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Unobtrusive electromyography-based eating detection in daily life: A new tool to address underreporting?

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ABSTRACT

Research on eating behavior is limited by an overreliance on self-report. It is well known that actual food intake is frequently underreported, and it is likely that this problem is overrepresented in vulnerable populations. The present research tested a chewing detection method that could assist self-report methods. A trained sample of 15 participants (usable data of 14 participants) kept detailed eating records during one day and one night while carrying a recording device. Signals recorded from electromyography sensors unobtrusively placed behind the right ear were used to develop a chewing detection algorithm. Results showed that eating could be detected with high accuracy (sensitivity, specificity >90%) compared to trained self-report. Thus, electromyography-based eating detection might usefully complement future food intake studies in healthy and vulnerable populations.

1. Introduction

Eating behavior research has mainly relied on dietary self-report, including food records, 24-h recall, food frequency questionnaires and diet history. Although frequently utilized, these methods come with several disadvantages in that they require high compliance and motivation and are subject to self-presentation and memory biases. Thus, unsurprisingly, when comparing subjective measures with more objective measures of energy intake (e.g., intake in controlled, residential programs, energy expenditure measures such as the Goldberg cut-off (Goldberg et al., 1991) or doubly labeled water methods) reported calories are frequently underestimated in a range from 4% to 37% (Livingstone & Black, 2003; Stice, Palmrose, & Burger, 2015; Thompson & Subar, 2008). A recent review even classified self-report based energy intake 'wholly unacceptable for scientific research' (Dhurandhar et al., 2015). These limitations and the advent of mobile measurement technology have sparked the use of smartphone devices and ambulatory psychophysiological measurements for assessing food intake. Many apps equip the user with databases to select food and portion size, possibilities of take photographs of their foods (Lieffers & Hanning, 2012), audio-recording, barcode scanning (Illner et al., 2012) or even automated food identification and portion size estimation (Boushey et al., 2017). While these approaches result in better self-monitoring adherence (Lieffers & Hanning, 2012) and control over temporal compliance (Shiffman, Stone, & Hufford, 2008), thereby outperforming paper based methods, they still rely on user activity: One needs to be aware of an eating episode and record it precisely (its start and end, any leftovers in case of photos).

Another group of methods therefore tries to bypass such user compliance. Laboratory measures include as video (Cunha, Pádua, Costa, & Trigueiros, 2014) or scale-based approaches (Manton, Magerowski, Patriarca, & Alonso-Alonso, 2016; Zhou et al., 2015) and have reported good precision but they are not (entirely) mobile and can thus not be used in free-roaming individuals. Other measures can be recorded in a natural environment and are focusing on eating episodes instead of calorie intake. E.g., 'bite counters' are based on the assumption that eating always involves characteristic dominant hand movements (to the mouth), hence an accelerometer-based wrist band might be able to capture bites taken (Dong, Hoover, Scisco, & Muth, 2012; Salley, Hoover, Wilson, & Muth, 2016; Scisco, Muth, & Hoover, 2014; Thomaz, Essa, & Abowd, 2015; Ye, Chen, Gao, Wang, & Cao, 2016). Apart from the

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limitation that eating with the non-dominant hand will be missed most bite counters still rely on the user input to press a start button before the eating episodes in naturalistic environments. Other approaches aim at detecting eating episodes based on *continuous measurements* of swallowing and/or chewing activities: For example, audio recording at the inner ear has been used (Amft, Kusserow, & Troster, 2009; Bedri, Verlekar, Thomaz, Avva, & Starner, 2015; Nishimura & Kuroda, 2008; Papapanagiotou, Diou, Zhou, van den Boer et al., 2016; Päßler & Fischer, 2014). Because of specialized algorithms that are needed to process the acoustic signals, most devices achieve acceptable results in laboratory setting with restricted food types and eating episodes, however, their accuracy in unrestricted, more challenging environments needs to be established. Privacy protection implications arise because voices in the vicinity are recorded as well. In this respect, non-audio-based physiological measures can be useful alternatives. While photoplethysmography (PPG) detects muscle related blood flow in the ear concha during chewing (Papapanagiotou, Diou, Zhou, Boer, et al., 2016), electroglottography (EGG) is used to measure impedance changes at the neck when a bolus of food passes through the larynx to detect swallowing (Farooq, Fontana, & Sazonov, 2014). However, the most common physiological measures used at present utilize electromyography (EMG) to detect swallowing (laryngography) (Amft & Troster, 2008; Carvalho-da-Silva, Van Damme, Wolf, & Hort, 2011) or chewing (masseter, temporal muscles; Farella, Palla, & Gallo, 2009; Kemsley, Defernez, Sprunt, & Smith, 2003; Kohyama, Mioche, & Bourdio, 2003; Mattes & Considine, 2013; Po et al., 2011).

Despite elaborated approaches to discriminate ingestive behavior from the various interferences and confounds (environmental sounds, speaking, laughing, coughing, sneezing, yawning, head movements, whistling, smoking), only few have been examined in free living individuals for longer durations (Farooq, Fontana, Boateng, Mccrory, & Sazonov, 2013; Po et al., 2011; Scisco et al., 2014). Scisco et al. (2014) had participants wear a wrist-band for 2-weeks to measure bite counts. Farooq et al. (2013) compared two machine learning procedures to detect food intake signals from jaw motion data collected from free-roaming subjects over 24 h. Po et al. (2011) used a previously validated time-frequency based algorithm (Farella et al., 2009) on 3 h of continuous EMG data and identified chewing behavior with good sensitivity and specificity. Such real live proofs of concepts are crucial because the long recordings in varied environments increase the potential sources of false positives due to artefactual EMG measurements, which the detection algorithm needs to reject. Night recordings seem important, as jaw movements are likely to occur during sleep (Po, Gallo, Michelotti, & Farella, 2013), particularly, but not only in individuals with bruxism. Long term recordings also require high individual and social acceptability (e.g., by low obtrusiveness and visibility of sensors) of the devices, which is crucial for any practical application in larger populations. Furthermore, high accuracy might be achieved in the laboratory but not generalize to the natural environment: accuracy decreased from 81% to 62% when applying laboratory based models of chewing behavior to free-roaming data (Fontana, Farooq, & Sazonov, 2014).

The present research focused on indirect, continuous recordings of chewing episodes based on mobile EMG in free-roaming individuals. Instead of targeting precise calorie intake or macro-nutritional composition (what and how much is eaten) our approach focused on the occurrence of eating episodes (when and how long, *episode frequency*) indicated by chewing activity. This choice is based on the reasoning that any fully automatic classification of food content and amount will always be imprecise and that omission of eating episodes is a key contributor. Under-reporting can, for example, be due to unconscious omission of eating occasions, recording fatigue or conscious misreporting (e.g., denial of consumption) (Maurer et al., 2006). Further suggesting that especially missing eating episodes contribute to under-reporting, Poppitt and Prentice (1996); Poppitt, Swann, Black, and Prentice (1998) found that although main meals were well reported, between-meal snacks were omitted from participants' 24-h report with more than one third of snack consumption being absent. Similarly, Johansson, Wikman, Åhrén, Hallmans, and Johansson (2001) found that underreporters (relative to their food intake level) seem to selectively underreport unhealthy snacks (less so healthy foods). In sum, although our EMG-based chewing detection approach misses food content and amount, it captures important eating episode characteristics: time, duration and frequency throughout the day.

We took advantage of EMG recordings from miniature, non-invasive electrodes behind the ear, which are dominated by activity of the lateral pterygoid muscle (the only muscle of mastication involved in opening the jaw). This simple measurement along with mobile lightweight amplifiers allows for long recording periods (including during night), low risk of sensor detachment, and is relatively unobtrusive for most users. However, the detected eating episodes have to be compared to a 'gold standard' of food intake. Although the most precise method might be doubly labeled water, it seems inappropriate since individual eating episodes cannot be identified. Thus, we test this method against (app and device assisted) self-report in a sample that was specifically trained to report every single eating episode. We expect that this EMG-based method alongside sophisticated data analysis will be able to capture eating episodes with high sensitivity. However, specificity is also of key importance: confusion of speaking, drinking, laughing, yawning, head movements, smoking or bruxism with eating episodes could lead to an overestimation of eating. Previous jaw-motion sensor/EMG research reviewed above has demonstrated excellent sensitivities but did not record continuously over the day and night in natural environments and can thus not speak to specificity. Hence, in our proof of principle research, 24-h recordings were obtained from 15 well trained 'calibration participants' in their daily life to obtain valid measures of sensitivity and specificity of EMG-based meal detection relative to self-report.

1.1. Participants

Participants were recruited from the master's students in clinical and health psychology at the University of Salzburg because these individuals could be expected to demonstrate the level of background knowledge and high motivation to comply with the self-recording instructions (described below). Participants had a mean age of 21.7 ($SD = 2.13$, range = 18–25), healthy BMI ($M = 22.0$ kg/m^2, $SD = 2.9$, range = 17.5–26.7) and normal-range scores on the *Eating Behavior and Weight Problems Inventory*, EWI (Diehl, 1999). A brief interview enquired about the presence of nail biting or bruxism.[1] Participation in the 24 h protocol was remunerated with € 12. One participant was excluded due to technical problems during the ambulatory recording, leaving 14 participants (six women). Ethical approval for the measurement protocol was granted by the local ethics committee.

[1] A previous study reported a prevalence of diagnosed nail-biting of 46.9%, however, a large number of analyzed participants (71.2%) spent less than 10 min per day on biting fingernails (Pacan, Grzesiak, Reich, Kantorska-Janiec, & Szepietowski, 2014). Awake bruxism was prevalent in 22.1%–31% of individuals as reviewed by Manfredini, Winocur, Guarda-Nardini, Paesani, and Lobbezoo (2013).