

# Non-contact temporalis muscle monitoring to detect eating in free-living using smart eyeglasses

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**Abstract**—We investigate non-contact sensing of temporalis muscle contraction in smart eyeglasses frames to detect eating activity. Our approach is based on infra-red proximity sensors that were integrated into sleek eyeglasses frame temples. The proximity sensors capture distance variations between frame temple and skin at the frontal, hair-free section of the temporal head region. To analyse distance variations during chewing and other activities, we initially perform an in-lab study, where proximity signals and Electromyography (EMG) readings were simultaneously recorded while eating foods with varying texture and hardness. Subsequently, we performed a free-living study with 15 participants wearing integrated, fully functional 3D-printed eyeglasses frames, including proximity sensors, processing, storage, and battery, for an average recording duration of 8.3 hours per participant. We propose a new chewing sequence and eating event detection method to process proximity signals. Free-living retrieval performance ranged between the precision of 0.83 and 0.68, and recall of 0.93 and 0.90, for personalised and general detection models, respectively. We conclude that non-contact proximity-based estimation of chewing sequences and eating integrated into eyeglasses frames is a highly promising tool for automated dietary monitoring. While personalised models can improve performance, already general models can be practically useful to minimise manual food journalling.

**Index Terms**—automatic dietary monitoring, eating detection, chewing detection, smart eyeglasses, wearable accessory

## I. INTRODUCTION

Automated Dietary Monitoring (ADM) aims to retrieve and record diet-related information to ease or remove manual diet journalling, and thus could assist in coaching healthy eating patterns [1]. While various wearable sensor approaches have been investigated to monitor chewing and food intake, robust and universally applicable solutions are yet not available. Over recent years, smart, but regular-look eyeglasses have become a central basis for ADM research. For example, Zhang et al. [2] proposed Electromyography (EMG) recordings within eyeglasses temples around ear bends to capture temporalis muscle activity of chewing. They validated EMG-based monitoring and algorithms to infer eating from chewing activity [3]. Recently, Selamat and Ali [4] proposed to attached a proximity sensor at an eyeglasses frame and capture distance variations between skin and temple during temporalis muscle contractions. More details on related work are described further below.

The temporalis muscle is a wide, fan-shaped muscle located at the temporal fossa, i.e. temporal head region. Anterior vertical fibres of the muscle are largely working as mandible

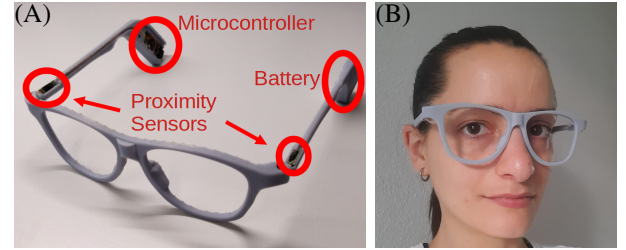


Fig. 1: Non-contact muscle monitoring smart eyeglasses. (A): Eyeglasses frame with bilateral proximity sensors, electronics, and battery. (B): Worn smart eyeglasses.

elevator, to close the jaw, to oppose gravity, and to provide crushing force when chewing food. Posterior fibres are mostly responsible for mandible retraction [5]. Muscle contractions can be detected by its volume changes. Eyeglasses frame temples are conveniently located next to the temporalis muscles, from forehead to ear bends. Estimating the varying distance between skin and temple during muscle volume changes could become an important alternative to existing eating monitoring approaches. Yet, the performance of an integrated system in free-living study conditions has not been investigated.

In this work, we implement regular-look smart eyeglasses that provide a complete setup for unobtrusive proximity sensor data recording. The smart eyeglasses can capture chewing activity as a basis to infer eating behaviour. In particular, the following contributions are made:

- 1) We present an eyeglasses frame-integrated monitoring system, comprising bilateral proximity sensors, signal acquisition, data storage, and battery.
- 2) We use smart eyeglasses in an in-lab and a free-living study to capture over 126 hours of representative data of different food types, activities of daily living (ADLs), and individual routine behaviour. We analyse parallel proximity and EMG recordings.
- 3) We present a novel signal processing and pattern recognition procedure for eating event detection using proximity sensors and report retrieval performance.

## II. RELATED WORK

We focus our review on literature that exploits the temporalis volume change to detect eating or chewing activity.

Zhou and Lukowicz [6] proposed Snacap to monitor snacking behaviour with a smart fabric. Snacap used mechanomyography (MMG) at the temporal region whereby a pressure-sensitive textile sensor inside a head cap detected muscle activity by mechanical coupling the muscle and the textile sensor. MMG couples muscle movement mechanically, i.e. not electrically, and therefore no skin-electrode contact is needed. The authors evaluated their approach with ten participants consuming different snacks and by simulating ADLs in an office building. Each participant recording lasted between 30 and 60 minutes. Chung et al. [7] presented GlasSense, i.e. eyeglasses for monitoring food intake patterns and facial activity by detecting chewing muscle contraction with load cells attached to the eyeglasses hinges. Temporalis muscle contractions would cause a slight movement at the frame temples, which results in increased pressure at the hinges.

Wang et al. [8] used a motion-based sensor to record mastication muscle contraction, detect eating, and count chewing cycles. They used a triaxial accelerometer attached to the temporalis area, and recorded EMG measurements to obtain ground truth. The accelerometer was embedded into a head-band to hold it in place. Authors observed that temporalis muscle contraction frequency corresponded to the one of chewing, and thus could be used to count chewing cycles. Bedri et al. [9] utilised a pair of eyeglasses for multi-modal sensing, including a camera to capture food images, a proximity sensor to detect hand to mouth motion, four gyroscopes for chewing monitoring, and an accelerometer to detect swallowing. Farooq and Sazonov [10] attached a piezoelectric sensor to a pair of eyeglasses to segment and characterise chewing activity. They attached the sensor element directly to the temple area interfacing with the temporalis muscle via a mechanical deflection. Selamat and Ali [4] mounted a proximity sensor within a 3D-printed housing at a frame temple to detect chewing. In their experimental analysis, proximity to the temporal region of one participant and one head side were recorded. The participant performed ten different activities, including eating, for a total dataset duration of 40 minutes. Push buttons were used to obtain labels for eating and chewing activity.

Most developments so far have attached bulky sensors, including proximity sensors, to eyeglasses frames. Due to the cross-influence of sensor integration and their performance, proximity-based eating detection in smart, non-stigmatising eyeglasses remains as an open challenge. Our present work explores the volume change in comparison to EMG recordings as well as analysed eating detection performance across free-living recordings from 15 participants.

## III. METHODOLOGY

### A. Smart Eyeglasses Design

We 3D-printed regular-look eyeglasses frames as a platform for sensors, microcontroller, data storage, and battery. Two

proximity sensors (Vishay VCNL4010) assembled at custom-designed boards were bilaterally embedded at frontal temple areas, angled toward anterior temporalis muscles. The proximity sensor detected reflected infra-red light, where closer surfaces correlate to larger reflected light intensity than surfaces further away. Measurement units were kept as basic, non-calibrated counts. Proximity sensor were sampled at 50 Hz by a microcontroller (ST STM32F4) and readings stored in 512 MB flash memory. Figure 1 illustrates the designed smart eyeglasses and integrated components.

### B. Participant Information

We performed an in-lab study and a free-living study, each with the same 15 participants (four females) between 23 and 33 years old. Body Mass Indices ranged between  $18.9 \text{ kg/m}^2$  and  $29.3 \text{ kg/m}^2$ , avg.  $23.93 \text{ kg/m}^2$ . Participants had no known dental or dietary-related disorder, nor vision impairment. The study was approved by an institutional ethical committee.

### C. In-lab Study

The in-lab study aimed to record temporalis muscle activity in a controlled environment with smart eyeglasses and an EMG reference (CamNtech Actiwave). Participants were asked to perform several activities, including eating, to simulate ADLs, while wearing the eyeglasses. A free choice of food items was provided, including baguette, carrot, apple, cheddar, chips, and beef jerky. Foods were provided in 2 g, 4 g, and 6 g slices. Participants were encouraged to eat at least two items.

*Annotation & ground truth:* We annotated activity timing with a stopwatch and a paper journal, plus recorded the study on video. Annotations were used to create ground truth, complemented by reviewing videos when there were doubts.

### D. Free-Living Study

After an in-lab session, participants were invited to wear the smart eyeglasses for one day, from wake up to bed time. Due to battery limitations, eyeglasses needed to be taken off for recharging. Participants were encouraged to start recordings at 8:00 am, and take a charging break of 90 min before lunch. A second charging break was needed before dinner. We suggested participants to schedule charging breaks to not conflict with their meal times. Moreover, we instructed participants to take off eyeglasses during physically intense or potentially damaging activities, including showering, bathing, and sports. Participants with an eye condition, e.g. myopia, and unable to wear contact lenses, were instructed to use their regular prescription eyeglasses instead for activities that required good vision, e.g. driving a car or working with machinery.

*Annotation & ground truth:* Participants were instructed to note down start and end of eating periods and when not wearing the smart eyeglasses, rounded to the nearest minute. To obtain ground truth, we synchronised and matched participant annotations with raw signal recordings. If there were conflicts or doubts, we interviewed participants about that particular time period and resolved mismatches.

### E. Chewing Sequence Detection Algorithm

We developed an algorithm to detect signal segments of chewing a food bite, i.e. chewing sequences [1]. Eating events were considered as periods of one or more chewing sequences within temporal bounds, following the approach of Zhang and Amft [11]. Figure 2 illustrates all processing steps.

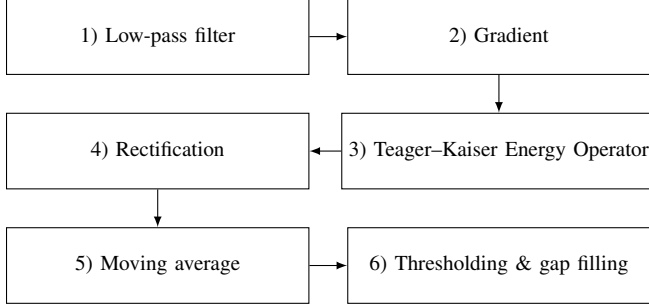


Fig. 2: Block diagram of the chewing sequence detection algorithm developed for proximity sensor signals.

1) *Low-pass filter*: We removed high frequency noises by a fifth-order Butterworth low-pass filter with a 2 Hz cutoff.

2) *Gradient*: Signal readings varied during mastication substantially more than during other ADLs. We obtained the signals' first derivative that highlight signal sections that possibly contain chewing activity.

3) *Teager-Kaiser Energy Operator*: The Teager-Kaiser Energy Operator (TKEO) [12] was used to remove high-frequent content of signal derivatives.

4) *Rectification*: Full-wave rectification was performed to obtain a signal envelope of chewing sequences.

5) *Moving average*: Envelope curves were smoothed by a moving average filter with a 5 sa. window and 1 sa. step size.

6) *Thresholding & gap filling*: A two-thresholding method was applied to envelop signals, thus estimating chewing sequences. A chewing sequence label was assigned if the envelop signal amplitude was between both thresholds. Gaps smaller than 5 min between detected chewing sequences were filled to derive eating event estimates, according to [11].

### F. Averaged vs. Personalised Threshold

1) *Averaged Threshold*: To obtain an average threshold pair that fitted all study participant, we analysed in-lab data. Across all chewing sequences, a grid search was performed to find the highest F1 score.

2) *Personalised Threshold*: To further investigate proximity sensor-based detection performance, we personalised the threshold pair using in-lab recordings of each participant. The threshold pair that resulted in the highest F1 score was selected per participant and applied to the free-living study data.

### G. Bilateral Proximity Fusion

Time-synchronous recordings of bilateral proximity sensor data, i.e. temporalis muscle volume changes from left and right side, were fused by logic AND operation over both eating label estimates to obtain the final eating event.

## IV. RESULTS AND DISCUSSIONS

### A. Recording Statistics

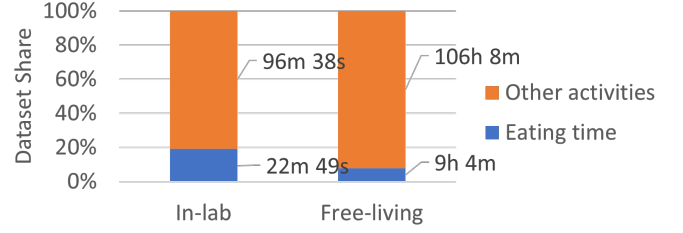


Fig. 3: Dataset statistics of eating and non-eating time according to our ground truth across all 15 study participants.

Our in-lab study yielded a total of almost 2 hours of data, with an average of  $\sim 8$  min per participant. Total eating time was  $\sim 22$  min. Total free-living recording time was  $\sim 115$  hours, with a cumulative eating time of  $\sim 9$  hours. Average recording per participant was  $\sim 7$  hours and 40 min, with  $\sim 36$  min average eating time. Figure 3 shows ratios of eating vs. other activities in our studies.

### B. Phenomena Analysis

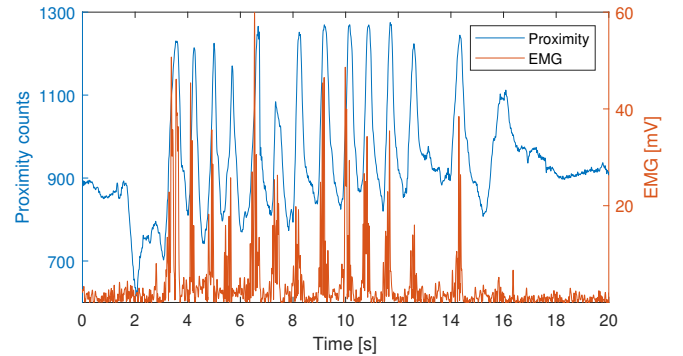


Fig. 4: Example of synchronised proximity sensor and EMG timeseries to support the analysis of muscle volume changes.

To better understand muscle volume change, proximity sensor readings, and muscle contraction during chewing, we analysed smart eyeglasses data and simultaneously recorded EMG of the temporalis muscle from the in-lab study. Filtered and rectified EMG data was synchronised by manually aligning dedicated teeth clenching signal marks of the timeseries, after up-sampling proximity data to the EMG rate of 256 Hz. Figure 4 illustrates an example of proximity and EMG timeseries data. Proximity and EMG signal peaks show temporal alignment, thus both signals mark contraction during chewing cycles. No visual agreement of proximity peak height and muscle work (i.e. EMG signal energy) was observable.

### C. Performance Analysis

Figure 5 shows eating event detection performance for in-lab study data. While there are noticeable improvements in

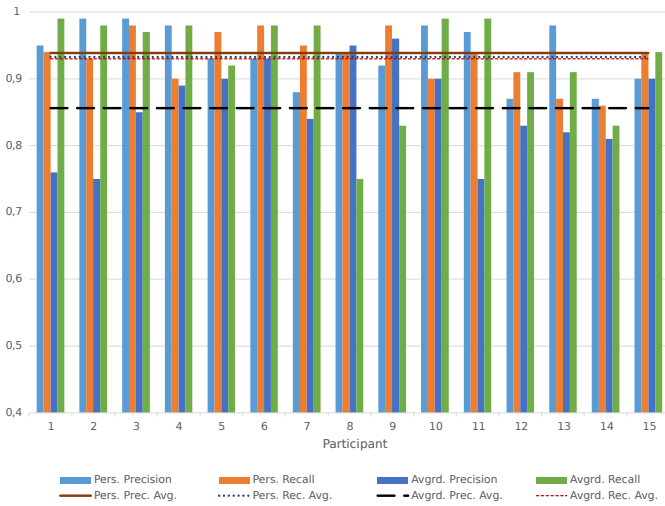


Fig. 5: In-lab study: Precision and recall of eating event detection with personalised and averaged thresholds.

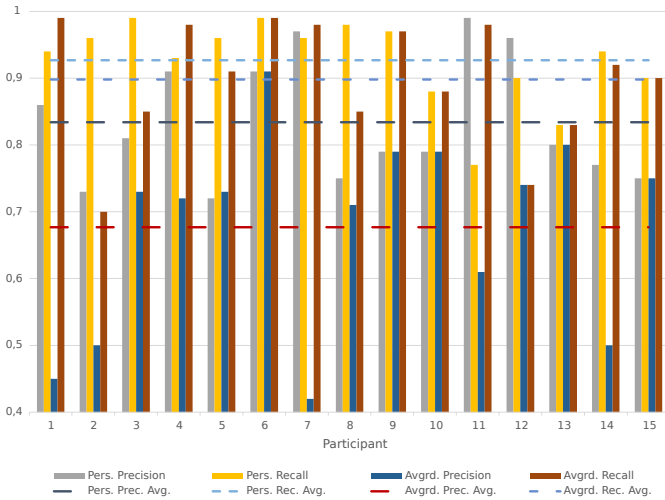


Fig. 6: Free-living study: Precision and recall of eating event detection with personalised and averaged thresholds.

average precision (0.94 from 0.87) when using personalised thresholds, both threshold methods show promising modelling performance. The in-lab results are not generalising, as threshold parameters were fitted with the same data. Figure 6 shows retrieval performances for the free-living data. As threshold settings were done based on in-lab data (see Sec. III-F), deployment performance can be approximated. Average recall showed that consistently most relevant eating events were retrieved, for both averaged thresholds (0.90) and for personalised thresholds (0.93). Average precision showed substantial increase (0.83 from 0.68) for personalised thresholds, indicating that proximity-based eating event detection is meaningful. However, inter-individual differences and artefacts limited performance for averaged thresholds.

## V. CONCLUSIONS & FURTHER WORK

Temporalis muscle contraction results in noticeable alteration in skin surface proximity to eyeglasses temples. We exploit the distance variation to detect chewing sequences and infer eating events using non-contact proximity sensors in-lab and free-living studies. Eating event detection analysis in free-living showed promising results that promote muscle contraction monitoring in smart eyeglasses as an alternative to established contact sensors. Due to the proximity sensing mechanism, sensor readings vary depending on individual head shape, activity, and lighting environment. In the present investigation, personalised thresholds could partially compensate for the variations. However, further investigations on sensors and algorithms may enhance robustness.

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