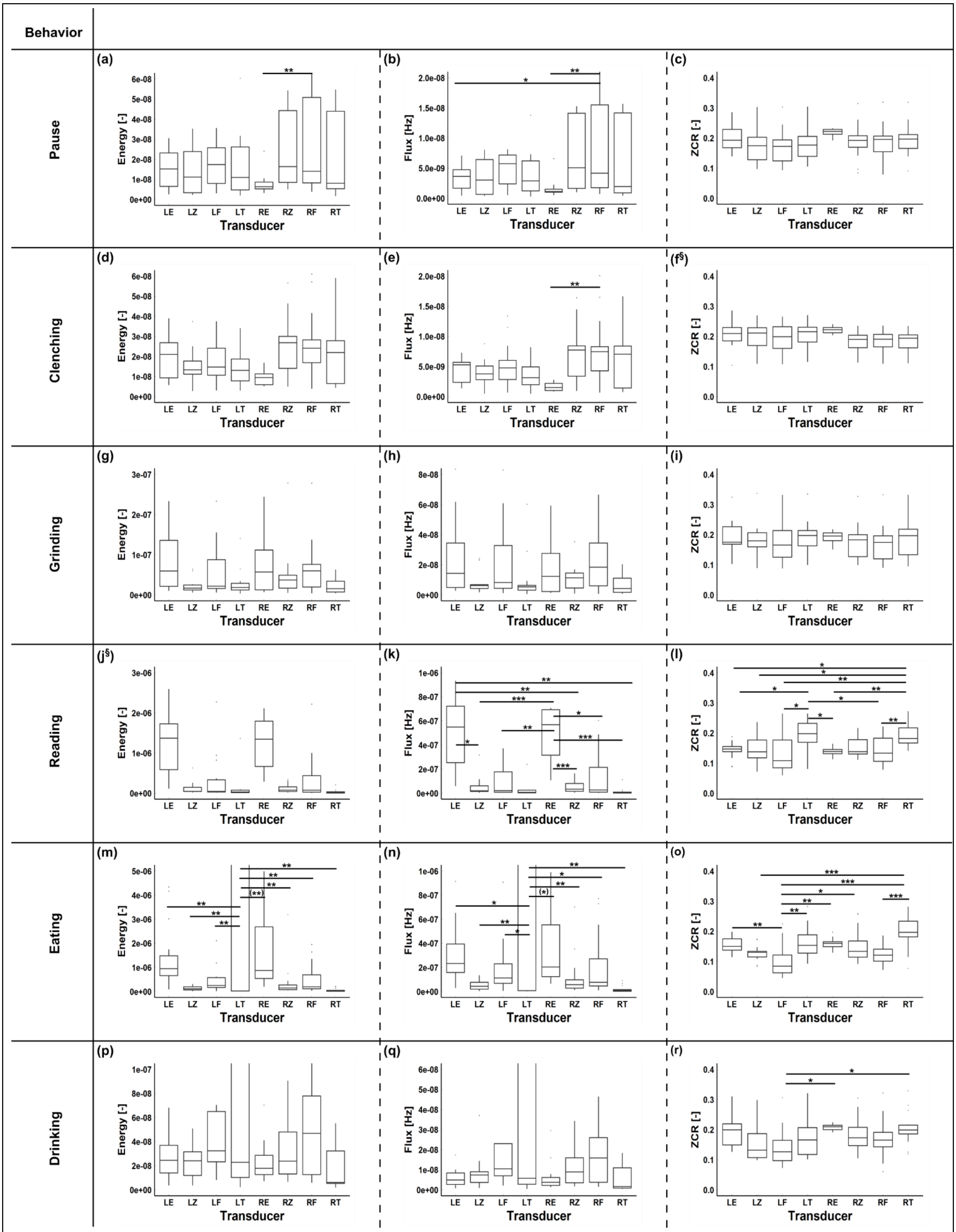
IV. Discussion

We recorded sounds of tooth grinding, reading, eating, and drinking when compared to the pause period as illustrated in Figure 5. We have noticed that the location of the transducer did impact the amplitudes of the metrics used in particular for the behaviors of reading and eating. However, for tooth grinding, the location of the transducer did not have any significant impact, as illustrated in Figure 5.

By examining the representation of the pause period as illustrated in Figures 5 (a) - (c), the placement of the transducer had no significant impact on the ZCR, and the differences between the placements could be related to variation in the background noise. However, for energy and flux, the sensitivity was a bit higher, and some placements significantly impacted the output listed in Table 2 of the supplementary material. That could also be related to background noise variation or the displacement of certain transducers.

The ranges of energy, flux, and ZCR for clenching and that of the pause period did not differ significantly, as illustrated in Figures 5 (a) - (c) and (d) - (f). This observation can be attributed to the occlusion type and the transducer placement in the earpiece. Such inference is supported by a pilot study comparing a fully occluded ear with a semi-occluded ear [30]. It indicated that the type of occlusion and the placement of the transducer in the ear canal affect the level of isolation the ear canal is enduring to record such a relatively weak signal. Nonetheless, for this particular study, the "semi-occlusion" approach was used for hygiene and practical reasons. The clenching behavior showed a distinct feature, a peak just before the shaded areas, as illustrated in Figure 4 (b) - (d). This peak could be related to tooth-tooth contact as the participant was getting ready to clench. The interpretation of such a peak is supported by noting that its amplitude is similar to that of the grinding behavior as illustrated in Figure 4 (c). This could mean that either this peak is a characteristic of the behavior itself or due to the protocol that requires the participant to intentionally perform certain actions altering the behavior itself, which requires further investigation.

For tooth grinding, energy and flux ranges were one-fold higher than the pause period. This observation reflects the possibility of recording tooth grinding sounds from different locations on the head. The placement of the transducer had no significant impact on the energy and flux as illustrated in Figures 5 (g) and (h) and listed in Table 1. The ear transducers had the highest 75th percentile, as illustrated in Figure 5 (g). Whereas for flux, multiple locations including the ear were advantageous to record tooth grinding reflected in the relatively high 75th percentile but the location of the transducer did not have any significant impact, as illustrated in Figure 5 (h) and listed in Table 1. In addition, the placement of the transducer did not have a significant impact on the ZCR, as illustrated in Figure 5 (i), inferring that the signal-to-noise ratio might be relatively constant while recording such behavior as the ZCR mirrors the noisiness of the signal.



Behavior
Pause
Clenching
Grinding
Reading
Eating
Drinking
(a)
(b)
(c)
(d)
(e)
(f§)
(g)
(h)
(i)
(j§)
(k)
(l)
(m)
(n)
(o)
(p)
(q)
(r)
Energy [-]
Flux [Hz]
ZCR [-]
LE LZ LF LT RE RZ RF RT
Transducer

Figure 5: Energy, flux, and the ZCR of all participants for each transducer and for each behavior: clenching (a - c), grinding (d - f), reading (g - i), eating (j - l), drinking (m - o), and pause (p - r). The transducers are depicted on the horizontal axis as follows: left ear (LE), left zygomatic (LZ), left frontal (LF), left temporal (LT), right ear (RE), right zygomatic (RZ), right frontal (RF), and right temporal (RT). The boxes marks represent the median, the bottom and top of the boxes represent the 25th (q1) and the 75th (q3) percentiles, respectively. Significant differences between the different transducer placements are indicated with * for $p < 0.05$, ** for $p < 0.01$, and *** for $p < 0.001$. A full range illustration of figures (j), (k), (m), and (n) can be found in Figure 1 of the supplementary material. **§**: showed a significant difference as listed in Table 1, but was not included in the pairwise tests. The p-values for the pairwise tests are listed in Table 2 of the supplementary material. Note: (**), (*) were added to two subfigures (m and n), it refers to instances were an additional non-parametric test was performed and the result was opposite to that of the ANOVA.

For reading, energy and flux are two folds higher than that of the pause period, as illustrated in Figures 5 (j) and (k). Both energy and flux, reflected that the ear transducers had the highest median and 75th percentile; this might be related to the properties of the transducers that are tuned to record voice. Another factor could be the occlusion effect. Occlusion of the ear increases the strength of the bone-conducted signal, as noted by [31]. Noting that the type of occlusion used in this study is a ”semi-occlusion”. Both flux and ZCR were sensitive to the placement of the transducer, as illustrated in Figures 5 (k) and (l) and listed in Table 2 of the supplementary material. However, en- ergy was less sensitive to reflect the significant impact of the placement inferred by the ANOVA test listed in Table 1.

For eating, the three metrics: energy, flux, and ZCR, reflected that the placement of the transducer impacted the recording significantly, as listed in Table 1. The left temporal transducer had the highest median and 75th percentile for energy and flux. Such a stark difference can be attributed to the transducer adjustment after it was detached. The likelihood for such explanation is supported by keeping in mind the experiment's timetable illustrated in Figure 2, since a similar observation can be noticed for drinking which succeeds eating. However, such observation is absent in the preceding behavior, grinding and reading, as illustrated in Figures 5 (h) and (k), respectively.

For both reading and eating, the impact of transducer placement on the recording can be attributed to the behavior itself, since the recording gets weaker or varies with time. While chewing, the signal-to-noise ratio changes with time as the consistency and the properties of the consumed snacks change. Additionally, other factors contribute to this variation, such as the distance between the location of the transducer and the source of the sound not being the same and the different tissues that the signal has to pass through. While investigating reading similar observations were made to that of eating since the different words have different characteristics affecting the signal. In addition, the speed and the loudness of the act of reading or eating affect the signal-to-noise ration as well, noting that the ZCR reflect the noisiness of the signal [36].

For drinking, the placement of the transducer had a significant impact when using the ZCR as listed in Table 1. Nonetheless, the output of the transducers had a relatively prominent difference, as illustrated in Figures (l) and (m). The difference can be related to the transducer displacement caused by the behavior, as the participants might have tilted their heads. On the other hand, the noise level is significantly different between some of the placements as the ZCR demonstrated a relatively high sensitivity compared to energy and flux as listed in Table 2 of the supplementary material.

V. Limitations

The transducers' attachment differed for each participant due to anatomy, such as the size of the head, the skin properties, and the size of the masseter muscles. In addition, the standard earpiece used in this study did not completely occlude the ear, due to the participants' different ear sizes and the properties of the rubber tip of the earpiece. Also, the position of the transducer in the earpiece differs slightly between the left and the right sides. The volunteers were not medically assessed if they had bruxism and the tasks associated with bruxism-like events were done on a voluntary basis. Thus, the movements would not accurately represent the behaviors under investigation. The participants might have relied more on one side of the jaw while grinding and eating, resulting in an imbalanced distribution of sounds.

VI. Conclusion

We conclude that the acoustic emission of various oral behaviors can be recorded from the head. However, we were not able of recording characteristic features of jaw clenching except we observed a peak just before the probable onset. From the observed differences, we can conclude that the position of the transducer affected the quality of the recording. Although the transducer placement did not significantly impact the recording of tooth grinding sounds, the ear is a good location for transducer placement compared to other location, since the ear compensates for the variances generated by certain behaviors such as eating and reading or physical requirements such as drinking. For example, physical movements such as arm movement while eating to grab food or water, head movement while drinking and eating. EMG electrodes on the masseter muscles can be highly affected by these movements where as an ear device that records sounds is isolated from these movements. Therefore, wearing an earplug for an extended period may be a trade-off for recording such sounds during everyday activities.

Conflict of Interest Statement

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Author Contributions

MKN, NG, and GR contributed to the conceptualization of this work. All authors had a substantial intellectual contribution to manuscript refinement, finalisation, and approved it for publication.

Data availability

The data that support the findings of this study are available upon reasonable request from the corresponding author.

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Supplementary material

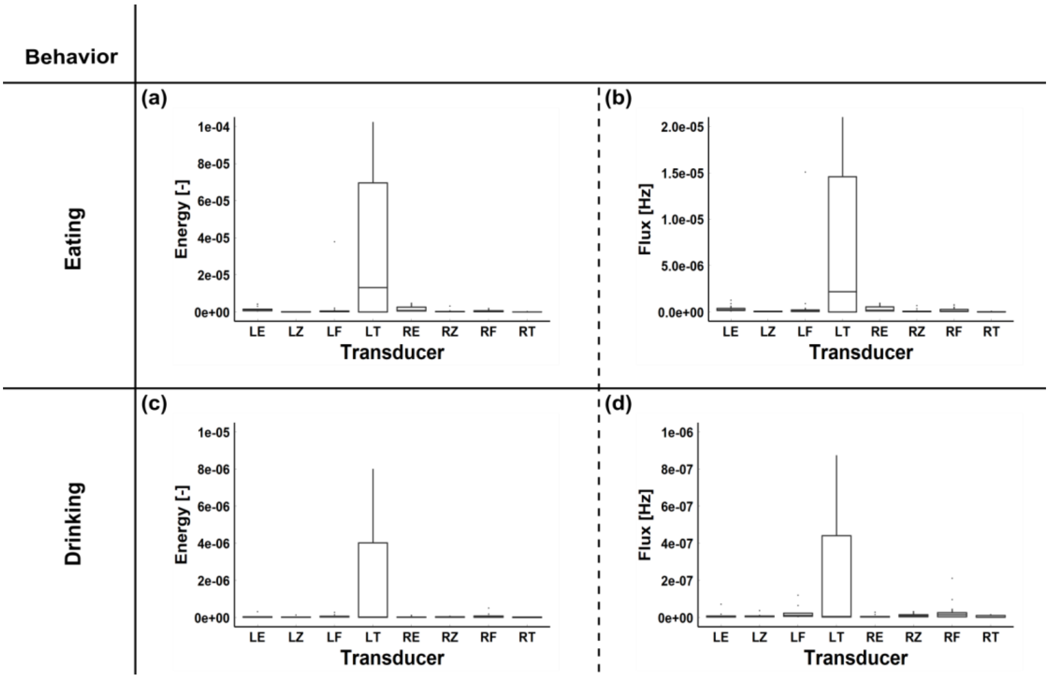

Figure 1: Energy and flux of all participants obtained for each transducer for: eating (a and b) and drinking (c and d). The marks in each box represent the median value and the bottom and top of the boxes represent the 25th (q1) and the 75th (q3) percentiles, respectively.

Table 1: Peak energy and spectral flux levels for each task within the shaded areas for third participant as determined by the left ear transducer.

metric	**Tasks**					
	T_1	**T_2**	**T_3**	**T_4**	**T_5**	**T_6**
Energy	-	4.4e-5	-	4.57e-5	32e-5	1.09e-5
Flux	-	1.07e-5	-	1.88e-5	6.58e-5	2.26e-6

Table 2: The p-value for the post hoc test with Bonferroni correction. The placement of the transducers is denoted by the initial letter of the side of the head (L: Left or R: Right) and the initial letter of the anatomical location (E: Ear, Z: Zygomatic, F: Frontal, and T: Temporal). LE: Left Ear, LZ: Left Zygomatic, LF: Left Frontal, LT: Left Temporal, RE: Right Ear, RZ: Right Zygomatic, RF: Right Frontal, and RT: Right Temporal.

Metric	**Behavior**					
	Clenching	**Grinding**	**Reading**	**Eating**	**Drinking**	**Pause**
Energy	-	-	-	p(LE-LT) = 0.007 p(LZ-LT) = 0.006 p(LF-LT) = 0.008 p(LT-RE) = 0.007 p(LT-RZ) = 0.006 p(LT-RF) = 0.006 p(LT-RT) = 0.006	-	p(RE-RF) = 0.007
Flux	p(RE-RF) = 0.002	-	p(LE-LZ) = 0.01 p(LE-RZ) = 0.009 p(LE-RT) = 0.003 p(LZ-RE) = 0.0002 p(LF-RE) = 0.005 p(RE-RZ) = 0.0002 p(RE-RF) = 0.01 p(RE-RT) = 0.0001	p(LE-LT) = 0.01 p(LZ-LT) = 0.009 p(LF-LT) = 0.015 p(LT-RE) = 0.01 p(LT-RZ) = 0.009 p(LT-RF) = 0.01 p(LT-RT) = 0.009	-	p(RE-RF) = 0.002 p(LE-RF) = 0.03
ZCR	-	-	p(LE-LT) = 0.02 p(LE-RT) = 0.01 p(LZ-RT) = 0.03 p(LF-LT) = 0.01 p(LF-RT) = 0.006 p(LT-RE) = 0.01 p(LT-RF) = 0.01 p(RE-RT) = 0.005 p(RF-RT) = 0.008	p(LE-LF) = 0.005 p(LZ-RT) = 0.0001 p(LF-LT) = 0.001 p(LF-RE) = 0.003 p(LF-RZ) = 0.01 p(LF-RT) = 3e-8 p(RF-RT) = 0.0001	p(LF-RE) = 0.01 p(LF-RT) = 0.01	-

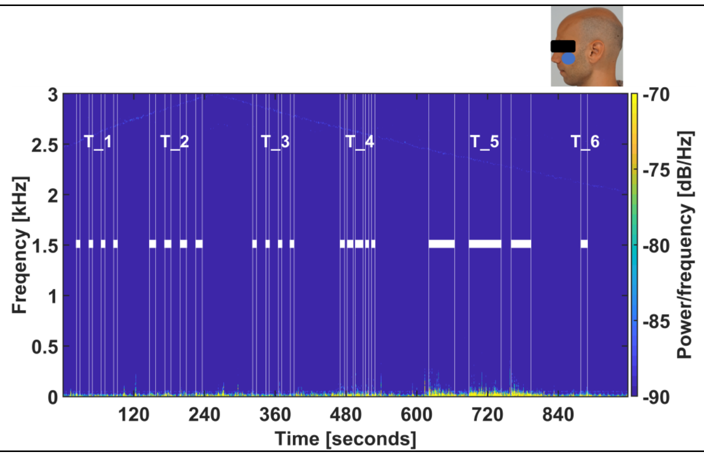

Figure 2: Spectrogram for the unprocessed recording from the left zygomatic transducer.

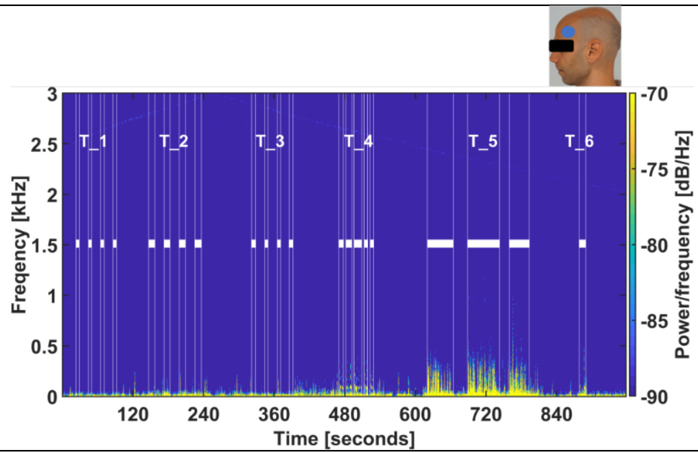

Figure 3: Spectrogram for the unprocessed recording from the left frontal transducer.

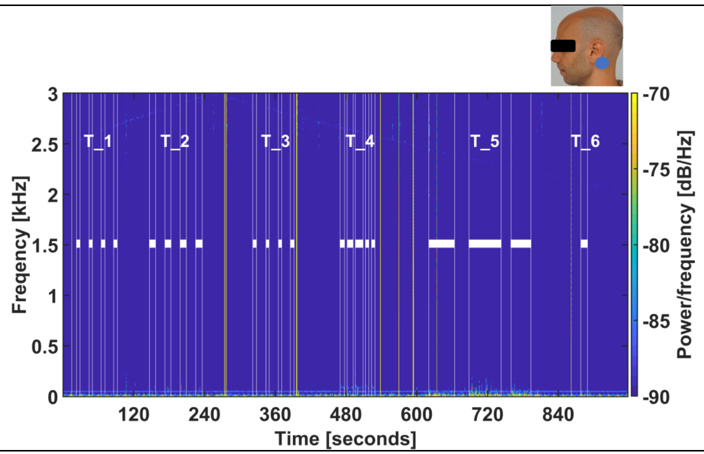

Figure 4: Spectrogram for the unprocessed recording from the left temporal transducer.

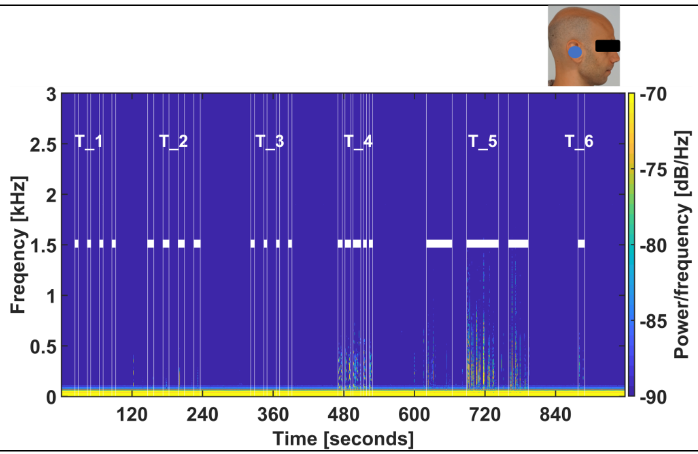

Figure 5: Spectrogram for the unprocessed recording from the right ear transducer.

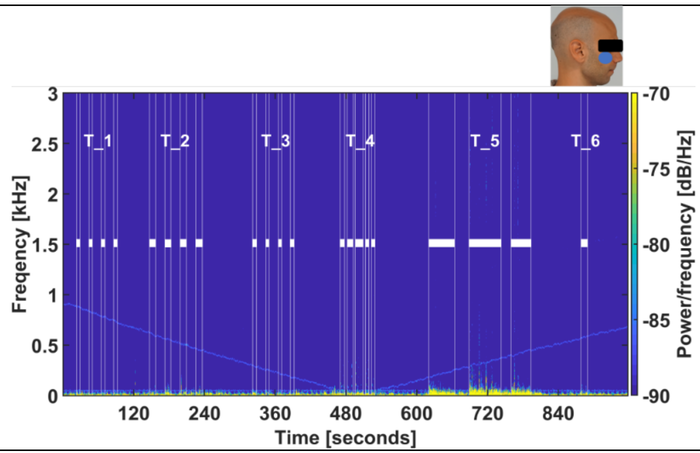

Figure 6: Spectrogram for the unprocessed recording from the right zygomatic transducer.

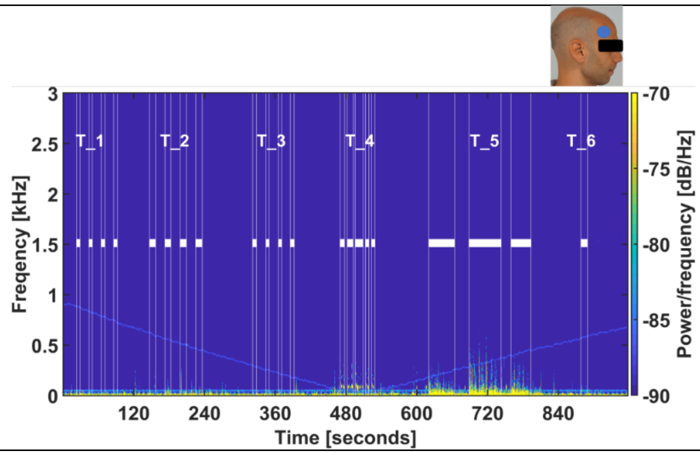

Figure 7: Spectrogram for the unprocessed recording from the right frontal transducer.

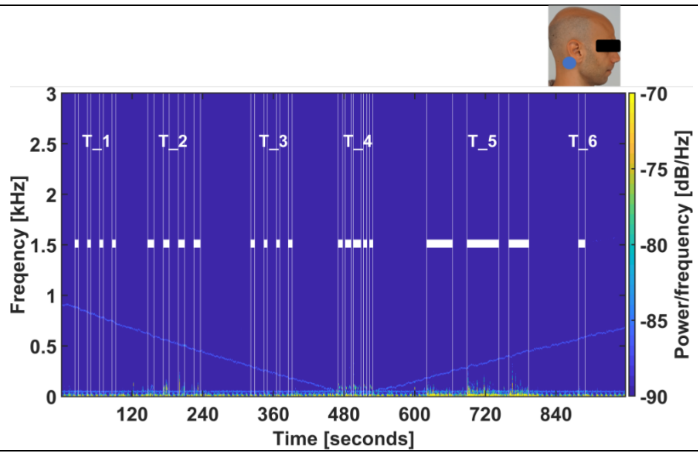

Figure 8: Spectrogram for the unprocessed recording from the right temporal transducer.

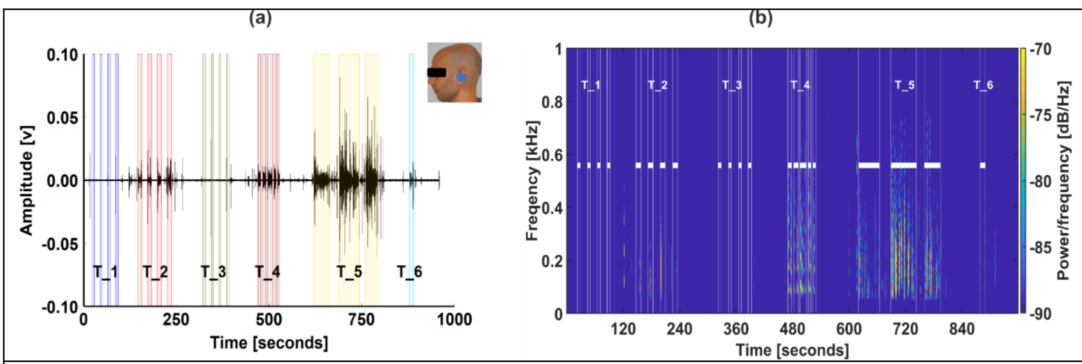

Figure 9: Plot of the time and frequency domains of the left ear transducer for participant number three after processing. The shaded areas in (a) represent the periods during which the participant was active as recorded by push button input. The active periods were represented in the frequency domain plots in Figure (b) as the area between the white lines. The experimental tasks were as follows: T_1: jaw clenching, T_2: tooth grinding, T_3: jaw clenching, T_4: reading, T_5: eating, and T_6: drinking.

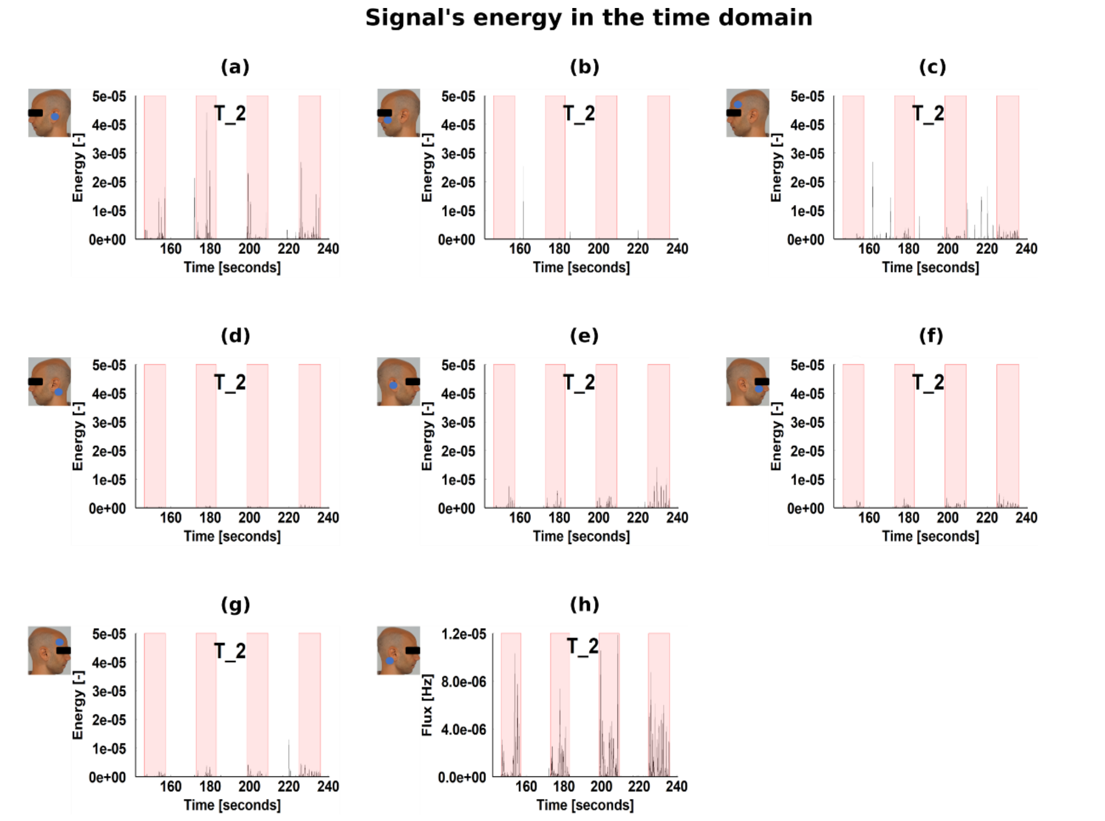

Figure 10: The energy of the signal in the time domain. Subfigures a – h represent the energy for T_2 (tooth grinding) obtained from the eight transducers for participant number three.

Chapter 5

Experimental classification of various oral behaviors using acoustic emissions obtained from the ear

Foreword and Overview

Looking at statistics that investigated if the transducer placement has a significant impact on the recording of oral behaviors we concluded that the ear is an optimal location fro reasons that includes the acceptability in society and convenience. Consequently, it is important to be able to distinguish the sounds of various oral behaviors to be able to use possible wearable devices in real-world environments. Therefore, this chapter describes an experimental work on the classification using deep learning of the 2D representation of sounds recorded from the ear.

Abstract

Objective: The goal of this work is to investigate the use of deep learning to classify image representations of voluntarily produced sounds of various functional and parafunctional oral behaviors.

Methods: Sounds produced by jaw clenching, tooth grinding, reading, eating and drinking were recorded from inside the ear. 18 participants participated in the study. The data were segmented into 1 second windows with 50% overlap. RGB images were used: the time series was assigned to the red channel, Short Time Fourier Transformation (STFT) was assigned the green channel, and the spectrogram was assigned the blue channel. The image representation was classified using ResNet-50 built-in Matlab-2021b. Three classifiers were examined, 2-Class (tooth grinding and pause), 4-Class (eating, grinding, pause, reading), and 6-Class (jaw

This chapter is based on a manuscript submitted for publication to IEEE Transaction on Biomedical Engineering in May 2024 [4]. Copyright and licensing information can be found in the Preface.

clenching, tooth grinding, reading, eating, drinking, and pause). In addition, leave one participant out cross-validation (lopocv) was used, with the dataset divided between testing and training.

Results: We reported that the overall accuracy of the classifier averaged over 18 participants was 84.31%, 72.79%, and 50.97% for 2-Class, 4-Class, and 6-Class challenge, respectively.

Conclusion: In conclusion, we were able to classify image representations of different oral behaviors, noting that the classification accuracy decreased as the number of classes increased.

5.1 Introduction

Bruxism is defined as "masticatory muscle activities that occur during sleep (characterized as rhythmic or non-rhythmic) and wakefulness (characterized by repetitive or sustained tooth contact and/or by bracing or thrusting of the mandible)"[107]. Approximately 8% of the population has severe sleep bruxism requiring treatment [21, 111]. Bruxism has various health implications such as tooth wear and temporomandibular joint disorder (TMD). The gold standard for diagnosing sleep bruxism is polysomnography with audio and video recording (PSG & AV), which requires patients to stay in a sleep laboratory [112]. PSG & AV require a lot of resources and can interfere with the patient's sleep patterns. However, a gold standard for the diagnosis of awake bruxism is still lacking [24]. Several research groups have investigated the use of wearable electromyography (EMG) devices to monitor bruxism [38, 45, 54], but since bruxism occurs throughout the day, wearing EMG electrodes on the facial area is neither convenient nor socially tolerable. Another modality are devices that are worn in or on the ear, sometimes called hearables [113, 114]. Hearables could be used to record bruxism-related sounds from the ear. In dentistry, recorded sounds have been used to study features of dental occlusion (*gnathosonics*) [23]. Bruxism events produce acoustic emissions via two mechanisms: (i) tooth grinding sounds that propagate through bone, (ii) jaw clenching sounds as a result of altering the blood flow around the ear and masticatory muscles and can deform the eardrum by activating middle ear muscles, thus altering the pressure the ear canal[2].

Since bruxism can occur throughout the day, wearable devices will also record non-bruxism events and are susceptible to external interference, so it is important to distinguish non-bruxism events from bruxism events, e.g. by classification algorithms. Various verbal and non-verbal voluntarily produced sounds, such as speech, eye blinking, and tooth grinding, obtained from an in-ear device were successfully classified using features such as Mel Frequency Cepstral Coefficients (MFCC), Zero Crossing Rate (ZCR), and Auditory Inspired Amplitude Modulation Features (AAMF) [95]. The authors used the following classifiers: Support Vector Machine (SVM), Gaussian Mixture Models (GMM), and Multi-Layer Perceptron (MLP). They also studied the effect of adding noise and temporal information to each frame on the accuracy of the classifiers, achieving an average accuracy of more than 73% for the noisy dataset with the GMM classifier [95]. A follow-up study was conducted using the Bag-of-Audio-Words (BoAW) algorithm. This was done by first clustering the acoustic emissions using GMM to create "audio words" histograms of different frequencies of occurrence were generated to be fed to the classifiers SVM and Random Forest. The classifier performed relatively well with an average sensitivity of 69.9% and an average precision of 78.8% in a quiet environment. However, in noisy environments like factory noise the sensitivity dropped to 63.4% and the precision to 72.9%. For babble the sensitivity was 55.5% and the precision was 64.2% [99]. In 2022, the classification of voluntarily produced sounds mimicking snoring, tooth grinding, and breathing was tested using 2D representations. A modified commercial earpiece was used by connecting the internal and external microphones to an external recorder. Data were collected from twenty participants in their homes, and participants were asked to wear the device themselves while being instructed remotely. The 2D representation was achieved by extracting the Short-Time Fourier Transform (STFT) and feeding it into a Convolutional Neural Network (CNN) with a modified temporal layer. The authors placed clenching as a subclass of grinding and they observed that such a classification approach is capable of achieving an accuracy higher than 60% [98]. Even though, in an experts consensus on bruxism tooth grinding and jaw clenching were differentiated from each other [107].

Given that jaw clenching occurs more frequently during wakefulness and tooth grinding during sleep, and given the different etiology and different heath implications, classifiers that are able to distinguish between different bruxism events would be a valuable addition for bruxism monitoring. In addition, eating is a behavior that activates similar muscles and movements as tooth grinding, and to our knowledge, the discrimination between tooth grinding and eating sounds has not been studied. Therefore, the purpose of this paper is to explore the classification using deep learning of voluntarily produced oral behavior sounds that are commonly produced in real-world environments. The oral behaviors of interest are jaw clenching, tooth grinding, eating, reading, and drinking sounds recorded.

5.2 Methods

5.2.1 Setup

The experimental setup consisted of eight bone-conducting transducers, six generic bone conduction transducers (MEAS, Dortmund, Germany) and two voice pick-up bone transducers (Sonion, Hoofddorp, The Netherlands), as illustrated in Figure 5.1. The voice pick-up transducers were integrated into two commercially available earpieces that occluded the ear (this type of ear occlusion will be referred to as 'semi-occluded' in this paper). The remaining six transducers were attached to the participant's head at the frontal, zygomatic, and temporal bones using medical tape. The participant was given a push-button to press during active periods of jaw clenching, tooth grinding, reading, eating, and drinking to label these activities. Also, two EMG devices (Advancer Technologies, USA), not processed for this article, were also attached to the masseter muscles. The transducers and the push button were connected to two data acquisition devices, DAQs (MCC, Bietigheim-Bissingen, Germany). Verbal and non-verbal sounds recorded via bone and tissue conduction have a limited bandwidth, less than 2 kHz [89, 95, 99]. For this study, the highest informative frequency was set at 3 kHz resulting in a sampling rate of 6 kHz. The data acquisition devices were connected to a PC via USB for data storage. Finally, a graphical

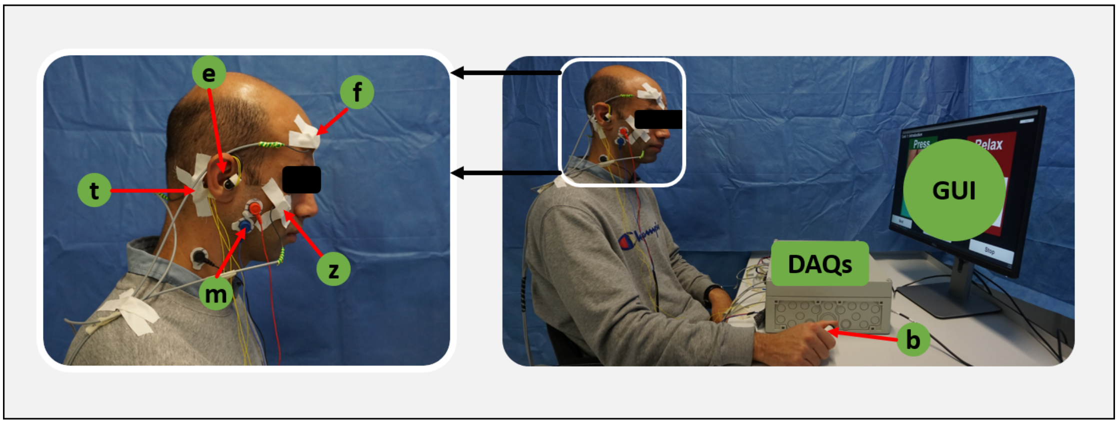

Figure 5.1: Experimental setup: 8 transducers were distributed symmetrically between the left side and right side of the head: (f) frontal bone, (z) zygomatic bone, and (t) temporal bone, (e) ear. EMG electrodes: (m) masseter muscle, a graphical user interface (GUI), push button (b), and two data acquisition units (DAQs)

user interface realized with Unity (Unity Technologies, California, US) was used to provide the participants with the cues and timers associated with the tasks. For this work, only sounds recorded by the ear transducers were used.

5.2.2 Participants

Eighteen volunteers (9 female and 9 male, age median 30.5 years, ranging in age from 24 to 43 years) participated in this study. The investigation was conducted after receiving approval from the regional ethics committee (Ethikkommission Nordwest- und Zentralschweiz, application number: 2021-002266). A signed informed consent was obtained from each participant after meeting the inclusion and exclusion criteria. Inclusion criteria were: ability to speak/read/write in English or German, age between 18 and 50 years. Exclusion criteria were: having dental implants (removable full or partial dentures), oro-facial pain, facial beard piercing, pregnancy, inability to perform the required tasks due to language or psychological barriers, allergy to silicone or medical tape, ear problems, wearing a hearing aid, Covid-19 symptoms, and finally people involved in the study design, family members, and staff or individuals dependent on people involved in the study. Volunteers were recruited mainly within the university and the surrounding area.

5.2.3 Protocol

First, the information about the study was discussed with the participant to clarify any misunderstandings, and then the participant was asked to complete a questionnaire - compiled by the author - to determine the possible presence of bruxism. The transducers were then attached to the participant's head and a shortened version of the main experiment was conducted to familiarize the participant with the setup. The experiment was divided into six tasks (Figure 5.2): T_1 (jaw

Classifier	Classes
2-Class	Grinding and Pause
4-Class	*Eating*, Grinding, Pause, and *Reading*
6-Class	*Clenching*, *Drinking*, Eating, Grinding, Pause, and Reading

Table 5.1: List of classifiers and the relevant classes (added classes are highlighted in italic font).

clenching), T_2 (tooth grinding), T_3 (jaw clenching), T_4 (reading), T_5 (eating), and T_6 (drinking), with participants having the option of taking a one-minute break between each task. Each participant was asked to sit in front of a computer screen that served as a guide throughout the experiment. The participant was asked to press the push button when performing an activity such as clenching, grinding, reading, eating, and drinking. As shown in Figure 5.2, each task was divided into different periods; for instance, T_1 and T_3 were a sequence of jaw clenching and pausing periods, T_2 was a sequence of tooth grinding and pause periods. During T_4, the participant read the passage "The North Wind and The Sun" which was divided into five sentences [115]. During T_5, the participant was asked to eat three different snacks: a piece of bread, a cracker, and a fruit. In T_6, the participant was asked to drink at least three sips of water. Finally, the participant was asked to sit quietly for one minute. The "pause" task refers to the time spent by the participant during the recording but was not an active period of the five oral behaviors. At the end of the experiment, the participant was asked to complete a second questionnaire - compiled by the author - to rate his/her experience. The evaluation of the jaw-clenching behavior was divided into two tasks (T_1 and T_3) to avoid any unnecessary stress on the participant's joint. In total, the six tasks resulted in recording the five oral behaviors: jaw clenching, tooth grinding, reading, eating, and drinking.

5.2.4 Data processing

Previous work by Bouserhal et al. investigated the classification of verbal and nonverbal sounds from the ear using SVM, MLP, and GMM with artificial features such as ZCR and MFCC. They reported classification accuracies ranging from 34% to 75.5% [95]. In addition, the image representation biosignals obtained from a PSG are usually labeled by experts to identify sleep bruxism events. Therefore, in this work, we decided to investigate the use of a pre-trained network to classify sounds of voluntarily produced oral behaviors using images. The data were processed and classified using Matlab 2021b (Mathworks, Massachusetts, US). The pre-trained network ResNet-50 from Matlab 2021b was used to classify the oral behaviors. For this work, only data recorded from the ears were used. The data were filtered with a linear phase FIR (Finite Impulse Response) low-pass filter (1000 Hz cut-off frequency, order of 20, and 30 % transition window) and a linear phase FIR high-pass filter (10 Hz cut-off frequency, order of 15, and 20 % transition window). It is described in the literature that teeth grinding or oromandibular episodes are defined using EMG data as phasic (3 EMG bursts lasting 0.25-2.0 s), tonic (EMG burst lasting more than 2 s), or mixed [116]. Therefore, for this work, we chose to segment the recording into 1 second windows with 50% overlap. In this way, we could be confident that bruxism-induced sounds

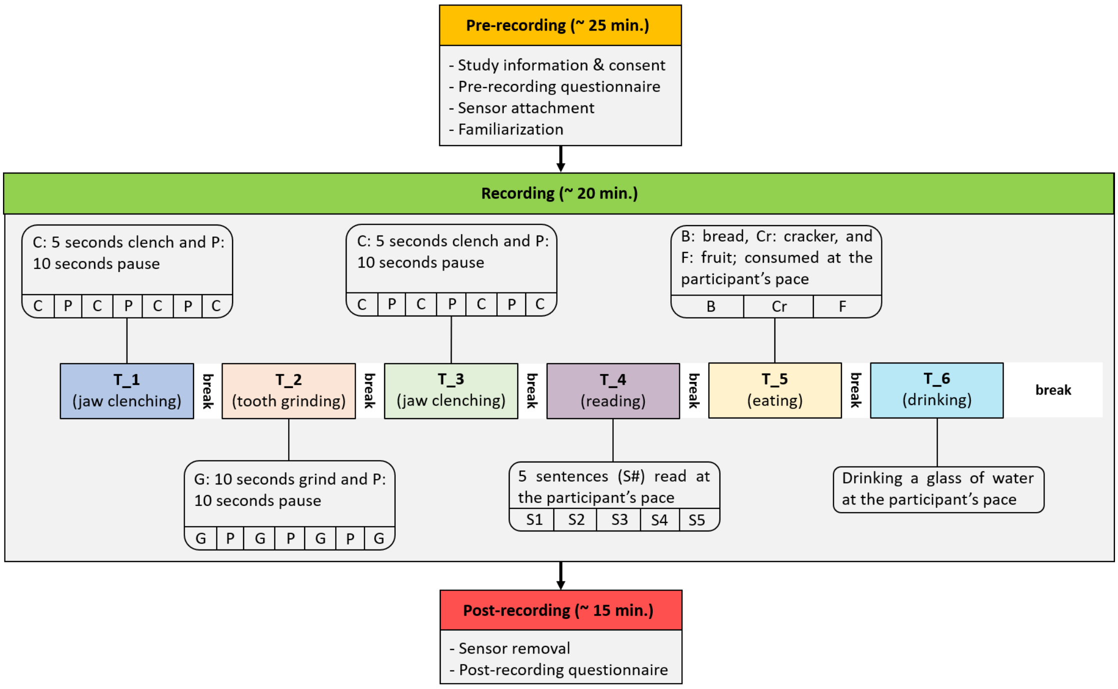

Figure 5.2: Pre-recording routine was performed for every participant. Recording experimental tasks: T_1 (jaw clenching), T_2 (tooth grinding), T_3 (jaw clenching), T_4 (reading), T_5 (eating), and T_6 (drinking). The participant had the option for a one minute break between the tasks labeled as "break", and the final one was compulsory for all participants. In the posr-recording period, the sensors were removed and the participant was asked to fill a questionnaire describing their experience of the study.

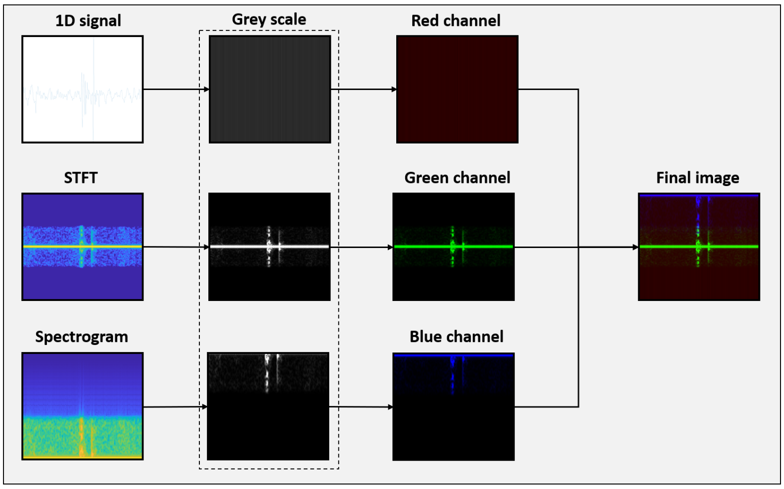

Figure 5.3: Schematic of the image generation. The 1-D signal, short time fourier transform (STFT), and the spectrogram were assumed to fill red, green, and blue channels, respectively.

would be captured. The windows were converted to RGB images by concatenating the time series, the STFT, and the spectrogram, as illustrated in figure 5.3. Each of the three channels had a size of 244 pixels $\times$ 244 pixels. The behaviors had different recording lengths, which resulted in an unbalanced data set as listed in table 5.2 in the supplementary material. The data were balanced for each subject by defining the class with the lowest number of images and then reducing the number of images for the remaining five classes to that particular value, as shown in tables 5.2 and 5.3 in the supplementary material. Leave One Participant Out Cross Validation (LOPOCV) was used, meaning that the classification was performed 18 times, each time leaving out the whole dataset of one of the participants for testing. The training data was split 70% for training and 30% for validation as illustrated in Figure 5.4. Three independent classification tasks were performed, which are listed in Table 5.1. Violin plots presented in this work were produced using the script developed by Bechtold [117].

5.3 Results

The overall test accuracy of the 2-Class classifier had the highest average test accuracy of 84.31% compared to the 4-Class and 6-Class classifiers with an average overall test accuracy of 72.79% and 50.97%, respectively, as illustrated in Figure 5.5. However, the 4-Class classifier showed a better performance compared to the 2-Class and 6-Class classifiers in terms of trivial prediction as illustrated in Figure 5.5.

Figures 5.6, 5.7, and 5.8 show the confusion matrix for the 2-Class, 4-Class, and 6-Class classifiers. The color scheme of the confusion matrices reflects the average of the accuracies obtained using the method described in Figure 5.4. The 2-Class classifier produced average

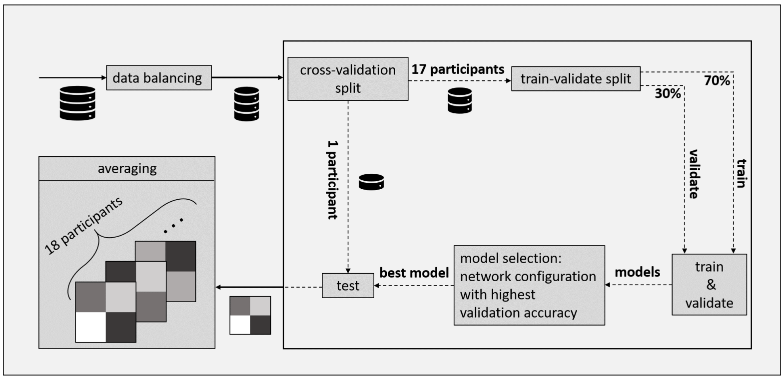

Figure 5.4: Scheme for classification procedure; the same procedure was used for the 2-Class, 4-Class, and 6-Class classification.

accuracies of 79.31% and 89.30% for correctly classifying grinding and pause, respectively as illustrated in Figure 5.6. However, the distribution of each test subject's data points has a wide range, as shown in the violin plots within each cell of the confusion matrix. In addition, the classifier achieved a test accuracy of 100% for some subjects.

The 4-Class classifier produced average accuracies of 83.35%, 79.06%, 74.21%, and 54.53% for correctly classifying Pause, Reading, Eating and Grinding, respectively as illustrated in Figure 5.7. Grinding was frequently misclassified as eating with an average of 30.69% and misclassified as pause with an average of 14.63% as illustrated in Figure 5.7.

The highest overall average accuracies produced by the 6-Class classifier were for reading and eating with 79.75% and 75.01%, respectively, as illustrated in Figure 5.8. Drinking had the lowest average classification accuracy, followed by clenching, grinding, and pausing with values of 22.09%, 34.25%, 43.12%, and 51.60%, respectively as illustrated in Figure 5.8. The 6-Class classifier often misclassified Clenching for Pause with an average misclassification of 54.25% as illustrated in Figure 5.8. It also misclassified Grinding for Eating with an average misclassification of 33.75% as illustrated in Figure 5.8. Finally, drinking was often misclassified as a break with an average misclassification of 39.82% as illustrated in Figure 5.8.

5.4 Discussion

The work presented in this paper aims to investigate the possibility of classifying image representations of voluntarily produced oral behavioral sounds. Three classifiers were introduced to classify sounds of jaw clenching, teeth grinding, reading, eating, and drinking. The classifiers successfully achieved an overall accuracy higher than their trivial prediction, as shown in Figure 5.5.

The wide range of test accuracies, represented by the black dots in Figure 5.5 may be due to

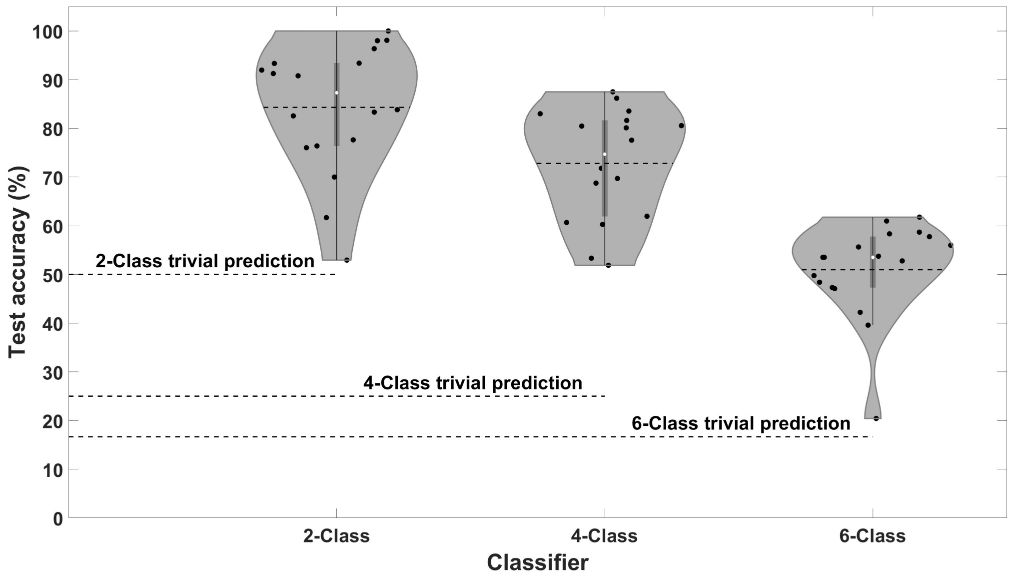

Figure 5.5: Total test accuracy of the classifiers, where the shaded areas are violin plots, the black dots within the shaded areas represent the classifier test accuracy of each test participant (using LOPOCV), the dashed lines within the shaded areas represent the average, and the white dots in the shaded area represent the median.

the balancing procedure, which reduced the size of the data set, thereby reducing the generality of the model. Also, the reduction in class size was done randomly, so some "mislabeled" images may have been present in the balanced dataset. Here, with "mislabeled" we refer to the presence of images, where the user was reporting grinding but in fact pausing, or time windows where no grinding sound was recorded due to absence of tooth contact while the participant was changing the movement direction of the jaw. Temporal information may help to distinguish tooth grinding from other behaviors, such as eating. However, the balancing of the data was done by randomly reducing the number of images of the classes to the size of the smallest class, thus losing the temporal information. This may explain the relatively high misclassification of teeth grinding as eating as illustrated in Figures 5.6, 5.7, and 5.8). Due to the nature of voluntary grinding containing both pauses and time periods without tooth contact, we did not consider these relatively high miss-classification as critical. For providing bio-feedback for grinding, we believe that either longer time windows or combining classification of multiple windows would be appropriate.

In addition, the test accuracy of 100% accuracy achieved for the 2-Class classifier as illustrated in Figure 5.5 can be attributed to either the data set being too small, causing the classifier to converge prematurely, or to the Grinding and Pause classes having a clearly identifiable difference within this particular test participant. In addition, the test accuracy of Grinding ranged from 0% to 100%, which can be attributed to either some images being "mislabeled" due to pauses between grinding instances. For the confusion matrices of the 4-Class and 6-Class classifiers shown in Figures 5.7 and 5.8, the misclassification of mostly Grinding as Eating can be attributed to the

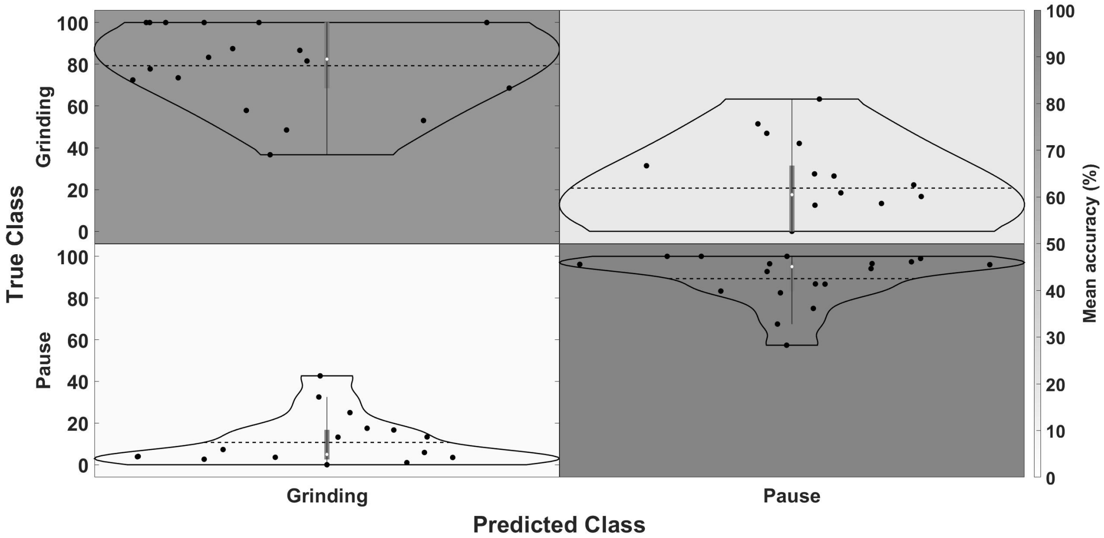

Figure 5.6: Confusion matrix of the 2-Class classifier averaged over 18 participants, where the black dots represent the test accuracy of each test participant (using LOPOCV), the dashed lines represent the average, and the white dots represent the median. The grey boxes in each cell represent the box plot. The color shading reflects the average test accuracy averaged over eighteen participants.

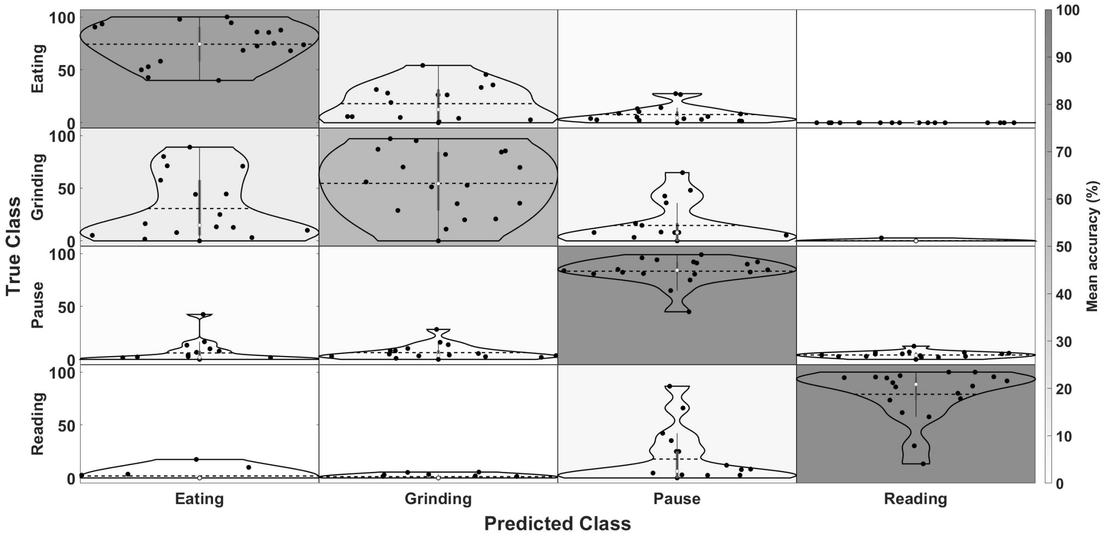

Figure 5.7: Confusion matrix of the 4-Class classifier averaged over eighteen participants, where the black dots represent the test accuracy of each test participant (using LOPOCV), the dashed lines represent the average, and the white dots represent the median. The grey boxes in each cell represent the box plot. The color shading reflects the average test accuracy averaged over eighteen participants.

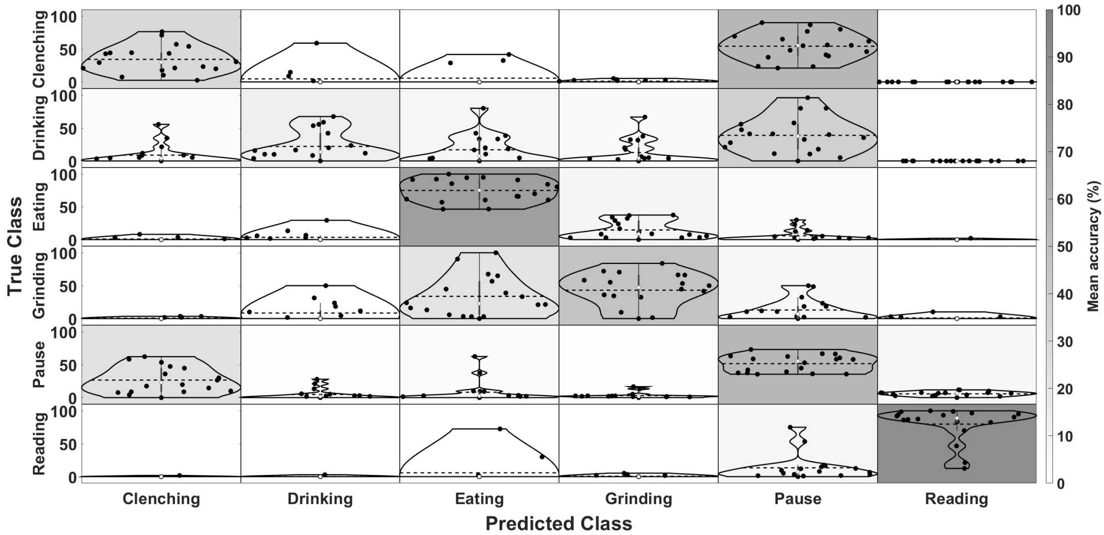

Figure 5.8: Confusion matrix of the 6-Class classifier averaged over eighteen participants, where the black dots represent the test accuracy of each test participant (using LOPOCV), the dashed lines represent the average, and the white dots represent the median. The grey boxes in each cell represent the box plot.The color shading reflects the average test accuracy averaged over eighteen participants.

fact that both behaviors use similar jaw movements and tooth contact may have occurred during eating. It can also be attributed to the lack of temporal information that can help discriminate between these two classes. However, the confusion between clenching and pausing as illustrated in Figure 5.8 may be due to the limitations of the setup, as the ear was not fully occluded, which may have affected the presumably weak clenching sounds. This observation is supported by a pilot study we conducted that compared the sound characteristics recorded from a fully occluded and semi-occluded ear [2].

In addition, it is assumed that during sleep bruxism, tooth grinding occurs more regularly, while during wake bruxism, jaw clenching may occur more frequently. Therefore, the average accuracy obtained with the 2-Class classifier would be sufficient to detect tooth grinding as shown in Figures 5.5 and 5.6. However, in the literature, tooth grinding has mainly been labeled by experts using data from EMG bursts with defined episodes, phasic, tonic, and mixed [116]. The definition of bruxism episodes based on sound is still missing. This would provide even more support for decisions about window size and other parameters that affect data segmentation.

An additional approach to overcome the low average accuracy of the 4-Class and 6-Class classifiers is to first develop multiple algorithms that perform binary classification of each of the "active" classes (jaw clenching, eating, reading, drinking), while "pause" can be the remaining class, and then introduce a sensitivity level that switches the device from binary to multi-class classifier based on user preference. Finally, future work should also address the question of what level of classification accuracy is clinically meaningful. For instance, a clinical study could be designed to compare the performance of the ear device with the gold standard for diagnosing sleep bruxism and to assess its efficacy on reducing the onset of sleep bruxism when using implementing bio-feedback in the ear device. This would help developers working on classification algorithms and bio-feedback mechanisms integrated into wearable devices.

5.5 Limitations

There are a few limitations that must be considered when interpreting the results. The performance of the ear devices may be affected by the anatomical differences between participants and may be influenced by the size of the ear and the location of the transducer within the earpiece. In addition, it should be noted that the behaviors studied in this study were performed voluntarily, so the intentional performance of an involuntary action could affect the characteristics of the recorded sounds. Also, the study was performed in a controlled environment.

5.6 Conclusion and future research

We were able to classify the sounds of jaw clenching, tooth grinding, eating, reading, drinking, and pause using ResNet50. The overall accuracy of the classifiers, averaged over eighteen participants, decreased as the number of classes increased, , which is not surprising since the overall task gets more challenging and the particularities of the different behaviors need to reach a higher level of refined recognition. At the same time, our classifiers resulted in accuracies way beyond chance. In addition, the current classification procedure resulted in higher accuracies compared to trivial prediction. Future work on the use of sound as a biomarker to detect bruxism events should focus on two main points. First, the recording and classification of involuntarily produced sounds of various oral behaviors, which is difficult to record in a lab environment. Second, further work should investigate the different levels of sensitivity, which refers to the number of classes that should be classified at a given time. In addition, it would be important to integrate a bio-feedback mechanism to the ear device and investigate its impact on the frequency of bruxing.

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Appendix

	Class					
Participant	**Jaw Clenching**	**Tooth grinding**	**Reading**	**Eating**	**Drinking**	**Pause**
1	216	190	138	902	*34*	1906
2	192	176	138	698	*38*	2000
3	176	162	160	524	*40*	2768
4	228	200	158	1322	*60*	2026
5	160	164	138	264	*24*	1772
6	174	176	154	538	*50*	1908
7	182	176	164	230	*30*	1870
8	178	174	196	458	*40*	1876
9	190	170	200	392	*98*	2920
10	190	174	156	540	*90*	1930
11	184	172	190	558	*36*	1666
12	190	178	152	1004	*68*	2154
13	190	174	184	590	*38*	1728
14	190	178	188	492	*52*	1854
15	188	178	148	726	*86*	2344
16	206	186	132	740	*96*	1724
17	184	188	212	794	*56*	1826
18	216	204	152	310	*68*	1838

Table 5.2: Number of images for each participant per each class. The class with the least number of images was highlighted with an italic font. In this work, drinking had the least number of images for all participants.

	Dataset													
	Test							Train						
Test participant	**Jaw clenching**	**Tooth grinding**	**Reading**	**Eating**	**Drinking**	**Pause**	***Total***	**Jaw clenching**	**Tooth grinding**	**Reading**	**Eating**	**Drinking**	**Pause**	***Total***
1	34	34	34	34	34	34	*204*	970	970	970	970	970	970	*5820*
2	38	38	38	38	38	38	*228*	966	966	966	966	966	966	*5796*
3	40	40	40	40	40	40	*240*	964	964	964	964	964	964	*5784*
4	60	60	60	60	60	60	*360*	944	944	944	944	944	944	*5664*
5	24	24	24	24	24	24	*144*	980	980	980	980	980	980	*5880*
6	50	50	50	50	50	50	*300*	954	954	954	954	954	954	*5724*
7	30	30	30	30	30	30	*180*	974	974	974	974	974	974	*5844*
8	40	40	40	40	40	40	*240*	964	964	964	964	964	964	*5784*
9	98	98	98	98	98	98	*588*	906	906	906	906	906	906	*5436*
10	90	90	90	90	90	90	*540*	914	914	914	914	914	914	*5484*
11	36	36	36	36	36	36	*216*	968	968	968	968	968	968	*5808*
12	68	68	68	68	68	68	*408*	936	936	936	936	936	936	*5616*
13	38	38	38	38	38	38	*228*	966	966	966	966	966	966	*5796*
14	52	52	52	52	52	52	*312*	952	952	952	952	952	952	*5712*
15	86	86	86	86	86	86	*516*	918	918	918	918	918	918	*5508*
16	96	96	96	96	96	96	*576*	908	908	908	908	908	908	*5448*
17	56	56	56	56	56	56	*336*	948	948	948	948	948	948	*5688*
18	68	68	68	68	68	68	*408*	936	936	936	936	936	936	*5616*

Table 5.3: Number of images for tain and test datasets after balancing the data.

Chapter 6

General Discussion

6.1 Achieved milestones

Polysomnography with audio and video (PSG A&V) recording is the gold standard for the diagnosis of sleep bruxism, while a gold standard for jaw clenching is being developed. Advances in wearable devices have the potential to be used in medical applications. During my Ph.D., I investigated the potential of using sound as a biomarker in a wearable device to detect bruxism-like events, that is a contribution towards the development of a hearable for the detection of bruxism.

Hearables have the potential to be used for the detection of bruxism. Hearables are convenient to use and inexpensive compared to PSG with A&V electromyographic (EMG) devices. In addition, hearables can be worn throughout the day, as the use of ear devices is widespread and socially tolerated compared to EMG devices that would be worn on the head (Chapter 2). This feature makes it a viable potential tool for detecting both sleep and awake bruxism.

Sound as a biomarker has been used in dentistry to detect malocclusion, but it hasn't been investigated whether sound can be used to detect bruxism and from which location it is best recorded. To answer the research question on whether the type of ear occlusion would affect the recording, I first conducted a pilot study with the help of one subject. Full occlusion of the ear canal with a deformable earpiece helped to record both jaw clenching and teeth grinding, as well as eating, reading, and drinking (Chapter 3). However, complete occlusion of the ear raises safety concerns, as the user would be isolated from the environment. I then investigated the possibility of recording sounds of bruxism-induced events, among other oral behaviors, from different locations on the head in order to answer the research question on the impact of transducer location on the recording.

I conducted a study - with the help of 18 participants - to record such sounds from the temporal bone, zygomatic bone, frontal bone and ear. I observed that sounds of different oral behaviors were recorded from different locations. However, I have found that identifying the characteristic feature of jaw clenching is difficult, except for a peak that is present just before the expected onset of clenching. I think that one of the main reasons for this challenge is the type of occlusion and the placement of the transducer in the ear, as I demonstrated in the pilot study (Chapter 3). Nevertheless, the ear still represents a strategic position from which to record the sounds, and by simply detecting tooth grinding sounds, a massive step has been taken in demonstrating the possibility of using hearables to detect bruxism (Chapter 4).

Finally, bruxism occurs throughout the day, and sounds are produced by bruxism-induced events and by other events such as talking or eating. Therefore, I investigated the potential of classifying 2D representations of sounds recorded from the ears using ResNet50. I investigated three classifiers: a 2-Class classifier (Grinding and Pause), a 4-Class classifier (Eating, Grinding, Pause, and Reading), and a 6-Class classifier (Clenching, Drinking, Eating, Grinding, Pause, and Reading). The overall test accuracy of the classifier decreased as the number of classes increased: 2-Class with a test accuracy of 84.31 %, 4-Class with a test accuracy of 72.79%, and 6-Class with a test accuracy of 50.97 % (Chapter 5). The accuracies of the classifiers were higher than that of the trivial prediction, as shown in Figure 5.5. I think that this is an important contribution to the ongoing research on the development of instrumental tools for the detection of bruxism in real-world environments.

6.2 Limitations

Throughout my dissertation, I noticed several limitations. First, bruxism is a parafunctional behavior that occurs unconsciously; for my work, I asked participants to consciously perform bruxism-like events. I believe that this has an impact on the recorded signal, as I demonstrated in the pilot study, as the amount of force exerted on the teeth and joint. This may also have affected the temporal characteristics of the bruxism events. Also, I invited participants who did not necessarily have bruxism, which could have an impact on the tasks performed related to bruxism. In addition, I had to balance the data for the deep learning investigation, which reduced the amount of data and resulted in the loss of temporal sequences that could affect the output of the classifiers. Nevertheless, I believe that the decision I made helped I move forward with the project and reduced some of the complexity and helped I show the potential of using sound and hearables for bruxism detection.

6.3 Outlook

6.3.1 Hearables for bruxism

For my Ph.D., I conducted a study in a controlled environment where participants had to consciously perform bruxism-like events. However, bruxism is a parafunctional behavior that occurs without the individual being aware of it. I believe that performing the behavior in a conscious manner affects the temporal structures of the behavior and the forces that the individual exerts on their teeth, muscles, and joints, thus affecting the sound levels. Therefore, future investigations should address the following: conduct studies that investigate the potential of recording bruxism-induced sounds from real-world environments using hearables, followed by a large clinical study to better understand the prevalence of bruxism in a population. Finally, the effectiveness of a biofeedback mechanism in a hearable to reduce the occurrence of bruxism events will be investigated. I also believe that the temporal information can be very helpful in improving the classification accuracy. Therefore, the development of categorization criteria similar to those used for EMG measurements, phasic, tonic and mixed [116], would help to better label the recorded sounds and better design study procedures, consequently improving classification accuracy.

6.3.2 Causes of the problem vs its symptoms

It is important to treat the symptoms of health problems in general. However, it is equally important and urgent to address the causes of the problem as well. Bruxism as a risk factor leads to various health consequences such as tooth wear, TMD, and other physical pain. One of the main causes of bruxism is emotional stress (chronic stress). In addition, the relatively high number of affected individuals supports the argument that bruxism can be listed as a public health issue. Keeping these two points in mind helps I realize that to deal with the roots of bruxism, structural determinants of bruxism need to be identified in order to design public policies that address them [18].

6.4 Conclusion

In conclusion, with this PhD thesis, I have demonstrated that it is possible to record bruxism induced events in particular tooth grinding from different locations of the head, however the ear was the ideal location as it can compensate for physical movements of the head and ear devices are socially tolerable. In addition, it is important to distinguish bruxism-induced from other oral behaviors as well as sounds from the environment. ResNet50 was used to classify 2D representations of sounds recorded from ear for the oral behaviors clenching, grinding, reading, eating, and drinking. I have achieved an overall test accuracy for the different classifiers: 2-Class classifier (Grinding and Pause) of 84.31%, 4-Class classifier (Eating, Grinding, Pause, and Reading) of 72.79%, 6-Class classifier (Clenching, Drinking, Eating, Grinding, Pause, and Reading) of 50.97 %. I believe that the accuracies achieved are good as they have practical implications on the occurrence of bruxism events. Finally, managing the symptoms of a health issue is important and further devices and methods should be developed, in addition, an important research direction that must be explored is to investigate the causes of bruxism by looking at it through the biopsychosocial model.

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