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.

Keywords: Ambulatory assessment; eating behavior; chewing; electromyography; chewing episodes detection algorithm

Introduction

Eating behavior research has mainly relied on dietary self-report, including food records, 24-hour 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%-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 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 hours. Po et al. (2011) used a previously validated time-frequency based algorithm (Farella et al., 2009) on 3 hours 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. Underreporting 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 underreporting, 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-hour report with more than one third of snack consumption being absent. Similarly, Johansson et al. (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-hour 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.

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/m², *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 24h 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.

Self-reported eating episodes

To provide a record that closely represents an accurate record of actual eating, our specifically trained participants marked eating on- and offset in the continuous signal using a marker button on the recording device. Using a customized smartphone app, they further reported the duration and type of eating (snack or a main meal). Time segments for meals not marked correctly on the device by the participants (with one marker missing) were reconstructed based on the app information (7% of the data reconstructed).

EMG measurement of eating episodes

To measure the muscular activity during chewing episodes, two pairs of disposable 24 mm diameter solid-gel snap electrodes (Ag/AgCl, sensor diameter 10 mm) were attached to cleansed skin sites with centers approximately 2 cm apart (the electrodes have been cropped to avoid shorts as indicated in Figure 1). Each pair of electrodes was placed on the bone structure behind one ear on a line between the mastoid and the masseter muscle (see Figure

[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 minutes per day on biting fingernails (Pacan et al., 2014). Awake bruxism was prevalent in 22.1% - 31% of individuals as reviewed by Manfredini et al. (2013).

1). The ground electrode was applied to the neck, close to the cervical spine. EMG activity was recorded using a VarioPort (Becker MediTec, Karlsruhe, Germany). The signals were digitized using a 512 Hz sampling rate and further processed using the EMGdetect module in the ANSLAB software suite (Blechert, Peyk, Liedlgruber, & Wilhelm, 2016; Wilhelm & Peyk, 2005) and MATLAB R2015a (Mathworks, Inc., Natick, MA, USA).

Procedure

After being welcomed and informed consent had been obtained, participants were equipped with the sensors. Quality of signals was verified and ambulatory recording was started. An in-lab *training and calibration sequence* familiarized participants with the types of movement artefacts and potential sources of false positives (eating falsely detected by EMG) by recording and displaying the EMG signal while participants repeatedly chewed on a cereal bar, made head movements, spoke and laughed. At the same time this recording allowed for a within participant standardization of the EMG signal (see below). The use of the device marker button and the smartphone app was trained by having participants mark beginning and end of the various eating episodes and enter smartphone data subsequently. Participants then left the laboratory and went about their daily routines without restrictions in terms of movement or eating (other than not to take a shower or wash their hair during recording). Additionally, participants received a take-home note, reminding them about the most important data entries. The ambulatory recording lasted until the next morning to potentially include breakfast as well. The sensors have been removed upon return of the recording equipment to the laboratory. Finally, participants completed a questionnaire asking about unpleasantness of wearing the device (0 - very pleasant to 100% - very unpleasant) and precision of self-reports (0 – very unprecise to 100% - very precise).

Data Analyses

The EMGDetect module in ANSLAB was used to process the data. After low-pass filtering (243 Hz), high-pass filtering (150 Hz), and rectification with implicit downsampling to 8 Hz to obtain a signal representing muscular effort, different thresholds[2] were applied to the spectral power of this rectified EMG signal within the frequency band of 1 to 4 Hz (range of typical chewing frequency). Prior to the detection, the spectral power was normalized using information from the calibration phase to make the algorithm robust against variability in

[2] As soon as the spectral power exceeds twice the minimum power during the chewing calibration, a potential chewing phase is assumed to start. The end of the phase is reached as soon as the spectral power falls below the minimum power during the calibration again.

terms of the intensity of EMG activity among participants. Detected chewing phases shorter than 5 seconds are then discarded to avoid false positives in case of short movement artefacts. In the remaining set of chewing phases, those phases not farther apart than 15 seconds are merged into larger ones. Chewing phases which are shorter than 20 seconds after merging are also discarded. In the next step phases in which the rectified signal exceeds the maximum rectified signal value during chewing calibration for at least 25% of the phase duration by at least 50% are also discarded. Finally, chewing phases affected by signal clipping for more than 10% of their duration are also removed to reduce false positives. Agreement between the dichotomized EMG signal (1=eating present, 0=eating absent, right EMG channel only, 1-minute resolution) and the self-reported marker periods is illustrated in Figure 2. This figure shows an excerpt from a rectified EMG recording along with the reported and detected eating episodes.

Results

An average of 20.4 hours were acquired (*SD* = 6.74, range = 4.33 – 24.7, exclusion of the two participants with <5 hours recording did not alter the results, so they were retained in the sample). Participants reported 29 main meals and 43 snacks with an average meal time of 12.1 minutes and 5.6 minutes, respectively. Participants' self-reported unpleasantness of wearing the device was *M* = 47.7, *SD* = 24.2. Subjective precision of eating reports was very high (*M* = 90%, *SD* = 9.1%).

Table 1 shows the sensitivity and specificity rates obtained for the different participants along with the mean detection rates and the respective standard deviations. In addition this table also includes information about the participants' habits with respect to bruxism and nail biting. Since the chewing of finger nails and bruxism results in potentially lower sensitivity or specificity values, Table 1 also shows the mean sensitivity and specificity rates when excluding the respective participants from the calculations.

Discussion

The present study compared an ambulatory EMG-based eating detector with self-reported eating in a sample of trained participants during ~20 hours of naturalistic activities. As reviewed above, previous research using physiological recording has reported relatively high sensitivities and specificities, however, was either lab-bound or ambulatory sensor placement was either obtrusive (well visible to the environment), or potentially privacy threatening (in-ear microphones). Still other research had focused on sensitivity and failed to record long stretches of non-eating episodes to test detection algorithms for specificity (Po et al., 2011) (i.e. the risk for false positives in case of head movements, speaking, yawning etc.). Our results indicate that under naturalistic conditions of daily life, eating can be detected with sensitivities and specificities >90% (when excluding bruxism and nail biting). These results are promising in light of a decade long search for automated eating detection approaches.

This optimistic outlook is given on the background of three key assumptions. First, as introduced above, our approach focusses on eating *episode frequency* rather than eating meal size and content: Chewing patterns do not allow us to conclude *what* and *how much* is eaten (i.e. calorie content, nutrients), just that eating is taking place. However, one of the main problems of underreporting is the omission of shorter between-meal snacks in traditional eating records (Johansson, Wikman, Åhrén, Hallmans, & Johansson, 2001; Poppitt & Prentice, 1996; Poppitt et al., 1998). In addition, recent evidence documents the high prevalence of these shorter snacks (Ovaskainen et al., 2006) and it becomes more and more evident that they are consumed for hedonic (subjective liking, craving or reward) rather than homeostatic (hunger) reasons (Cleobury & Tapper, 2014; Reichenberger et al., 2016). Thus, any interventions for heathy and intuitive eating (i.e. eating in line with homeostatic needs, i.e. (Tylka & Wilcox, 2006)) would have to focus on these 'micro-eating' episodes. Thus, the omission of smaller, shorter or 'on the go' eating episodes could be curbed by an EMG-based detector. Nevertheless, in case total calorie intake is of interest (e.g., in participants with obesity or diabetes), the EMG-based detector could be combined with a subjective content recording app (maybe with camera, barcode or voice-recording assistance), thereby gaining cross-validating information about certain underreporting features (see below).

Our second assumption here is that self-reports in the present 'calibration' sample are valid and therefore represent a 'gold standard' or a viable reference to compare our chewing detection against. This might appear as conflicting with the above described prevalent problem of underreporting that motivated this study in the first place. However, firstly, no superior method with sufficient temporal resolution is known to us and we have taken particular care to motivate and train our sample. Second, the high agreement between both data types seems to validate our approach: if self-report was very unreliable, such high accuracy would not have been possible. Supporting this assumption, subjectively perceived precision of self-reports was very high. We do not expect these self-reports to generalize to the general public at all (in fact we expect lower protocol adherence and precision of self-reports in an untrained and maybe less educated sample). Yet, future studies in other populations should now be able to rely on the EMG-based detection with considerable certainty based on the present sensitivity and specificity data.

A third assumption or consideration during study design was that visibility or 'social intrusiveness' of any recording device is crucial for its acceptance. For example, a study of Pettitt et al. (2016) observed that a wearable device taking pictures of the eating episodes did affect peoples' activities and they felt uncomfortable wearing it in public, and most importantly, might have affected their eating behavior. Hence, in our study the sensor placement was in a region that is relatively hidden or at least not as attention grabbing as more central sites at face or throat, where signals may have been of even higher quality and specificity. Our more remote sensor placement was not without costs: Based on visual inspection of signals during the calibration phase, it is likely that sensors did not capture chewing activity exclusively, but to some extent also strong head movements. With the advent of wireless, battery operated surface sensors (EMG, plethysmography, impedance measurements, distance sensing), several additional placements could be made at innocuous sites to improve robustness of detection despite unobtrusive placement. Combinations with other sensors such as microphones, video or even neural activity from EEG (Debener, Emkes, De Vos, & Bleichner, 2015) might further increase detection accuracy (e.g., combination of jaw motion and accelerometer sensors in Fontana et al. (2014)

Based on these assumptions, the following *future directions* appear particularly promising. A first set of future directions would optimize the food-intake detection algorithms by a) provoking eating-irrelevant muscular activity (nail biting, bruxism, smoking), b) discriminating eating and drinking, and c) recording naturalistic behaviors that triggered false positives. Individual differences in dental health, nail biting, bruxism, and smoking could further be considered correlatively. Subjective recording mode (marker button on the recording device vs. smartphone entry) would be a worthy topic for future research because it would yield an index of reliability of self-report. Technology-wise, future basic research might combine more sensors at different sites while balancing the sensor number with their visibility. A *second* set of future directions could treat self-report as a dependent variable, especially in samples that are vulnerable for underreporting. Utilizing the EMG-based approach could aid in characterizing underreported eating episodes based on time point (e.g., morning vs. evening?), and duration (snack vs. main meal). In addition, one could aim to elucidate specific reasons for such underreporting: To illustrate, comparing self-report and EMG-based eating detection could allow for discriminating unconscious versus conscious omission of eating episodes (e.g., ‘just forgot’ vs. ‘no time’, ‘distracted’, ‘uncomfortable reporting’, ‘stressed’, ‘in company’). Likewise, comparing both assessments over longer periods could tap into recording fatigue, which should influence self-report only. *Third*, an important future direction would be an automated prediction of underreporting and corresponding motivational prompting/interventions, specifically in vulnerable individuals (e.g., elevated BMI, restrained eating style) in order to attain more accurate food records and/or to promote eating awareness. While an end user product (e.g. including wireless, light weight EMG sensors) is not yet available, hardware development is advancing rapidly and real-time detection of chewing/eating would be very feasible with current computing capabilities of smartphones. Hence, a last and obvious future direction is to combine the detection of eating events with self-report: An EMG-based chewing detection could trigger input prompts on the smartphone which could confirm and specify eating episodes (whether, what, how much, contexts, etc.). This could be expected to effectively undermine at least the unconscious sources of underreporting and strongly reduce memory biases. Thus, the EMG-based chewing detection could aid in influencing eating behavior by accurately capturing the number and duration of eating episodes. Such ‘omission free’ reporting of food intake could advance basic eating behavior research and inspire new awareness-based eating behavior interventions.

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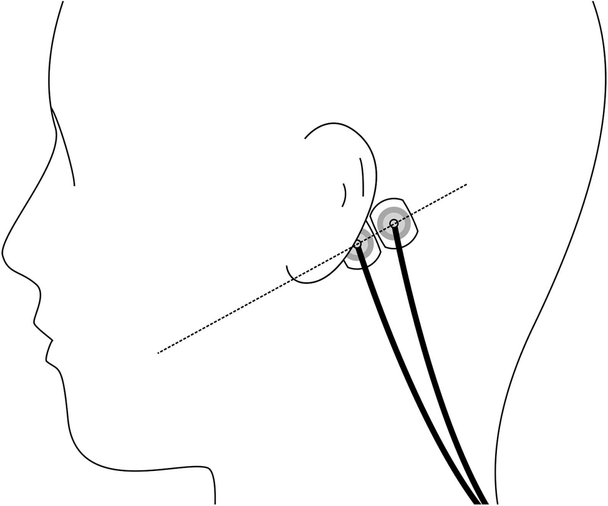
Table 1: *Detection results of the algorithm. The columns Nail biting and Bruxism show whether the participant reported to nail biting or to have bruxism, respectively. The last row shows the statistics after excluding participants who either have bruxism or reported chewing of finger nails.*

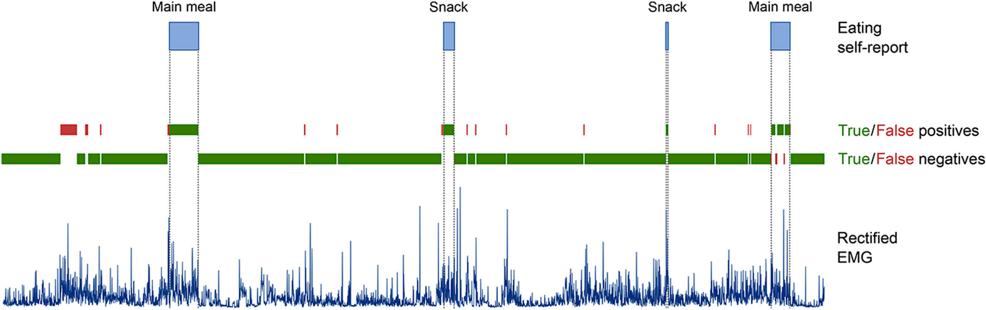
Subject	**Nail biting**	**Bruxism**	**Sensitivity (%)**	**Specificity (%)**
1			100.0	84.1
2			94.1	96.0
3			96.7	90.7
4			94.4	96.6
5			100.0	87.3
6		x	*42.0*	*98.6*
7			94.6	89.1
8			35.5	98.5
9	x	x	*74.2*	*96.4*
10	x		*92.3*	*59.6*
11	x		*100.0*	*40.0*
12		x	*98.0*	*93.1*
13			100.0	89.2
14			100.0	97.6
		Mean (*SD*):	**87.3 (21.7)**	**86.9 (16.8)**
Mean (*SD*) after exclusion:			**90.6 (20.8)**	**92.1 (5.2)**

Figure captions

Figure 1. Electrode placement for the EMG assessment.

Figure 2. Rectified EMG signal, EMG-based eating detection and self-reported eating episodes classified into main meals and snacks. The upper part of the detection result shows false positives in red and true positives in green. In the lower part false negatives and true negatives are shown in red and green, respectively





Main meal
Snack
Snack
Main meal
Eating self-report
True/False positives
True/False negatives
Rectified EMG