Intraoral Temperature and Inertial Sensing in Automated Dietary Assessment: A Feasibility Study

Keum San Chun
The University of Texas at Austin
Austin, Texas, USA
gmountk@utexas.edu

Sarnab Bhattacharya
The University of Texas at Austin
Austin, Texas, USA
sarnab2008@utexas.edu

Caroline Dolbear
The University of Texas at Austin
Austin, Texas, USA
cedolbear@utexas.edu

Jordon Kashanchi
The University of Texas at Austin
Austin, Texas, USA
jordonkash@utexas.edu

Edison Thomaz*
The University of Texas at Austin
Austin, Texas, USA
ethomaz@utexas.edu

ABSTRACT

Recent advances in Automated Dietary Monitoring (ADM) with wearables have shown promising results in eating detection in naturalistic environments. However, determining what an individual is consuming remains a significant challenge. In this paper, we present results of a food type classification study based on a sub-centimeter scale wireless intraoral sensor that continuously measures temperature and jawbone movement. We explored the feasibility of classifying nine different types of foods into five classes based on their water-content and typical serving temperature in a controlled environment (n=4). We demonstrated that the system can classify foods into five classes with a weighted accuracy of 77.5% using temperature-derived features only and with a weighted accuracy of 85.0% using both temperature- and acceleration-derived features. Despite the limitations of our study, these results are encouraging and suggest that intraoral computing might be a viable direction for ADM in the future.

CCS CONCEPTS

• **Human-centered computing → Empirical studies in ubiquitous and mobile computing**; • **Applied computing →** *Health informatics*;

KEYWORDS

Automated Dietary Monitoring, Intraoral Sensing, Intraoral Temperature, Human Activity Recognition

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*This is the corresponding author

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Figure 1: A sub-centimeter scale (7 mm x 5 mm) intraoral sensor was placed on a U.S. Quarter for size comparison. The device samples temperature and acceleration data at a rate of 54 Hz.

1 INTRODUCTION

Gold standard methods of dietary assessment are self-report-based approaches such as food frequency questionnaires (FFQ), 24-hour recalls, and food diaries [9, 12, 13, 20]. While these methods have been used by nutritional scientists and medical professionals for decades, they are fraught with biases, which increase the risk of false characterization of dietary habits [10, 14, 20]. In addition, the need for active input from people makes dietary monitoring highly dependent on people's own motivation and honesty for accurate accounts of dietary habits[19]. As a result, Automated Dietary Monitoring (ADM) continues to be an active area of research.

Over the past decade, the most promising ADM efforts have been mostly centered on improving eating detection performance (i.e. detecting eating or drinking) in naturalistic environment. Significantly, recent approaches have become increasingly more practical and usable in naturalistic environments [2, 3, 5, 21, 24]. However, in spite of these encouraging developments, the ability to infer additional, objective information about diet such as the *type* of food individuals consume remains a challenge. This is one of the key areas where ADM approaches lag significantly behind self-report-based methods.

Researchers have explored numerous options to characterize what individuals consume [8, 17, 22, 23]. Due to the richness in information that imaging provides regarding food type, food type classification based on the automated analysis of photographs has

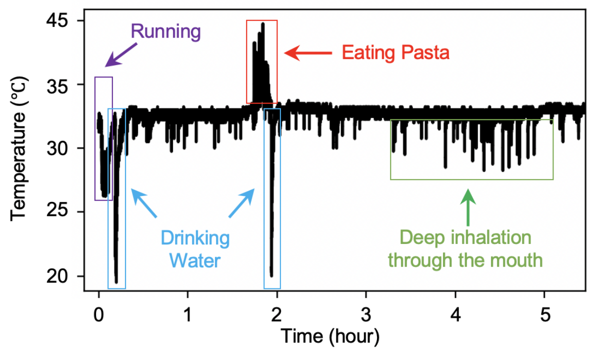

Figure 2: The intraoral temperature was measured from a subject for a day. During running activity (purple), the subject breathed through the mouth, which lead to a decrease in the intraoral temperature. Drinking water at room temperature (25 °C) produced sharp downward spikes (blue). The consumption of hot pasta increased the intraoral temperature (red). Throughout the day, the subject's sporadic inhalation through the mouth lead to a brief decrease in the intraoral temperature (green).

been a popular approach [8, 17]. However, this approach often requires active engagement from users as the photos of foods need to be manually and individually taken. Additionally, identifying foods and food groups with computer vision techniques has turned out to become a very difficult task considering the large space of food options and how they are prepared. An alternative to food photos has been to try to identify food type with wearable-based approaches using acoustic and inertial sensors [1, 15]. Since these sensors are not in direct contact with the food, only indirect information about foods, such as chewing sounds, is available for food type classification. While intraoral sensing has been also explored, the need for dedicated radiofrequency receiver or wired connection limits the broad adoption of the technology [11, 22, 23].

In this paper, we present an intraoral device designed for ADM that can measure intraoral temperature and acceleration. The device is small (5 mm by 7 mm), Bluetooth-enabled, battery-powered, and waterproof. It is designed to be placed on the inner side of two central incisors on the lower jaw, and continuously measure intraoral temperature and motion of the jawbone. Moreover, it can transmit the data to an Android device via Bluetooth Low Energy (BLE). Due to its intraoral placement, the wearable has a unique advantage over other systems designed for this purpose, as the sensors can come in contact with foods, thereby enabling direct measurement of diet-related information.

2 INTRAORAL TEMPERATURE SENSING

While intraoral temperature is influenced by breathing patterns, talking and smoking, the intake of food and fluid is associated with quicker changes of intraoral temperature than other factors [16]. Throughout a 24-hour period, the mean intraoral temperature fluctuates between 33.9°C and 35.9°C [4]. However, when food is ingested, the intraoral temperature can quickly deviate from this range depending on the temperature of the ingested food (See Figure 2) [16]. With this observation, we hypothesized that the sharp change in intraoral temperature could be leveraged to detect dietary intake events and provide further insight into consumed diet such as the volume of fluid ingested or the temperature of foods.

3 SYSTEM DESIGN

For intraoral sensing, the sensing device has to be small enough to be placed inside the mouth. In addition, a robust sensing system that can withstand high level of humidity and mechanical stress inside the oral cavity is a prerequisite. To this end, a sub-centimeter scale, wireless and low-powered sensing device was developed (See Figure 1). In this section, the hardware design and sensor implementation for the intraoral sensing device are described.

3.1 Hardware Design

The overall system is comprised of a microcontroller (MCU), an accelerometer sensor and a battery. A wireless MCU (nRF52811, Nordic Semiconductor) was used to enable wireless communication via BLE, and the MCU's internal temperature sensor was used for temperature sensing. A 3-axis accelerometer (MC3635, mCube) was used to track the motion of the lower jawbone. To minimize the size of the system, hardware components were placed on both sides of a flexible, two layer, printed circuit board (FPCB) with thickness of 0.13 mm. The overall system was designed to be powered by a battery. A coin cell battery (XR7734, ZPower) with 7.7 mm in diameter was used to power the device [26]. This particular battery was chosen because it is rechargeable, non-toxic, non-inflammable, and more energy dense than lithium ion battery [25]. The nominal voltage and capacity of the battery were 1.86 V and 32 mAh, respectively. [26]

3.2 Hardware Programming and Configuration

The Serial peripheral interface (SPI) was used to connect the accelerometer to the MCU. The accelerometer was configured to sample at a rate of 54 Hz, and the MCU was put into sleep-mode and only woke up for transmitting data. BLE uses 2.4 GHz frequency at which signals get significantly attenuated by living tissues [7]. Within the mouth, the sensor is surrounded by living tissues, therefore the transmission power of the sensor was increased to +4 dBm, the maximum value supported by the MCU, for communication and data transfer to the smartphone app.

3.3 Moldable Mouthpiece

The sensor was embedded into a personalized and moldable mouthpiece. Prior to the study, the participants' lower incisor teeth were molded using thermoplastic, a material that softens when heated and stiffens when cooled. Then, the intraoral sensor was inserted on the inner surface of the mold, facing the intraoral cavity (See Figure 1). Next, the sensor was sealed by applying an additional, thin layer of thermoplastic over the intraoral sensor. To ensure that the intraoral sensor does not detach from the teeth during the study, the plastic mold was secured to the teeth with dental floss.

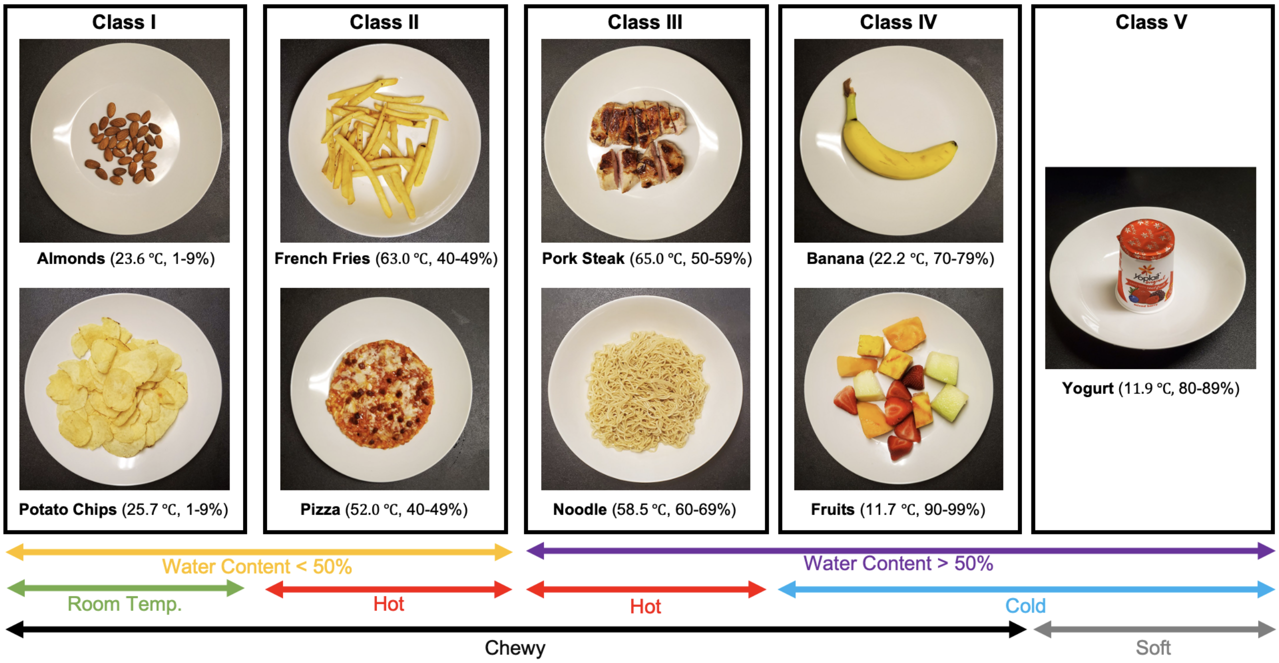

Figure 3: The list of foods consumed during the food intake data collection is shown along with their served temperature and approximate water-content level. The temperatures of the foods were measured directly before consumption and the water-content for each food was referenced from the study by Popkin *et al.*. [18]

4 DATA COLLECTION

To examine the feasibility of detecting and classifying food categories based on intraoral temperature and accelerometer data, we conducted two user studies. One of the studies was controlled in that we gave specific foods for participants to eat. In the other study, one participant collected data in fully naturalistic settings. Both studies were approved by the Institutional Review Board at our university and are described in detail in the following sections.

4.1 Food Type Classification Study

In this experiment, five data sets containing intraoral temperature and jawbone acceleration were collected from four participants (3 males and 1 female) aged between 19 and 31 years old (26.5 ± 5.4). A total of 9 types of foods shown in Figure 3 were consumed by each participant. The foods were chosen because they are frequently consumed in human daily lives and represent wide variety of serving temperature and texture. The foods were classified into five categories. **Class I** represents dry foods (water-content < 50%) that are typically consumed at room temperature. **Class II** represents dry foods that are consumed at hotter temperature. **Class III** includes foods that are moist (water-content > 50%) and served at hotter temperature. And **Class IV** represents foods that are moist and served cold. Lastly, **Class V** contains cold foods that require minimal chewing such as yogurt.

Before each food was consumed, its temperature was measured using an infrared thermometer. Figure 3 shows the temperatures of the foods and their approximate water-content. The water-content of each food was referenced from the study by Popkin *et al.* [18]. The average duration of food intake activity from all subjects was 28 minutes and 49 seconds. The food intake duration for each type of food is shown in Table 1.

Table 1: Average Food Intake Durations

Food	Duration (s)	Food	Duration (s)
Banana	139.9 ±28.9	Nuts	150.4 ±50.1
Chips	149.0 ±39.3	Pizza	194.6 ±51.7
French Fries	157.0 ±42.3	Pork Steak	268.6 ±96.8
Fruits	177.9 ±76.4	Sandwich	211.3 ±32.0
Noodle	243.4 ±90.8	Yogurt	119.8 ±53.5

4.2 Eating Detection Study

In the *in-the-wild* study, intraoral temperature and acceleration data was collected for 9.5 hours from one participant. During this time period, normal daily activities were performed, and the data was manually labeled on an smartphone as the data was collected. The participant reported two eating events (eating bread and pasta). Non-eating activities included talking, reading out loud, running, walking, sitting, lying on a bed, watching a video, washing dishes and typing on a computer.

5 DATA ANALYSIS

5.1 Food Type Classification

The data obtained in the controlled study was used to create a food type classification algorithm. To reiterate, a total of five data

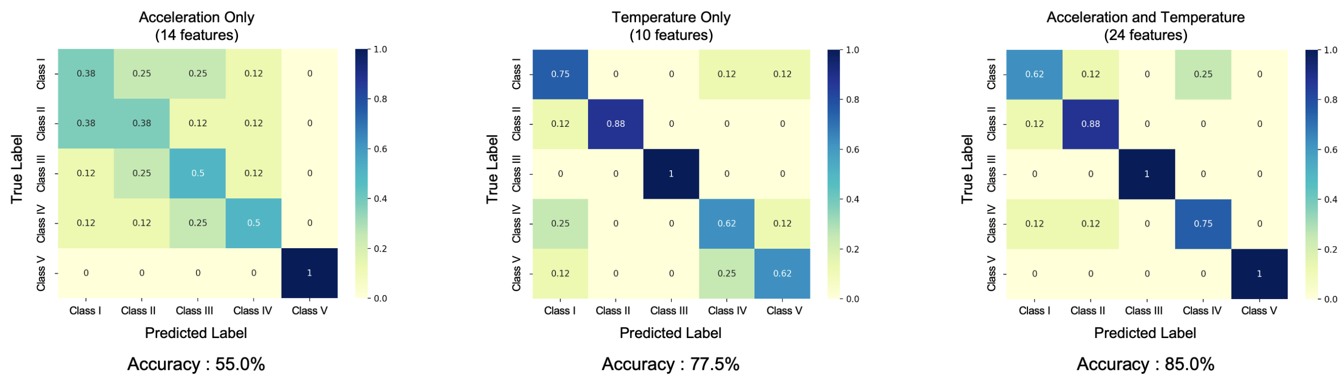

Figure 4: With only acceleration-derived features, the five classes of foods were classified with a weighted average accuracy of 55.0%. The acceleration features are shown to be effective at differentiating Class V (e.g. yogurt) from the rest of the classes. When only temperature-derived features were used, the classification accuracy improved significantly. However, with temperature only, fruits and yogurt are confounded as they are typically consumed at similar temperature. When both acceleration- and temperature-derived features were used, the best weighted average accuracy of 85.0% was obtained.

Table 2: Summary of Features for Food Type Classification

Feature	Description	Feature	Description
1	variance	13	sum of FFT for 0.5 Hz < f <2 Hz
2	maximum	14	signal power
3	minimum	15	max temp. slope
4	mean	16	mean temp. slope
5	max. - min.	17	min temp. slope
6	root mean square	18	variance
7	sum of FFT for 1 Hz < f <5 Hz	19	minimum
8	max of FFT for 1 Hz < f <5 Hz	20	maximum
9	sum of FFT for 5 Hz < f <15 Hz	21	mean
10	max of FFT for 5 Hz < f <15 Hz	22	max. - mean
11	sum of FFT for 15 Hz < f	23	max. - min.
12	max of FFT for 15 Hz < f	24	begin temp. / (max. - min. temp)

sets were collected from four individuals. Each data set represents consumption of 9 types of foods shown in Figure 3. From each food consumption data, a set of features listed in Table 2 was extracted. The temperature-derived features are shaded, and the acceleration-derived features are unshaded in Table 2. A Random Forest (RF) classifier was trained with the data; its accuracy was evaluated with leave-one-fold-out (LOFO) cross validation.

5.2 Eating Detection

To examine the feasibility of eating detection with the intraoral sensor, we collected an additional 3rd data set representing non-eating activities such as running, walking, talking, sitting still and washing dishes. With this non-eating dataset and the controlled data set, a RF classifier was trained. The *three-phase* signal processing pipeline proposed by Chun *et al.* was applied for eating detection [6]. In this pipeline, a sliding window of 4-second with 50% overlap was used to generate frames. From each frame, features were extracted to train the RF classifier, and the trained classifier was applied to the free-living data set for testing. The predictions for each frame represent chewing activity. The predictions were subsequently clustered to infer eating events.

6 RESULTS AND DISCUSSION

With LOFO cross validation, 9 types of foods were classified with weighted average accuracy of 77.5% when the features derived from the intraoral temperature were used (See Figure 4). When only acceleration features were used, the weighted average accuracy was 55.0%. However, with both acceleration and temperature-derived features, the weighted average accuracy increased to 85.0%. With only acceleration features, the classifier was only effective at distinguishing **Class V** (e.g. yogurt) from the rest. This is because **Class V** foods require minimal chewing while the other classes require significantly more mastication. The acceleration features were not effective at distinguishing foods from **Class I** through **Class IV**. On the other hand, the temperature-only features were effective at differentiating the five classes. **Class IV** (e.g. fruits) and **Class V** (e.g. yogurt) were confused because they were typically consumed at similar temperatures. However, when both acceleration and temperature features were used, **Class IV** and **Class V** could be differentiated. For eating detection, we collected a free-living data set for 9.5 hours in a naturalistic environment from one participant. In this data set, two eating activities were present. With a RF classifier, the eating activities were detected with precision of 93% and recall of 96%.

7 CONCLUSION

In this work, we explored the feasibility of using a novel sensor for intraoral food type classification and eating detection. Through a study with 5 participants, we demonstrated that 9 types of foods can be classified into 5 categories with 85.0% weighted accuracy. Eating activities were detected with 93% precision and 96% recall. Despite limitations in terms of the number of study participants and food types, we believe our results are encouraging, and suggest that additional intraoral sensing research is warranted towards developing new and alternative avenues for ADM methods.

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