Chewing Detection from Commercial Smart-glasses

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ABSTRACT

Automatic dietary monitoring has progressed significantly during the last years, offering a variety of solutions, both in terms of sensors and algorithms as well as in terms of what aspect or parameters of eating behavior are measured and monitored. Automatic detection of eating based on chewing sounds has been studied extensively, however, it requires a microphone to be mounted on the subject’s head for capturing the relevant sounds. In this work, we evaluate the feasibility of using an off-the-shelf commercial device, the Razer Anzu smart-glasses, for automatic chewing detection. The smart-glasses are equipped with stereo speakers and microphones that communicate with smart-phones via Bluetooth. The microphone placement is not optimal for capturing chewing sounds, however, we find that it does not significantly affect the detection effectiveness. We apply an algorithm from literature with some adjustments on a challenging dataset that we have collected in house. Leave-one-subject-out experiments yield promising results, with an F1-score of 0.96 for the best case of duration-based evaluation of eating time.

1 INTRODUCTION

Detection of chewing sounds is one of the first approaches that have been studied in the field of automatic dietary monitoring [3]. The idea is to capture (by audio) the distinct sound that occurs when food is crashed between the teeth. Different placements of the microphone have been considered, but the one that seems naturally advantageous is the outer in-ear canal, as it captures the chewing sounds naturally amplified by the skull, while external sounds are attenuated. Typically, microphones have been mounted on custom housing to support this placement, which creates the need for custom-made hardware.

In recent years, various approaches have also emerged, focusing on different sensor solutions such as detection of swallowing sounds [4, 25, 1]. The naturally optimal placement of the microphone for this task is close to the neck, where swallowing sounds originate from. Other approaches attempt to leverage the power of modern wearables, such as smart-watches, by using the inertial sensors (i.e. accelerometer and optionally gyroscope) that are commonly found on such devices, in order to detect and identify eating gestures [15, 14, 12].

Other approaches rely on the availability of cameras to identify food type [6, 5] from single plate photographs, or to directly segment food images into food components [7, 9]. It is also possible to estimate food volume using a depth camera [16] and the caloric content based on a photograph using a reference object [11]. In [10], authors reconstruct a 3D model of the food that is placed on a plate in order to estimate food volume; however, their approach requires two different views (photographs) of the plate. While such approaches can clearly extract very detailed information, they require the active participation of the user by taking a photograph and triggering the analysis, or in some cases specialized cameras (such as depth camera) or multiple views. However, combining with monocular depth-estimation methods [18] can help reduce user and hardware input requirements and simplify the estimation process.

Besides smart-watches, another wearable that has received attention for dietary monitoring is the smart-glasses. Smart-glasses are mostly in experimental state currently, however, many alternative sensors have been mounted and evaluated in the literature. In [29], authors use 3D-printed glasses that incorporate an electromyography (EMG) sensor and evaluate its potential on detecting chewing and identifying food types, on a dataset of eight participants and five food types. The best reported chewing detection effectiveness is 0.8 for both recall and precision, and classification accuracy is reported in the range of 0.64 to 0.84. In [27], they combine it with a vibration sensor. In [28], authors use 3D printed smart-glasses with a bilateral EMG sensor to detect chewing. They evaluate both in lab and free-living conditions. Results for free-living conditions in chewing detection achieve 0.79 recall and 0.77 precision.

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CCS CONCEPTS
• Human-centered computing → Ubiquitous and mobile computing systems and tools.

KEYWORDS
automatic dietary management, wearables, chewing, smart-glasses
device. They propose an algorithm based on feature extraction and classification, using either support vector machines (SVMs) or random forests, targeting three classes: chewing, non-chewing, and walking (as a challenging counterpart for chewing). They evaluate on a dataset from five volunteers, and achieve a classification accuracy of 0.74, however, the prior probability of each class in the dataset is not given.

A pair of glasses with mounted EMG and additional electronics to support communication over Bluetooth with a smart-phone is used in [13]. The proposed algorithm is made of two parts: one that runs on the electronics mounted on the glasses and detects eating periods (vs. non-eating periods) and one that runs on a more powerful processing unit (after the data transfer via Bluetooth) that detects individual chews. Chewing detection is evaluated on dataset of four individuals that eat, drink, and talk, while sited for 40 minutes each, and achieves 0.96 accuracy.

The authors of [8] propose a different approach by using 3D printed glasses that incorporate load cells. The principle of operation is that during chewing, the temples of the glasses (the part that is closer to the ear) is slightly pressed outward, and this increases the load on the cell that is placed at the hinge. The algorithm includes extraction of both time-domain and frequency-domain features and training of an SVM classifier with a radial-basis function (RBF) kernel. Authors evaluate on a dataset of 10 subjects on 6 classes that include left/right side chewing, left/right side winking, talking, and head moving, and report an average F1-score of 0.94.

In this current work, we try to combine the advantages of multiple approaches into a single solution. We employ audio-based chewing detection, as it can provide very accurate results, detailed (per chew) detection, can be used to identify food type [19], food texture [21], and even bite weight [2, 24], and also does not require active user input. We employ a commercial, off-the-shelf device to remove the requirement for specialized/custom-made hardware. We opt for a pair of Bluetooth-enabled smart-glasses by Razer. Finally, we employ a chewing-detection algorithm from literature that has been previously employed on a sensor that combines audio, photoplethysmography, and acceleration signals [22]; the algorithm is resilient to the challenges that this device introduces, such as the non-optimal placement of microphones. To evaluate our work, we conducted a data-collection trial.

The rest of this work is organized as follows. Section 2 describes the sensor, data-collection process, and the algorithm for chewing detection. Section 3 presents the evaluation framework and results and discusses them. Finally, section 4 concludes the paper.

2 MATERIALS AND METHODS

2.1 Hardware and data-collection

The hardware we use in this work for recording audio is the commercially available off-the-shelf smart-glasses by Razer, the Razer Anzu (Figure 1). They are regular glasses (which can also be used as sunglasses) that include stereo speakers and microphones, and communicate with smart-phones and laptops wirelessly via Bluetooth. The microphones are placed on the glasses temples, facing inside, and very close to the glasses end-pieces. They are essentially facing the subject’s eyes from the outer sides. Figure 1 marks the microphone placement with the red symbols: the microphone on

![Figure 1: The commercial smart-glasses that are used for collecting audio, Razer Anzu. (Photo from https://www.razer.com/mobile-wearables/razer-anzu-smart-glasses). There are two microphones marked by the red circle (left side) and arrow (right side, microphone not visible due to perspective).](image-url)
To analyze and evaluate our method we collected a dataset of audio data. A total of 5 subjects (1 male and 4 female, age range 23 to 28) participated in the collection process. Subjects had no reported or diagnosed medical issues relevant to eating and digestion. Each recording lasted approximately an hour, and we collected 6 such recordings (one subject contributed twice). Subjects were instructed to perform the following activities: eating, talking, walking, and resting. Subjects were free to perform these activities in any order, and in any way they wanted. The only instructions that were given were to perform each activity for at least 10 minutes, and have at least 2 eating sessions (so at least 20 minutes of eating).

The recorded audio signals were inspected in Audacity1. We used the eating session annotations that were provided by the subjects via the Android application interface as guides; based on the session annotations we manually annotated each individual chew with start and stop timestamps. In total, the dataset contains 6 hours and 14 minutes of audio, 12 eating sessions (meals), and 9,562 individual chews. For the chew duration, the mean is 0.348 sec and the standard deviation is 0.046 sec. Consumed food types include bread, cucumber, ice-cream, snack bars, and biscuits.

The study was approved by the Ethics committee of the Aristotle University of Thessaloniki (151279/2022). The Ethics committee has also approved the public publishing of derivatives of the dataset (such as mel-frequency cepstral coefficients) along with the manual ground-truth annotations and demographics. All participants were informed about the study, the use of their data, and potential public publishing, and have signed a written consent form.

### 2.3 Detection algorithm

To detect chewing activity, we employ an algorithm from literature [22]. The algorithm includes several steps: a pre-processing filter, feature extraction from short, overlapping windows, training of a binary SVM classifier (chewing vs. non-chewing), and SVM-score post-processing smoothing. The detector yields a sequence of binary labels which correspond to chewing activity.

Based on that, individual chews, chewing bouts, and then eating sessions can be obtained, using a set of heuristic rules. The code for aggregating the classification labels to meals is available online2 from [23].

The biggest challenge for detecting chewing sounds in this work is the different placement of the microphones, compared to the “traditional” in-ear placement commonly found in literature. The natural amplification of chewing sounds through the skull is not present here, while talking sounds are better amplified (since this is the target use-case of the smart-glasses). Based on that, we choose the algorithm of [22] as it is resilient to both challenges.

First, each audio window is normalized before extracting the features by dividing each audio sample with the standard deviation of the audio samples within said window. This step, in combination with the high-pass filtering (with a very low cut-off point) during the pre-processing stage of the algorithm, essentially result in the standardization of each audio window (i.e. forces a mean of 0 and a standard deviation of 1). It should be noted that based on our observations, the captured audio is already zero-mean, so the application of the high-pass filter is redundant.

Second, the algorithm uses a small set of carefully selected features, some of which are exceptionally good at differentiating talking from other sounds, such as the fractal dimension [20], the condition number of the auto-correlation matrix, and skewness [23].

Finally, the sensor we use in this work includes two audio channels, left and right. Based on visual inspection of the signals we have identified that the left and right channels are practically equivalent, and can be used interchangeably. However, we also perform some aggregation tests to confirm our inspection conclusions. We examine the following cases:

1. Early fusion of features: for each window, the full feature set is extracted from each channel and the two feature vectors are then concatenated into a single feature vector

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1.https://www.audacityteam.org/
2.https://github.com/mug-auth/chewing-detection-challenge
We first compare the two channels using the early and late fusion methods described in section 2.3. Early fusion yields an average (across subjects) F1-score (on window based evaluation) of $0.657 \pm 0.078$. Late fusion yields $0.647 \pm 0.063$ using the max operator and $0.64 \pm 0.076$ using a third SVM. Finally, using only the left channel (2) we obtain an F1-score of $0.657 \pm 0.079$ and using only the right channel $0.642 \pm 0.08$. Based on these results, we may pick any of the two channels. All following analysis is based on the right channel.

We then examine the effect of the window size and step. The work of [22] uses two different window sizes: 0.2 sec for some of the features and 0.1 sec for the rest. In this we follow the simpler approach and use the same window size for all features; we test values 0.2, 0.4, and 0.6. We also test the following window step values: 0.05, 0.1, 0.2, 0.3. Figure 3 presents the evaluation results in terms of the F1-score for the window-level classification. The effectiveness benefits from smaller window sizes. The value for 0.2 sec window size and 0.3 window step is expected to be worse since the window step is larger than its size, creating “gaps” of unused signal between successive windows. Based on these results, we select the values of 0.2 and 0.05 for size and step.

Finally, we formulate chews as “pulses” of the binary SVM score, and aggregate to chewing bouts and then eating events and evaluate based on duration. We then plot the precision-recall curve by varying the threshold for the SVM score (default is 0), to examine the limits of our approach in terms of precision and recall. Figure 4 shows the result. Results are very encouraging, as the area under curve (AUC) is 0.9874. We have chosen three points, one with very high precision, one with very high recall, and one balanced, and show the exact values in Table 1. F1-score is equal or greater than 0.92.

3 EVALUATION FRAMEWORK AND RESULTS

3.1 Classifier training

Our dataset includes 5 subjects. To train the binary SVM classifier we perform leave-one-subject-out experiments. We use the radial-basis function (RBF) kernel. For each training, we select the hyperparameters $C$ of the SVM classifier and $\gamma$ of the RBF kernel by performing cross-validation on the training data. The hyperparameters space is traversed using Bayesian optimization (instead of a plain grid-search). Finally, to reduce the computational time we do not use all the available training data each time, but we randomly sample only 500 positive and 500 negative windows. Experimental results with greater samples (1,000 and 2,000 per class) yield similar results but significantly increase the computational time.

We first evaluate the effectiveness of the trained classifiers directly by computing a binary confusion matrix based on the window labels. We compute precision, recall, and F1-score for each subject and also the mean across subjects.

We also construct precision vs. recall plots by varying the decision threshold of the SVM scores (after the filtering).

3.3 Results and discussion

We first compare the two channels using the early and late fusion methods described in section 2.3. Early fusion yields an average (across subjects) F1-score (on window based evaluation) of $0.657 \pm 0.078$. Late fusion yields $0.647 \pm 0.063$ using the max operator and $0.64 \pm 0.076$ using a third SVM. Finally, using only the left channel (3) we only use one channel, either the left or the right one.

It is important to note that the algorithm of [23] is originally applied on audio signals with 2 kHz sampling rate. In this work, we adjust the thresholds, filters, and feature extraction parameters accordingly, to accommodate the higher sampling rate of the smart-glasses.
work includes making a variant of our dataset public to enable leveraging the two microphones and examine the possibility of its effectiveness for eating vs. non-eating time is very promising, yielding a bust, chewing-detection algorithm from literature, and evaluate on available hardware for automatic eating detection. We perform Figure 4: Precision-recall curve for duration-based evaluation of eating time. Each point is the average (across subjects) for a different threshold of SVM scores (default is 0). Exact values for the three red points are shown in Table 1. Area under curve (AUC) is 0.9874.

4 CONCLUSIONS
In this work we examine the feasibility of using off-the-shelf, commercially-available hardware for automatic eating detection. We perform chewing detection based on audio captured by Bluetooth-enabled smart-glasses, the Razer Anzu. We combine this choice with a robust, chewing-detection algorithm from literature, and evaluate on an in-house yet challenging dataset of over 6 hours. Detection effectiveness for eating vs. non-eating time is very promising, yielding F1-score above 0.92 and as high as 0.965 for the best case. Future work includes making a variant of our dataset public to enable direct comparison of similar approaches on this hardware, better leveraging the two microphones and examine the possibility of identifying the side of chewing (left, right, or middle), and finally evaluating on larger and more challenging datasets.

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