An Assessment of the Accuracy of an Automated Bite Counting Method in a Cafeteria Setting

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Abstract

Advances in body-worn sensors and mobile health technology have created new opportunities for empowering people to take a more active role in managing their health. Obesity has been recognized as a target of opportunity that could particularly benefit from this approach. Self-monitoring of dietary intake is critical for weight loss/management, but currently used tools such as food diaries require users to manually estimate and record energy intake, making them subjective, prone to error, and difficult to use for long periods of time. Our group is developing a new tool called the "bite counter" that automates the monitoring of caloric intake. The device is worn like a watch and uses sensors to track wrist motion during a meal. Previous studies have shown that our method accurately counts bites during controlled and uncontrolled meals in the lab. This thesis describes a study to evaluate the accuracy of the method in a cafeteria setting. A cafeteria booth that can seat 1 to 4 people was instrumented with tethered wrist motion trackers, embedded scales, and video cameras, to enable recording of wrist motion, changes in food weight, and actual activities during eating. A total of 276 subjects were recorded eating uncontrolled meals. The data was manually reviewed and the times of all actual bites taken were recorded as "ground truth". The wrist motion data was then analyzed using the automated bite counting method to determine the times of automated bite detections. These were compared against the ground truth to evaluate the accuracy of the bite counting method. In total, 22,383 bites were evaluated, consisting of 380 different foods, eaten using 4 different utensils from 4 different containers, across a variety of subject demographics. Results show that the method varied in accuracy from 39 % (for ice cream cones) to 88% (for salad bar) across the 39 most commonly eaten foods (>=100 bite occurrences in the data set). The average accuracy found across all bites was 76% with a positive predictive value of 87%. A second test of the bite counting method using modified timing thresholds resulted in 82% accuracy with a 82% positive predictive value. These results indicate that the method works well across a

wide variety of foods, utensils, containers, and subject demographics. The results also indicate that eating rate may be the most important variable to consider in the search for improvements to the method.

Acknowledgments

Table of Contents

List of Tables

List of Figures

Chapter 1

Introduction

Advances in body-worn sensors and mobile health technology have created new opportunities for empowering people to take a more active role in managing their health [17]. Obesity, which now afflicts one in three adults and one in six children in the United States [12, 22], has been recognized as a target of opportunity that could particularly benefit from technological innovation [11, 18, 32]. Self-monitoring of dietary intake has been consistently found to be associated with successful weight loss and maintenance [3, 19]. However, currently used tools, including food diaries and 24 hour recalls, require users to manually estimate and record energy intake, making them prone to error and difficult to use for long periods of time [31]. While the technology of body-worn sensors has advanced the assessment of energy expenditure in the form of accelerometer-based physical activity monitors [34], the development of a similar tool for monitoring energy intake has proven elusive. Previous research has been limited to using cumbersome measurements of sound and muscle activity at the throat and ear, and multiple sensors tracking torso and limb movements [1, 25].

Our group is developing a new tool called the "bite counter" that automates the monitoring of caloric intake [10]. The device is worn like a watch and uses sensors to track wrist motion. It is turned on/off at the beginning/end of a meal. During eating, the device recognizes a pattern indicative of the user taking a bite (defined as the intake of food or liquid into the mouth). Tested on 47 people eating the meals of their choice, our method correctly detected 86% of bites [9]. A study of 83 people using bite counters for two weeks found an average per-meal correlation of 0.53 between bites and calories [27]. The same study found that 76% of participants preferred using the bite counter over a 24-hour recall, and that the automation provided by the tool could save people

an average of 25 minutes per day in estimating and recording energy intake.

The purpose of the work described in this thesis is to test the method on a very large data set of bites, and to systematically analyze its accuracy across different foods, utensils, containers, and subject demographics including age, gender and ethnicity. The rest of this thesis is organized as follows: The first chapter gives a brief introduction to the obesity problem, sensors used to track wrist motion, and the previous studies of the bite counting method. The second chapter describes the new data collection and methods used for evaluating the bite counting method. The third chapter described the results, breaking down the accuracy of the method across all the variables tested. The fourth chapter provides discussion, conclusions, and insights for future work.

1.1 Background and motivation

Obesity is an epidemic problem, not only in the U.S., but also in other parts of the world [4]. According to data released by the Centers for Disease Control and Prevention (CDC) on August 2010 [15], there were more than 72 million obese adults in the United States. There was no state having an obesity rate less than 15 %. People with obesity had to spend more on medical costs than those of normal weight at the average cost of $1,429. In 2007-2008, the prevalence of obesity among the adult US population was 33.8% [13].

According to National Institutes of Health (NIH), the term obesity refers to a body condition in which a person's weight exceeds what is considered as healthy for their height [21]. The typical method to measure obesity is to calculate body max index (BMI). BMI is defined as body weight divided by the square of height. A value of BMI between 25.0 and 29.9 is considered overweight; a value 30.0 and above is considered obese [23]. Obesity is correlated to several major diseases, such as diabetes, heat disease, stroke, and higher rates of some cancers [33]. For people who are obese, losing even 5 to 10 percent of body weight is likely to improve health [14].

The terms energy intake and energy expenditure are used to reflect the energy (calories) consumed and used by a person. People diagnosed with obesity are losing balance between their energy intake and energy expenditure [26]. Energy intake and expenditure are commonly used in studies on obesity [26, 2, 7]. In order to maintain weight, energy intake and energy expenditure should be balanced. The most common method to monitor energy intake is to keep a food consumption log on a regular time basis. However, studies have shown that people tend to under-report the amount

of consumption for their diets [16, 20, 5].

The long-term goal of this research project is to develop a simple and accurate method, which is automated and objective, to calculate energy intake during a meal. It is also intended to keep a long-term log for review. With this method, people can more easily observe and review energy intake. The device can tell the wearer that a target intake has been reached and it is time to stop eating, thereby helping people create long term healthy eating patterns.

1.2 Micro-electromechanical systems sensors

Micro-electromechanical systems (MEMS) are micro systems consisting of micro mechanical components and micro electronics. MEMS sensors are a particular kind of sensor based on the techniques of MEMS and are integrated in a single chip. Typically, the mechanical components in a MEMS sensor monitor physical quantities, and the electrical components record the quantities and output them as electrical signals. MEMS sensors are small and economic for power consumption. With these advantages, MEMS sensors are widely used in portable devices, such as cellular phones, portable computers and GPS navigators. Popular MEMS sensors installed in these devices include accelerometers, gyroscopes, compass sensors, gravity sensors, etc. The work in this thesis uses two kinds of MEMS sensors, accelerometers and gyroscopes.

The theoretical basis for the accelerometer is Newton's second law and Hooke's law. Consider a spring-mass system. According to Hooke's law, the force applied to the spring is in direct proportion to the offset of the spring from its equilibrium position, as shown in Equation 1.1.

$$F = -kx \tag{1.1}$$

According to Newton's second law, the force is in direct proportion to the acceleration as shown in Equation 1.2.

$$F = ma \tag{1.2}$$

The relation between the acceleration and the offset of the spring can be derived by combining these two equations together, as shown in Equation 1.3.

$$a = -\frac{k}{m}x \tag{1.3}$$

In this spring-mass system, the spring constant k and mass of the spring m are constant and known. By measuring the offset of the spring from its equilibrium position , the acceleration can be calculated from the above equation. An accelerometer follows the principles of this spring-mass system.

A MEMS gyroscope, which is based on the principle of the Coriolis effect, measures the angular velocity of an object around one or several axis. For a 3-axis gyroscope, it can measure the rotation about yaw, pitch and roll at the same time. In our work, we combine accelerometers and gyroscopes to track and monitor wrist movement in 3D space.

1.3   Previous related work done by our group

Dong et al. [10] developed an automated bite counting method that uses a wrist worn device to track wrist motion. The method was based on the finding that the roll motion of the wrist can be used for sensing and detecting the occurrence of a bite. The device uses a gyroscope to sense the roll velocity of the wrist. An algorithm was developed to detect a pattern indicative of a bite. The pattern can be defined in four events. The first two events are the positive and negative threshold for the roll velocity and the last two events are the time thresholds between the roll motions (positive and negative) for a bite, and between the end of a bite and the beginning of the next bite. In the algorithm, T1 and T2 are defined as the two roll velocity thresholds; T3 and T4 are defined as the two time thresholds. By looking for this pattern during a meal, the device can detect the bites that occurred and count the number of these bites. Dong used tethered sensors for recording wrist motion to develop and test the method [8, 9]. Bite Technologies currently manufactures a stand-alone, untethered device for use in research[1].

In preliminary studies [10], the research team conducted three experiments to test the accuracy of the bite counting method. The first and second experiment were done in laboratory settings. The first experiment tested the method on 51 subjects, most subjects eating 3 times, for a total of 139 meals. All variables in the meal were held constant, including the utensil (fork), container (plate), and food (waffles). The second experiment was less controlled. Forty-seven subjects were tested eating 49 meals (two subjects participated twice) with their own foods and beverages. In the third experiment, four subjects wore an early untethered prototype device for 54 meals outside the laboratory. The results of these tests are summarized in Table 1.1. They show that the accuracy of

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[1]http://www.icountbites.com/

Test	Settings	Sensitivity	Positive predictive value
1	controlled conditions	94%	80%
2	laboratory meals	86%	81%

Table 1.1: The results of preliminary tests.

the method generally decreased slightly as the restrictions of the eating conditions lessened.

1.4 Novelty

The work in this thesis follows the work described in the previous section. We extend the previous experiments testing the accuracy of the bite counting method to an even larger data set. We performed the experiment in a cafeteria setting. A total of 276 subjects were recorded consuming 518 courses. The food range is extensive, consisting of 380 different types of food and liquids. There were also multiple choices for utensils and containers. The large number of participants allowed us to test the effect of subject demographics on the accuracy of the method, including gender, ethnicity and age. Based on all the data collected, we built a bite-level database, which includes a total of 22,383 bites. Each bite is stored with its contextual details, including food type, hand used, subject demographics, and other variables.

Using the bite database, we performed a comprehensive analysis of the accuracy of the bite counting method. We analyze the impact of variables that affect the detection accuracy. The variable in this study refers to a field of the bite related information for a particular bite. For example, the utensil used for the bite is bite related information, thus utensil is considered to be a variable. The variable can take different number of values depending on the type of the variable. In this thesis, we only analyzed the impact caused by single variables. However, the detection accuracy of the bite counting method could be affected by a combination of several variables. We have not explored the analysis in this much detail, but discuss its importance for future work.

Chapter 2

Research Design and Methods

2.1 Overview

This chapter covers in detail the assessment of the accuracy of the automated bite counting method [10]. First, with all the bite and demographic information collected for each meal from the campus cafeteria, we introduce a database file built to facilitate the analysis process. The bite information has two different parts, sensor reading data information and ground truth data information. They are stored in two different sets of files separately on a per meal basis. Demographic data for all the participants involved in this study is stored in one file. The database file incorporates all information in the above files and breaks down meal basis information into units of ground truth bites. It has 22,383 total ground truth bites and all the related information we need to conduct our study. This related information is also what we called variables. Second, we built two tools for our analysis. For the first tool, it is built to combine one or multiple variables and group bites with the same value of variables to calculate their counts and detection rate of bites. The second tool combines one or multiple variables with selected values and outputs the corresponding bites with the name of sensor data files and ground truth file for each bite, as well as the time stamp in the ground truth file for this bite occurred. This tool is used to cooperate with a reviewing tool [9](page 83-84), for reviewing the eating video with recorded data, whenever a review or an evaluation of video is needed. Third, we evaluate each variable of our interest that affects the accuracy of the bite detection based on the outputs of the above tools with our intended inputs. Moreover, we analyze each of these variable on the eating rate of bites. Finally, we calculate the true positive rate and the

positive predictive value with the adjusted time thresholds.

2.2 Data

2.2.1 Data Collection

Data used in this study was recorded and collected in the Harcombe Dining Hall of Clemson University by a large group of people. The author of this thesis was also involved in this process.

This dining hall is a cafeteria, one of the largest dining places on the Clemson campus, which provides a vast variety of foods and beverages. People select their foods from several different buffet style serving stations. Choices include a salad bar, French fries, vegetables, pasta, pizza, chicken, hamburger, sandwich, bread, shrimp and fruit. Popular beverages include soda, water, diet soda, coffee, milk, juices, tea and sweet tea. Foods and beverages are served in several types of containers, including plate, bowl, glass and mug. People use different kinds of utensils during meal consumption, typically spoon, hand, fork and chopsticks.

An instrumented booth with four seats was designed and built to assist the collecting of data from participants. A custom motion tracker was attached by cables and connected to two laptops nearby. The raw sensor data was stored in the laptop in terms of files and each meal of a participant has a unique sensor data file associated to it. Four trays were positioned in front of each seat with a digital scale set beneath each of the tray to detect the change of food weight during a meal. This information was stored in the laptop as well. The model of the laptops we used was Dell Latitude E6520. The digital scale we used was Ohaus SP401 scale, which was also connected to the laptops.

Figure 2.1 shows a an image of the instrumented table.

Four digital cameras were mounted on the ceiling. Each of them was targeted at one of the participants. The cameras were adjusted with proper position to shoot the participant's face, both hands, tray and foods in the video. They were used to monitor the whole process of the meal for the participant. The recorded videos are used to review off line for a couple of different purposes, such as ground truth, labeling and other studies. Figure 2.2 shows an example of the snapshot of the video.

We built a custom wrist motion tracker to track the motion of the wrist of participants during the meal. The tracker was built based on the method in [10, 9]. This custom wrist motion

Figure 2.1: The instrumented table.

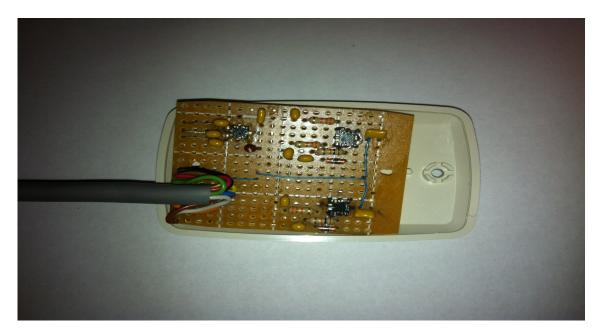Figure 2.2: A snapshot of the video shot in the cafeteria.

Figure 2.3: A picture of the inside of the wrist motion tracker.

tracker contains of three sensors, two gyroscope and one accelerometer, built on a small circuit board. The MEMS sensors being utilized were STMicroelectronics LIS344ALH [28], LPR410AL [29], and LPY410AL [30]. The LIS344ALH is a three-axis linear accelerometer. The LPR410AL is a two-axis gyroscope that detects roll and pitch, and the LPY410AL is another two-axis gyroscope that detects pitch and yaw. One of the pitch signals is redundant and ignored in the device. The person who uses this device should wear it on the hand that is mostly used when eating.

This device uses a plastic case to embed the circuit board inside. The case has a band, which is used to wear on the wrist. The circuit board is fixed inside the case firmly when screws are tightened to reduce the possible noise. A hole was drilled to fit in the cable that transmits signals of the sensors to the attached computer. The device records the wrist motion of participants in terms of acceleration in 3-axes and changing rate of angles of roll, pitch and yaw while eating. All of these data are transmitted to the laptop and transformed from analog signals to digital signals through a Measurement Computing USB-1608G A/D board connected to the laptop. Figure 2.3 shows the inside of the wrist motion tracker.

The model of the camera used was a Cisco PVC300 [6]. It is a zoom Internet camera. With its zoom function, we could adjust it to the best angle of view as we needed in the experiment. The resolution was 640×480 and it was clear enough for us to review the whole eating process. Along

9

with this camera, Cisco also provided a video monitoring software. We utilized this software to record the video.

There were 276 participants with successful data collection in total, 131 males and 145 females with age ranging from 18 to 75. Each participant was given a particular ID for the study and different courses during a meal for a single participant were also differentiated. All participants involved were asked to wear the device while eating, except when they went away from the table to fetch some food during the meal (this separated data into courses). There were no restrictions for food choices, they could pick up whatever they want to make their meal. There were also no restrictions on body movements or hand movements as well, they could act freely when they were having their meals. One person stood by the table offering instructions and being ready to answer questions for the participants. Food and beverages, container and utensil information was recorded for each meal. Questionnaires and surveys of certain demographic information were performed and recorded for each of the participants for our study. The sensor data, videos and other related information are classified by the participant's ID and each participant's different courses.

For detailed information about the questionnaires and protocols, please refer to Salley's Master's thesis [24].

2.2.2   Ground Truth

The recored videos were reviewed by ground truthers to mark and label the actual bites taken during the meal. A reviewing tool was developed to facilitate the work [9]. Figure 2.4 shows the GUI interface of the tool. This tool integrates and synchronizes the sensor data and video footage. It displays the video on the top right and concise instructions on the bottom right as shown in Figure 2.4. Oscillograms of sensor data were also included. It also displays the time and index on the top. There are three function labels in this tool, which are File, Axis and Record. File label is used to load in the data of a specific participant for a specific meal, synchronization of video and sensor data is done automatically. The function of the Axis label is to change the oscillograms of sensor data on the left, such as, changing the oscillogram of yaw data to roll data. When the user finds out that there is a bite occurred in the video, then the record label is used. When the user hit the Record label, a window prompts for bite related information as shown in the bottom left of Figure 2.4.

The tool is designed to allow time navigation by stroking some computer keyboard keys

Figure 2.4: The GUI interface of the ground truth reviewing tool.

as instructed on the interface. Marking the bite is performed by viewing the content of the video, recording the time stamp, food taken by the subject, hand, utensil and container used at that time. The user can review the video back and forth to determine the time frame when the bite was taken. After all the bites in the meal were found and recorded, A text file is generated with a list of all the information recorded in it. This file is stored in the same path with the video and sensor data for the meal of the participant.

2.2.3   Acknowledgments

The data collection described in this thesis took the effort of a large group of people, including the author of this thesis. The data is being used for several different studies including the one described herein. Professor Adam Hoover led the team that constructed the eating station. Mike Wilson constructed the table and cabinet. Ziqing Huang designed and debugged the custom wrist motion tracker. Sanjay Patil chose the model of video camera and designed the video recording process. Kuang Yuan chose the model of digital scales and prototyped their recording. John Hicks did cabling and circuit board soldering for the custom wrist motion tracker. Yujie Dong did the system integration for the eating station, and did the programming for the recording software. Professor Adam Hoover did programming for the reviewing software with assistance from Yujie Dong

and Ryan Mattfeld. The reviewing software was used to manually mark all the bites in the data, including times, utensils, containers, and foods consumed. It was piloted by Ziqing Huang, Sanjay Patil and Kuang Yuan.

Professor Eric Muth organized a large group of graduate and undergraduate students who manually marked the entire data set. James Salley oversaw the team of undergraduates, including Courtney Jackson, Francklin Blaise, Lauren Piekarsky, Mallory Westmoreland, Olivia Williams, Deanna Burns, Rebekah Dixon, Kelly Jeanes, Kevin Kohm, Lauren Rampey, Regan Schroer, Laura Timmons and Leah Williams.

James Salley and Prof Adam Hoover reviewed and correlated all the daily menus and meal food logs to create consistent food labels across the entire data set. The author of this thesis created the bite database and evaluated the performance of the bite counting method on the cafeteria data set.

2.3 Database File

We developed a command line tool in the C programming language to generate the bite database file. The database file in this study is a bite-level text file that includes all the ground truth bites information. It allows us to test the accuracy of bite counting method in a comprehensive way across a range of different variables. These variables include the type of food, age, gender, hand used for the bite, handedness, containers, utensils and ethnicity, which potentially affect the accuracy of the bite counting method. Some other information is also included in the database file for future use. This database file is organized in such a way that each row represents a unique bite and all related information, each column is one piece of the information relating to that bite. Among these columns, one column is special. It indicates whether this ground truth bite is detected by the bite counting method or not. In order to obtain this information, a two phase method is utilized. In the first phase, the bite counting detection method is running on all of the sensor data to find out all the bites detected by the method. In the second phase, all these automatically detected bites are compared and matched with manually marked bites (ground truth bites). For a specific ground truth bite, if it is matched with an automatically detected bite, then it is considered to be detected and vice versa. The classification (evaluation) methods were developed by Dong et al. [10]. Most of the other information are automatically extracted from two sources: the files that store the ground

12

Column	Information	Remarks
1	participant Identification	p with 3 digits,for example, p005
2	path of ground truth file	
3	path of sensor data file	
4	the ground truther's initials	
5	time index the bite occurs	time in second $\times$ sensor sample rate(15Hz)
6	hand used for the bite	
7	utensil	
8	container	
9	food	
10	time since previous bite	0 if it is the first bite for the meal
11	time until next bite	0 if it is the last bite for the meal
12	detect or not	Y = detected; N = not detected
13	handedness	
14	age	
15	gender	
16	height	inches
17	weight	pound
18	body fat	percentage
19	BMI	
20	waist	inches
21	hips	inches
22	ethnicity	

Table 2.1: Information in the bite database file.

truth information and the file that stores the demographic information, as mentioned in the previous section.

Table 2.1 shows all the information included in the bite database file, classified by columns.

2.3.1 Preparation

All collected data is classified and organized by using the participant's ID number and the label of the meal to name the directory. These directories contain all associate files belonging to the meal of the participants. For example, path "p005/c1" contains all the bite information for the first course (c1) recorded for the participant with ID "p005". Some participants had more than one course. Thus, if the participant had two or more courses , there would be several directories under the directory with the name of that participant's ID. Three kinds of files contribute to the bite database file, which are sensor data files, ground truth files and the demographic file (only one file). In order to extract all the bite information from these files by our tool, two ordered lists are generated for both sensor data files and ground truth files. The lists contain the full paths for all

the sensor data files and ground truth files respectively.

2.3.2 Computer detection of the ground truth bite

The information of whether a ground truth bite is detected by the bite counting method is crucial in the database file. Only after this information is available for all the ground bites in the database file can we conduct any tests to evaluate the accuracy of the bite counting method. There are two steps to get this information. The first step of this method is to find out all the bites detected by the bite counting method, and the second step is to classify these computer detected bites with the ground truth bites.

2.3.2.1 Bites detected by the bite counting method

The bite counting method is already described in the first chapter. The detail of the algorithm will not be covered in this section (please refer to [10, 9]). As mentioned before, sensor data is collected from participants during the meal to reflect the wrist motion of them. The algorithm works on the sensor data by finding the predefined pattern of the bite in the data set, which is actually the pattern of the wrist motion. The command line tool accepts the list with the full paths for all the sensor data files and runs the bite counting method posteriorly on the data. A intermediate result, which is a list of bites and their time stamp is generated.

2.3.2.2 The classification of computer detected and ground truth bites

The classification method used here is identical with the classification method used in [10] (Evaluation subsection in Method section). Figure 2.5 shows the classification method. This figure is used with permission from [10] (Fig. 6).

The overview of the classification is as follows. The computer detected bites and ground truth bites of the same meal of a participant are compared. Computer detected bites are ignored if time stamps are 10 seconds earlier than the first ground truth bite or 10 seconds later than the last ground truth bite. All ground truth bites and remaining computer detected bites are labeled as unmatched bites first. The evaluation is performed from the first computer detected bite to the last, and each computer detected bite is evaluated each time. The current evaluated bite is only matching to the ground truth bite which is the first unmatched ground truth bite with time stamp between the previous evaluated computer detected bite and the next computer detected bite to be
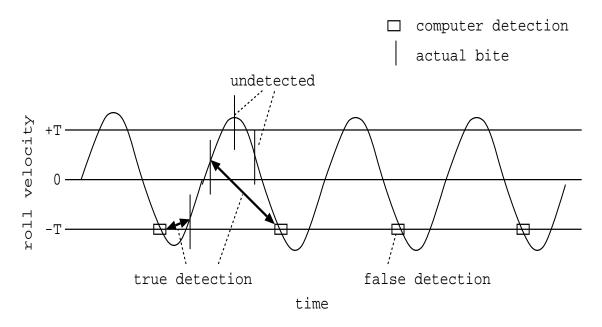
Figure 2.5: Classification of results.

evaluated. If matching is accomplished successfully, then evaluate the next bite; if no ground truth bites meets this criteria, then proceed with next bite directly. After all the computer detected bites of a meal are evaluated, ground truth bites with a matching computer detected bites are considered to be true detections. Computer detected bites not matching with a ground truth bites are classified as false detections. Ground truth bites without matching computer detected bites are classified as undetected bites. The detection information for all the bites in the bite database is ready when bites of all the meals are evaluated.

2.3.3   Extraction of other information related to ground truth bites

All the other information related to bites are extracted from the ground truth files and the demographic file. The tool can extract all the information using the list of full paths of all the ground truth files and the demographic file. Participant identification is used to relate the bite to its corresponding participant's information in the demographic file.

After this step, the bite database file is generated, as shown in figure 2.6.

15

Figure 2.6: A snapshot of the bite database file.

2.4   The query tools

Two command line query tools were developed to assist in this study. The first query tool processes the request and outputs the results of the request. The request is made by inputting the name of variables of interest. The interface of the tool lists all the variables studied and these variables are indexed by numbers. The user can either input the index number of the variable or the name of the variable to make a request. After the request is made, the tool processes the request by finding and grouping all the bites with the same pattern of the variables and calculates the counts, detected rate and some other values for each group of bites. Bites with the same pattern, in other words, are those taking the same value for every variable that are requested. For example, if we request two variables "Container" and "Utensil", all bites with the same container and the same utensil used will be grouped together. The number of bite groups depends on the number of combination of variables, or the number of different patterns. The second tool is different from the first one. It needs to specify a certain pattern for the bites, or it needs to specify values for each variable. The output of this tool is a list of bites of the specified pattern with their time stamps, participant ID, sensor data file and ground truth file. The first tool is used to analyze the accuracy of detection for bites with different patterns while the second tool is used to look into bites with a particular pattern. Both tools were developed in C. The design for both tools are similar, thus only the overview of the first tool is described in this section.

The query tool works in four steps. First, the tool reads in all the bites data from the bite database file and stores it in the memory as a full copy of the bite database. The bites in this copy are indexed and keep the same order as the bite database. Second, the tool accepts inputs of names of variables as a request. Third, according to the request of variables, the tool generates a specifier for each bite. The specifier consists of the values of all the requested variables and keeps the same order of the values with variables. The tool then begins to traverse the specifiers when all the bites have its specifier generated. In this process, the tool reads and compares the specifiers for every bite, groups all the bites with the same specifiers. Hence, bites with the same patterns are within one specific group and each group of bites represents a particular bite pattern. Finally, the tool calculates the counts, the average detection rate and some other information we are interested in for each group, that is, for each bite pattern. Figure 2.7 shows the interface and sample output of the first query tool.

Figure 2.7: The interface and result of the first query tool.

The second query tool is a supplementary tool. It is used when a review for a certain type of bite pattern is needed. The output of this tool is used by the reviewing tool to target the position of the bite. This query tool has sub-menus for each variable to let the user choose specified values of the variables form the options. Figure 2.8 shows the interface and sample output of the second query tool.

2.5   Evaluation of single variable on correct detection

The evaluation of the bite counting method involved a wide range of different utensils, containers, foods, etc. In this section, we study several variables that may affect the accuracy of the bite counting method. Each single variable is evaluated one at a time. For the variables we are interested in, each of them can take values form several to hundreds. In this study, the variable gender can only take two values while food can take several hundred. Each value of a variable for a bite can be considered a particular bite pattern. If more than one variable is taken into account, the combination of values for a bite can be very large, thus the number of bite patterns can be very large. For example, if we consider three variables for the bite pattern, say, food, utensil and

```
Field to query:
 1)age
 2)container
 3)ethnicity
 4)food
 5)gender
 6)handused
 7)handedness
 8)utensil
 0)done

Please enter numbers or letters:
0

Query for:
Query 1: age = 23
Query 2: food = kiwi_strawberry_juice
Query 3: gender = female
Query 4: container = glass
Query 5: utensil = hand
Query num: 5
p401 c1/gt_DB.txt 20120426112913541.txt 11415
p401 c1/gt_DB.txt 20120426112913541.txt 18159
p401 c1/gt_DB.txt 20120426112913541.txt 18234
p401 c1/gt_DB.txt 20120426112913541.txt 21267
p401 c1/gt_DB.txt 20120426112913541.txt 22858
p401 c1/gt_DB.txt 20120426112913541.txt 24058
p401 c1/gt_DB.txt 20120426112913541.txt 24118
p401 c1/gt_DB.txt 20120426112913541.txt 25093
p401 c1/gt_DB.txt 20120426112913541.txt 25993
p401 c1/gt_DB.txt 20120426112913541.txt 27493
p401 c1/gt_DB.txt 20120426112913541.txt 27688
Total number of times the pattern occurs: 11
```

Figure 2.8: The interface and result of the second query tool.

containers, and if there are 400 different foods, 4 utensils and 4 containers in this set, the number of bite patterns can reach as high as 6400. The more the variables being considered, the more patterns exist for the bites. This study limits the evaluation to bite patterns to those with only one variable. It helps us understand how each variable affects the accuracy of bite counting method and also helps to explore the potential to improve the accuracy of the method.

The evaluation of accuracy for a single variable is done by calculating the detection rate for different bite patterns of a variable. We use the query tool to group bites with the same pattern and calculate the corresponding detection rate for the bite group.

2.5.1 The variables

The variables tested in this study include food, age, gender, hand used, handedness, container, utensil and ethnicity. Each variable may affect the accuracy of the bite counting method in some way. As mentioned above, different variables can take a different number of values. We study most of the bite patterns of the variables. The detailed description of each variable is discussed below.

2.5.1.1 Food

There are 380 different types of food in the bite database. In this study, food refers to food and drinks. The most common foods include salad bar, shoestring French fries, water, pasta, etc. Different foods may affect the accuracy of the bite counting method by the way that people eat them. The bite counting method detects the pattern of the wrist motion of the eater and determines if the motion refers to a bite or not. Among all these foods, people eat most foods with a typical wrist motion that matches the predefined pattern of the bite counting method, while they eat some particular foods with wrist motions that are not congruent with that pattern.

We group bites in the bite database with different foods as different values, and we only evaluate the types of food with bites more than 100. The consideration for it is that the bites of food with occurrence less than 100 do not give sufficient samples for the analysis and there are too many different types of food for analysis. We need to classify food with different groups before we can analyze all different types of food. Consistency of food, energy density of food can be used to classify foods. This work can be done in the future.

2.5.1.2 Age

The age range for the participants are from 18 to 75. We group the participants by four different age groups: 18-30, 31-40, 41-50 and above 50. Thus, the variable age has 4 different values. As the cafeteria is inside the campus, the younger the age group is, the more occurrence of bites are in the group. However, all the groups provide enough samples for the analysis.

2.5.1.3 Gender

The variable gender can only take two values, male and females. According to the video, females tend to talk and gesture more during the meal. A slower eating rate is expected.

2.5.1.4 Hand used and handedness

The variable hand used is which hand the participant used when they took the bite. This variable can take three values, right hand, left hand and both hands. For some foods, people prefer to use both hands when they are taking a bite. Typical foods in this category include hamburger, sandwich and cakes. For other foods, people use either their right hand or left hand when taking a

No.	Variable	Values
1	Food	salad bar, water, ... a total of 380 different foods
2	Age	18-30, 31-40, 41-50, 50+
3	Gender	male, female
4	Hand used	right, left, both
5	Handedness	right, left
6	Container	plate, bowl, glass, mug
7	Utensil	hand, fork, spoon, chopsticks
8	Ethnicity	Caucasian, African-American, Asian or Pacific Islander, Hispanic

Table 2.2: Variables and their values.

bite. Handedness represents the dominant hand people use during their daily life. Most people are right-handed, they use their right hands to write, eat, and play. For people that are left-handed, they wore the device on their left hands when the data was collected.

2.5.1.5 Container

There are four containers used for this study. They are plate, bowl, glass and mug. Glass and mug are typically used for liquids, like beverages and water. Plates are used for most kinds of main foods. Bowl is used for salads, some kind of semi-solid foods, etc.

2.5.1.6 Utensil

Utensils include fork, spoon, chopsticks and hand. In the bite database file, for several bites, a knife is marked as the utensil. We exclude these bites since knife is normally not considered a utensil for eating.

2.5.1.7 Ethnicity

The ethnicities include Caucasian, African-American, Asian or Pacific Islander, Hispanic and other. We exclude the category "other" due to a low number of samples.

Table 2.2 provides a full list of variables and their possible values.

2.5.2 Detection rate

The detection rate can be calculated as follows:

$$\textbf{detection rate} = \frac{\textbf{detected GT bites}}{\textbf{detected GT bites + undetected GT bites}}$$
$$= \frac{\textbf{detected GT bites}}{\textbf{total GT bites}} \tag{2.1}$$

Related to the detection rate is the positive predictive value (PPV), a measure of the number of false positives. It can be calculated as follows:

$$\textbf{positive predictive value} = \frac{\textbf{true positive}}{\textbf{true positive + false positive}} \tag{2.2}$$

In the process of generating the bite database file, all the bites in the database were attached to the information of whether they were detected by the bite counting method or not. In order to calculate the detection rate for the bite patterns of interest, bites with the same pattern need to be classified first. The query tool is designed that when a single variable is accepted as input, all the bites are classified by the values of that variable, each classified group represent a unique bite pattern. Bites in the same group are bites with the same patterns. In the meantime, the query tool counts the total number of ground truth bites and the total number of ground truth bites detected by the bite counting method for each group. Once these numbers are available, the detection rate for the bite pattern can be calculated using the above equation. The detection rates for all the bite patterns of all the variable are evaluated in the next chapter.

2.6 Evaluation of single variable on eating rate

Eating rate in this study is defined as the average duration for the bites. For a particular bite, the duration for the bite is defined as time from this bite to the next bite. If the bite is the last bite for the meal, then eating rate is undefined. Relative to the eating rate for all the bites in the bite database file, we are more interested in how the eating rate related to some bite patterns, for example the eating rate for bites taken by different genders, or the eating rate for bites taken using different utensils.

In the bite database file, there is already a field with the bite duration information, which

is "time until next bite". This field for a bite is calculated using the time stamp for the next bite subtracted from the time stamp for the current bite. If the bite is the last bite in the meal, there is no next bite, thus the field of "time until next bite" is set to 0. In the bite database file, the unit of time stamp for a bite is not second. It is in fact the time from the beginning of meal in seconds multiplied with the frequency of the sensor reading, which is 15 Hz. We use seconds as the unit for eating rate, the time duration for a bite is adjusted by dividing by 15.

The average eating rate for a bite pattern can be calculated as follows.

$$\textbf{eating rate} = \frac{\textbf{sum of bite duration for all the bites}}{\textbf{number of bites}} \tag{2.3}$$

Eating rate for a bite pattern equals the sum of bite duration for all the bites for this pattern divided by the total number of bites for this pattern. The query tool is used to calculate the eating rate for each pattern. It grouped all the bites with the same patterns and summed their corresponding bite durations, which can be directly obtained from the bite database as mentioned above. The count of bites for a pattern is already calculated by the query tool.

The eating rate reflects a stable property for a bite pattern, and can be used to assist the evaluation of accuracy for the bite counting method. With this information, we are able to find out the relation between the accuracy of the bite counting method and the eating rate for a bite pattern. Moreover, the eating rate is also related to the time thresholds in the bite counting method. It can be used if the time thresholds are adjusted.

2.7   Adjustment of the time threshold

As mentioned in the first chapter, in the bite counting method, there are two time threshold T_3 and T_4. They define the time intervals for the bite counting method to be triggered when a sensor pattern is captured. The default settings for these two threshold are $T_3 = 2$ sec and $T_4 = 8$ sec. After reviewing the accuracy of the bite counting method using the default threshold values, we discovered that eating rate played an important role in its accuracy. We therefore adjusted the thresholds and conducted a second evaluation. Specifically, we tested $T_4 = 6$, speeding up the trigger between consecutive bites.

Chapter 3

Results

This chapter describes the results of the evaluations we have performed. In the previous chapter, we mentioned that we run tests on 22,383 total bites collected from 276 participants in the campus cafeteria. We aim to analyze how each variable we evaluated affects the accuracy of bite counting method, and how each variable affects the eating rate of bites. Furthermore, we want to know how the method performed overall compared to the previously published studies.

We conducted three sets of tests. For the first set of tests, we evaluated the bite detection rate for each variable one at a time. Some values of the variable do not provide enough samples of bites for us to analyze, so we ignore these patterns. For the second set of tests, we calculate the eating durations for each of the variables. These tests help us to determine the effect of each variable on eating rate. Finally, we adjust the time threshold T_4 in the bite counting method and determine its effect on the overall true positive rate and positive predictive value for all the bites in the database. We think that for the meals recorded in this study, people tended to eat faster than for the meals previously studied, so we shortened the time threshold for the bite counting algorithm to detect the pattern of a bite and observed the subsequent results for this adjustment.

3.1 Overall accuracy

We calculate the overall true positive rate and positive predictive value for all the bites with the default time thresholds, which are $T_3 = 2$ and $T_4 = 8$. The result of overall true positive rate and positive predictive value for the default set is 76% and 87%.
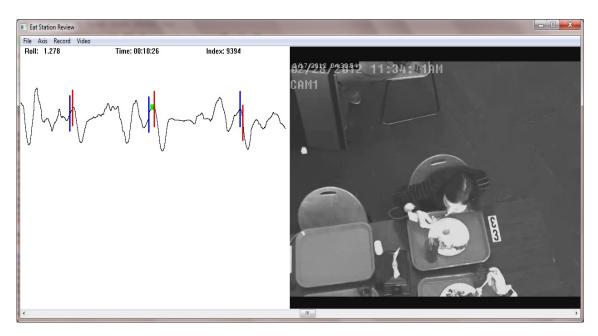
Figure 3.1: An example of a true detection.

We first show some figures demonstrating some examples of the detection results. These figures are made with the help of the custom reviewing tool described in chapter 2 (Ground Truth subsection of Data section). This reviewing tool is a custom version of the reviewing tool used for ground truthing the data as described in chapter 2.

Figure 3.1 shows an example of a true detection. The left side of the figure is the diagram of the roll signal, where the y axis is the signal of roll and the x axis is the time. The blue bars marked in the diagram are the computer detected bites, the red bars are the ground truth bites. The small green square indicates the time stamp where the video on the right side is playing. There are three true detections in this figure.

Figure 3.2 shows an example of a false detection. The participant in the video was wiping his hand with a napkin, which caused a false detection.

Figure 3.3 shows an example of an undetected bite. We can see that the participant was drinking in the video.

Figure 3.4 shows an example of a fast eating rate. We can see in the figure that the participant was eating fast. She took several bites in a short time period and the bite duration was short. Some bites were not detected due to the fast eating rate.

Figure 3.2: An example of a false detection.

Figure 3.3: An example of an undetected bite.

Figure 3.4: An example of fast eating rate.

3.2 Detection accuracy for each variable

In the previous chapter, we mentioned that eight variables are evaluated in this study: food, age, gender, hand used, handedness, container, utensil and ethnicity. Each variable is evaluated one at one time with the same methodology.

3.2.1 Food

There are 380 different foods represented in the bite database. Of these, 39 had more than 100 bites. Figure 3.5 shows the detection rate for these foods. The detection rates are grouped into three categories, best detected rate, middle detected rate and worst detected rate.

In the figure, the number in the middle of the rate bar is the number of bites for that food. Overall, most of the foods had a good detection rate. In the category of best detected rate, almost all the foods in this category had a detection rate greater than 80%, except hamburger. Most of the foods have detection rage ranging from 70 % to 78 % in the category of middle detected rate. Foods in the last category are typically with a detection rate between 60% to 70%, but three of them have notably low detection rates among all the foods.

Detection rate varies with different kinds of foods. In general, solid foods have a better
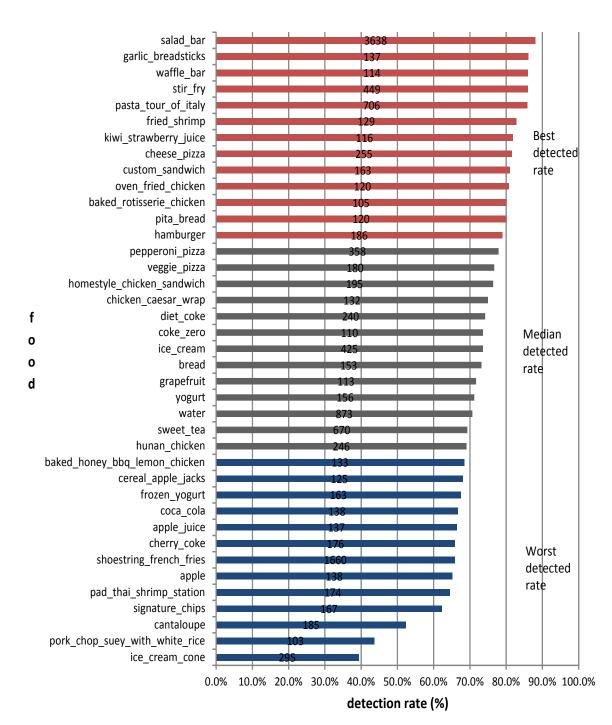
Figure 3.5: Detection rate for foods with bites greater than 100

detection rate than beverages. In the category of best detected rate, almost all the foods are solid. Salad enjoys the highest detection rate despite that it is the most frequently chosen food in the cafeteria. In our data base, there are 3,638 bites associated with salad and its detection rate is as high as 88%. For typical semi-solid foods, like yogurt and frozen yogurt, the detection rate is around 70%. Most of the drinks have detection rates from 65% to 75%. The detection rate for fruits is relatively low. There are three kinds of fruit in the food set, apple, grape and cantaloupe, corresponding to detection rates of 65.2%, 71.7% and 52.4%. In the set of foods, cantaloupe, pork chop suey with white rice and ice cream cone are the only three with a detection rate lower than 60%.

Several factors may contribute to relatively a low detection rate for a particular type of food. Eating rate could be a reason that affects the detection rate. We will evaluate the eating rate for this set of foods and explain why the eating rate affect the accuracy in the next section. The wrist motion of bites of the particular food is another factor that could decrease the detection rate. We reviewed the videos for some foods with low detection rates. These videos include fruits, semi-solid snacks and some other foods. People prefer to use their hand to eat fruits and they do not present the typical wrist motion of a bite pattern. The roll motion of the wrist is not obvious for these bites. Some semi-solid foods eaten with hands tend to have the same problem.

However, only 13,683 bites were studied in this section, or approximately 60% of all bites in the database. In order to study more bites for food types, we need to better identify and categorize the foods as there are too many types of food in the database. One possible classification method is to take into account some identifiable attributes such as food consistency and energy density.

3.2.2 Age

The age of participants ranged from 18 to 75. We divided the ages into four groups, 18 to 30, 31 to 40, 41 to 50 and above 50. Figure 3.6 shows the detection rate for each age group.

Different age groups have different numbers of bites. It is natural that in a campus setting there will be more young people than old people. In the figure, it is easy to observe that the detection rate rises with an increase of age group by group. The detection rate ranges from 73.9% to 87.4%. The older the people are, the more likely the bite would be detected.
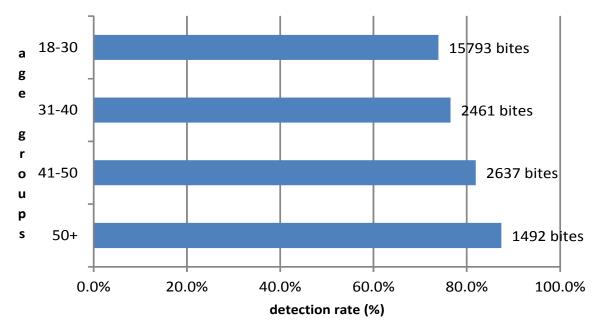
Figure 3.6: Detection rate for different age groups.

3.2.3 Gender

We evaluate the detection rate for different genders. Figure 3.7 shows the plot of results. The bites for males and females are almost evenly distributed. They are 10,940 bites taken by females and 11,443 taken by males. The detection rate for females is 80.3% while the detection rate for males is 72%.

3.2.4 Hand used and handedness

In this section, we discuss the results based on hand used and handedness of the participants. Hand used refers to the hand used by the participant when a bite is taken. Handedness is used to describe the dominant hand a participant uses in daily life. As these two variables both are related to the participant's hand, we combine these two variables and treat them as only one variable. As we know, people are either right handed or left handed, and most of the people in the world are right handed. When people are eating food, they can use their right hand, left hand or both hands to take the bite. Thus, the possible values for this combined variable are right handed using right hand, right handed using left hand, right handed using both hands, left handed using right hand, left handed using left hand and left handed using both hands. We call these hand patterns.
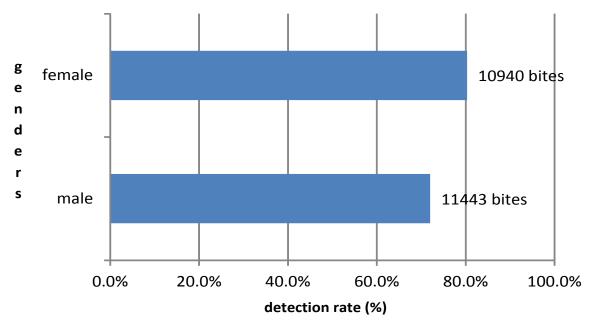
30

Figure 3.7: Detection rate for different genders.

When the bite data was collected in the campus cafeteria, the participants were free to wear the device on either of their hands during the meal as long as they use this hand most for eating. Hence, the hand with the device may not be the dominant hand of the participant. Also, the hand used for a bite is not necessarily the dominant hand of the participant. There is the possibility that a participant used their non-instrumented hand to take several bites during the meal.

Figure 3.8 shows the detection rate for all the possible values. From the point of view of handedness, there are 20,560 right handed bites and 1,823 left handed bites. The bites taken by right handed people are 10 times more than bites taken by left handed people. From the perspective of hand used, the right hand is also the predominant hand used for eating. There are 17,293 bites taken by the right hand of participants. The number of bite taken by left hand of people is 3,710 bites. There are 1,379 bites taken using both hands. This kind of bite typically occurs when people use their hands to eat hamburgers and sandwiches. Many people feel comfortable using both hands when eating these foods.

Bites taken by the dominant hand have a relatively high detection rate. The bites taken by the right hand of right handed people have a detection rate of 79.5%, and bites taken by the left hand of left handed people have a detection rate of 77%. The detection rate of bites taken by both hands of people is a little lower, 72.2% for bites taken by both hands of right handed people
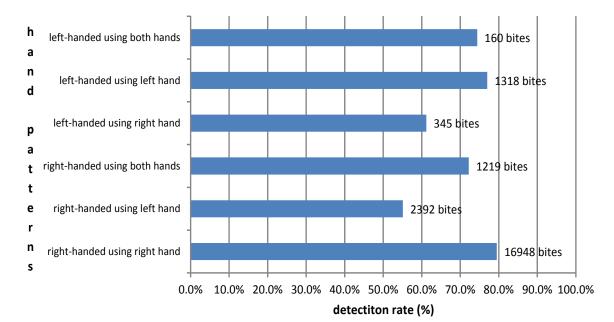
Figure 3.8: Detection rate for bite patterns related to hand.

and 74.4% for bites taken by both hands of left handed people. Bites taken using the non-dominant hand are less likely to be detected. The detection rate for bites taken using the left hand of right handed people is 55.1%, and the detection rate for bites taken using the right hand of left handed people is 61.2%.

A reason for the low detection rate of bites taken using the non-dominant hand is that most people wear the device on their dominant hands while some bites are taken by their non-dominant (non-instrumented) hand. The participants were unaware of this behavior, but the ground truther may mark this bite as a ground truth bite later. As there is no signal of a bite pattern generated by the instrumented hand, the bite can not be detected by the bite counting method. These undetected bites lower the total detection rate for the category. For the bites taken by both hands of people, the detection rate may be affected by the wrist motion of people. When people eat with both hands, their wrists need to roll a little in order to put food into the mouth. However, when people use both hands to eat, unlike they use only one, the roll motion of wrist is not so conspicuous when they put food into the mouth.
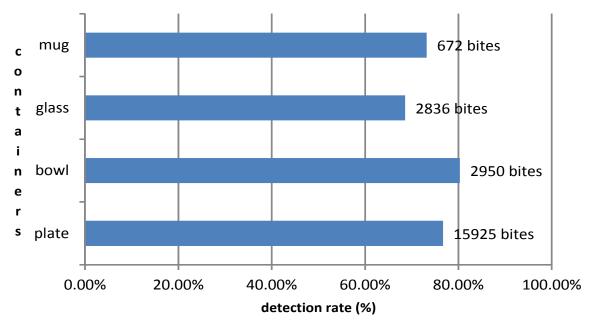
Figure 3.9: Detection rate for containers

3.2.5 Container

The type of food container is another variable to be considered. Four containers were used by participants. Figure 3.9 shows the detection rate for different containers.

It can be observed that more bites were taken from a bowl or plate than from a glass or mug. The detection rate for bites take from a plate or bowl are also higher than bites take from a glass or mug. Foods are served on plates and bowls while drinks are served in glasses and mugs. People normally take more food bites than drink bites during meals. We expect drink bites to have a lower detection rate than food bites as discussed above.

3.2.6 Utensil

Several utensils were provided in the cafeteria. In our database, five types of utensils were recorded: hand, fork, spoon, chopsticks and knife. In our study, we consider hand as a special kind of utensil. We exclude the knife, as there are very few bites taken with this utensil. Figure 3.10 shows the detection rate for different utensils.

It can be observed that the majority of bites were taken using the hand or fork. Some bites were taken with a spoon and only a small portion of bites were taken with chopsticks. The detection
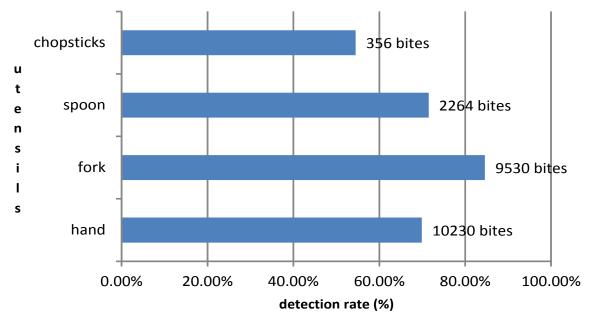
Figure 3.10: Detection rate for utensils

rate for bites using a fork is 84.6%. The detection rates for bites using a hand or spoon are 69.9% and 71.5% separately. The detection rate for bites using chopsticks is 54.5%.

3.2.7 Ethnicity

Figure 3.11 shows the detection rate for each ethnicity. The bites taken by African-American people have the highest detection rate. The detection rate for bites taken by Caucasian and Hispanic people are a little lower. The bites taken by the Asian or Pacific islander people have the lowest detection rates.

3.3 Eating rate

We expect that a faster eating rate would reduce the detection rate of the bite counting method. As mentioned earlier, the bite counting method uses two time periods T_3 and T_4 to threshold expected events. Only motion patterns that exceed the two time thresholds can trigger the bite counting algorithm to capture the ongoing bite. Otherwise, the bite would be missed. For a particular type of food, if eaters consuming this food tend to eat fast, there may be some undetected by the bite counting method as the bite duration times will be too short to exceed the
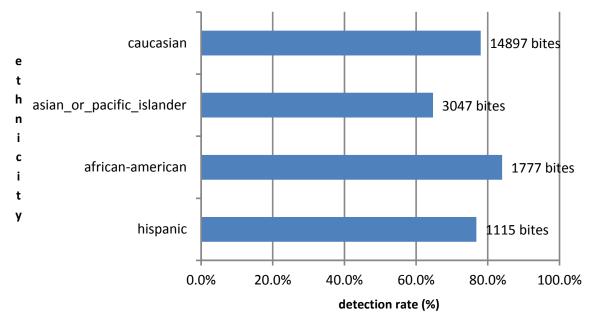
Figure 3.11: Detection rate for ethnicity

time thresholds. On the other hand, the ground truthers mark the bites as best as they can, no matter how long the bite time is. Thus, with scenario of fast eating rate, the ground truthers and the bite counting algorithm do not agree when the bite time is shorter than the thresholds. In this section, we analyze the eating rate of bites across all the same variables as in the previous section.

3.3.1 Food

Figure 3.12 shows the eating duration for the same set of foods evaluated in the previous section based on the same set of 13,683 bites.

In the figure, we can see that foods with a high detection rate and a moderate detection rate have a higher average eating duration than foods with the worst detection rate. There are some foods with a high detection rate having a relatively short eating duration. We can also find some foods with low detection rate having relatively long eating duration. For the three foods with the lowest detection rate, the eating duration for them are all low. The average eating duration for all the foods in this figure is 14.94 seconds per bite.
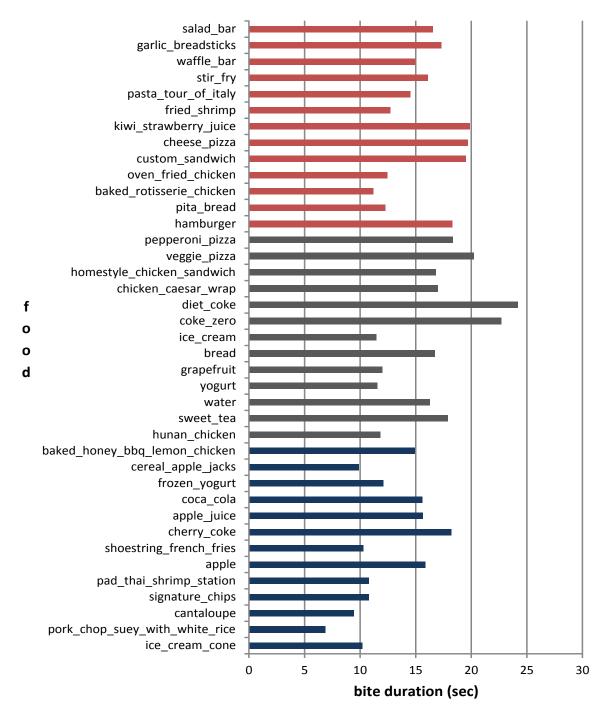
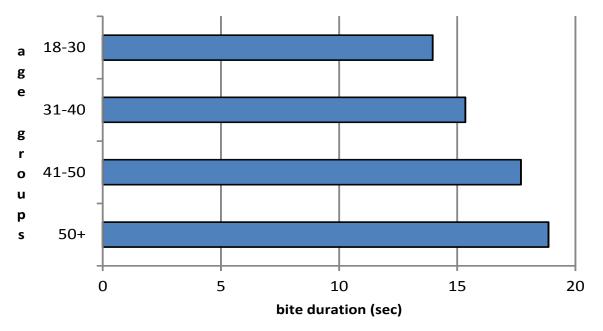Figure 3.12: Eating duration for foods with bites greater than 100.

Figure 3.13: Eating duration for different age groups.

3.3.2 Age

We calculated the eating rate for each age groups as shown in figure 3.13. The figure shows that the eating rate drops as age goes up. The eating rate is from 14.0 seconds per bite to 18.9 seconds per bite. This figure of eating rate shows the same trend as compared to the figure of detection rate in terms of age groups. For the age groups, higher eating rate corresponds to lower detection rate and vice versa. This result suggests that older people tend to eat slower and chew more than young people.

3.3.3 Gender

Figure 3.14 shows the eating duration for males and females. According to the figure, females eat a little slower than males, which explains why we observed a higher detection rate for females. For the videos we have reviewed, some females prefer to talk with others and gesture with their hands, males seem to be more concentrated on their meal. This may contribute to the disparity of eating rate between males and females.
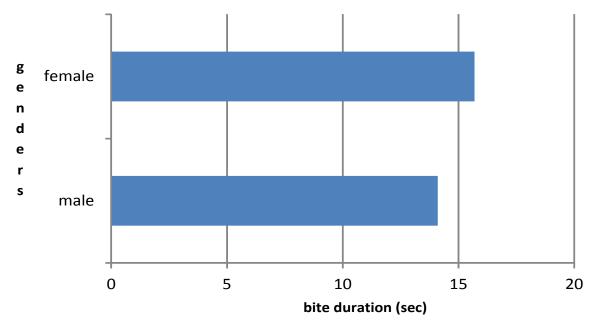
Figure 3.14: Eating duration for different genders.

3.3.4 Hand used and handedness

Figure 3.15 shows the eating duration for different hand patterns. It can be observed that the hand pattern "left-handed using both hands" has the longest eating duration, which is over 20 seconds per bite. The eating durations for all the other hand patterns are less than 20 seconds per bite. The eating durations for the hand patterns do not appear to correlate to the detection rate for them.

3.3.5 Container

Figure 3.16 shows the eating duration for different containers. Unlike the detection rate, the eating durations for mug and glass are longer than those of bowl and plate. The eating durations for these containers do not appear to be correlated with the detection rate of them.

3.3.6 Utensil

We calculate the eating duration for different utensil as shown in Figure 3.17. The eating duration for bites taken with chopsticks are the fastest, which is 7.83 seconds per bite. The eating rate for bites taken with a spoon is a little slower. The eating rates for bites taken with a fork and
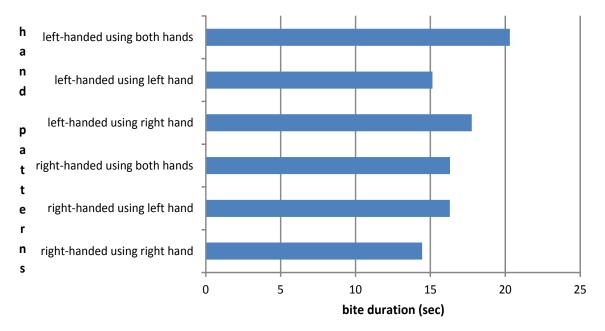
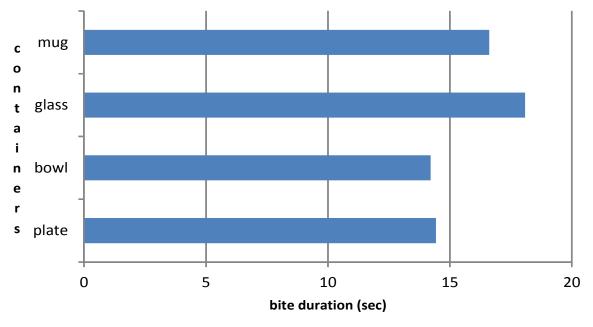Figure 3.15: Eating duration for bite patterns related to hand.

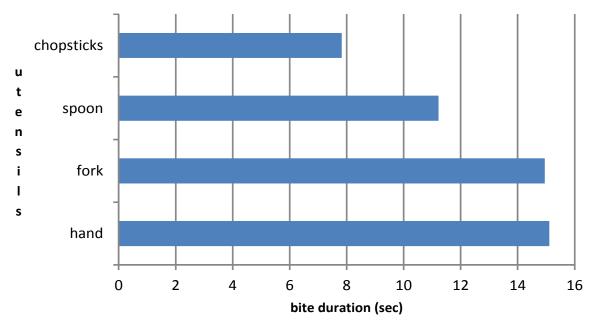Figure 3.16: Eating duration for containers.

Figure 3.17: Eating duration for utensils.

with a hand are almost the same, which are the slowest. All the utensils except hand still indicates that a slower eating rate relates to a higher detection rate.

3.3.7 Ethnicity

We plot the eating rate for ethnicity in Figure 3.18. It can be observed from this figure that the detection rate appears correlated with the eating duration for each ethnicity. The slower the eating rate, the higher the detection rate. For bites taken by Asian or Pacific islander people, besides the faster eating rate for the bites, another reason for the low detection rate is that they use chopsticks more frequently. As mentioned in a previous section, chopsticks have the lowest detection rate for different utensils, which leads to a lower total detection rate for bites taken by Asian and Pacific Islander.

3.4 Time adjustment to bite counting method

The previous section indicates that eating rate is important for the correct detections. We calculate the overall true positive rate and positive predictive value using adjusted time thresholds, which are $T_3 = 2$ and $T_4 = 6$. The default time thresholds are $T_3 = 2$ and $T_4 = 8$ as mentioned

Figure 3.18: Eating duration for ethnicity.

previously. The result for the adjusted time thresholds is 82% and 82%. The adjusted time thresholds increase the true positive rate, but decrease the positive predictive value. However, a balance between these two statistics is more desirable as it causes false positives to accrue at the same rate as undetected actual bites. This has the effect of keeping the automated bite count near the actual bite count, even when individual bites are not being counted perfectly.

Chapter 4

Conclusions

In this thesis, we have evaluated the accuracy of the bite counting method on an extensive set of bites across a range of different variables. We have calculated the eating duration for the same set of variables. We have also calculated the overall true positive rate and positive predictive value with the default time thresholds and the adjusted time thresholds.

The results of the accuracy of the bite counting method for a set of single variables show that the detection rate of the method is affected by different values of a certain variable. For example, the detection rate tends to go up with the increase of the age. The detection rates for different utensils show some differences. The results of the eating duration of the variables indicate that the eating duration can be affected by different variables. For example, the eating duration tends to go up with the increase of the age, which is consistent with the detection accuracy. For some variables, specifically age, utensil, gender and ethnicity, their eating durations with different values are somewhat consistent with the detection rate. For the other variables, the eating durations with different values are not consistent with the detection rate.

The overall true positive rate for all the bites is 76% and the positive predictive value is 87%. These two values are calculated with the default time thresholds of the bite counting algorithm. If the time threshold of two consecutive bites(T_4) is decreased by 2, the true positive rate is increased to 82% while the positive predictive value dropped to 82%. This result shows that the sensitivity of the bite counting method can be increased by shortening the time threshold of the two consecutive bites. However, this adjustment also increases the number of false positives for the bite counting method.

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