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A review of chewing detection for automated dietary monitoring

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ABSTRACT

A healthy dietary lifestyle prevents diseases and leads to good physical conditions. Poor dietary habits, such as eating disorders, emotional eating and excessive unhealthy food consumption, may cause health complications. People's eating habits are monitored through automated dietary monitoring (ADM), which is considered a part of our daily life. In this study, the Google Scholar database from the last 5 years was considered. Articles that reported chewing activity characteristics and various wearable sensors used to detect chewing activities automatically were reviewed. Key challenges, including chew count, various food types, food classification and a large number of samples, were identified for further chewing data analysis. The chewing signal's highest reported classification accuracy value was 99.85%, which was obtained using a piezoelectric contactless sensor and multistage linear SVM with a decision tree classifier. The decision tree approach was more robust and its classification accuracy (75%–93.3%) was higher than those of the Viterbi algorithm-based finite-state grammar approach, which yielded 26%–97% classification accuracy. This review served as a comparative study and basis for developing efficient ADM systems.

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Automated dietary monitoring; chewing; wearable sensors

1. Introduction

Food intake is the main source of human nutrition and necessary to maintain life. Monitoring daily food intake behavior directly affects human health (Bell et al. 2020). Understanding food intake behaviors helps in the diagnosis and treatment of eating disorders, such as bulimia, binge eating and anorexia. The balance between basal metabolic energy consumption and food energy intake is an important factor in maintaining body weight stability (Fontana, Farooq, and Sazonov 2020, 2014). The imbalance between these two components can lead to weight changes, which may result in abnormal weight loss or increase. For many people, hunger and malnutrition are still problems.

Obesity has surpassed hunger as a major global health threat. Excessive food intake may be a significant cause of obesity. Individuals who are overweight and have obesity receive highly valued health services. In 2016, the WHO reported that 39% of adults aged over 18 years were overweight, and 13% of adults aged over 18 years had obesity (Selamat and Md Ali 2020). For these reasons, personal eating behavior must be monitored to manage people's health. Various methods have been used to explain diet by recording chewing. Free-living automated dietary monitoring (ADM) is proposed to detect dietary events in diet management accurately (Papapanagiotou et al. 2017).

Eating behavior is assessed by self-reports, such as questionnaires, which are unreliable to a large extent because people tend to underestimate their food intake (Zhang and Amft 2020). Therefore, this method cannot be used for analysis and further operations.

The development of mobile computing technology, computer networks and wearable sensors has provided tools for establishing a reliable, objective and noninvasive monitoring system for nutrition and diet habits. However, to date, a device that can automatically detect eating behavior under free-living conditions is not commercially available. The behavioral indicators of eating behaviors need to be defined to develop automatic food intake monitoring

Food intake involves a process through which an individual performs a hand-to-mouth movement, biting, chewing and swallowing. Hence, all dietary activities start and end in a given temporal relation. This work aims to propose a method for evaluating chewing activities and meeting the need for ADM. This project focuses on helping people plan their food consumption better. Users can comprehend their food intake per day and make suitable arrangements for planning. Chewing activity detection is a small part of ADM, but it is fundamental in dietary activities.

Figure 1 depicts the two main parts of this work, namely, detectors and sensors. Important characteristic chewing patterns, such as motion, chewing velocity and jaw kinematics to food hardness, are presented. The features of chewing and the collection and processing of chewing signals are demonstrated. Different kinds of sensors, which are significant parts of the project, are identified (Hossain, Imtiaz, and Sazonov 2020; Nakamura et al. 2021).

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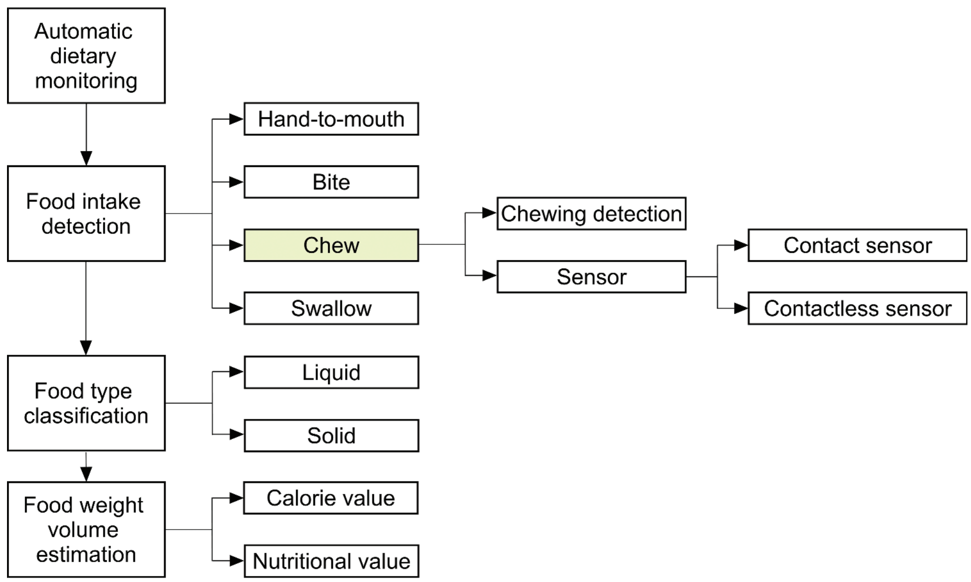


Figure 1. Scope of the chewing detection review.

2. Food intake and chewing activities

The basis of obesity and eating disorder treatments is monitoring food intake, which can be planned and managed by dietary controls. Therefore, food intake monitoring is important for understanding, identifying and modifying the food intake patterns of individuals.

2.1. Food intake monitoring

In the past, tracking real-time food intake and eating behavior was a long-term attempt. The first questionnaire assessment was used in the 1940s. Some coaches and clinicians still choose to self-report and obtain advice on healthy eating choices (Zhang and Amft 2020). With the popularity and development of smartphones, various methods, such as diet-diary applications, have improved.

The network function of smartphones also gives this method more functions, such as real-time self-monitoring and doctors' quick responses. Wohler et al. developed a food intake survey system that functions on a Motorola Q9h smartphone to record and analyze daily eating. A similar system is proposed to focus on calorie intake by taking notes. This method depends on memory, which is impractical for some people, especially users with memory impairment or disabilities (Mamud et al. 2021; Tsai et al. 2007). In recent years, various methods have been studied by using many devices, including sensing methods, such as visual, glottis, inertial, acoustic, piezoelectric, electromyography and capacitive sensors.

2.2. Chewing activities and characteristics

Chewing is a dynamic process that involves regular motions, including simultaneous movements of the jaws, tongue and cheeks and the use of molars to crush the bolus. After the food enters the mouth, it is subjected to a series of chewing until the bolus is swallowed. The regularity of chewing is generated through a central pattern generator (CPG), which activates the motor drives that coordinate the movement of the facial muscles, tongue and jaw. All these behaviors constitute an individual's chewing pattern. The chewing function adjusts itself according to food characteristics; for example, the hardness of food affects chewing activity (Tonni et al. 2020).

The effect of food hardness on the number of chewing cycles is significant throughout the chewing process, from the beginning of food intake to the end of the first swallowing cycle. It involves tongue pull-back movement (TPM), which moves food from the front of the mouth to the back of the canines to allow chewing with maximum jaw opening (San et al. 2020). TPM is followed by tongue squeeze-back motions (TSM), which push food to the pharynx for swallowing. These movements show that chewing cycles, TPM and TSM increase from soft food to hard food.

Chewing efficiency is the number of chewing cycles up to half the initial particle size. Chewing performance is the median particle size obtained after chewing a certain number of times (Tewksbury et al. 2018). Chewing habits show that slow and less effective chewing leads to changes in food texture. Subjects who chew more efficiently tend to chew the product in less time.

The effect of age on masticatory activity shows that older people compensate for the lower muscle contraction amplitude by longer masticatory time and achieve the same total muscle work as younger people; young and older people exhibit different chewing strategies and muscle activities.

3. Chewing signal processing

Manual recording based on a self-reported questionnaire leads to inaccurate data and loss of people's interest in conducting food intake monitoring. Manual recording via a smartphone significantly depends on user records and memory.

3.1. Chewing signal data acquisitions

Electromyography (EMG) is a technique that records the electrical activity causing muscles to contract during chewing. EMG can record muscle activities in the chewing process and provide information about the interaction between food and an individual during the entire chewing activity. However, the EMG standard practice has not been established, and issues remain (Ashiga et al. 2019).

Photoplethysmography (PPG) is a technique used to detect changes in reflected light levels due to alteration in venous blood characteristics. It is commonly utilized in smartwatches and activity monitors that measure the heart rate. A PPG signal is not completely noise-free. Sudden changes in ambient lighting can produce important artifacts and cause signal saturation (Papapanagiotou et al. 2017).

Electroencephalography (EEG) is an electrophysiological monitoring method that records the reaction of multiple electrodes by touching the subject's scalp and forehead; it includes a new technology involving passive or active biosensors that connect to multiple electrodes for measuring the voltage fluctuation caused by ion current in the cerebral neuron synaptic region. EEG-based brain wave measurement requires specific equipment, software and larger test space, which means high cost (Songsamoe et al. 2019).

Proximity techniques refer to the utilization of proximity sensing devices to detect motion or change. Proximity sensors have comparatively high accuracy in detecting chewing performance. They are usually composed of nine types of sensors, namely, inductive, capacitive, photoelectric, ultrasonic, piezoelectric, infrared red photodetector, time of flight (ToF), VCSEL and organic crystal sensors. The details of these nine types of sensors are illustrated in Section 4.

3.2. Chewing detection protocol and experiments

Chewing protocols are designed as rules and processes determined to obtain experimental results similar to practical situations because of the diversity of occasions and situations related to food intake. Päßler and Fischer (2011) demonstrated that the chewing activities of 40 participants aged 15–77 years were recorded. The instructions to participants included eating seven types of food with 10 pieces and drinking 30 sips of pure water or juice. The seven food types were pudding, peanut, apple, chocolate, potato chip, carrot and walnut. Then, 17 hours of data were collected.

Zhang and Amft (2020) investigated eating food with different hardness, where 10 pieces of raw carrots, cucumbers and bananas were offered, respectively. The participants were instructed to eat one piece at a time. Food was taken as follows: banana > cucumber > carrot, indicating the increase in food hardness. Moreover, they explored free-living eating monitoring by using integrated smart eyeglasses. Each participant was required to record full-day life for 10 days while cooking, eating, walking, talking, sports, attending lectures, taking public transportation, working in offices and taking eyeglasses off. Thomaz et al. invited 21 right-handed participants between the ages of 20 and 43 years to discriminate eating and non-eating activities (Thomaz, Essa, and Gregory 2015). Food intake activities were experimentally recorded with an average of 31 min and 21s. A smartwatch was placed on the arm of each participant for recording. The food and drink of the subjects were not limited.

Selamat and Ali recorded 10 sets of a series of chewing activities involving eating carrots, bananas and apples within 90, 30 and 30s, respectively (Selamat and Md Ali 2021). Resting periods of 15s were set at the beginning and end of the recording, and resting periods of 30s were allotted between food intakes. Hence, each data set contained 240s of recording, and this experiment protocol achieved more than 90% of classification accuracy.

3.3. Chewing data signal processing

Signal filtering is used to recover a signal from the observed noisy data while preserving its important features, such as smoothness. Low-pass filtering algorithm (LPFA), high-pass filtering, Wiener filtering and other filtering methods are utilized to filter the signal.

Signal normalization compensates for differences in signal amplitudes amongst subjects. Normalization helps make the signal consistent without losing signal information. Ferriday et al. showed that the intake data generated from the filtered weight loss data are normalized by subtracting the first signal value from the whole time series (Ferriday et al. 2016).

Signal segmentation is one of the fundamental problems of digital signal processing in various information, prediction and control systems. Sazonov et al. divided chewing signals into decision epochs, which are non-overlapping windows of fixed duration in a chewing signal. A decision epoch is defined as food intake detection time resolution; a shorter one leads to a higher temporal resolution and a shorter time to determine food intake (Sazonov and Fontana 2012). Feature extraction is used to transform high-dimensional feature information into a low-dimensional feature by mapping or to transform and compress feature information. Farooq et al. divided all detected signals into non-overlapping epochs for feature computation and chose the appropriate epoch size to detect short snacking episodes. Moreover, Farooq and Sazonov (2016b) computed the set of 68 times and frequency features for each epoch. The feature set includes time and frequency domain features. Time domain features are related to time statistics of epoch data and crossing characteristics. Frequency domain features are based on the spectrum's peak frequency and standard deviation.

Signal classification is used to discriminate signal data with different features and properties. Neural network (Liu et al. 2012; Bahador et al. 2021), artificial neural network (Bell et al. 2020), convolutional neural network (Turan and Erzin 2018), k-nearest neighbor, random forest (Fontana, Farooq, and Sazonov 2013; Chen et al. 2020) and support vector machine (SVM) (Farooq and Sazonov 2016a) are the widely used algorithms in signal classification. Farooq and Sazonov (2016b) used a linear SVM for classification after data are reduced to four different classes, including eating while walking, walking, sedentary and eating while sitting. Table 1 summarizes the performance of the selected classifiers reported in a previous work.

Table 1. Summary of classifiers.

Reference	Detection method	Classifier	Performance
(Liu et al. 2012)	Acoustic sensor	(MLF) NN+ELM	Accuracy: 82.51%
(Fontana, Farooq, and Sazonov 2020)	Jaw motion sensor & accelerator	ANN	Accuracy: 86.86%
(Turan and Erzin 2018)	Acoustic sensor	CNN	Accuracy: 78.3% F1: 77.8%
(Fontana, Farooq, and Sazonov 2013)	AIM	Random Forest	Accuracy: 73.2%
(Farooq and Sazonov 2016a)	Piezoelectric sensor & accelerator	Single Multiclass Linear SVM & Multi-stage Linear SVM + Decision Tree	F1: 99.85%

Table 2. Summaries of food type classification based on chewing data.

Reference	Classifier	Food	Accuracy
(Päßler, Wolff, and Fischer 2012)	Viterbi algorithm-based finite-state grammar	Carrot	97.0%
		Apple	90.0%
		Walnut	74.0%
		Peanut	76.0%
		Chocolate	86.0%
		Potato chip	92.0%
		Drink	26.0%
(Bi et al. 2016)	Decision Tree (DT)	Cookie	87.7%
		Apple	86.3%
		Walnut	83.4%
		Peanut	75.5%
		Carrot	84.9%
		Chip	82.9%
		Water	93.3%

3.4. Chewing performance measurement and data analysis

In performance measurement, statistical evidence is utilized to determine progress toward specifically defined objectives. Zhang and Amft (2020) measured performance via leave-one-participant-out (LOPO) cross-validation. They selected the best combination of parameters based on the performance of training data and used the test data to estimate the performance of the algorithm. In measuring the performance of signal detection systems and classification methods, precision, recall and accuracy are the most common parameters used. True positive (TP) is the number of epochs correctly classified as 'chewing'. False positive (FP) is the number of epochs incorrectly classified as 'chewing' by the model. False negative (FN) is the number of times that the model fails to classify an epoch as a 'chewing' epoch. In Figure 1, the processed chewing data can be used to detect food intake and further classify food type.

$$Precision = \frac{TP}{TP + FP}, \tag{1}$$

$$Recall = \frac{TP}{TP + FN}, \tag{2}$$

$$Accuracy = \frac{Precision + Recall}{2}. \tag{3}$$

In food intake detection, the general process and patterns of chewing events can be determined by grouping and labeling the chewing data; algorithms can be created and improved on the basis of these patterns to identify the food intake activities. Papapanagiotou et al. (2017) integrated the selected chewing events for the time range of 0.1–0.8 s during which these chewing events adjoin each other. The time interval between two chewing events is an important parameter. Hence, the start and the end of a chewing event must be defined. In this case, chewing events likely form chewing bouts and then combine to be detected as one eating behavior. Under this situation, a snacking event can be easily differentiated from chewing events.

Chewing data can also be used for food type classification. Päßler, Wolff, and Fischer (2012) completed the classification of eight kinds of food and drink. They used the Viterbi algorithm-based finite-state grammar to evaluate them in two tracks. One of them is for training model participants, and the other is for new participants. Päßler et al. obtained accuracy levels varying from 74% to 97% and yielded an overall performance of 66% accuracy for the test set. Bi et al. (2016) detected the events by HMM and then extracted the time domain, frequency domain and nonlinear features. For classification, they used a decision tree (DT). Bi et al. also chose seven types of food for performance measurement and found that the food type detection accuracy varies from 75.5% to 93.3%, with an average accuracy of 84.9%. The food type classification based on chewing data is summarized in Table 2.

4. Chewing detection using wearable sensors

Chewing activity detection is greatly influenced by the type of wearable sensors. Chewing wearable sensors can be roughly divided into two parts, namely, contact and contactless sensors.

4.1. Contact sensors

An electrode sensor is based on the current detecting function of electrodes, which can be used as two ends of input or output current in a conductive medium. In a sensing system, electrodes are typically utilized in sensors to detect and collect the signal of EMG, EEG and other biosignals by skin contact. Zhang and Amft (2020) proposed a novel design of smart eyeglasses for food intake monitoring by using frame-integrated EMG electrodes; the personalized eyeglass frames provided skin contact for dry stainless-steel electrodes. BioRadio is a multichannel and wireless monitoring device for detecting and capturing physiological signals, such as electrical activities from the heart, brain and muscle. It is a versatile, wearable, programmable and easy-to-use tool. The biosignals that BioRadio can capture are ECG, EEG, EMG, EOG, PPG and heart rate (BioRadio). BIOPAC is a company that provides various kinds of elements and systems related to exploring life sciences. It has a wide range of products, such as accelerometers for MRI, active EMG electrodes, Ag-AgCl electrodes and more (BIOPAC). A comparison of contact sensors is shown in Table 3.

Table 3. Contact sensor table of comparison.

Type	Schematic diagram	Sensing type	Performance to detect chewing
Electrode (Zhang and Amft 2020)		Detect wave (like EMG) or voltage change	Average recall: 94.0% Precision: 94.4%
BioRadio		Multiple	N/A
BIOPAC		Multiple	N/A

4.2. *Contactless sensors*

The inductive sensor comprises of four parts, namely, a Schmitt trigger, an oscillator, an output amplifier and a ferrite core with a coil (Kinney 2001). The oscillator produces a symmetric oscillating magnetic field radiated from an induction end ferrite core and a coil array. When a metal target enters this magnetic field, a small independent current known as eddy current is generated on the metal surface. It changes the magnetic resistance (natural frequency) of the magnetic circuit and reduces the oscillation amplitude. As more metals enter the induction field, the oscillation amplitude contracts and eventually collapses. When the target finally moves out of range of the sensor, the circuit begins to oscillate again, and the Schmidt trigger returns the sensor to the previous output.

Two conductive plates with different potentials are placed on the sensor head and positioned as an open circuit capacitance (Kinney 2001). Air acts as an insulator. When stationary, the two plates have minimal capacitance. These plates are connected to Schmitt triggers, oscillators and output amplifiers. When the target enters the sensing region, the capacitances of the two boards increase, thereby changing the amplitude of the oscillator and the state of the Schmitt trigger to generate the output signal.

Photoelectric sensors comprise an emitter light source (LED), a photodiode, or a phototransistor receiver to detect emitted light (Kinney 2001). Supporting electronic equipment is also present to amplify receiver signals. The emitter transmits a beam of visible or infrared light to the receiver. Ultrasonic sensors can detect objects by using sound waves. In this case, color and transparency do not affect objects.

The standard configurations of ultrasonic sensors are retro-reflective, diffuse versions and through beams. Ultrasonic diffuse proximity sensors use sonic transducers, which emit a series of sonic pulses and then monitor them from reflected targets (Kinney 2001).

A piezoelectric sensor can be embedded in retractable necklaces to acquire the skin movements of the jaw and neck and record chewing and swallowing patterns. This kind of sensor is accurate in soft food detection. It is advantageous because of its strong immunity to environmental noise. Hussain et al. proposed a data acquisition system consisting of a piezoelectric sensor embedded with a necklace, a simple microcontroller and a smartphone application. In this system, the piezoelectric sensor collects eating patterns that comprise chewing and swallow events and cooperate with other parts to achieve its tasks (Hussain et al. 2018).

An IR photodetector, which is an infrared proximity sensor, consists of infrared LED, PD and signal processing units. Its basic working principle involves an infrared LED that emits an infrared signal to objects that need detection. Some signals bounce back and become detected by a PD sensor. Then, photocurrent is produced. It is directly proportional to the degree of the closeness of the object and the magnitude of the detected infrared light (Chen et al. 2020; Wu 2013).

The function of ToF sensors is to detect the distance between a sensor and an object. This type of sensor measures the time of receiving light; irradiation is performed with an infrared ray transmitted from the sensor to the object and then goes back to the sensor to detect the distance to the object. Hence, ToF sensors can complete the distance measurement without affecting the object's reflectance. They have the advantages of small size and low price; however, its accuracy is low when the distance to the object is ≤10 mm (Tsuji and Kohama 2020).

A vertical cavity surface-emitting laser (VCSEL) is a surface-emitting semiconductor light source that emits laser beams in a direction perpendicular to its top surface. Individual VCSEL emitters are small, typically around 10 microns in diameter; they are often grouped into 2D arrays that collectively generate a much higher output power level (VCSEL).

For organic crystal sensors, in 2018, Wang et al. proposed a novel type of ultrasensitive flexible proximity sensors in which the point is a small flexible organic monocrystal that serves as a proximity-sensing device. An organic monocrystal is free from disorders and defections. Thus, it is significantly suitable for a sensing mechanism study. Unlike conventional capacitive proximity sensors, electrodes in organic monocrystal sensors are located on both ends of the monocrystal to form a two-terminal planar device configuration. These sensors can accurately perceive external objects, such as fiber and human fingers (Wang et al. 2018). The comparison of different contactless sensors is shown in Table 4.

5. Chewing detection design framework

The detection of chewing activities helps elucidate the food intake behavior and automatic dietary monitoring system. Based on this detection, a response system can be developed to mitigate the effect of behavioral changes in food consumption. The process involves chewing activity detection, chewing signal data acquisition, chewing signal processing and wearable sensor selection. A framework is developed on the basis of the essential components of the chewing activities measured using the selected sensor. The general process flow of the automatic chewing detection framework is illustrated in Figure 2.

5.1. Chewing activity detecting system

In most human eating activities, people repeat putting food into the mouth by hand, which is the hand-to-mouth (HtM) gesture. Continuous collisions occur between the jaw and teeth. These two actions are the premise and essence of chewing. A chewing activity detection system integrates a proximity sensor embedded in a VCNL4040 package, a microcontroller unit, a local microSD memory card and a 400 mAh lithium

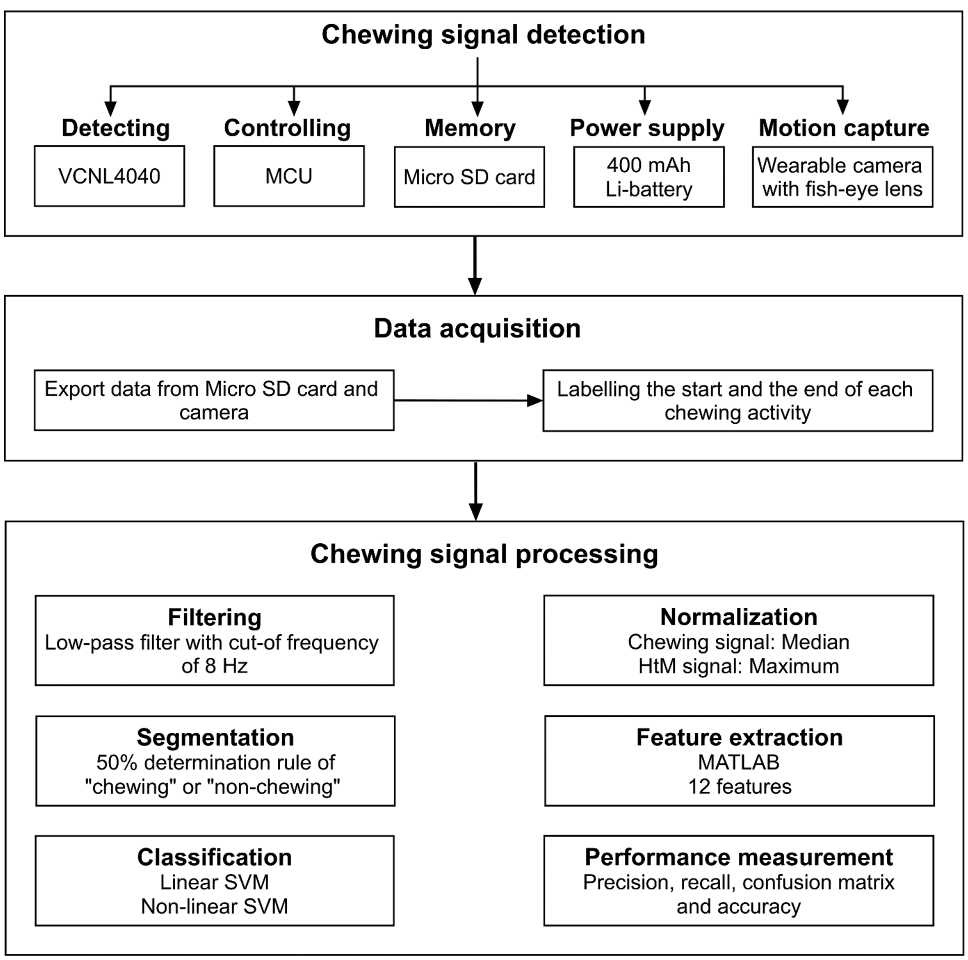


Figure 2. General process flow of automatic chewing detection.

battery (Hussain et al. 2018). This system is designed to capture chewing-related signals. All these elements are embedded in a necklace.

The VCNL4040 package consists of a proximity sensor (PS), an ambient light sensor (ALS), a high-power infrared-LED and another component. It utilizes a photodiode, an amplifier and an analogue-to-digital conversion circuit, and it is integrated by CMOS technology. The 16-bit high-resolution ALS has an excellent sensing ability, which is suitable for detecting moving objects. A proximity sensor (PS) has an intelligent elimination function, effectively eliminating a crosstalk. The PS on the necklace pointing toward chin monitors the changes in signals during chewing. ALS's reading drops when the HtM gesture is completed. The microcontroller unit (MCU) is used to save energy and connected to the PS output of the VCNL4040 package. It collects the PS output data through an I2C interface when the proximity sensor outputs a chewing activity signal. It enters the standby mode and runs at the lowest power consumption when the PS stops the signal output. The chewing signal data collected by the MCU are transmitted to the local micro SD card embedded in the necklace. Moreover, a 400 mAh Li battery is added to support the whole system.

5.2. Chewing signal data acquisition and processing

Chewing signals are detected after the sensing system is used, whereas signal data are stored in a local micro SD card embedded in the necklace. In this step, signal data in the local micro SD card are exported and processed. Videos and audios from a wearable camera need to be extracted to help with labeling. For further signal segmentation, the signal is labeled roughly with 'chewing' (+1) and 'nonchewing' (−1) by determining the beginning and end of each chewing activity. If HtM gestures take longer than 0.25 s and shorter than 7.5 s, they are considered food intake activity associated with chewing.

The segment and meaningful features contributing to data analysis are specified and extracted for further analysis. The chewing detection process is presented in Figure 3. In the beginning, chewing and HtM signals are acquired by the detection system and subjected to first-stage labeling by using the recorded video and audio. Next, signal preprocessing, filtering and normalization are performed, followed by segmentation and feature extraction. The signal segmentation model is shown in Figure 4. The chewing signal is classified by linear SVM. Lastly, performance measurements are conducted to evaluate the proposed system.

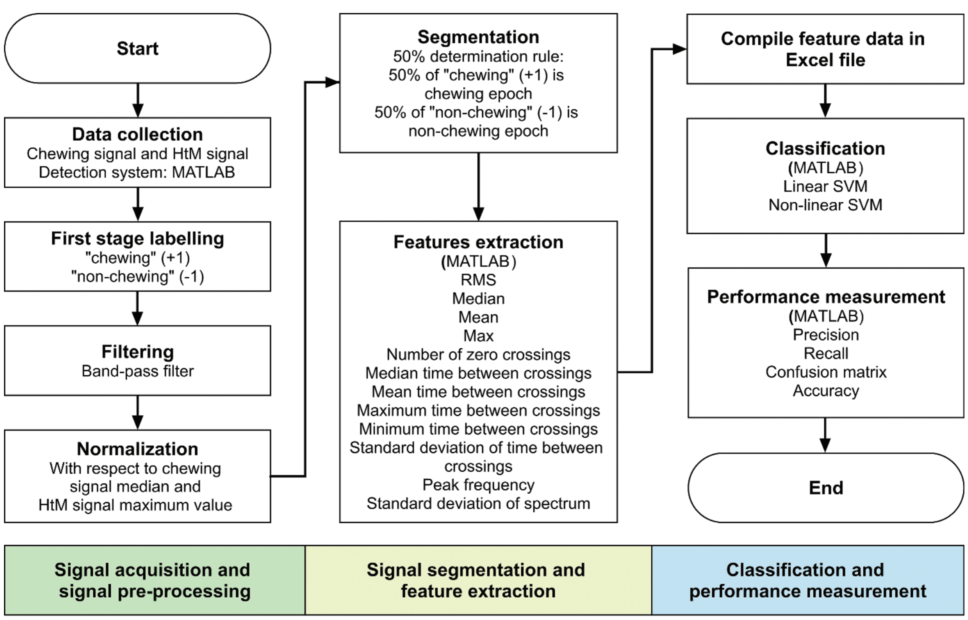


Figure 3. Process flow of chewing signal processing.

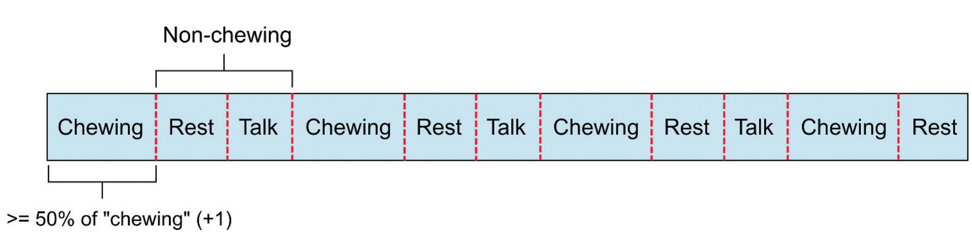
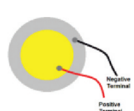
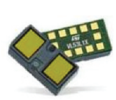


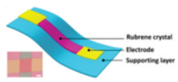
Figure 4. Signal segmentation model.

Table 4. Comparison of contactless sensors.

Type	Schematic diagram	Sensing type	Performance to detect chewing
Inductive (Kinney 2001)		0.8–60 mm	N/A
Capacitive (Kinney 2001)		3–60 mm	84.4% accuracy when embedded in neckband
Photoelectric (Kinney 2001)		1–60 mm	N/A
Ultrasonic (Kinney 2001)		3–30 mm	N/A
Piezoelectric (Hussain et al. 2018)		N/A	F1-score of about 85% on solid and liquid foods
IR-Photodetector (Wu 2013)		2–10 cm	95.3% Accuracy
ToF (Tsuji and Kohama 2020)		Up to 400 cm	Depends highly on the sensor orientation and affected by small movements. Precision: 91.2% Recall: 92.6%
VCSEL		20 cm	N/A

(*Continued*)

Table 4. (Continued).

Type	Schematic diagram	Sensing type	Performance to detect chewing
Organic Crystal (Wang et al. 2018)		Depend on the charge quantity	Excellent reversibility and stability

According to the Nyquist theorem, in analogue/digital signal conversion, when a sampling frequency is more than twice the maximum frequency in a signal, the sampled digital signal completely retains information in the original signal. For signal filtering, a low-pass filter with a cutoff frequency of 8 Hz is utilized to filter high-frequency noise because sampling frequency in the VCNL4040 package is 20 Hz. Chewing signal normalization concerning the signal median is necessary to minimize signal variations in the subjects. Moreover, HtM gesture signals are normalized in terms of their maximum value.

After signal normalization is completed, the signal needs to be divided into several epochs, which are non-overlapping with one another. Epoch values are used to define the time revolution of chewing activity detection. The divided epochs may have parts of chewing and non-chewing signals. Thus, these parts should be labeled 'chewing' and 'nonchewing'. Moreover, the 50% determination rule is applied to determine if an epoch should be categorized as 'chewing' or 'nonchewing' (Bell et al. 2020; Sazonov and Fontana 2012). An epoch with more than 50% of 'chewing' labels (+1) is categorized as 'chewing'; otherwise, it is treated as a 'nonchewing' epoch. The decision epoch feature vector is a combined set of scalar features extracted from each epoch's filtered and unfiltered signals. The widely used features include the signal's mean, max, number of zero crossings, the mean time between crossings, the median time between crossings, the maximum and minimum time between crossings, the standard deviation of time between crossings, the peak frequency and the standard deviation of the signal spectrum.

For classification, the obtained signal data are divided into two parts, namely, 70% as a training dataset and 30% as a test dataset. The training dataset is trained using the selected features and has 'chewing' and 'nonchewing' labels.

The SVM is a supervised learning algorithm that helps address classification and regression problems. SVM has two kinds, namely, linear SVM and nonlinear SVM. A linear SVM is a maximum margin classifier, which can formalize the notion of the best linear separator, whereas a nonlinear SVM extends the linear one with kernels. It presents data into a higher-dimensional space to make them linearly separable. In this project, a linear SVM is used to classify signals. The separating hyperplane created by the linear SVM is shown in Equation 4.

$$w.\ x + b = 0, \tag{4}$$

where w is the weight vector, x is the data feature, and b is a scalar. This project is composed of many epochs labeled with 'chewing' and 'nonchewing' and separated accordingly. Furthermore, the average classification accuracy is calculated using Equation 5 to identify the classification performance.

$$x = \frac{t}{n} \times 100, \tag{5}$$

where t is the number of instances classified correctly, and n is the total number of instances.

For the performance measurement of the proposed classification model, the average precision and recall value result in the accuracy value, which is a significant parameter for evaluating performance.

According to this review, the chewing signal obtained using a piezoelectric sensor and classified by single multiclass and multistage linear SVM with a decision tree classifier achieved the highest classification accuracy (99.85%). Overall, the decision tree approach (75.5% to 93.3% accuracy) performed better than the Viterbi algorithm-based finite-state grammar method (26% to 97% accuracy) in terms of recognizing the food type based on the chewing data. Ongoing research activities are essential in developing a robust and stable system in automatic dietary monitoring and chewing detection. Such a detection system may empower humans in food intake monitoring to help manage food consumption and provide beneficial guidance.

6. Conclusion

This study investigated various chewing signal detection approaches and their sensing tools. The scope of the review included chewing activity detection methods and chewing signal processing strategies as a part of automatic dietary monitoring. The general process flow for chewing detection was used to design the detecting sensing system, acquire a helpful chewing dataset and utilize the proper methods for signal filtering, segmentation, classification and performance measurement. Chewing detection based on noncontact sensors in various applications showed potential for application in comfortable wearable sensors and high classification accuracy. In future studies, chewing data will be analyzed in relation to chew count and food classification. Various food types and many samples will be used to develop a robust automated dietary monitoring system. The outcome of this research will enhance current food intake energy monitoring, analysis and estimation.

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Nomenclature

ADM	Automated dietary monitoring
b	Scalar
CPG	Central pattern generator
EEG	Electroencephalography
EGG	Electroglottography
EMG	Electromyography
HtM	Hand-to-mouth movement
LOPO	Leave-one-participant-out
LPFA	Low-pass filtering algorithm
n	Total number of instances
PPG	Photoplethysmography
SpO_2	Pulse oximetry
t	Number of the instances that are classified correctly
ToF	Time of flight
TPM	Tongue pullback movements
TSM	Tongue squeeze-back movements
VCSEL	Vertical cavity surface-emitting laser
w	Weight vector
Wtot	Total muscle work
x	Data

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