Food Intake Detection and Classification Using a Necklace-Type Piezoelectric Wearable Sensor System

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SUMMARY Automatic monitoring of food intake in free living conditions is still an open problem to solve. This paper presents a novel necklace-type wearable system embedded with a piezoelectric sensor to monitor ingestive behavior by detecting skin motion from the lower trachea. Detected events are incorporated for food classification. Unlike the previous state-of-the-art piezoelectric sensor based system that employs spectrogram features, we have tried to fully exploit time-domain based signals for optimal features. Through numerous evaluations on the length of a frame, we have found the best performance with a frame length of 70 samples (3.5 seconds). This demonstrates that the chewing sequence carries important information for food classification. Experimental results show the validity of the proposed algorithm for food intake detection and food classification in real-life scenarios. Our system yields an accuracy of 89.2% for food intake detection and 80.3% for food classification over 17 food categories. Additionally, our system is based on a smartphone app, which helps users live healthy by providing them with real-time feedback about their ingested food episodes and types.

key words: wearable sensor, nutrition monitoring, machine learning, wireless health

1. Introduction

Healthy eating is key factor in maintaining a healthy lifestyle with a reduced risk of obesity-related chronic diseases such as heart disease, cancers, stroke, and diabetes [1]. Accurate food intake detection and food classification is an important step towards estimation of the volume and calories of food in the field of automatic dietary assessment.

There have been efforts to develop an automated non-invasive system that detects food ingestion behavior and classifies types which further assist in estimating ingested food weight and determining caloric density of each food class. Various sensors such as microphones, piezoelectric sensors, accelerometers, gyroscopes, cameras, weight scales, textile pressure sensors, and electromyographs have been used for automated intake monitoring as discussed comprehensively in [2], [3]. Among these sensors, microphones have been widely used because they are more accurate than other sensors [4]–[9]. On the contrary, audio sensing can fail over soft foods due to background noise as reported in [10]. Therefore, they employed additional sensors to their system along microphone for classifying broad categories of food and reducing the effect of environmental noise [11]. Another study [7] utilized microphone of smartwatch to monitor and evaluate ingestive behavior. However, microphone of smartwatch stays further away after bite and hence their smartwatch modality may face more challenges with background noise in real environment. Besides, sound recognition algorithms are computationally intensive as they rely on sophisticated time-frequency decomposition to represent the signal which limits battery life of wearable system [12].

On the other hand, piezoelectric sensors, also known as vibration sensors, can be embedded within stretchable necklaces to record chewing and swallowing patterns by sensing skin movement of the jaw and neck. These sensors not only provide better user comfortability and detect soft foods accurately than a microphone-based wearables, but also are robust to surrounding noise. We describe representative works based on piezoelectric sensors in Sect. 4.

In this work, we employ swallow and chewing patterns to differentiate the food types. In order to achieve this, we exploit the advantages of a piezoelectric system embedded in a necklace, and present a smartphone-based nutrition monitoring system that detects food ingestion behavior and classifies food types. The contributions of our research are best described in three aspects. First, our wearable in necklace form has detected ingestion pattern of 17 food categories in the presence of speech and motion artifacts with the accuracy of 89.2%. Second, we have achieved a classification accuracy of 80.3% in real-life settings over 17 food categories. Our system outperforms the state-of-the-art piezoelectric sensor based method [13]. Third, we have developed a smartphone application that sends real-time feedback to the user about the number of swallows detected by the necklace for each food category, and suggests time for the next meal and exercise.

Although there here have been some prior studies which performed well in a challenging environment [14]–[18] for the food intake detection, but most of them have not addressed the problem of food classification. Therefore, we present a novel wearable system whose overview is shown in Fig. 1. Our designed system not only helps detecting food intake but also recognizes food categories in real-life conditions. We demonstrate that carefully designed raw data...
collection in the time domain, along with an optimal feature selection, enables our method to outperform the state-of-the-art piezoelectric sensor-based method [13], [19] that employs spectrogram features for food recognition. We have found that, a prior chewing sequence combined with a successive swallowing event, forming a temporal pattern of 70 samples (3.5 seconds) with swallowing located towards the end of the frame, generates the most effective features for classification. For the 17 food categories, we have achieved f-measures of 78.0%, 79.1%, and 80.3% using the k-NN, Support Vector Machine, and Random Forests, respectively. Our method has comparable accuracy to existing methods, with the additional advantage of avoiding extra sensor for noise cancellation [11] and restrictive or immovable models such as tables [20], [21].

This paper is organized as follows. Section 2 describes the acquisition of raw data using a piezoelectric sensor embedded with necklace and experimental procedure along with data processing. Feature selection and classification are described in Sect. 3. Section 4 presents related work based on piezoelectric sensor. In Sect. 5, we discuss and evaluate the system performance for food intake detection and food classification.

2. Acquisition of Raw Data

A piezoelectric sensor is used to collect eating patterns that comprise chewing and swallow events. Piezoelectric sensor is embedded with necklace which can be worn easily and comfortably by the user as shown in Fig. 1 (b). Figure 1 (c) shows the simblee microcontroller and necklace. A simblee microcontroller coordinates the sensor and the smartphone application and instructs the sensor to obtain 20 samples/second as the user presses the button for a specific food category for its chews and swallows pattern acquisition as displayed in Fig. 2. Participants receive the feedback through wireless interface between the microcontroller and the smartphone application whose screenshots are shown as Fig. 2. Our smartphone app provides statistics about swallows detection and recognized food classes and suggests the time for the next meal and recommends exercise. Those received suggestions (i.e., notifications), displayed as Fig. 2 (d), are termed as health feedback, because users can maintain healthy dietary behavior by following these suggestions.

2.1 Necklace-Type Wearable System Embedded with a Piezoelectric Sensor

Piezoelectric sensors embedded in stretchable necklaces are available in two different forms: stretchable sports bands and pendants [22]. Unlike [7], [13], [19], [23], we have se-
lected a stretchable sports band design. This band can be adjusted to the neck diameter of the user, so people of different physiques can wear it without any extra effort. As stated in [22], a sports band necklace has the enormous advantages of stability and comfortability. The sports band maintains high priority in algorithm evolution, data collection and clinical environments. The second necklace design, the pendant [13], [19], [23], has the disadvantage of leaving its target position during motions such as walking, running or vigorous head-turning. Therefore, a stretchable sports band necklace has been used to embed a piezoelectric sensor in our envisioned system, as shown in Fig. 1 (c). The employed necklace design has the advantage of collecting accurate experimental data on throat motion using a single vibration sensor.

The piezoelectric sensor varies its output voltage based on the motion of the skin. During eating, muscular contractions move the skin in a way that pushes the vibration sensor away from the neck and towards the necklace. Hence, the sensor generates an output voltage that represents a unique temporal pattern of chewing and swallowing, as shown in Fig. 3 (b). One end of the piezoelectric sensor is connected to the general-purpose input/output (GPIO) pin of the simblee microcontroller, which has built-in analog to digital converters (ADCs), and the other end of the sensor is grounded. The specification of selected sensor is LDT0-028K vibration sensor manufactured by Measurement Specialties. The sensor consists of a 28μm PDVDF polymer film laminated to a 0.125mm substrate, and produces voltages within standard CMOS input voltage ranges when deflected directly. The sensor can operate under thermal conditions ranging from 0 to 85°C. The LDT0 is available with additional masses at the tip that reduce the resonant frequency, but can also increase the sensitivity of the device. In the configuration without an additional mass at the tip, the sensor has a sensitivity of approximately 50 mV/g at baseline and 1.4 V/g at resonance [24]. The simblee microcontroller board is the center of coordination between the sensor and the smartphone application. It propagates orders from the smartphone application towards the sensor to activate its monitoring of the user’s skin movement. Therefore, the sensor is enabled and can continuously record skin
motion until it is disabled again by the user after ingestion has ended.

Thus, the hardware system acquires an amplitude varying voltage signal over time, representing the eating pattern at a rate of 20 samples/second. The simblee microcontroller is easily programmed and is more compact than the system in [5]; hence, it can be placed in a pocket during real-environment usage, as shown for the subject in Fig. 1(c).

The hardware system is interfaced to the smartphone application through Bluetooth. The smartphone application has a major role in the successful design and implementation of an automated nutrition monitoring system. The application serves as a data manager and an interface between the user and the diet monitoring system. The application facilitates nutrition intake experimentation, food intake detection and food classification by providing different options of food types and swallows intake statistics for each food. It also helps annotating ground truth and provides friendly suggestions based on the user’s caloric intake and hydration level (see screen-shots from the application in Fig. 2). A 3-volt coin battery is used for energy-efficient powering of simblee microcontroller. Unlike in [13], [22], the user can control the power level of the nutrition monitoring system to prolong the battery life by changing the mode of the simblee microcontroller [25], i.e., from Active mode to Ultra-Low Power (sleep) mode and vice versa.

2.2 Experiment

We have recruited 20 participants, 15 males and 5 females, whose mean (±SD) age was 33 ± 10 years (range: 18–58 years) and a mean body mass index (BMI, in kg/m2) of 22.7 ± 3.2 (range: 17.1–28.8). All participants were healthy and had no history of eating disorder. The participants signed consent form before the experiment, and their rights have been protected. Each subject consumed 3 full meals in 3 different visits, each of which consisted of three parts: 1) subject recorded artifacts for 20 minutes: head movement after a particular interval for 10 minutes and 5 minutes each spent in speaking and walking; 2) a meal period of unlimited time to eat three food items; 3) subject recorded artifacts for 20 minutes: head movement after a particular interval for 10 minutes and 5 minutes each spent in speaking and walking. Three visits by each subject constituted the total of 60 visits for analyzing this study. The purpose of head movement, walking, and talking is to examine the ability of the sensor and food recognition algorithm to differentiate the pattern of ingestion activity from the patterns of speech and motion artifacts.

Visits occurred roughly one day apart, at a different meal of the day in order to cover complete ingestion behavior of each user for breakfast, lunch, and dinner. Each subject was asked to choose 2 food types and 1 drinks in each visit according to their own preferences from the menu offered by Sungkyunkwan university food court. Users were allowed to select different food in each visit and eat the food in their natural style. Because we have designed a group model which cross validated over food types. It doesn’t require calibration for individual participants. Therefore, we lift restriction of eating same food in more than one visit as it was done in prior study [26] with a purpose to achieve calibration of individual models. Apple, banana, bagel, burger, chips, cookie, coffee, carrot, chocolate milk, chicken nuggets, juice, meatballs, muffin, milk, pizza, potatoes, salad, sandwich, waffle, and water were used for analyzing food intake ingestion behavior. Coffee, chocolate milk, juice, milk, and water were included in one category of liquid because of having similar ingestion patterns. Therefore, the number of the food categories is 17 for food intake detection and food classification. The food types ingested during the meal period were selected to represent different chewing properties of food common in daily life. Those chewing properties include “hardness”, “crunchiness”, and “tackiness”. Participants were directed to eat only one food at a time and were prohibited to eat other foods in between these foods, so that the experimental data for each food category could be saved with the correct label in memory. Participants ate most of the food categories while walking except some food categories which were not usual to eat while walking such as chicken nuggets, pizza, meatballs, etc. And participants were allowed to walk around while consuming discrete foods such as apple, banana, bagel, muffin, carrot, chips, and cookies. The users were instructed to eat a bite from a same food which was selected by them in smartphone application and press pushbutton for establishing the ground truth for swallowing detection as shown in Fig. 3 (b). Ground truth using pushbutton assisted in evaluating the performance of the sensor regarding how many swallows are detected and how many swallows are missed by the sensor.

Hardness, crunchiness, and tackiness are three main properties people consider for the analysis of food texture when chewing food. The 17 food categories we have employed in this work include food categories that have been commonly used in previous works [13]. Their distributions regarding the properties of hardness, crunchiness, and tackiness are shown in Fig. 4. These properties are important in determining how each food category behaves during manipulation and mastication in the mouth because they demonstrate themselves as the reaction of the food to applied stress. However, each food category spans a large degree of variation regarding the hardness, crunchiness, and tackiness properties. Thus, we recoded the participants’ responses or feedback through a user survey in which they rated food categories in terms of hardness, crunchiness, and tackiness. We have scored the relative strength of each food used in our experiments out of scale 10 according to the sensory score approach [27], [28].

2.3 Data Processing

The acquired amplitude-varying signal from the piezoelectric sensor is further processed to retain important events and remove unnecessary silent phases of data. It is
important to process the data before extracting features and developing any statistical model. Prior researchers [29]–[31] have divided the process of swallowing into three phases: the oral preparation phase (food is chewed to form the viscous bolus), the pharyngeal phase (the bolus travels through the pharynx and passes the upper esophageal sphincter), and the esophageal phase (the bolus moves to the stomach from the esophagus). We have combined the pharyngeal and esophageal phases to represent swallowing, and have used the oral preparation phase to represent chewing. The main purpose is to acquire the temporal signals generated according to the user’s eating patterns for different foods.

The most important stimuli relate to food texture (crispness, hardness, dryness, size, and shape) and flavor [32], [33]. Chewing repeatedly adjusts these stimuli, allowing efficient food breakdown and creating a food bolus that can be swallowed. We have given equal importance to both eating actions: chewing and swallowing. As shown in Fig. 3(b), the major peaks represent swallowing patterns and the minor peaks represent chewing patterns.

Different foods require different amounts of force during each attempt of food breakdown. Therefore, the different forces exerted to bite foods with different levels of hardness generate unique chewing patterns along with each swallow. Taking advantage of the unique ingestion patterns generated for foods of different textures, we have combined the chewing pattern with swallowing to best represent the ingestion pattern data. We have used frames to cover the desired ingestion pattern, ultimately enabling efficient extraction of discriminatory features. Rectangular boxes have been used to highlight particular frames, as shown in Fig. 3(b).

The window length has been chosen on the condition of classifier performance. As shown in Fig. 5, the window length of 70 samples (3.5 seconds) is most suitable, based on comparison of food recognition performance of the models over different window lengths of the samples. Resulting frames are obtained when each 70-sample long section of signal is multiplied with a non-overlapping sliding window as shown in Fig. 6(a). The frame boundaries are indicated by two vertically adjacent sides of red rectangle. A swallowing event can be represented by four to five samples, but a suitable number of samples are required for the chewing sequence; the performance of the model can slightly decrease if the number selected is too large or too small.

A drop-out technique is applied to all frames or segments of the signal to search for informative frames containing the swallowing peak. Frames are accepted or rejected by a thresholding operation on the magnitude of a peak. Frames containing the swallowing peak are moved forward or backward according to the location of swallowing peak as shown in Fig. 6(a), in order to capture the preceding pattern of chewing in which the food was converted into a viscous bolus. The viscous bolus is the final form of food before it is swallowed. It has been established that people usually do not add new food to their mouth before swallowing the bolus.
in their mouth [9]; thus, the intake, chewing and swallowing events of one intake cycle belong to the same type of food. Therefore, the frames cover 65 samples of chewing before the swallowing peak (pre-swallow samples) and 4 samples after the swallowing peak (post-swallow samples), covering the complete swallowing event.

All empty or uninformative frames are rejected, as shown in the drop-out part of Fig. 6 (a). If window has one swallow event, that window is included in the training set. In case that multiple peaks are detected in a single window as shown in windowing part of Fig. 6 (a), we capture chewing sequence for each swallow event. In Fig. 6 (a), the first and second windows contain a single peak of $a$ and $b$ respectively, but there are two peaks, $c$ and $d$ in the third window. The position of windows is set according to the swallow position in order to cover pre-swallow chewing sequence as shown in the framing part. Prior chewing sequence covered successfully for three peaks: $a$, $b$, and $c$. Therefore, their chewing sequences are automatically taken as training data, but the fourth frame for peak $d$ also contains peak $c$. We safely delete $c$, the first peak of the fourth frame and replace its value with the average value of neighboring magnitudes, assuming that we could still capture the texture and physical properties of food with the preceding swallow signals deleted. Discriminatory features are extracted from the resulting frames containing information about each swallow and the prior chewing patterns for different food categories.

![Data Acquisition](image1)

![Windowing](image2)

![Framing](image3)

![Drop out](image4)

Fig. 6 Swallow detecting techniques of the proposed algorithm and the previous work [13] (a) proposed data processing technique; (b) previous data processing technique [13].

### Table 1 The performance of swallow detection.

| Food type   | Detected swallows | Missed swallows | Intake detection error % |
|-------------|-------------------|-----------------|-------------------------|
| Apple       | 455               | 87              | 16.05                   |
| Banana      | 240               | 25              | 9.43                    |
| Bagel       | 76                | 9               | 10.59                   |
| Burger      | 127               | 11              | 7.97                    |
| Muffin      | 191               | 29              | 13.18                   |
| Pizza       | 580               | 31              | 5.09                    |
| Carrot      | 150               | 6               | 3.85                    |
| Potatoes    | 58                | 9               | 13.43                   |
| Salad       | 953               | 109             | 10.26                   |
| Chicken Nuggets | 139           | 11              | 7.33                    |
| Sandwich    | 238               | 17              | 6.67                    |
| Chips       | 533               | 81              | 13.19                   |
| Cookie      | 510               | 65              | 11.3                    |
| Meatballs   | 76                | 8               | 9.52                    |
| Eggs        | 130               | 20              | 13.33                   |
| Waffle      | 84                | 12              | 12.5                    |
| Liquid      | 949               | 227             | 19.3                    |

Average intake detection error % = 10.76
Average intake detection accuracy % = 89.2

#### 2.4 Food Intake Detection

Food intake is detected through identifying swallow events. Swallow events are recognized based on thresholding of sensor signal. The food ingestive behavior has been monitored for 17 food categories. For each food class shown in Table 1, the ratio of missed swallows to total ingested
swallows is defined as absolute error. Liquid and apple have highest error of missed swallows. A high rate of missed swallows for liquid may be due to the absence of chewing and softening characteristics. Apple has an absolute error of 16.05%, in spite of being hard crunchy food. It may be due to the final form of a bolus of apple which is in smaller size than the bolus of other foods. Most portion of apple bite is converted into juice and the bolus contains only its peels. So, sensor exhibits a higher missed swallow error for apple.

Intakes of carrot and pizza are detected with lowest missed swallow error. Carrot is harder food than apple and its bolus formed after chewing is not of a small size. So, the accuracy of carrot intake detection, unlike apples, achieved the lowest intake detection error of 3.85%. Intake of pizza is detected with the second lowest swallow error because of its viscous and composite characteristics.

3. Features Selection and Classification

Features are selected based on their discriminatory power to classify the target accurately. Eighteen statistical features as listed in Table 2 are extracted from the processed or informative frames to identify different food categories based on variations in the chewing and swallowing patterns for different foods. We have employed a heuristic filtering method to select features with high discriminating capabilities to differentiate foods of different categories.

Different filtering methods can be used to estimate important features and weight them accordingly. Here, an instance-based method, RELIEFF [34], is used to assign the relevance weight to each feature. The weight of each feature represents its ability to differentiate the different categories. Features are ranked in descending order of weight, and the bottom three less-weighted features are discarded. Accordingly, fifteen high-weighted features constitute the final set of features for learning classifiers.

3.1 RELIEFF

RELIEFF is a heuristic-based filtering method which ranks features according to their weights. The algorithm estimates features based on their ability to differentiate between the instances that are near a randomly chosen instance. The RELIEF algorithm is stated as algorithm 1.

Algorithm 1 The basic algorithm of RELIEF

| Algorithm 1 | The basic algorithm of RELIEF |
|-------------|-----------------------------|
| 1: set all weights \( W[A] \leftarrow 0.0 \) |
| 2: for \( i \leftarrow 1 : n \) (number of random instances) do |
| 3: begin |
| 4: Randomly select an instance \( R \) |
| 5: Find nearest hit \( H \) (same class) and nearest miss \( M \) |
| 6: for \( A \leftarrow 1:\text{all attributes} \) do |
| 7: \( W[A] \leftarrow W[A] - \sigma(A, R, H)/n \) + \( \sigma(A, R, M)/n \) |
| 8: end for |
| 9: end for |

The function \( \sigma(A, R, H)/n \) finds the difference in attributes between two instances. The variable \( A \) represents number of different attributes. Whereas \( R \) and \( H \) show random instance and its nearest instance in the same class, respectively. Discrete attributes differ by either 1 (different values) or 0 (equal values), whereas continuous attributes differ by the actual difference normalized to the interval [0, 1]. The weights estimate the quality of the attributes. The weight update formula is based on the idea that a good attribute should have the same value for instances of the same class and should differentiate between instances of different classes. Relief estimates the attribute weight \( W[A] \) using Eq. (1) as below.

\[
W[A] = P(A \mid \text{nearest instance from different class}) - P(A \mid \text{nearest instance from same class}) \quad (1)
\]

The RELIEFF algorithm is applied to the eighteen features to estimate their discriminatory information weight-age, which are enlisted in Table 2. The z-score, inter-quartile range and the RMS to mean ratio ranked at the bottom of the important features list after the RELIEFF algorithm is applied. This indicates that three of the features are less important and carry redundant and nondiscriminant information about classes of food. Eliminating those three features reduces the complexity of the model and also improves its accuracy. Three different baseline classifiers are trained with the remaining fifteen most-weighted features for food recognition.

3.2 Classification

All instances carrying chews and swallow, detected successfully by the sensor, constitute the training data. The data collected are randomly divided into 5 sets, so that data from each category can be evenly distributed over the 5 sets. The classifiers are trained using 4 sets and cross-validated using the remaining set. Thus, the result is the average of 5 validations.

We have employed three supervised machine learning algorithms of kNN, SVM, and random forests to recognize food categories based on their ingested patterns. For the present study, kNN, SVM, and random forests classifiers are trained using classification learner tool in MATLAB2015b. For kNN, \( k \) is set to the value of 3 and Euclidean distance is selected as a distance metric. For SVM, one-vs-all strategy
and linear kernel function $k(\vec{x}, \vec{x}_i) = \vec{x}_i \cdot \vec{x}$ is used whose penalty $C$ parameter is 1 by default in the classification toolbox of MATLAB2015b. One hundred trees were selected along with the learning rate of 0.1 for random forests. The classification performance is evaluated through comparing the recognized class with its actual class.

4. Related Work

There are various methods of measuring and recording daily dietary information. Different researchers have developed automated non-invasive food monitoring methods using different sensors such as accelerometers [29], microphones [4], [5], [7]–[9], [30], [31], cameras [35], gyroscopes [36]–[39], proximity sensor [17], textile pressure sensors [21], strain gauges [40], piezoelectric sensors [6], [13], [15], [16], [19], [22], [23], [26], [41], orientation sensors [10], [42], [43], electromyography [18], electroglottography [44], and wrist band [45].

We have opted to employ a piezoelectric sensor in the form of a necklace for food intake detection and food classification. The dietary intake monitoring systems using piezoelectric sensors are summarized in Table 3. Alshurafa et al. designed a wearable system for nutrition monitoring in the form of necklace [13], [19]. Their method of food classification was limited to categories such as solid and liquid, hot and cold, and hard and soft. They developed a classification model using statistical features collected from a spectrogram. We show that time-domain features represent food ingestive patterns equally well or better than spectrogram features as experimentally demonstrated in the next section.

Kalantarian et al. introduced a low-cost necklace-embedded system with a piezoelectric sensor [22], [23]. The sensor generated a unique voltage pattern that allowed water, potato chips, and sandwiches to be recognized according to skin movement on the user’s neck. This group reported food classification accuracy of 85.3%, 81.4%, and 84.5% for chips, water, and sandwiches, respectively. The authors achieved a reasonably better performance than [13], [19] by processing the sensor data in the time domain and avoiding the complex computation of short-time Fourier transform (STFT).

Sazonov et al. presented a simple automated intake monitoring system using a piezoelectric sensor which helped detecting eating episodes by measuring chewing [41]. Their methodology performed well over 20 subjects and attained food detection accuracy of 80.98%. Later, Fontana et al. improved their previous system [41] by adding a microphone for energy intake estimation based on the counts of chews and swallows [26]. Swallows were also utilized in [4], [11], [26], [41], [46] to monitor ingestive behavior and estimate the amount of food. Their individually cal-

| Sensor type | Description | Sensor form | Food classes and (subjects) | Accuracy (%) |
|-------------|-------------|------------|----------------------------|--------------|
| Piezoelectric | A novel wearable systems were presented to detect skin motion of the neck caused by ingestion [13] and [19]. | Necklace. | Hot tea, water, nuts, chocolate, and patty (20). | 87% [19] and 90% [13] for solid and liquid. 90% for hot and cold. 80% for solids. |
| | A mobile-based nutrition intake monitoring system [23] using a necklace similar to [13] and [19] was designed to estimate meal volumes. | Necklace. | Water, sandwich, and chips (10). | 85.3% for chips, 84.5% for sandwich, and 81.4% for water. |
| | A simple sensor system was designed to detect periods of intake through recognizing chewing events [41]. | Medical tape is used to attach their sensor on jaw. | Pizza, yogurt, apple, peanut butter sandwich, and water (20). | 80.98% for food intake detection. |
| Piezoelectric and Accelerometers | The wearable system of [13], [19], and [23] was improved by the addition of an accelerometer in [22] to minimize false positive detection of swallows. | Necklace. | Sandwich, chips, and water (30). | 85.3% for chips, 84.5% for sandwich, and 81.4% for water. |
| | A novel form of wearable device was designed by embedding piezoelectric and accelerometer sensors to the temple of eyeglasses which helped to detect food intake in the presence of speech and motion artifacts [15]. | Eyeglasses. | Pizza and granola bar (10). | Food intake episodes were detected with accuracy of 99.85%. |
| Piezoelectric, Accelerometer and Proximity | A novel wearable system was designed to detect food intake by monitoring jaw movement, hand to mouth gestures, and body motion under free-living conditions [14]. | Below the earlobe, neck, and wrist. | Forty foods were ingested (12). | Food intake detected with average accuracy of 89.8%. |
| Piezoelectric or/and Microphones | The performance of piezoelectric and microphone sensors for swallowing detection was compared in [6], and used separately. | Necklace and throat microphone. | Sandwich, chips, and water (10). Patty, mixed nuts, and two small chocolate Snickers (20). | 91.3% and 88.5% (microphone). 75.3% and 79.4% (necklace). |
| | A microphone and piezoelectric sensors were employed to detect chews and swallows for energy intake estimation [26]. | Below the ear and throat microphone. | Forty five food categories were ingested (30). | Individually calibrated models based on chews and swallows had the mean error of 15.83% during training and 32.23% during validation. |
ibrated models estimated energy intake with the mean training error of 15.83% over 45 food categories. They attached piezoelectric sensor below the outer ear with tape which may loosen the contact of sensor with skin and hence the performance of sensor detecting chewing may decrease after a few hours of usage. We have used a single piezoelectric sensor embedded with a stretchable necklace for detection of chews and swallows. The necklace worn around users’ neck doesn’t get loose over a period of time, exhibiting consistent performance throughout until it is removed.

Fontana et al. presented a novel wearable system in another study[14] which had an ability to monitor ingestive behavior objectively and continuously for 24 hours in free living conditions. They detected food intake by training artificial neural network (ANN) on the extracted features from jaw motion, hand to mouth gesture, and accelerometer signals. Their system was not appropriate for detection of liquid intake due to absence of chewing. Besides, their methodology doesn’t include classification of food types.

Mirtchouk et al. proposed a multi-modal sensing system that consisted of audio and motion sensors to classify food types[10]. They employed random forests classifier and achieved a classification accuracy of 82.7% over forty food categories for patterns collected from six individuals. Food categories reduced to eighteen for food weight estimation. Their system is not practical in free living conditions, because users are required to wear four sensors which is quite unrealistic in real-life use.

Faroq et al. designed a wearable device for food intake detection by attaching piezoelectric and accelerometer sensors to the temple of the eyeglasses[15]. Their system showed the state-of-the-art performance for detection of food intake periods of solid categories, but it is yet to be tested for liquid categories. Since, their system utilized only chewing pattern for detection of eating episodes, therefore it is expected that it may not perform well over liquid food categories. Moreover, their system was evaluated over 10 subjects and two food classes which was too small to generalize over a large population. Later, they extended their work to identify chewing events using the energy envelop of signal in laboratory and real-environments and achieved the detection rate of 96.28% [16]. Their work showed the state-of-the-art performance for food intake detection, but it didn’t address food classification. Moreover, they attached the sensor with temporalis muscle with tape which might cause discomfort and lower the accuracy in long-term usage if the sensor contact gets loose.

Kalantarjan et al. presented an objective comparison of a piezoelectric sensor and a microphone for automated dietary intake monitoring systems [6]. They were able to classify food more accurately with microphone than with piezoelectric sensor. In the piezoelectric sensor based method, data processing became ineffective because of the small frame size and unsuitable position of swallow in frames. As the authors were motivated by [13], [19], they extracted features from the spectrogram. The spectrogram-based statistical approach was reported to be superior to matching pursuit and scalogram-based Gabor wavelets. However, as we mentioned earlier, effective features can be extracted from time-domain signal if a chewing sequence of proper frame length is selected.

5. Results and Discussion

Many previous studies considered food intake detection when participants were sedentary[4]–[9], [13], [19]–[23], [29]–[31], [36]–[40], [42], [43], [47]–[51]. Our method is intended to monitor participants’ ingestive activity while they were moderately active (i.e., ingesting on the go). We presented small and inexpensive piezoelectric sensor in the form of a necklace for capturing chewing and swallowing events. A single sensor was employed in our proposed approach to detect food intake and classify food categories by capturing the neck skin movement during chewing and swallow events rather than two sensors [15], [22] and three sensors [14]. Some studies [6], [13], [19], [23], [41] used a single sensor for food intake detection and food recognition. However, their food categories were small for food recognition [6], [13], [19], [23], and food intake detection accuracy of [41] was lower than the food intake detection accuracy of our system. One of the goals of our study was to evaluate the piezoelectric sensor ability of detecting the food intakes in the presence of artifacts. Our wearable in the form of necklace has detected ingestion pattern of 17 food categories with an accuracy of 89.2% as shown in Table 1.

Although a prior study acquired the state-of-the-art accuracy for food intake detection, it was performed over only two categories[15]. There were forty food categories employed in [14], and they considerably designed a robust system to detect chewing sequence of forty food categories with an accuracy of 89.8%. They detected food intake slightly better than our approach because they used three sensors. They attached their sensors with tape which might lower their system accuracy in long time usage. Comparing the food intake detection performance of the prior study [14] with our study, our system exhibited almost similar food intake detection accuracy of 89.2% despite of a single sensor.

The other objective of the proposed automated intake monitoring system is to classify broader categories of food in the presence of the artifacts to examine the effectiveness of our wearable device in the real-life settings. For analyzing the effects of other motion artifacts such as head, walk, and speech, participants’ activity of head movement, walking, and speaking were recorded before monitoring their ingestive behavior. We have observed that peaks of these artifacts are smaller in magnitude than peaks corresponding to food swallow events as shown in Fig. 3. This agrees with the prior study [15]. We also recorded spontaneous swallows of users when they were at rest before the start of eating episode and after they finished eating. Spontaneous swallows, shown in Fig. 3(a), were observed to be smaller in magnitude than actual food swallows. This is also in agreement with the previous study in [26].

The necklace-embedded piezoelectric sensor (our data-
collection source) is not influenced by surrounding noise; its waveform changes when the neck skin exerts force. In contrast, when microphone-based nutrition monitoring systems are used in real environments, surrounding noise is always problematic and degrades the classification accuracy. Therefore, they required an extra microphone to cancel the effect of environmental noise [11].

Alshurafa et al. generated spectrogram [13] for extracting their features for training classifiers. They were not completely successful in extracting distinct statistical features for food classification. They applied short-time Fourier transforms (STFT) to the collected data to generate a

| Target Class | Apple | Banana | Bagel | Burger | Carrot | Chips | Cookie | Chicken | Egg | Meatballs | Muffin | Pizza | Potatoes | Salad | Sandwich | Waffle | Liquid | Precision % |
|--------------|-------|--------|-------|--------|--------|-------|--------|---------|-----|-----------|--------|-------|----------|-------|-----------|-------|--------|------------|
| (a)          | 244   | 5      | 0     | 0      | 0      | 0     | 0      | 0       | 13 | 0         | 0      | 0     | 0        | 0     | 0         | 0     | 109      | 0.95 |
| (b)          | 249   | 7      | 0     | 3      | 10     | 0     | 0      | 0       | 12 | 0         | 0      | 0     | 0        | 0     | 0         | 0     | 107      | 0.94 |

**Fig. 7**  Food classification performance using kNN (a) our proposed method; (b) previous proposed method [13].

| Target Class | Apple | Banana | Bagel | Burger | Carrot | Chips | Cookie | Chicken | Egg | Meatballs | Muffin | Pizza | Potatoes | Salad | Sandwich | Waffle | Liquid | Precision % |
|--------------|-------|--------|-------|--------|--------|-------|--------|---------|-----|-----------|--------|-------|----------|-------|-----------|-------|--------|------------|
| (a)          | 244   | 5      | 0     | 0      | 0      | 0     | 0      | 0       | 13 | 0         | 0      | 0     | 0        | 0     | 0         | 0     | 109      | 0.95 |
| (b)          | 249   | 7      | 0     | 3      | 10     | 0     | 0      | 0       | 12 | 0         | 0      | 0     | 0        | 0     | 0         | 0     | 107      | 0.94 |

**Fig. 8**  Food classification performance using SVM (a) our proposed method; (b) previous proposed method [13].
spectrogram which helped them achieve moderate accuracy at the cost of complex computation. With those extracted features, the authors were unable to build an accurate prediction model. The confusion matrix tables in Figs. 7, 8, and 9 suggest that our approach based on amplitude based features has achieved higher food classification accuracy than [13]. However, they captured swallowing peaks well as shown in Fig. 6 (b), which may prove advantageous for people with eating disorders due to certain diseases.

Amplitude-based features extracted from sensor signal were employed in conjunction with machine learning classifiers to develop subject independent food intake classification model that prevented extra effort for individual calibration. Amplitude based features were extracted from frames whose window length of 70 samples (i.e., 3.5 seconds) gave the best results of classification. The window length of 70 samples (3.5 seconds) almost coincides with [13], [15], and some research groups have used even smaller window of 200ms in [10], [18], and 500ms in [51] for capturing the full chew so as to extract audio features and identifying chewing events.

The performance of food recognition using our method is represented in the confusion matrices of Figs. 7 (a), 8 (a), and 9 (a). Liquid exhibited the highest classification accuracy over all three classifiers. Actually, water has no common characteristics with other foods, so the users’ ingestion pattern for liquid achieved highest classification than rest of food categories. Soft solid food classes such as banana, bagel, egg, and waffle obtained low classification accuracy as compared to food categories with high hardness and viscosity (thickness) such as apple, carrot, pizza, and salad. Soft food classes might have very little difference in their chewing ingestive pattern due to similar texture of softness. Their recognition accuracy can be improved by adding extra sensor to the automated food monitoring system. The confusion matrices of our method indicate that some swallows of cookies and pizza were misclassified as the other. These foods may have minor textural characteristics in common that cause incorrect classification.

A possible limitation of our present study is to put coffee, chocolate milk, juice, milk, and water in one category of liquid. Liquid categories are important to differentiate because each liquid class carries different calorie number. This problem may be solved with the advancement of new sensor technologies. Another limitation is the design of the necklace which might not be convenient to wear in real-life settings if it is launched in its current form as a commercial product. Further research is needed to explore wireless sensor technologies which can transfer food ingestive samples to data collection module.

6. Conclusion

We have presented a novel necklace-type wearable system embedded with a piezoelectric sensor. Our system detected successfully food intake patterns of 17 categories in real-life settings with an accuracy of 89.2%. The most optimal features extracted from ingestive patterns in time domain outperformed the previous state-of-the-art piezoelectric sensor system that employed spectrogram features. We have found that it is important to fully exploit the chewing pattern before the swallowing event in the raw signal, and that
at the same time, it is essential to select the proper length of samples to classify foods more accurately. Our smartphone app has the additional advantages of automatically annotating the data for chews and swallows and providing real-time feedback to users through smartphone application.

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