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Development of an Eyeglass-type Chewing Detection Device with a Pressure Sensor Array

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Eating is an essential part of our daily lives. Detection of accurate food intake leads to automatic dietary assessment. Conventional chewing (mastication) detection methods primarily use electromyography which requires attaching and detaching myoelectric pads. In this study, we developed a wearable chewing detection device that uses a pressure sensor array and a shock-absorbing material integrated into a temple frame of eyeglasses. The proposed design eliminates the need for adjusting the sensor placement in advance, as the developed eyeglass-type device ensures consistent contact with the wearer's temporal region. The deformation of the temporal region during chewing is captured by the pressure sensor array as the pressure changes. We analyzed the data when wearers chewed food samples and proposed an algorithm to detect chewing by using a dynamic adaptive threshold. The fundamental experiment showed that the algorithm can detect the timing of chewing with a maximum delay of 58 ms from the detection time point to the sound peaks of the food breakdown sound as a reference.

1. Introduction

Food intake and eating habits have a significant impact on our health.[(1)] In the food intake process, chewing is the most obvious behavior because it is repeated during food intake.[(2)] Accurate food intake detection and food classification are important steps towards the estimation of the volume and calories of food for automatic dietary assessment.[(3)] In addition, the ability to chew and swallow deteriorates with age. To reduce the risk of aspiration, leading to asphyxia or pneumonia,[(4)] a softened food (mousse meal) is provided at nursing facilities. However, softened foods reduce the enjoyment of eating because of the loss of texture.[(5,6)] The perception of crispness is affected by sounds produced during biting,[(7,8)] so a method to provide food breakdown sounds when eating softened foods during chewing has been proposed in related studies.[(5–7)] The chewing detection during eating is a key element to realizing the system for monitoring health or improving the enjoyment of eating by providing food breakdown sounds.

Chewing can be detected by several methods. Acoustic measurements to detect chewing when eating foods using condenser microphones,[(9)] ear microphones,[(10)] bone conduction

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microphones on the ear canal,[11] and microphones of commercial smart glasses[12] have been proposed. Methods using chewing sounds are easy to implement, but it is difficult for softened food because the chewing sounds will be weakened. Electromyography (EMG) is commonly used to detect chewing.[4,5,13,14] The EMG of jaw, neck,[13] and masseter muscles[4,5] showed promising performance. However, its applications remain limited owing to low wearing comfort[14] because this method requires wearers to attach electrodes to their faces, which is inconvenient for daily diet monitoring. Consequently, an eyeglass-type device with dry electrodes has been developed, but the results were affected by the ear position and hair because the dry electrodes could not sufficiently come in contact with the skin compared with normal electrodes.[14,15] Therefore, a method for detecting chewing using deformation sensors has been proposed. An eyeglass-type wearable device with a curved piezoresistive bend sensor attached to the right temple realized measurement of the contraction of the temporalis muscle.[16] Eyeglass-type devices enables fixing of the sensor coordinates because their positions are fixed when they are worn. However, the discussion about real-time detection is insufficient. The real-time chewing detection during eating is also important for chewing measurement devices because these devices can be used to enhance the eating experience of softened foods by extending the sense of chewing food that people perceive by presenting sounds generated during chewing. Although several studies showed good results in the detection of food intake, previous detection methods require a certain duration of data frame. A detection algorithm for data from the strain gauge sensor showed an average accuracy of 80.98% in detecting chewing at a time resolution of 30 s.[17] A hidden Markov model was used to detect chewing from audio every 500 ms.[18] The real-time detection of chewing events enables us to display food breakdown sounds at the right time points.

Therefore, we developed a wearable chewing detection device that uses a pressure sensor array and a shock-absorbing material integrated into a temple frame of eyeglasses. The proposed design eliminates the need for adjusting the sensor placement and attaching the sensors on wearers' skin in advance. The deformation of the temporal region during chewing is captured by the pressure sensor array as the pressure changes. We analyzed the data obtained when wearers chewed food samples. Finally, we here propose an algorithm to detect chewing by using a dynamic adaptive threshold.

2. Materials

The system should allow for natural measurements during daily eating activities without the need for expensive or uncomfortable hardware.[19] In this study, we mounted a pressure sensor array on the frame of eyeglasses by focusing on the expansion and contraction of the muscles of the temporal region during chewing. Measuring muscle movements is a promising method for detecting chewing with a wearable device. The placement of the sensor on the muscle affects the chewing measurement results. Therefore, to measure the muscle movement during chewing, we used a pressure sensor array and a shock-absorbing material on the temple of eyeglasses. Therefore, the proposed device does not require wearers to attach the sensors directly to their skin.

Figures 1(a) and 1(b) show a schematic diagram and a developed prototype of the proposed device, respectively. Eight pressure sensors (FSR400, Interlink Electronics Inc.) were installed

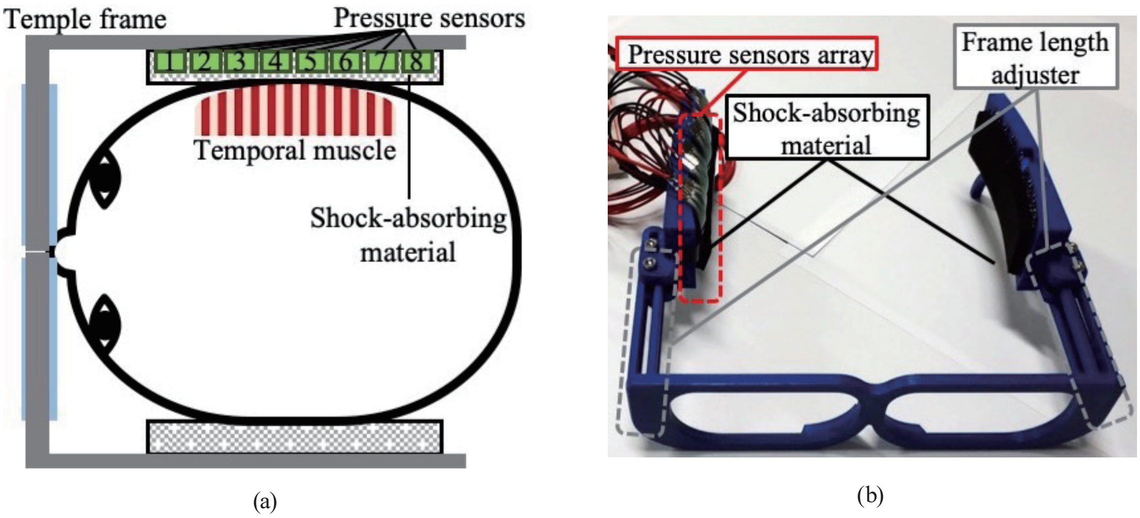


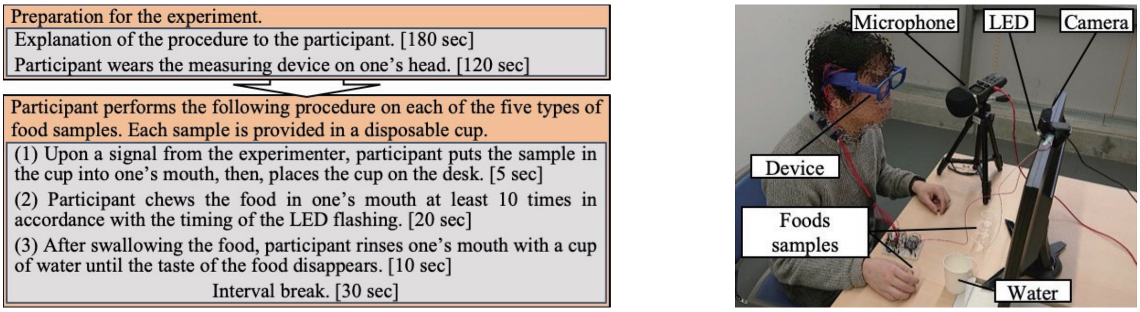
Fig. 1. (Color online) (a) Schematic diagram and (b) developed prototype of eyeglass-type chewing measurement device.

between the shock-absorbing material (Sunpelca L-2500, Sanwa Kako) and the right temple frame in a 10 mm pitch. The frame was printed using a 3D printer with poly-lactic acid to adjust the sensor placement to individual size and shape of the head. As the wearer chews, the temporal region expands and contracts, which generate the deformation of the shock-absorbing material. We measured this deformation of the shock-absorbing material using pressure sensors. This material enables measuring the muscles movements with a larger contact area because it fills the gap between the head and the sensors. When the sensors are directly attached to the frame, measurements will only be taken at the point of contact between the head and the sensors. The sensor values were read using a 12-bit 8-channel analog digital converter (MCP3208, Microchip Technology) at a sampling rate of 200 Hz. A microcontroller (ESP32-WROOM-32D, Espressif Systems) stores the sensor values and transmits them to a laptop computer via Bluetooth.

3. Experiments

The expansion and contraction of the temporal region were measured by pressure sensors. The procedures and protocols were approved by the Research Ethics Committee, Institute of Systems and Information Engineering, University of Tsukuba (Approval No. 2021R460). In this study, two participants agreed to provide informed consent and performed the experiments.

To make the participant chew food at the presented frequency, we used a flashing LED as an indicator. First, the participant chewed in synchronization with the LED, which switched ON/OFF at 1.5 Hz (chewing at 0.75 Hz). In previous studies, various types of food such as carrots, apples, bananas,[16] crackers,[6] chips,[20] and softened foods[5] were used. To evaluate the capability of the device in detecting food samples with different hardnesses, we used jelly, bananas, carrots, apples, and potato chips in this experiment. Figures 2(a) and 2(b) show the experimental procedure and the experimental environment, respectively. The experiment was



(a) (b)

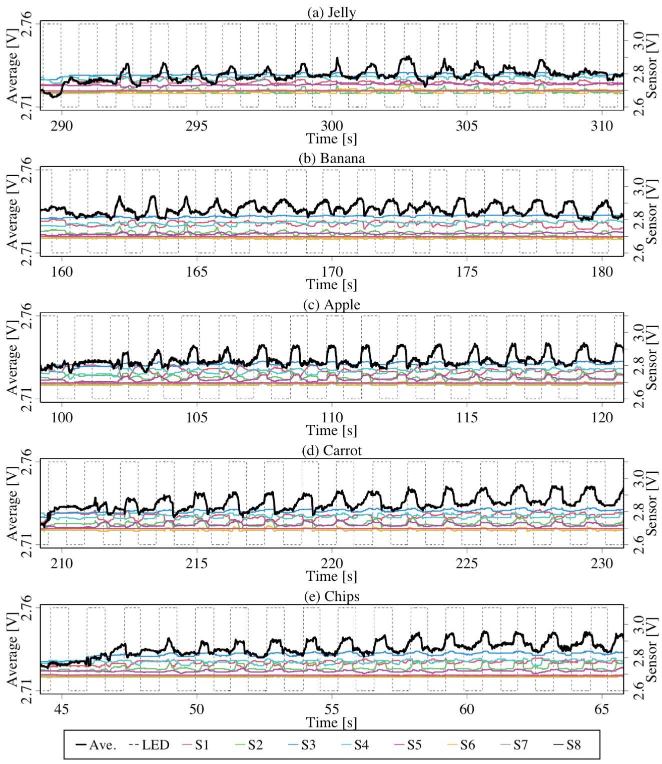
Fig. 2. (Color online) (a) Procedure and (b) setup of the experiment.

conducted as follows: (1) the participant took the sample into their mouth with a spoon, (2) the participant naturally chewed the food at least 10 times in synchronization with the flashing of the LED, and (3) after swallowing the food, the participant rinsed their mouth with mineral water until the taste of the consumed food disappeared. Processes (1) to (3) were performed using five food samples that were provided randomly. The data obtained from the eight pressure sensors were recorded using a laptop connected to the device via Bluetooth. Simultaneously, chewing sounds (food-breaking sounds) were recorded with a microphone (H5, Zoom) as references for the actual time point of chewing. To synchronize sound data with sensor data, we used beeps from a speaker installed on the device. The rising waveforms of sound data were matched to the change in digital pin's output.

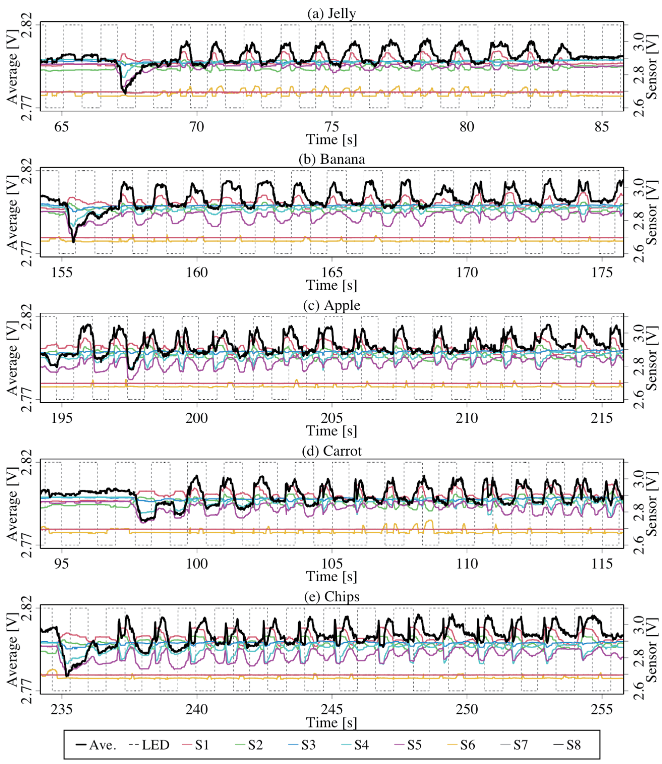
4. Results

The values obtained from the sensor array while chewing different food samples are shown in Fig. 3. The placement of the sensors that captured the pressure change was different between the participants because of their different head sizes; thus, we calculated the average of the eight pressure sensors, as indicated by the black lines in Fig. 3. In all ten cases, the voltage increased when the participants closed their mouths and decreased when they opened their mouths. Furthermore, we confirmed that the voltage increased and decreased in conjunction with the flashing of the LED. This implies that the voltage value changes on the basis of the chewing action. However, the flashing LED timing was inappropriate for the ground truth of the chewing timing because there was a delay between the participant observing the flashing LED and initiating the chewing action.

The chewing motion changes when consuming foods with different hardnesses.(16) The obtained values differ when chewing food samples with different hardnesses. When chewing relatively soft food such as jellies or bananas, only one voltage peak was observed during one chewing sequence. When chewing relatively hard foods such as carrots, apples, and chips, two voltage peaks were observed in one chewing sequence [Fig. 3 (b)]. The anterior and posterior regions of the temporalis shows different behaviors during chewing.(21,22) We believe that these behaviors were observed because the sensor array covered the side of the head.



(a)



(b)

Fig. 3. (Color online) Sensor values from (a) participant 1 and (b) participant 2.

5. Discussion

The development of a chewing detection algorithm and the evaluation of the detection based on the time error between the chewing sound occurrence and the chewing time point detected by the algorithm are discussed. We processed the experimental data to obtain the optimal threshold.

5.1 Detection of time of chewing

First, we examined the relationship between sensor values and chewing sounds from the data when participants consumed potato chips because this food sample can generate audible chewing sounds. The voltages obtained from the sensor array were smoothened using a moving average filter shown in Eq. (1) to reduce noise, where f_s is the sampling frequency of the sensor array, T_f is the duration of the filter size for the moving average, and $V(i)$ and $V_f(i)$ are the raw and filtered values at sampling point i, respectively. The filter size was set to 10 samples (f_s = 200 Hz and T_f = 0.05 s). The audio information was processed using a bandpass filter with a range of 7,000 to 10,000 Hz to extract regional peaks corresponding to food breakdown sounds.

The temporal region movement activated during mouth closure for chewing was measured using the developed device as the sensor voltage increased. To identify the increase in voltage associated with chewing, the proposed algorithm captures this phenomenon using a dynamic adaptive threshold. In addition, chewing detection should be realized with the data of current and past time points to realize the real-time detection of chewing while eating. The proposed chewing detection method uses an algorithm comprising four steps (see Fig. 4). Step 1: The sensor voltage increases when the wearers close their mouths; therefore, it is determined whether the current sensor value is larger than the sensor value sampled at the previous sampling point. Step 2: The system determines whether the current value of the threshold calculated from the current sensor value is larger than the threshold calculated at the previous sampling point. Step 3: This threshold responds with a delay in the actual sensor value. Therefore, when the mouth opens immediately before closing, the sensor value became low but the threshold is still high. To detect this condition, we determined whether the previous threshold was larger than the previous sensor value. Step 4: When the mouth is closed (time point of chewing), the sensor value shows a

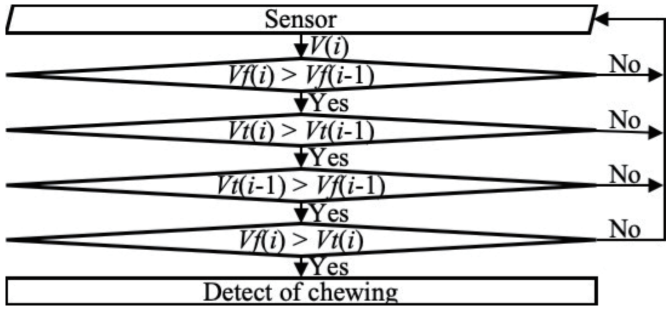


Fig. 4. Chewing detection algorithm.

sudden increase. The system determined this increase when the voltage was greater than the threshold.

The dynamic adaptive threshold was calculated using Eqs. (2) and (3), where $V_t(i)$ and $V_o(i)$ are the threshold and offset values for chewing detection, respectively. The first term on the right side of Eq. (2) represents the average voltage value calculated from the previous data for a certain time duration T_t. The second term represents a baseline to account for reducing the influence of noise when the wearers are wearing the device and not chewing. This baseline was calculated by multiplying the gain k and the voltage difference between the maximum and mean voltages acquired during a certain period T_o. Finally, we used the past 0.5 s to calculate thresholds (f_s = 200 Hz and T_f = 0.5 s) and the past 2.5 s to calculate offsets (f_s = 200 Hz and T_o = 2.5 s and k = 0.05). To minimize the time delay, we used the raw data to calculate the threshold. The typical chewing rhythm ranges from 1 to 2 Hz.[6,23,24] Therefore, the detection process was temporarily halted for a duration equivalent to half the minimum chewing frequency (0.5 s) after detecting one chewing to prevent multiple detections from a single chewing sequence.

$$V_f\left(i\right)=\frac{1}{f_sT_s}\sum_{n=0}^{f_sT_s-1}V\left(i-n\right) \tag{1}$$

$$V_t\left(i\right)=\frac{1}{f_sT_t}\sum_{n=0}^{f_sT_t-1}V\left(i-n\right)-kV_o\left(i\right) \tag{2}$$

$$V_o\left(i\right)=\max\left(V\left(i-n\right):n=0,\ldots,f_sT_o-1\right)-\mathrm{mean}\left(V\left(i-n\right):n=0,\ldots,f_sT_o-1\right) \tag{3}$$

The calculated dynamic adaptive thresholds are plotted on the break lines in Fig. 5. Red and blue dotted vertical lines indicate the time points of the threshold exceedances and the regional peaks corresponding to the food breakdown sounds, respectively. We analyzed the first 10 chewing detection results. The peak of the audio signal and chewing timing detected by the dynamic adaptive thresholds showed an average error of 51 ms in the negative direction and 24 ms in the positive direction (range: −131 to 58 ms). A positive error indicates detection occurring after the sound peak, while a negative error indicates detection occurring before the sound peak. The error distribution is shown in Fig. 6. Kaneko *et al.* reported a time difference of approximately 50 ms in the positive direction, which is considered a negligible problem for practical use[6] and Nakajima *et al.* reported that a time difference of less than 100 ms cannot be perceived.[25] In this study, the maximum detection time delay was 58 ms and the average delay was 24 ms. Therefore, the proposed method can be practically used including systems to enhance the eating experience of softened foods by extending the sense of chewing food that people perceive by presenting sounds generated during chewing. Moreover, for 55% of chewing detection results, the proposed threshold can detect chewing before the regional peak of food breakdown sounds. The proposed dynamic adaptive threshold can predict the mouth closure before actual chewing. To eliminate delays in sound perception during sound presentation, it is important to predict mouth closure.

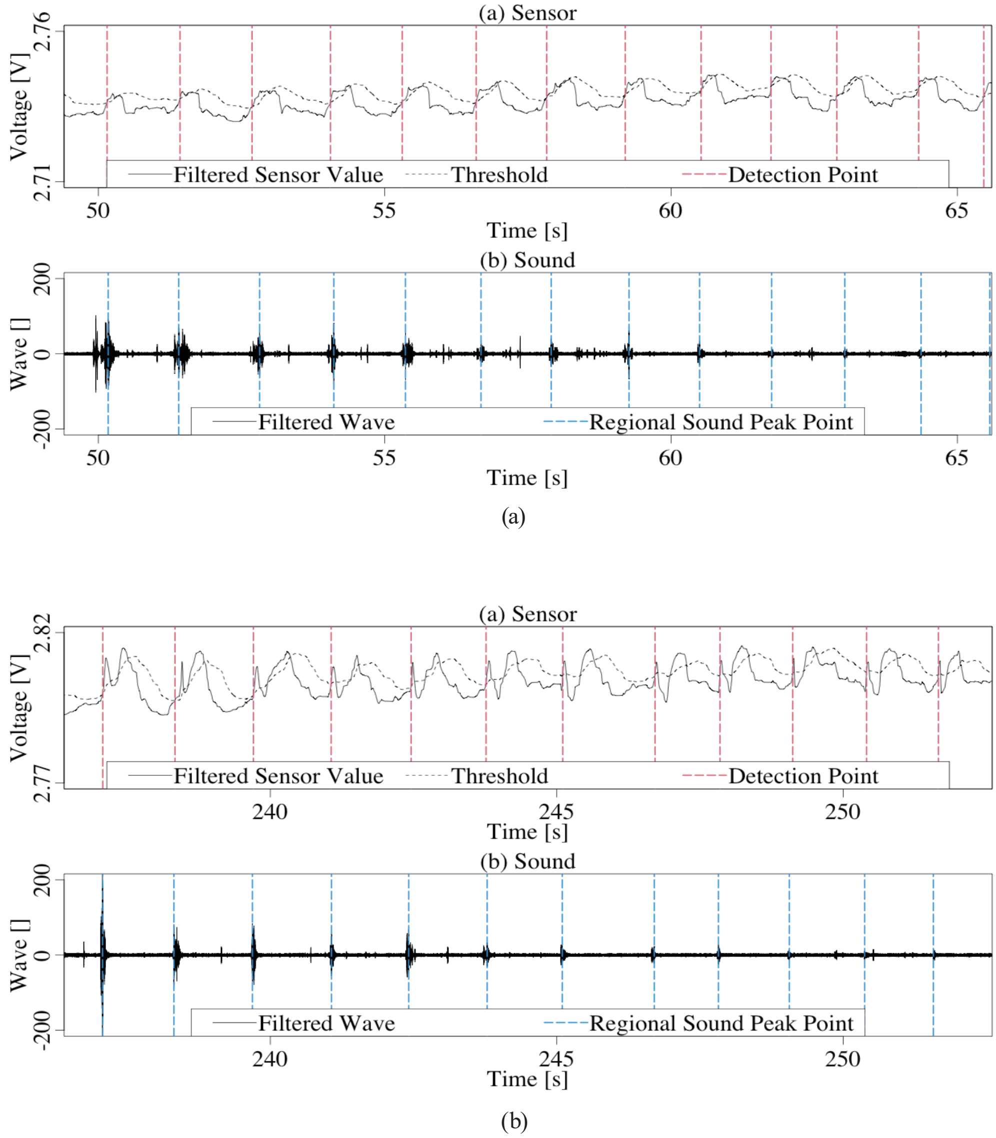


Fig. 5. (Color online) Detected chewing and food breakdown sounds of (a) participant 1 and (b) participant 2.

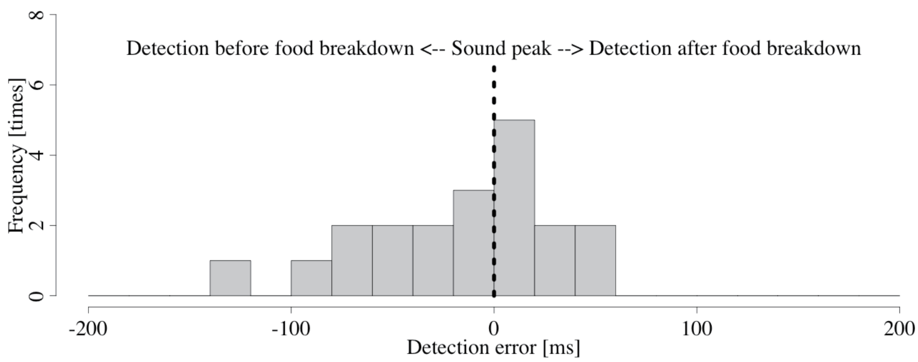


Fig. 6. Error distribution of chewing detection time points and food breakdown sound regional peaks.

Chewing changes when consuming foods with different hardnesses. To assess whether the proposed algorithm can be applied to food other than chips, we applied the same algorithm to the data obtained from two participants who consumed jellies, bananas, apples, and carrots. On the basis of the detection results, we validated whether chewing was correctly detected for the first ten chews of five food samples for the two participants by referring to the recorded video and audio. The results showed that it was possible to detect 99 out of 100 chews in the experiments.

5.2 Limitations

There were cases where chewing was not detected at the appropriate time and other cases where chewing was detected twice in a single chewing or chewing was detected even though no chewing occurred. A possible reason for these errors is that the sensor value contained high-frequency noise. To avoid errors caused by the delay of digital filters, incorporating coupling capacitors for low-pass filtering is needed to remove DC components. Moreover, we did not test the device and detection methods in daily life environments where the sensor data are influenced by the head movements and speaking of the wearers. For practical applications, it is necessary to increase the number of participants and types of food. Furthermore, the experiments should be conducted under the conditions of daily life so that reliable data can support the results of this study.

6. Conclusion

In this study, we developed an eyeglasses-type chewing detection device using a pressure sensor array. The proposed glass-type device does not require wearers to directly attach sensors to their skin. Moreover, the device can be adopted to the different head sizes of wearers. Specifically, to measure the displacement of the temporal region caused by temporal muscle movement while chewing, eight pressure sensors and a shock-absorbing material were attached to the frame of an eyeglass-type device using pressure sensors. In addition, we proposed a dynamic adaptive threshold for detecting the mouth closure using the average value from the sensor array. The proposed thresholds detected 99 of 100 chewing samples obtained from 2 participants, five food samples, and 10 counts of chewing. The peak of the audio signal and the chewing timing detected by dynamic adaptive thresholds showed a negligible error for practical sound presentation devices, with a maximum time delay of 58 ms. Our future tasks include an analysis of the error distribution depending on the samples other than chips, an experiment that provides food breakdown sounds at the time of detected chewing. It is necessary to develop a complete system for chewing detection and sound presentation. Thus, the extension of the sense of chewing food that people perceive to enhance the eating experience will be evaluated.

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