TRACKING WRIST MOTION TO DETECT AND MEASURE THE EATING INTAKE OF FREE-LIVING HUMANS

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ABSTRACT

This dissertation is motivated by the growing prevalence of obesity, a health problem currently affecting over 500 million people worldwide. It is composed of two studies. In the first study, a new method is developed to detect how many bites a person takes during a meal in real time. A pattern has been found that the wrist of a person undergoes a characteristic roll motion as food is picked up and placed into the mouth. This motion can be tracked by a gyroscope sensor placed on the wrist. This work could be used in many weight loss and obesity treatment applications, including monitoring intake, slowing eating rate, and providing a cue for mindful eating. In the second study, a new method is developed to automatically distinguish eating activity from other activities in natural daily living. Accelerometers are used to detect the typical burst activity at the beginning and the end of each eating activity and gyroscope roll motion features are used during hypothesized detections to differentiate eating activities from other activities. This work has many potential applications. It could be used by individuals for self-monitoring for weight loss and weight maintenance. It could be combined with a food diary, 24-hour recall or food frequency questionnaire to improve compliance and accuracy in measuring consumption. The two methods could potentially be combined to automatically count bites of intake all day. The methods could also be used by clinical practitioners to monitor the eating patterns of patients (for example during diabetes treatment), or by researchers in epidemiological and genetic studies (for example in studies of the physical activity or eating habits of specific demographics).

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CHAPTER 1

OVERVIEW

As a field, the study and treatment of obesity faces several obstacles. First, there is a long history of placing the responsibility for the problem on the individual [67]. There is an ongoing debate of its recognition as a condition or a disease, motivated at least in part by the desire of researchers to increase options for its treatment and reduce the stigma and discrimination experienced by the obese [1, 35]. As the incidence of obesity has grown from a small percentage of the population to over one third of Americans and over 500 million people world wide [101], there has been a growing recognition that the problem is due to more than an individual's failure to regulate consumption [1, 67].

The second obstacle is that because everyone eats, everyone brings a personal bias to the problem. Many people have a long history of dieting and different types of fitness regimes, leading to a general impression of expertise and bias as to how to treat the problem. This can be contrasted with the study of other topics, such as thermodynamics or entomology, for which the average person has little knowledge and is therefore more accepting of the idea that the problem requires scientific study.

Third, the common unit of measurement of how much a person consumes is the kilocalorie (or in common U.S. vernacular, the capitalized "Calorie"), a laboratory measure of the heat released by burning food. While a measure of kilocalories is repeatable for the same quantity of food of the exact same type, it cannot be made without destroying the food. In addition, unlike other measurement tools such as a ruler, scale, or clock, a bomb calorimeter is a relatively complicated and expensive instrument, so that the typical experience with kilocalories is only through measurements reported by food producing companies on packaging and labels. In practice, it is not actually measured, but rather counted or totaled throughout the day based upon second-hand observations, memory, and simply guessing.

Fourth, it is well known that different types of foods such as sugars and carbohydrates provide different amounts of kilocalories per gram, and that different food types are oxidized within the human body differently than in a bomb calorimeter [87]. Thus there is the continuing development of knowledge about the ratios of food types that should be eaten, making the practice of measuring kilocalories even more complicated when different types of foods are measured independently.

For purposes of motivating this dissertation, the biggest obstacle affecting the study of obesity is the dearth of participation by the engineering community. In 2006, a joint U.S. National Institutes of Health (NIH) and National Science Foundation (NSF) workshop was held to bring focus to the ways that engineers could help in obesity research [26]. Although this workshop resulted in new targeted NIH funding opportunities, the participation of the NSF and engineering community is still very limited. The Obesity Society (U.S.) counts over 2,000 researchers as members [60], and the International Obesity Society counts over 10,000 researchers as members [37], but almost none are engineers. Position papers in 2010 within a leading journal in the field of dietetics again advanced the call for technological innovation in the tools used to measure eating intake [54, 92]. It seems reasonable to assume that the same societal and personal biases that have affected attitudes about obesity have also affected the engineering community's perception of the field, and have thus prevented a stronger engagement.

Among the findings of the above described 2006 workshop [26]:

> Measurement of each component of the energy balance equation presents unique challenges. For example, the difficulty of ascertaining food intake with acceptable levels of accuracy is well known to nutritionists. Standard recall techniques (such as self-report questionnaires) can provide valuable data on dietary patterns, and can be improved by electronic information technologies and by judicious use of results from cognitive process research [88]. These approaches are time-consuming and inconvenient. Furthermore, considerable under-reporting of total energy intake is typical, with this error more severe in overweight than non-overweight individuals [94]. At the other extreme of precision and cost is the research technique of providing a controlled diet with all food intake measured and defined by chemical analysis. Use of this controlled feeding method generally is limited to hypothesis-testing physiology research and therapeutic investiga-

> tions, because of high cost, small sample size, and demands on participants that restrict enrollment to highly motivated individuals [19, 57]. Therefore, new and improved methods of determining energy intake are critically needed for research as well as practical purposes.

This dissertation is motivated by the "critical need" described in that last sentence.

Our vision is a tool that can be worn like a watch, and is capable of automatically measuring the eating intake of the wearer. Ideally the tool would measure energy (kilocalories), nutrition (food types), eating rate (duration and pace), environmental context (where the eating takes place), social context (alone or in company), and mixed activities (eating while working or engaging in other activities). This would be the "dream tool" for the obesity research community.

The work described in this dissertation takes a step towards this vision. In chapter 2, novel methods are described using wrist tracking to automatically measure the number of bites taken during a meal, along with evidence that the number of bites has some correlation with kilocalories. Obviously there are numerous variables in such a proposition. The important first step is the building of the tool, an assessment of its accuracy for counting bites, and a preliminary investigation of the utility of the tool for measuring energy intake. Chapter 3 then describes novel methods that use wrist tracking to automatically detect periods of eating throughout normal daily activities. Again, there are obviously many variables to consider. The first steps taken in this dissertation are the description of this new tool, and a preliminary investigation of its utility for detecting eating activities. Chapter 4 describes a few other monitoring eating related projects in which I have been involved throughout my graduate studies. Chapter 5 concludes these studies.

The rest of this chapter provides some background on several fields of research which help form the basis for this dissertation. These fields include obesity, accelerometers and gyroscopes, activity recognition, and wrist motion tracking.

1.1 Obesity

Overweight[1] and obesity are a growing concern in the United States and worldwide.

[1] The term "overweight" is most often used as an adjective in vernacular English, but in the medical community, it is also commonly used as a noun.

Body weight can be classified by the body mass index (BMI), which is weight (in kilograms) over the square of height (in meters). A person whose BMI is between 25 and 29.9 is overweight; if the BMI is more than 30, the person is obese; if the BMI is above 40, the person is extremely obese [62]. In 2007-2008, the National Health and Nutrition Examination Survey showed that 34.4% of Americans were overweight and 33.9% of Americans were obese [28]. The World Health Organization reported in 2008 that one billion adults (age 20+) were overweight and 500 million adults were obese [101]. Obesity is strongly associated with several major health risk factors, such as diabetes, heart disease, high blood pressure, stroke and higher rates of certain cancers [97]. In the United States, the annual medical expense of obesity has been estimated to be $147 billion in 2008 compared to $78.5 billion in 1998 [27]. Obesity has become one of the largest avoidable causes of death [29, 56].

There are numerous approaches to weight loss and management. These include pharmacotherapies, low-calorie or very-low-calorie diets, gastric bypass surgery, and behavioral interventions [90]. For weight loss, the goal of all of these approaches is to expend more energy than is consumed. For weight management, the goal is to balance energy consumption and expenditure. Self-monitoring of intake consumption has been consistently correlated to weight loss and weight management [13]. It is reasonable to suppose that new tools that help people improve self monitoring, by automating the measurement of eating intake, could benefit many treatments for obesity.

1.2 Tools for measuring eating intake

Table 1.1 lists known methods for measuring energy intake. Doubly labeled water (DLW), considered the gold standard for measuring energy expenditure [84], is water in which the hydrogen and oxygen elements are replaced with uncommon isotopes for tracing purposes. The typical procedure is for a subject to consume DLW and then undergo daily urine analysis. It has been validated in laboratory studies in which subjects lived in a whole room calorimeter for up to a week, while all foods eaten were controlled and energy expenditure was directly measured through respiratory gas analysis. Under these conditions, the accuracy of the technique for indirectly measuring energy intake (calculated as energy expenditure $\pm$ stored energy change due to weight gain/loss) was shown to be 2-8% error per

method	unit of measure	typical process
doubly labeled water	energy expenditure	daily urine analysis
food record	kilocalories	daily recall
accelerometry	activity patterns	daily indirect approximation
scale	grams	weighed at fixed settings
cameras	image change	post-review of each meal

Table 1.1 Comparison of methods for monitoring intake.

day [77]. A meta-analysis [8] of 25 studies using DLW in free living conditions found an 8-15% range for repeatability of energy intake measurements.

Due to the expense and technical expertise required for DLW, food records are the most commonly used laboratory tool for measuring intake. Tool variations include 7 day food diaries, 24-hour recalls, and food frequency questionnaires [91]. The typical procedure is for a subject to write down everything eaten or go through a daily directed-interview process. Numerous studies have shown that people have a tendency to underreport their consumption using these methods [15, 32, 38, 47, 58, 93]. Estimates of underreporting range from 10-30% for normal weight subjects to 20-50% for obese adults and children [15]. A meta-analysis [14] of 15 studies using food records found a range of 19-41% error per day when evaluated against DLW. This general range of accuracy of food records has also been observed in long epidemiological studies when compared to DLW [11] and blood nutrient analysis [18].

Several uses of technology to improve food record methods have been explored, such as using the Internet for dietary recalls [5] and using a personal digital assistant to record an eating diary [103]. However, while these methods can help lessen the burden for the record-keeping portion of the process, it has been shown that the measurements themselves do not improve [7, 103].

Accelerometer based tools for measuring energy expenditure use waist, back and/or leg sensors to measure raw motion throughout the day. Similar to DLW, an indirect measure of energy intake can be calculated, typically at a daily interval. A meta-analysis [66] of 28 articles found correlations between energy expenditure derived from accelerometry as compared to DLW corresponding to error rates of 36-91% per day, so these tools are rarely used for the purpose of measuring energy intake.

A scale embedded in a dining table can be used to continuously weigh food [43]; tables can be configured to measure gram changes in different areas [16]. This method is typically only used in fixed settings.

In the camera-based approach, pictures of foods are taken before and after eating, and the amount consumed is estimated by a trained observer who compares the pictures to a database of portion-varying images of the same foods. The accuracy of this approach has been shown to be comparable to both weighed and direct visual estimation of portion sizes [50, 98]. A similar accuracy has also been shown when subjects take the pictures themselves [51], although it was noted that this approach still places a burden on the trained observers analyzing the images. Some researchers have suggested using automated image processing instead of a human post-reviewer to determine the amount of food consumed [69, 89, 105]. This has been demonstrated on a small set of foods [104], but the foods were carefully separated and the background was carefully controlled. Some studies have shown that people prefer the camera approach to traditional pen and paper food records [10, 82].

1.3 MEMS sensors

The new tools described in this dissertation make use of micro-electro-mechanical systems (MEMS) sensors, a class of devices that builds very small electrical and mechanical components on a single chip. With their low power consumption and small size, MEMS sensors can be comfortably attached to the human body and operated for hours without stop. Research involving wearable MEMS sensors has studied problems where the sensors are worn on the ear [6], neck [80], shoulder [102], upper arm [96], wrist [25, 65], chest [41], waist [40, 46, 102], hip [25], thigh [68, 102], ankle [65], and foot [71]. Typical sensor types include accelerometers [6, 25, 40, 41, 46, 52, 65, 68, 71, 80, 96, 102], gyroscopes [31, 70], magnetometers [102], electrocardiography (ECG) sensors [25, 46, 68], Global Positioning System (GPS) sensors [25], light sensors [102], microphones [96, 102], pressure sensors [71] and temperature sensors [25, 102]. This work makes use of accelerometers and gyroscopes.

1.3.1 Accelerometers

An accelerometer is a device that measures linear acceleration along three axes (x, y, and z) as shown in Figure 1.1. In the case of wrist motion tracking, an accelerometer can

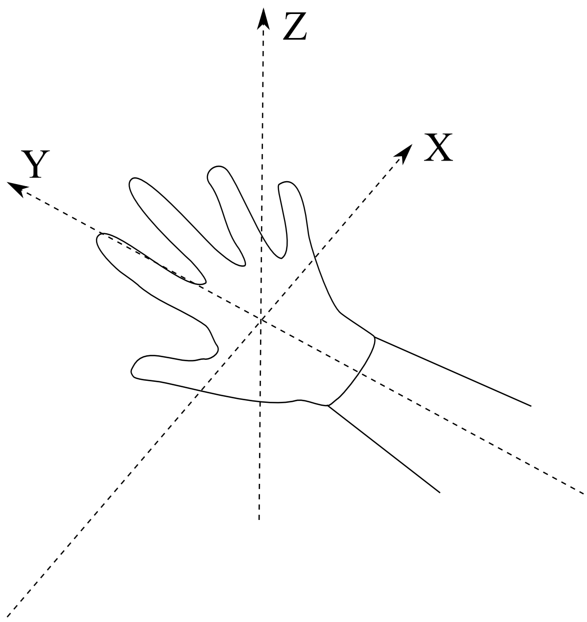

Figure 1.1 The x, y, z coordinate system used by an accelerometer to track wrist motion.

measure the linear motion of the wrist as it moves about in space.

The concept of an accelerometer is based on the mass spring system shown in Figure 1.2. According to Hooke's law, the extension of a spring is in direct proportion with the load applied to it. Mathematically, it can be stated as Equation 1.1.

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

where F is the force; k is the spring constant; x is the displacement of the spring's end

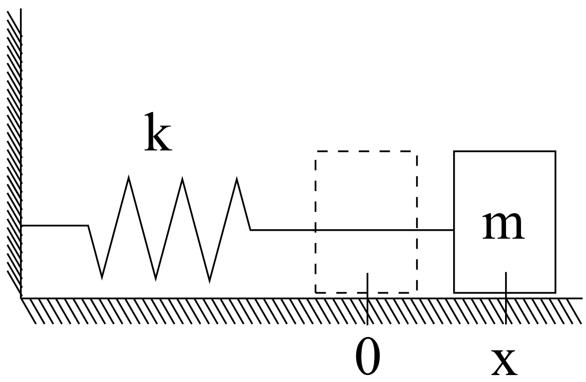

Figure 1.2 A mass spring system.

from its equilibrium position. In Newton's second law of motion, the force is related to acceleration shown in Equation 1.2.

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

where F is force; m is the mass of the body; a is the body acceleration. Combining these two equations allows the measurement of acceleration using the displacement of a mass shown in Equation 1.3.

$$a = -\frac{kx}{m} \tag{1.3}$$

In a MEMS accelerometer, capacitive components are commonly used to convert the mechanical motion into an electrical signal. Most accelerometers have a low latency, and can keep up with physical movements quicker than human motions. In addition, the power consumption of the accelerometer is small. For example, the power consumption of a STMicroelectronics LIS344ALH accelerometer is less than 1 mW [85].

An accelerometer is affected by the force of gravity, which appears in its measurement. Strictly speaking, accelerometers can only measure linear motion in the absence of any rotation and when the direction of gravity is known, so it can be subtracted out. In practice, gyroscopes (and sometimes magnetometers) are used to simultaneously track rotation so that linear motion can be calculated. A combination of accelerometers and gyroscopes is typically referred to as an inertial measurement unit (IMU). A deeper discussion of this issue as it relates to wrist motion tracking can be found in [24].

1.3.2 Gyroscopes

A gyroscope is a device that measures rotational velocity along 3 axes. The naming of the axes as yaw, pitch, and roll were initially used to describe an aircraft rotation as shown in Figure 1.3. Yaw means left or right about an axis running up and down; pitch means up or down about an axis running from wing to wing, and roll means rotation about an axis running from nose to tail. In the case of wrist motion tracking, the yaw, pitch, and roll are defined as shown in Figure 1.4 and define the rotational motion of the wrist as the hand turns.

A gyroscope measurement is based on the Coriolis effect shown in Equation 1.4

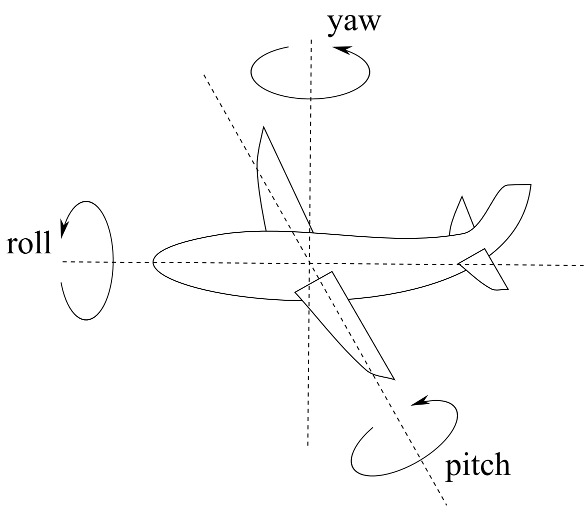

Figure 1.3 The yaw, pitch, roll coordinate system used in aircraft systems.

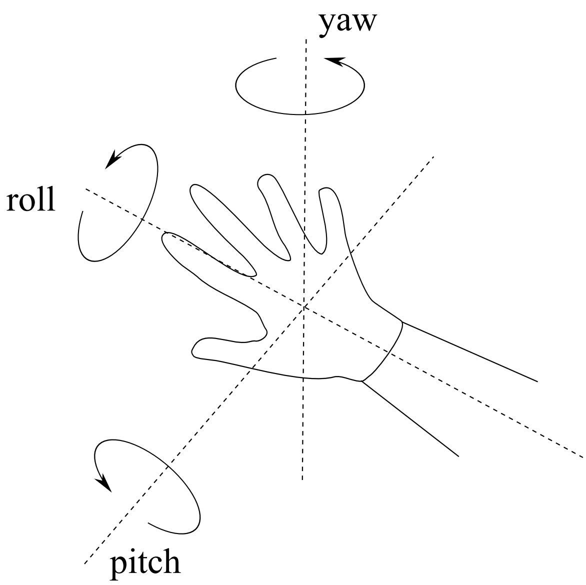

Figure 1.4 The yaw, pitch, roll coordinate system used by a gyroscope to track wrist motion.

$$\vec{F} = -2m\vec{\Omega} \times \vec{v} \tag{1.4}$$

where F is the force, m is the mass of the body, Ω is the angular velocity of the reference frame, and v is the body velocity.

Compared to a MEMS accelerometer, a MEMS gyroscope typically consumes 10 times more power [86]. This is important because if the sensors are to be worn comfortably, they will likely be powered by coin-sized or smaller batteries. While a typical coin-sized battery can power a MEMS accelerometer for a week on a single charge, the same battery can power a MEMS gyroscope for less than one day. Even though activity recognition research is typically carried out in a lab, where sensors are hardwired to constant power supplies, the majority of research papers exploring various types of activity recognition use accelerometers [6, 25, 40, 41, 46, 52, 65, 68, 71, 80, 96, 102] while only a few utilize gyroscopes [31, 70].

Perhaps the primary finding in this dissertation is the fact that the rotation of the wrist about its roll axis has great utility for detecting and measuring consumption. Therefore our primary sensor of interest is the gyroscope. As was said in the last paragraph, this is in contrast to the majority of previous research in activity recognition. Although this work is only focused on eating activity recognition, it may be that other types of activities could be more reliably recognized if rotational motion was more commonly analyzed.

1.4 Activity recognition

MEMS sensors have enabled new opportunities for activity recognition. Researchers have investigated their application on recognizing common daily activities such as walking, running and resting, in order to monitor a person's physical regimen [40, 41, 46, 52]. Some specific sport activities, such as cycling and playing football, have been differentiated [25, 65]. MEMS sensors have also been used to study the biomechanics of leg and arm motions during sitting, standing, kneeling and lying down [31, 40, 41]. In medical monitoring, they have been used to recognize accidental falls [102], dysphagia [80], tremors associated with Parkinson's disease [70], and motor activities associated with stroke [68]. They have also been used to monitor assembly tasks [96].

The use of MEMS sensors to detect patterns related to eating has received relatively less attention. Some overviews of body sensing methods for monitoring eating can be found in [4, 73]. Junker et al. [39] defined 4 body motion patterns associated with eating, and tracked them using 5 MEMS sensors, one on the lower and upper segment of each arm, and one on the back. Sequences of sensor data were compared against training patterns using several statistics, such as the mean pitch and roll angles from upper and lower arms, with preliminary results demonstrated on four subjects eating four different food types in a laboratory setting. The same group used ear and neck mounted sensors to detect chewing sounds and swallowing motions [3, 4]. Sejdic and colleagues [80] used a neck-worn sensor to detect swallowing activities and classify swallowing difficulty. Sazonov et al. [75] used a set of sensors including microphones on the laryngopharynx and mastoid bone portions of the throat, an ambient outward-directed microphone, a microphone in the ear, and a strain sensor on the throat; trained analysts showed high reliability for identifying bites, chews and swallows from signals recorded from these sensors. In further studies, trained analysts showed high reliability for detecting periods of eating activity between periods of quiet rest, talking, and meals of various sizes from the sensor data [74]. Automated detection of swallowing events was demonstrated on the same data [72] and subsequently a reduced sensor set was demonstrated to provide similar accuracy [48]. While all these approaches show promise for detecting eating related patterns, none of them have been tested on subjects in normal free living; all data was collected in brief, controlled laboratory visits.

1.5 Wrist motion tracking

The wrist is a natural place for instrumentation, as compared to other areas of the human body. A wrist-mounted package enables greater freedom of motion and activities, and has a higher likelihood of social acceptance due to its resemblance to the common watch. Sharples and Beale [81] reviewed a variety of monitoring devices worn on the wrist. Such devices have been proposed or built to measure health properties. For example, Harland et al. [33] described a wrist-worn device for ambulatory monitoring of the human electrocardiogram (ECG). Gagnadre et al. [30] proposed a wrist-worn device to measure heart rate, breathing frequency, blood pressure variations, and breathing amplitude. Ching et al. [17] calculated heart rate using a microphone on the wrist. Ouchi et al. [63, 64] used a wrist-worn device to acquire pulse wave, skin temperature, perspiration and movement.

Wrist-worn devices have also been used in non-health-monitoring applications. Heil et al. [34] used a wrist-worn light sensor to document that indoor lighting for a particular day-shift work environment could serve as the primary light exposure dosage for humans. Maurer and his colleagues [53, 83] developed an "E-watch" targeted to several applications. It acted as a normal watch to show the current time, it used light sensors and a microphone to recognize location, it used a thermometer to measure the ambient temperature, and it had a calendar function which could communicate with a cell phone or a computer. Blasko et al. [9] used a small wrist-worn projector to project a large image for display purposes.

Wrist motion tracking has also been used to study hand motion and gesture recognition for various problems. Howard et al. [36] designed a lightglove, a virtual typing and pointing system, which was worn around the wrist. Ogris et al. [61] used ultrasonic sensors, accelerometers and gyroscopes to measure the distance and the motion to determine the gesture of a pre-defined bicycle repair task. Schmidt et al. [76] conducted a study about a wrist-worn computer and platform to analyze orchestra beating. Lementec et al. [45] used sensors to recognize arm gestures to control unmanned aerial vehicles.

1.6 Contribution and novelty

As shown in this Figure 1.5, the contribution of this dissertation crosses a number of research fields. Specifically, this dissertation describes new wrist-worn tools which use MEMS sensors to track wrist motion in order to detect eating activities and measure eating intake. The primary applications of this research involve the study and treatment of obesity, but the ideas presented could be applied to many other problems including anorexia, eating pace, hydration, and other problems involving consumption.

In the obesity research area, these new tools could be used in several research paradigms, including genetics, epidemiology, and clinical outcomes assessment. For example, being able to measure the actual eating habits of groups of people with different genetic markers could provide clues regarding genetic propensity to obesity. Measuring the eating habits of different demographics could help uncover societal indicators, for example differences in

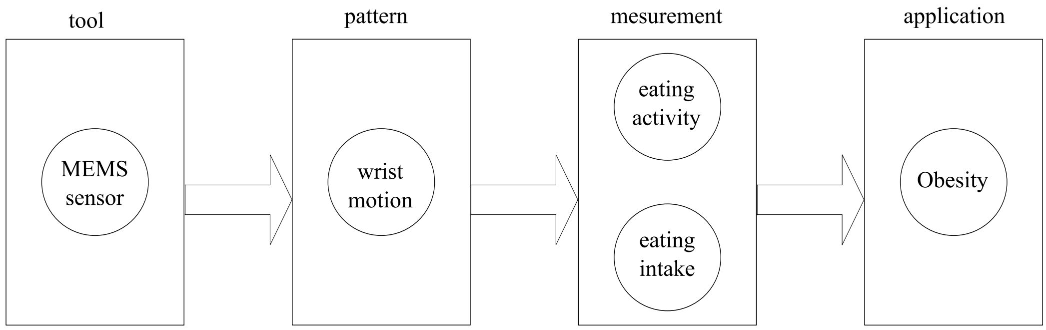

Figure 1.5 Fields involved in this work.

environment. The tracking of eating habits is also important for the treatment of several maladies linked to obesity, such as diabetes. Finally, such tools could help individuals with weight loss and weight maintenance. The current state of the art is essentially pen and paper, where a person writes down and manually measures everything eaten. The goal of this work is to engineer new tools that help automate this process. For research studies, this increases the number of subjects and the length of time that people can be monitored at a reduced cost. For the individual, this helps alleviate the burden of self-monitoring, potentially increasing compliance and accuracy.

The development of two different tools is described in this dissertation. They both use MEMS sensors to track wrist motion, so that in form they resemble a common wrist watch. The first tool, called the "bite counter", tracks wrist motion to determine when the wearer has taken a bite of food, thus providing a measure of consumption during eating. This work is described in detail in Chapter 2. The bite counter device is worn like a watch, and can be worn generally during most of the waking period of a day. Before eating, the user presses a button to turn it on; afterward, the same button turns it off. While operating, the device uses a gyroscope to track wrist motion, automatically detecting when the user has taken a bite of food. The device counts and time-stamps bites, storing a long-term log. The user can wear the device anywhere and use it discreetly with little effort.

Since there are so many variables involved with eating, the experiments described in this dissertation to evaluate the bite counter are designed to test the accuracy and utility of the tool under a decreasing set of restrictions. The first experiment tested the method across a large number of subjects eating the same food with the same utensil, to determine whether or not the pattern recognition used in the device is sensitive to the individual. The second experiment tested the method across a large variety of foods when the number of subjects is still large, in order to determine whether or not the pattern recognition used in the device is sensitive to the type of food. The third experiment tested the relationship between bites and kilocalories consumed, to determine if any correlation existed. While the first two experiments were carried out in the lab, the third experiment was carried out during normal free living in unrestricted conditions. Although these experiments cannot answer all possible questions about the accuracy and utility of the bite counter device, they do provide evidence that the tool has great promise and that further studies are warranted.

The second tool described in this dissertation tracks wrist motion throughout the day to determine when the user is eating, thus detecting eating activities amongst all other daily activities. This work is described in detail in Chapter 3. The bite counter needs the user to turn the device on and off before and after each meal. The work in Chapter 3 is motivated by the desire to eliminate this need, automatically detecting eating activities during continuous all-day tracking. In the experimental test, a total of 30 subjects were recruited for participation. Subjects were asked to start the custom program soon after waking in the morning, and to conduct all activities throughout the day as naturally as possible while the device continuously recorded their wrist motion.

The biggest innovation of this dissertation is the use of MEMS sensors to track wrist motion to detect eating activities and measure consumption. However, from an engineering perspective, there are additional aspects of novelty. First, research on activity recognition tends to use a large set of sensors [6, 25, 68, 102], connected with complicated wiring, in order to focus on identifying body motion patterns that correlate with tasks or activities of interest. Due to the limitations of device memory, sensors are typically tethered to nearby computers [40, 41, 102]. While this approach allows researchers increased recording capability in the lab, it ignores the practical implications of the "wearability" of any resulting device. In contrast, this work was motived by wearability and therefore explores a minimal amount of sensors, contained specifically only on the wrist. Second, previous experiments in activity recognition were typically performed in a laboratory setting where subjects were asked to repeat certain activities of interest, or to follow a pre-determined protocol [6, 25, 40, 41, 46, 65, 68, 70, 71, 96]. In contrast, in the penultimate experiments in this dissertation, subjects were asked to conduct their activities as naturally as possible during natural daily living. A great deal of iterative engineering is required to proceed from a tethered laboratory prototype to a self-contained, wearable device. Some of the work described in this dissertation details the evolution of the bite counter device and eating activity monitor device through several iterations. In order for body motion tracking using MEMS sensors to become practical, it is the humble opinion of this author that these approaches should be the standard for activity recognition research.

CHAPTER 2

A NEW METHOD FOR MEASURING MEAL INTAKE IN HUMANS VIA AUTOMATED WRIST MOTION TRACKING

This chapter describes the development and testing of a new tool called the "bite counter". The tool is intended to be worn like a watch, and to track wrist motion during eating to detect when the user has taken a bite of food ("bite" is used in the conventional sense, meaning the placing of food into the mouth). By automatically detecting when the wearer has taken a bite, the new tool can count the number of bites and store the total, time, and duration of eating in a log. This data could potentially be used to quantify how much a person eats during a meal, day, week or other period of time. It could potentially be used to quantify eating pace (bite to bite interval). It could potentially be used to compare patterns of eating of the same person day to day or week to week, or to compare the patterns of a person eating under different conditions, or to compare the patterns of eating of different people.

The preliminary work for the development of this tool is described in [20], this author's master's thesis. In that work, a tethered MARG sensor (combined magnetometer, accelerometer, and gyroscope on each axis) was used to study wrist motion during eating. It was found that out of the 6 axes of motion, the roll of the wrist corresponded the most with the taking of a bite of food. A pattern based upon wrist roll was defined and used in an experiment to detect bites. Tested on 10 people eating one meal each, the device was shown to have 91% sensitivity in detecting bites.

This chapter picks up where that work left off. While the original test of the principle of tracking wrist motion for detecting bites was encouraging, more tests needed to be conducted. There is a far larger variety of foods, utensils, containers, and manners in which people might eat, than can be tested within a small number of people and meals. In addition, success at detecting and counting bites does not necessarily provide evidence of success at measuring eating intake. The simplest way to provide that evidence is to show some correlation between automatically measured bite count and kilocalories consumed.

Therefore the primary concern of the work described in this chapter was to expand upon the preliminary test in a manner that iteratively probed the most important variables in eating.

In the course of conducting additional tests, further development of the bite counter device was necessary. The original test used a large, expensive sensor that could not be used in the final envisioned tool, due to both its size and cost. Therefore one of the tests in this chapter describes a comparison of a much smaller, less expensive sensor against the original. Additional tests outside the lab required the development of an untethered version of the device. During these tests, the development of the bite counter was disclosed to Clemson University's Office of Technology Transfer, a patent was filed, and the technology was subsequently licensed for manufacture. Therefore the details of the circuit diagram in the final version of the device described in this dissertation are being held in confidence. Nonetheless, it is important to note that the full set of experiments described in this chapter could not have been undertaken without the iterative development of the bite counter, and so several versions of the device are described.

2.1 Methods

In preliminary studies, data was examined from all three linear and rotational axes of the wrist during eating [20]. A high correlation was found between a simple pattern of wrist roll and the taking of a bite of food. Figure 2.1 emphasizes the key motion. Compared to body sensing approaches [2, 3, 4, 39], which use additional sensors on other parts of the body, this approach requires only one wrist-mounted sensor. Instead of trying to classify different types of eating activities, it was discovered that a simple pattern of wrist roll occurs during any bite. Our research team believes that this can be explained by looking at the necessary wrist orientation to pick something up (fingers aimed downward) versus the necessary wrist orientation to put something into the mouth (fingers aimed sideways). For most eating situations, regardless of the type of food or liquid, and regardless of the utensil (or fingers) used, a roll of the wrist must occur.

By using roll velocity to characterize the motion, a pattern can be described that is independent of the actual orientation of the wrist. This means that the pattern holds regardless of the position of the subject's body (e.g., sitting or lying down), and regardless

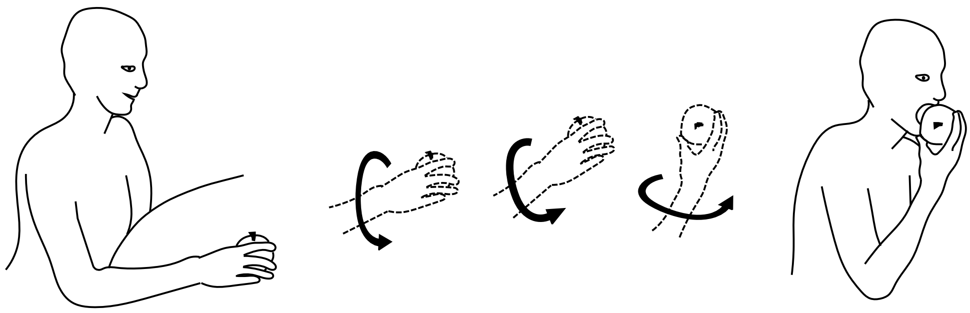

Figure 2.1 Wrist roll during taking a bite.

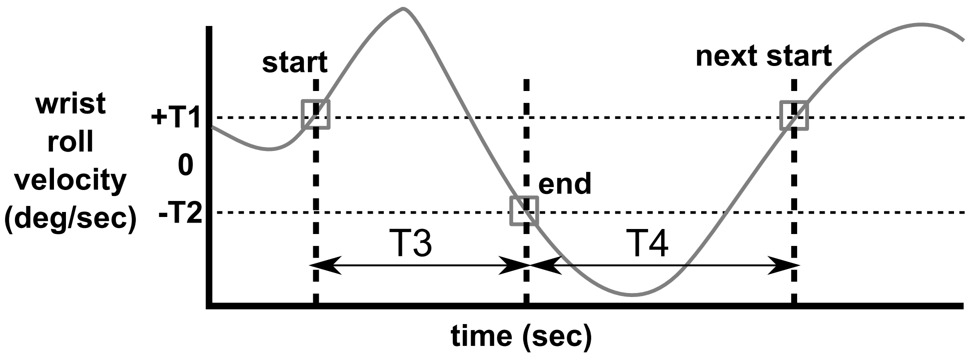

Figure 2.2 Wrist roll motion pattern.

of the specific configuration of the wrist relative to the rest of the arm. In [20], the original pattern described used three events. Subsequently it was discovered that a fourth event improved device sensitivity. The new pattern is shown in Figure 2.2.

First, the velocity must surpass a positive threshold; second, the velocity must surpass a negative threshold. The third and fourth events are the minimum amounts of time between the two rolls of one bite, and between consecutive bites. These minimum times help reduce false positives during other motions. The algorithm for detecting a bite based on this motion pattern can be implemented as follows:

```
Let EVENT = 0
Loop
  Let Vt = measured roll vel. at time t
  If Vt > T1 and EVENT = 0
    EVENT = 1
    Let s = t
  if Vt < T2 and t-s > T3 and EVENT = 1
    Bite detected
    Let s = t
    EVENT = 2
  if EVENT = 2 and t-s > T4
    EVENT = 0
```

The variable $EVENT$ iterates through the events of the cycle of roll motion. The thresholds $T1$ and $T2$ define the roll velocities that must be exceeded to trigger detection of the roll events. The threshold $T3$ defines the interval of time that must elapse between the first and second events of the roll motion, while the threshold $T4$ defines the interval of time that must elapse between the end of one bite and the beginning of another bite.

Although the method is simple, this is its strength. It does not need to be calibrated to the individual, or trained for specific eating patterns. The actual values used for thresholds are described below.

In [24], another member of our research team investigated tracking the linear motion of the wrist during eating. It was found that no pattern was readily apparent, or occurred with sufficient regularity, to detecting the taking of a bite based purely upon tracking linear motion. Our team believes the tracking of wrist roll to be the key innovation to building wrist-worn tools for monitoring eating.

2.2 Sensors and prototypes

Three versions of hardware were used in our experiments. Each is briefly described here.

Prototype #1

The first prototype used a wired InertiaCube3 sensor manufactured by InterSense Corporation (InterSense, Inc., 36 Crosby Drive, Suite 150, Bedford, MA, 01730, www.isense.com). Figure 2.3 shows a picture of the relatively expensive ($2,000 U.S.) sensor. It combines readings from a magnetometer, gyroscope and accelerometer on each axis, to produce an orientation heading. Radial velocity about any axis can be calculated by taking the derivative of consecutive headings. It was wired to a nearby computer (approximately 1m distant) for processing of the data.

Prototype #2

The second prototype used a wired MEMS gyroscope sensor. Figure 2.4 shows a picture of the device. While the InertiaCube3 sensor may be practical for laboratory use, its cost and size raise questions as to its applicability for general wearability. In the second prototype, a much less expensive sensor ($5 U.S.) was tested, that is also much smaller (see Figure 2.5). The STMicroelectronics (STMicroelectronics, Inc., 39 Chemin Dd Champ Des

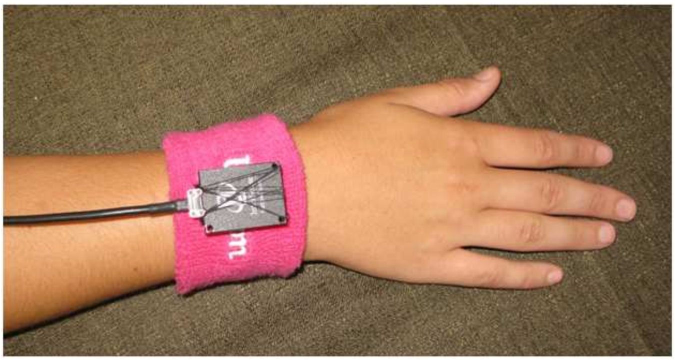

Figure 2.3 Wired hardware prototype #1.

Figure 2.4 Wired prototype #2 device using MEMS gyroscope.

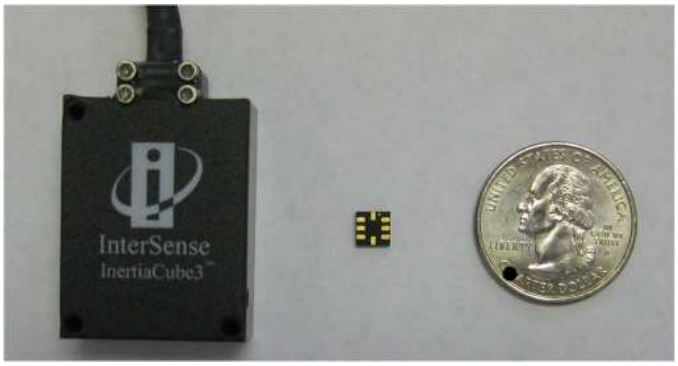

Figure 2.5 MEMS gyroscope (middle) used in prototype #2.

Filles, 1228 Plan-Les-Ouates, Geneva, 00000, www.st.com) LPR530al is a MEMS gyroscope that directly measures radial velocity. The wrist-worn package was wired to a nearby computer (approximately 1m distant) for processing of the data.

Prototype #3

The third prototype used the same MEMS sensor as the second prototype, but was completely self contained. Figure 2.6 shows a picture of the device. It contains a microprocessor, battery, gyroscope, LCD, memory, and USB port connection. Because it is self-contained it does not need to be tethered to an external computer during operation. However, its memory is not large enough to store raw gyroscope sensor data; it only stores the dates

Figure 2.6 Self-contained prototype #3 device using MEMS gyroscope.

	experiment #1	**experiment #2**	**experiment #3**
# of subjects	51	47	4
# of meals	139	49	54
food	waffles	any	any
utensil	fork	any	any
environment	lab	lab	free-living
prototype	InertiaCube3	InertiaCube3 & wired gyro	self-contained gyro

Table 2.1 Overview of experiments.

and times of recording sessions and the total number of bites detected during each session. A button on the device turns it on and off, and is intended to be pressed before the user begins eating and after the user finishes eating.

2.3 Data collection

This study was approved by Clemson University's Institutional Review Board for the protection of human subjects. All subjects signed an approved consent form prior to participating in data collection.

Overview of Experiments

Table 2.1 shows an overview of the experiments. The first experiment was intended to test if the bite counter can work across a large number of subjects, all eating the same food and using the same utensil. This would determine if the pattern found in the preliminary study was useful across a larger population or if it was somehow biased by the small number of people (10) originally tested. It could also potentially uncover repetitive biases, such as for left- or right-handedness, male or female, or other demographic differences.

The second experiment was intended to test if the bite counter can work across a reasonably large variety of foods and utensils. A large number of people were tested again to prevent finding a potential bias from the repetitive eating habits of a few individuals regardless of the foods chosen. In addition, each participant wore both the InertiaCube3 sensor and the MEMS gyroscope to test the difference of the method for detecting bites depending on the noise characteristics (and hence expense) of the sensor.

The third experiment was intended as a very preliminary exploration of the relationship between automatically detected bites and kilocalories consumed. There are many variables that may affect this factor, including the energy density of the foods consumed; gender, age, weight and BMI of the participant; social context of eating; time of day and duration of eating period; and many others. This experiment was intended only to provide a preliminary glance at the potential relationship between the two primary variables, in order to determine if additional experiments, where various variables are controlled, are warranted.

The first two experiments were conducted in a laboratory setting. Each subject sat at a table and slipped the prototype device over his or her dominant hand, onto the wrist. A video camera was placed on a tripod a few meters from where the subject sat, and aimed and zoomed in order to record the eating of the meal. The video was only used to establish ground truth for evaluating the automated detection of bites from the sensor data. A custom piece of software (Figure 2.7) was written that enabled simultaneous playback of the sensor data with the video. A sync time was established by manually observing the video along with the sensor data, and manually aligning them, based upon a review of the initial motions of the subject. Figure 2.8 shows a picture of the environment in which subjects ate, with the video synchronized to the sensor data.

The third experiment was conducted while subjects ate meals during their normal daily routine. The details of each experiment follows.

Experiment #1

In the first experiment, a total of 51 subjects (14 male, 37 female, ages 18-38) were monitored eating 139 meals (21 subjects ate once and 30 subjects ate four times, with two meals excluded due to missing data). In each meal, the subject was given three servings of toasted Kellogg's Eggo cinnamon toast waffles (276 g, 870 Cal) to eat. Each mini-waffle was cut in half, creating fixed-sized pieces for a total of 72 possible bites. The food was placed on a plate and a fork was provided. This meal was chosen because waffles are a common

Figure 2.7 The graphic user interface to review the eating video and recorded data.

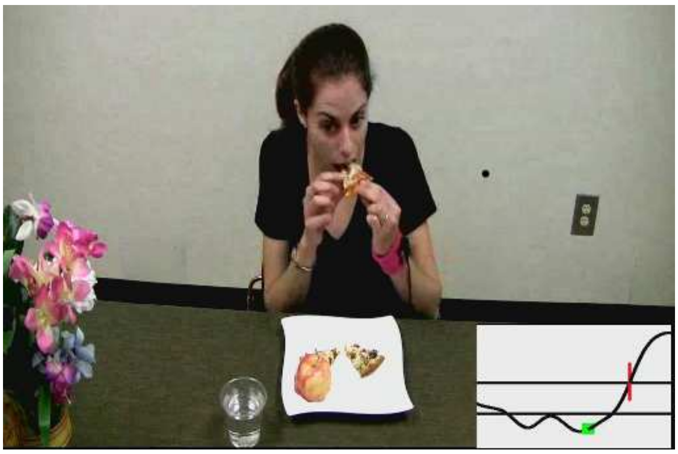

Figure 2.8 Synchronized video and sensor data.

breakfast food, easy to cut into uniform size bites, and easy to prepare in the laboratory. Two-hundred and fifty milliliters of water were provided in a cup, but the intake of liquid was not considered for this test, because the goal was to determine an accuracy for the method under relatively ideal conditions. The subject was given the following instructions: "I would like you to eat as you usually would. However, please eat only one piece of waffle at a time. You can take as much time as you like to complete the meal, and I would like you to stop when you are full. It is not necessary to eat all of the food on the plate. Please do not engage me in conversation while eating the waffles. But, if you would like more waffles or more water, you may ask me to bring them to you. Additionally, please drink only with your non-dominant hand which is the one that you do not have the sensor on. Similarly, if you use the napkin, please do so with your non-dominant hand, the same one you are using to take a drink of water."

Experiment #2

In the second experiment, many of the conditions were relaxed. Participants brought their own foods and liquids and ate however they wanted. The experimental supervisor engaged subjects in casual conversation in order to make the eating experience as natural as possible. The experimenter sat at a desk next to the table. The sensor package was wired to a computer on that desk. The experimenter operated software on that computer to record the raw sensor data while the subject ate. A total of 47 subjects were monitored eating 49 meals (two people participated twice). The subjects ranged in age from 18 to 31; 23 of them were male and 24 of them were female. BMIs were neither measured nor restricted because the goal of this experiment was to first determine the accuracy of the method across other variables, namely unrestricted foods.

Experiment #3

In the third experiment, all meals were eaten outside the laboratory in unrestricted settings. Tested environments included homes, offices, restaurants, and social settings (e.g., a party). Four different subjects (3 male, 1 female, ages 24-42) wore the device for a total of 54 meals. Subjects kept written food diaries noting the foods eaten and estimated or measured the amount of each food eaten. Kilocalories were estimated by laboratory personnel from the diaries using food packaging labels, website information (for restaurants), and calorie look-up tables. The goal of this experiment was to determine if there was any correlation between bite count as measured by the device and kilocalories. Obviously many confounding factors must be considered; this experiment was intended only to determine whether further study of the utility of this device for measuring kilocalories is warranted.

2.3.1 Evaluation

In order to evaluate the performance of the bite detector in the laboratory, the correspondences of computer-detected bites to manually marked bites were calculated. Figure 2.9 illustrates how detections were classified. For each computer detected bite (small square in the figure), the interval of time from the previous detection to the following detection was considered. The first actual bite taken within this window, that has not yet been paired with a bite detection, is classified as a true detection (T). If there are no actual bite detections within that window, then the bite detection is classified as a false detection (F). After all bite detections have been classified, any additional actual bites that remain unpaired to bite detections are classified as undetected bites (U). The reason for this approach is to define an objective range of time in which an actual bite must have occurred in order to classify a detected bite as a true positive. The reason the window must extend prior to the actual bite is that it is possible in some cases for the wrist roll motion to complete just prior to the actual placing of food into the mouth. Sensitivity (true detection rate) of the device was calculated for each subject as (total Ts)/(total Ts+ total Us). Because the methods do not allow for the definition of a true negative, the specificity (false detection rate) cannot be calculated. Therefore the positive predictive value is calculated instead as a measure of the performance of the device regarding false positives. The positive predictive value (PPV) of the device was calculated as (total Ts)/(total Ts+ total Fs).

2.3.2 Parameter Tuning

In order to select values for the thresholds in the algorithm, the following ranges for each were considered: $T_1 = T_2 = \{5, 10, 15, 20, 25\}$ degrees/second, $T_3 = \{1, 2, 3\}$ seconds, and $T_4 = \{2, 4, 6, 8, 10\}$ seconds. Every combination of values from these sets was tested, running the algorithm on all the data collected with the STMicroelectronics sensor. For the 75 total combinations, the sensitivity ranged from 61% to 97% and the PPV ranged

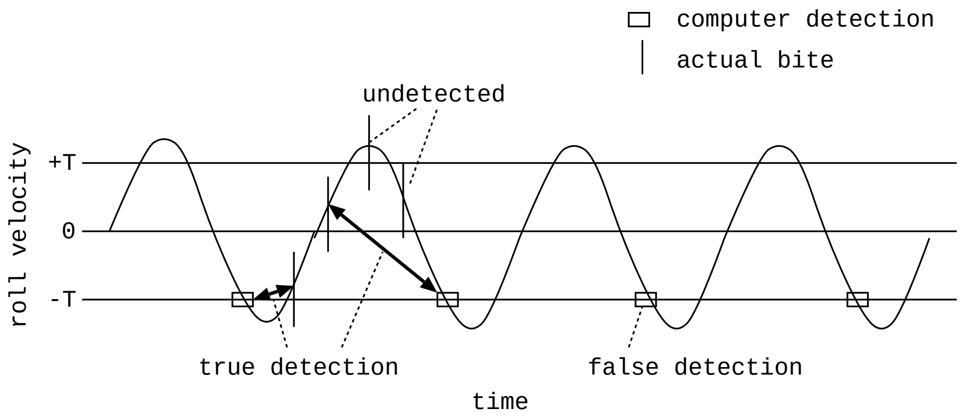

Figure 2.9 Classification of results.

from 38% to 93%. A wide range of combinations performed well, with over half giving a sensitivity and PPV above 70%, showing that the method is not overly sensitive to the values chosen. Each set was scored according to the formula $\frac{3 \cdot PPV}{7} + \frac{4 \cdot sensitivity}{7}$, placing slightly more importance on the sensitivity. The parameter set with the highest score was $T_1 = T_2 = 10$, $T_3 = 2$, $T_4 = 8$.

2.4 Results

Experiment #1

Across the 139 meals, the subjects ate a range of 8 to 72 bites, 34 bites on average. The sensitivity of the device was 94% and only 6% of the actual bites were undetected. The positive predictive value was 80% (about one false positive per 5 actual bites). Table 2.2 shows the sensitivity and PPV of the device for each subject. While the conditions in this test were restrictive in terms of food type eaten and utensil used, it showed that the technique works across a large number of subjects.

Experiment #2

As no restrictions were placed on foods or utensils, subjects brought their own foods and liquids and consumed them however they wanted. Table 2.3 shows the list of foods consumed along with how they were eaten. Nine of the subjects used a straw while drinking, but none used a knife.

Actual bites were timestamped by reviewing the correlated video, as described previously. Each bite was classified as food or liquid, and dominant or non-dominant according to which hand was used. Table 2.4 shows the manual classification of the 1,675 total bites taken across all 49 meals. A range of 12 to 72 bites was taken per meal, with an average of 32 bites. In total, 83% of the bites taken were food, 17% liquid; 86% of the bites were taken with the dominant hand, 14% with the non-dominant hand. These data show that most intake tends to happen with the dominant hand.

For food bites, $1281/(1281+105) = 92\%$ were taken with the dominant hand. For liquid bites, $165/(165+124) = 57\%$ were taken with the dominant hand. This indicates that most people tend to eat most of their food with the dominant hand, but tend to consume about half their liquid bites with the dominant hand. This may have repercussions for specific

Subject	SEN	PPV	Subject	SEN	PPV	Subject	SEN	PPV
1	69%	98%	48	100%	79%	95	95%	100%
2	64%	65%	49	83%	96%	96	95%	95%
3	63%	100%	50	100%	97%	97	94%	89%
4	25%	24%	51	94%	44%	98	100%	86%
5	98%	94%	52	100%	94%	99	85%	100%
6	96%	96%	53	100%	96%	100	100%	88%
7	100%	98%	54	98%	96%	101	88%	96%
8	100%	77%	55	100%	71%	102	96%	82%
9	89%	100%	56	93%	100%	103	97%	95%
10	82%	97%	57	90%	100%	104	100%	97%
11	78%	95%	58	97%	97%	105	100%	95%
12	92%	87%	59	95%	100%	106	100%	39%
13	100%	86%	60	96%	92%	107	96%	96%
14	100%	72%	61	100%	83%	108	100%	90%
15	95%	69%	62	100%	79%	109	100%	89%
16	100%	31%	63	88%	90%	110	100%	70%
17	88%	96%	64	81%	94%	111	100%	100%
18	71%	100%	65	64%	97%	112	100%	100%
19	89%	96%	66	87%	100%	113	93%	96%
20	100%	79%	67	87%	93%	114	100%	80%
21	100%	82%	68	76%	100%	115	100%	83%
22	97%	94%	69	96%	96%	116	100%	95%
23	100%	91%	70	100%	88%	117	100%	94%
24	100%	16%	71	89%	89%	118	100%	71%
25	100%	75%	72	100%	90%	119	96%	97%
26	100%	80%	73	92%	80%	120	100%	69%
27	100%	45%	74	100%	75%	121	98%	90%
28	100%	73%	75	100%	80%	122	95%	95%
29	100%	97%	76	100%	86%	123	96%	96%
30	99%	94%	77	100%	93%	124	100%	100%
31	93%	97%	78	100%	62%	125	100%	100%
32	100%	85%	79	92%	98%	126	96%	93%
33	69%	97%	80	100%	86%	127	98%	96%
34	61%	94%	81	90%	93%	128	100%	89%
35	95%	100%	82	100%	77%	129	96%	96%
36	100%	94%	83	92%	97%	130	80%	95%
37	14%	10%	84	90%	97%	131	90%	100%
38	100%	89%	85	100%	97%	132	90%	93%
39	100%	94%	86	97%	100%	133	100%	93%
40	100%	64%	87	100%	100%	134	100%	69%
41	100%	70%	88	100%	91%	135	84%	96%
42	95%	88%	89	81%	100%	136	78%	95%
43	100%	100%	90	100%	81%	137	92%	100%
44	93%	76%	91	100%	81%	138	100%	93%
45	100%	92%	92	100%	87%	139	100%	52%
46	98%	98%	93	100%	96%			
47	100%	97%	94	100%	77%			

Table 2.2 Sensitivity (SEN) and positive predictive value (PPV) for each subject in experiment #1.

Subject	Meal	Utensil
1	sandwich, orange slices	hand
2	sandwich, yogurt, water	spoon
3	sandwich, banana, water	hand
4	pizza, carrot, water	hand
5	Mex. chicken gumbo, water	fork
6	salad, soda	fork
7	chicken nugget, fries, soda	hand
8	turkey wrap, water	hand
9	sandwich, carrot, green tea	hand
10	beans, rice, apple, water	spoon
11	rice pilaf, bottled water	fork
12	sandwich, chips, juice	hand
13	sandwich, vitamin water	hand
14	turkey sandwich, chips, soda	hand
15	rice, tofu, vegetable, cola	spoon
16	pizza	hand
17	cheeseburger, fries, soda	hand
18	pizza, water	hand
19	bean soup, bread, water	spoon
6	chicken wrap, bottled water	hand
20	chicken teriyaki sub	hand
21	sandwich, chips, water	hand
22	sushi	chopsticks
23	sub, doritos chips, water	hand
2	pizza, water	hand
24	sandwich, o-rings, powerade	hand
25	pizza, water	hand
26	pasta, water	fork
27	sandwich, yogurt, cola	spoon
28	orange, almond	hand
29	sandwich, water	hand
30	bagel with cheese, water	hand
31	sandwich, banana, water	hand
32	chicken toaster, fries, soda	hand
33	sub, juice	hand
34	sandwich, juice	hand
35	sandwich, tater tots, water	hand
36	subway spicy Italian	hand
37	sandwich, juice	hand
38	chicken salad, cola	fork
39	sandwich, water	hand
40	sandwich, peach drink	hand
41	sandwich, crackers, water	hand
42	sandwich, fries, soda	hand
43	corn	fork
44	sandwich, banana, chips, soda	hand
45	mushroom burrito, water	hand
46	sandwich, banana	hand
47	sandwich, fries, water	hand

Table 2.3 Meals consumed by subjects.

	dominant hand	**non-dominant hand**
food	1281	105
liquid	165	124

Table 2.4 Breakdown of bites taken during 49 uncontrolled meals.

monitoring efforts, e.g., for tracking liquid intake only.

As described above, the subjects wore two sensors on one wrist-mounted package, in order to test the effect of the cost of the sensor. The sensitivity of the STMicroelectronics device was found to be 86%, positive predictive value 81%. The sensitivity of the InertiaCube sensor was found to be 85%, positive predictive value 81%. Table 2.5 shows the sensitivity and PPV of the device for each subject. Thus, the methods are unaffected by the difference in measurement noise and can work with generic quality MEMS gyroscopes.

False positives occurred most frequently when the subject used a napkin, unwrapped food from a container or paper (e.g., a sandwich wrapper), adjusted glasses or touched hair, organized food (e.g., stirring or moving food without actually eating), and occasionally due to gesturing while talking. These motions tend to mimic the characteristic eating motion tracked. Undetected bites tended to occur most frequently when the subject ate several times from a utensil or fingers without returning the utensil or hand to the table. Since a bite is operationally defined as the moment when food enters the mouth, this type of behavior would result in a missed bite.

The average time a subject spent eating a meal was 11.1 minutes, with a range of 4.6 minutes to 25.2 minutes. On average, subjects spent 45% of their time on activities other than taking a bite. For example, subjects were engaged in general conversation with the experimenter throughout eating. If the experimenter noticed that a subject was deliberately avoiding using the non-instrumented hand, the subject would be reminded to eat as normally as possible, including using either hand at any time. In order to provide some context to the naturalness of the eating sessions, the videos were reviewed and activities were noted that involved arm motions. Table 2.6 summarizes the findings. For each type of activity, the number of times were counted that the activity happened between bites. The first two entries, both involving conversation, are exclusive of each other; the remaining entries

	InertiaCube		STMicroelectronics	
Subject	**SEN**	**PPV**	**SEN**	**PPV**
1	84%	93%	81%	93%
2	83%	100%	83%	100%
3	100%	93%	100%	93%
4	94%	86%	98%	81%
5	98%	78%	100%	73%
6	78%	96%	80%	96%
7	81%	94%	86%	95%
8	85%	97%	84%	98%
9	91%	89%	91%	93%
10	88%	91%	92%	94%
11	100%	64%	100%	64%
12	86%	59%	84%	63%
13	97%	90%	97%	88%
14	94%	84%	91%	82%
15	88%	100%	88%	100%
16	74%	100%	76%	100%
17	91%	86%	88%	85%
18	70%	100%	85%	100%
19	83%	100%	81%	100%
6	81%	84%	78%	83%
20	63%	100%	63%	100%
21	68%	100%	72%	100%
22	100%	75%	100%	71%
23	93%	76%	95%	75%
2	90%	100%	95%	100%
24	100%	80%	100%	77%
25	54%	72%	54%	72%
26	88%	98%	90%	100%
27	89%	73%	89%	71%
28	97%	76%	100%	77%
29	81%	100%	81%	100%
30	84%	71%	81%	68%
31	90%	93%	86%	89%
32	97%	47%	97%	48%
33	53%	100%	47%	89%
34	60%	100%	72%	100%
35	69%	100%	71%	100%
36	90%	96%	90%	96%
37	80%	97%	80%	97%
38	100%	39%	100%	39%
39	97%	85%	97%	85%
40	100%	70%	100%	70%
41	94%	52%	94%	54%
42	59%	86%	59%	90%
43	89%	100%	89%	100%
44	70%	58%	73%	57%
45	94%	71%	89%	70%
46	100%	64%	100%	67%
47	81%	87%	79%	89%

Table 2.5 Sensitivity (SEN) and positive predictive value (PPV) for each subject by different prototypes (InertiaCube and STMicroelectronics) in experiment #2.

action	number of occurrences
speaking without gesturing	776
speaking with gesturing	350
unwrapping food	78
using a napkin	294
touching glasses, hair, face	449
other (adjust chair, check phone, etc.)	67

Table 2.6 Other actions during eating.

may overlap (for example, a subject may have spoken and used a napkin between bites). Note that subjects were engaged in conversation for roughly 2/3 of the time between bites (776+350 out of 1675 = 67%). Amidst all these natural activities, the methods accurately and reliably detected bites across a large number of subjects and meals.

Experiment #3

Figure 2.10 shows the plot of kilocalories per meal against automatically counted bites. The relationship is obviously noisy due to the natural variation in caloric density of foods in different meals as well as the kilocalorie estimation methods employed. Nonetheless, a moderate linear correlation (R=0.6) was found. It is important to note that the significance of this correlation is weak without a deeper statistical analysis of many factors that could affect it. This experiment was only intended to begin to explore whether or not there is a relationship between kilocalories and bite count as measured by the device when used in free living, but it does suggest that further studies are warranted where the effect of a number of factors are analyzed.

2.5 Conclusions and future work

The obesity epidemic is "undoubtedly attributable to dietary and behavioral causes" ([59], p. 612) coupled with an "obesogenic environment" that promotes energy overconsumption and under-expenditure [42]. Hence, the overweight or obese individual is faced with the difficulty of trying to reliably measure and reduce intake with complicated and inaccurate tools while living in an environment that encourages intake. Studies of individuals who have lost significant amounts of weight and maintained that weight loss indicate that a common behavior is self-monitoring of intake [99, 100]. A recent meta-review found that in all 15 studies reviewed, there was a significant relationship between self-monitoring

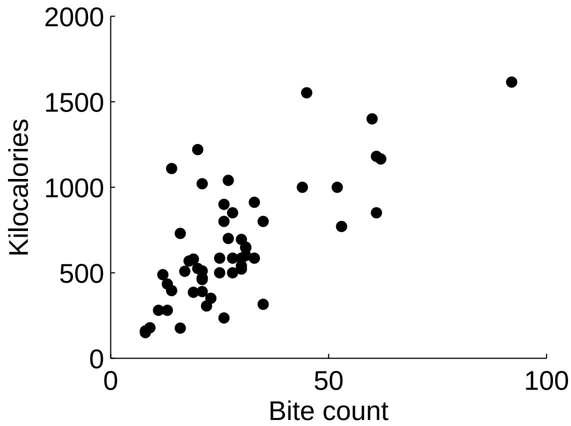

Figure 2.10 Bite count as measured by the tool, versus kilocalories, for 54 meals eaten in unrestricted conditions.

dietary intake and weight loss [13]. While numerous tools exist to help an individual measure energy output and are commonly used during exercise (e.g. odometers, speedometers, "calories burned" estimates, and even simple clocks), there are no tools in common use that automatically measure energy intake, leaving the manual burden of continuous measurement entirely on the individual.

Research into the automated monitoring of intake is difficult. Eating activities vary by person, food, utensil, location and other factors, all of which could have an impact on evaluating the performance of any method used to measure intake. The use of body sensing for directly monitoring eating has only recently begun to be explored [4, 73]. One group showed how sensors located on the back, lower and upper arms could be used to differentiate motion patterns among 4 different types of eating [39], and how ear and neck mounted sensors could be used to detect chewing sounds and swallowing motions [3, 4]. Another group used neck- and ear-worn sensors to detect and classify swallowing activities [48, 72, 74, 75]. The primary advantage of our method over these is the inconspicuous nature of a wrist-mounted sensor in the form of a watch.

The experiments reported in the current work are also preliminary. Laboratory studies are necessary to provide for ground truth measures of intake, but artificially restrict eating conditions. The progression of our experiments was intended to show that (1) the method works across a reasonably large number of subjects, (2) it works across a reasonably large variety of foods, and (3) there is some correlation with kilocalories on a per-meal level. A number of additional studies need to be undertaken to more thoroughly evaluate its accuracy and limitations under various conditions as well as further validate the relationship between bites taken and kilocalories consumed before the bite counter can be used as a proxy for energy intake.

2.5.1 Limitations

There are several limitations to our method that must be discussed. First, the device requires that the user turn it on before eating, and off when finished, and therefore forgetfulness could be a problem. However, all other existing methods, including the food diary and camera approach, also require the user to remember to use the tool to take measurements. The advantage of our approach is that the measurement process itself is automated, requiring less manual work than other methods. A further study is needed to examine compliance with remembering to use our method as compared to others.

A second limitation concerns the variation in bite count relative to kilocalories consumed. The data presented in experiment #3 are only a pilot study meant to determine if any correlation exists at a meal level. We would expect this correlation to differ between individuals, between different types of foods, between social settings, and possibly many other factors such as BMI, gender and age. However, it is important to note that kilocalories are commonly measured daily when it comes to weight management, weight loss is commonly evaluated weekly, and kilocalories goals are always targeted to the individual. Although our unit of measurement is a single bite, we believe its utility for correlating to kilocalories should be evaluated customized to an individual at a daily or weekly period, when we could expect some of the variation to smooth out. Further studies are needed to examine these correlations and the factors that affect them.

A third limitation concerns the potential effect of false positives, which could positively bias the measure. In our first two experiments our method detected the same amount of false positives on average (approximately one per five bites), even though the eating conditions changed drastically (common food, utensil, no liquid and minimum conversation; versus unrestricted foods, any utensils, any liquids, with heavy conversation). Further study is needed to determine if social setting or other factors affect the number of false positives. It can also be imagined that a person with particular habits, such as frequent napkin use or adjustments of glasses, would conduct these tasks with similar frequency across different meals; in this case the bias could be calibrated to the individual. Again, a further study is needed.

A fourth limitation concerns the use of the uninstrumented hand during eating and drinking. The subjects in the studies reported herein consumed 92% of food bites with the dominant hand but only 57% of liquid bites. Further study of this statistic is needed, especially if our method is to be used to measure liquid intake only. It may be that training an individual to use the instrumented hand could help alleviate this issue if it was necessary for a specific study. We also noted that many times during eating, a subject would make an eating-like motion with the dominant hand even while using the non-dominant hand to actually place food into the mouth. An example is the setting down of a sandwich while using the other hand to take a drink; the setting down of the sandwich could trigger the bite counter algorithm. Further study of this issue is needed.

The summary of all these limitations is that there are still many important questions about our method. It is impossible to address all of them in a single chapter. The execution of many of the studies suggested here could provide additional insight into eating habits as well as help to improve or further validate our method.

2.5.2 Future work

There are several aspects of our method not pursued in this chapter but that are notable possibilities for future work. First, our method can provide real-time feedback based upon its measurement *while a person is eating*. Other methods such as the food diary and camera method can only be used to assess consumption after the user has finished eating, typically at a much later time. One example of the type of feedback our method could provide is a real-time display of the numeric count of bites. The user could glance at the count while eating, and use this information to self-adjust eating behavior. Another example of the type of feedback our method could provide is an audible or vibrotactile alarm based upon the numeric count of bites. The user could set the alarm to go off with each bite past a custom threshold for different meals of the day, days of the week, or when a total daily count had been reached.

Second, it is possible that our discovery of the relationship between wrist roll and eating could be used to passively detect eating activities throughout the day. This would eliminate the need for the user to turn the device on and off for each meal. Two challenges would need to be met. First, battery life would be a concern because the gyroscope needed for tracking rotational motion can only operate for about 10-14 hours on a coin-sized (appx 120 mAh) battery [86]. Second, we would need to develop a new algorithm that differentiated eating activities from other daily activities based upon wrist motion. In a preliminary study [22], we piloted this idea on 4 subjects with some success. A larger study is ongoing.

Third, our method may improve the accuracy of measurement of eating intake in some circumstances. For example, a simple multiplication of bites $\times$ kilocalories-per-bite may provide a more accurate estimate of consumption than when a person has to guess or rely only upon memory. Given the relatively low user burden of our method as compared to existing methods, this may cause people who otherwise use no tools to use our method and thus improve their accuracy. As another example, the use of our method simultaneously with another method may improve compliance and accuracy with the secondary tool. As a third example, the continuous monitoring described in the previous paragraph could be used to alert the user to use a secondary tool to help measure consumption, thus improving compliance and accuracy. All of these possibilities are the topics of future work.

CHAPTER 3

DETECTING THE EATING ACTIVITIES OF A FREE LIVING HUMAN BY TRACKING WRIST MOTION

This chapter describes the development and testing of a new tool to detect the eating activities of a free-living human. The tool is intended to be worn like a watch, and to track wrist motion throughout the day to detect when the user starts and stops eating. The bite counter needs the user to turn the device on and off before and after each meal. The work in this chapter is motivated by the desire to eliminate this need, automatically detecting eating activities during continuous all-day tracking. This tool could also be used in combination with a food diary, 24-hour recall or food frequency questionnaire. Upon detecting that a person is eating (or has recently finished eating), the tool could prompt the user to complete a diary or recall method to provide information about nutrition and social context.

The work described in this chapter spans two iterations of development. In the first iteration, the primary goal was simply to determine if it was possible to detect eating activities amongst all other daily activities only by tracking wrist motion. A cumbersome tethered apparatus was used, where a wrist mounted MARG sensor was hard-wired to a laptop computer carried in a backpack. Four subjects were asked to wear the MARG sensor and carry the backpack to record their wrist motion data throughout the day. The subjects were asked to record the timestamps of changes of activities in a written log book, for example, 11:00:05 eating, 12:14:38 walking, 14:23:10 talking, etc. A heuristic method was developed that achieved a detection accuracy of 82%, suggesting that it is possible to detect eating activity throughout a day by only tracking the wrist motion data. This encouraging result motivated a second iteration of development where both the hardware apparatus and method for detecting activities were improved.

Wearing a sensor tethered to a laptop carried in backpack makes it difficult for the user to perform normal daily activities. In addition, it is difficult for the user to keep a manual log of all activities in a free-living condition. To overcome these inconveniences, the second experiment was conducted using an iPhone 4 device to simplify the apparatus. The iPhone 4 device was chosen because it can be worn completely on the wrist; it contains a 3-axis gyroscope and 3-axis accelerometer so both rotational motion and linear motion can be tracked; it has a sufficiently large memory (16GB) to store continuous data for an entire day; and it has a sufficiently large battery (1420 mAh) to power the data collection for an entire day. By reducing the device size and weight, it is possible to collect data from more subjects under more natural daily living conditions. In the iPhone experiment, 30 subjects kept a manual log of their eating activities. During the development of a more sophisticated method, the performance of the detection of eating activities using accelerometers and gyroscopes was compared. This is important because a MEMS accelerometer uses approximately 10% of the power of a MEMS gyroscope. The performance of features derived from different axes was also compared, motivated by the finding in the bite counter that the roll axis was the key motion feature. One goal of the iPhone experiment was to determine if features derived from tracking wrist roll motion would be key to detecting eating activities amongst all other daily activities.

3.1 Backpack experiment

This was the first experiment conducted to see if it was possible to detect and classify eating activities amongst all other natural daily activities, purely based upon tracking wrist motion. Because of this, the hardware was based upon available lab resources. A very small number of subjects, four, participated in the experiment. The intent of the experiment was to determine if further investment in hardware and algorithm development was warranted.

3.1.1 Methods

The backpack experiment was broken into two steps: classification and detection. The classification portion of the experiment sought to determine if eating activities could be correctly classified using wrist motion data that was segmented according to the manual logs kept by subjects. In other words, assuming the all-day wrist motion data was segmented perfectly at task boundaries, could eating activities be differentiated from all other activities. The detection portion of the experiment sought to determine if the boundaries of the eating activities could be automatically identified.

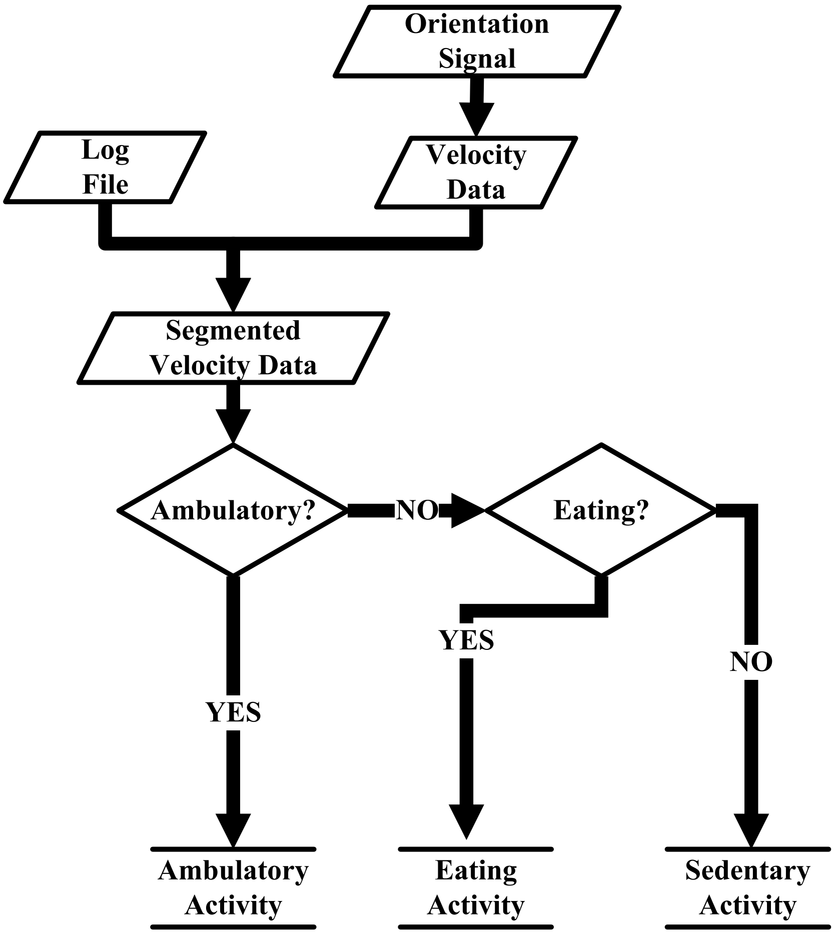

Figure 3.1 Diagram of offline classification.

3.1.1.1 Offline eating classification

An outline of the process for the classification method is shown in Figure 3.1.

In order to compensate for potential differences in the absolute angle of orientation of the device, derivative data was calculated from the absolute orientation data. With data recorded at 60Hz, the simplest way to calculate the derivative data is in Equation 3.1 where d_t is the derivative data at time t and o_t is the orientation data at time t.

$$d_t = (o_t - o_{t-1}) \times 60 \tag{3.1}$$

The derivative data was segmented into tasks based on the log file. In the log file,

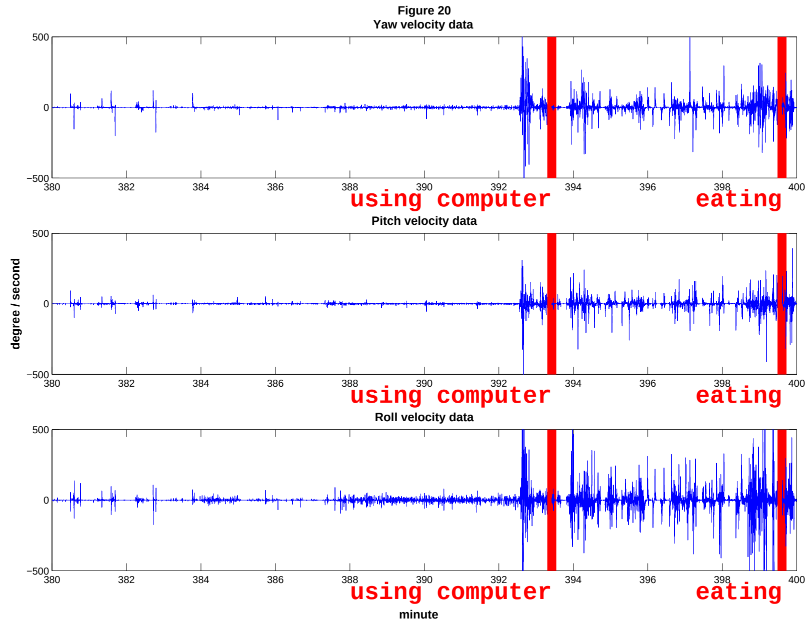

Figure 3.2 Twenty minutes of velocity data with manually logged tasks.

subjects recorded the start time for each new task. The start time of the current task was used as one boundary and the start time of the next task as the end boundary for the current task to segment the derivative data. Figure 3.2 shows an example segmentation of the velocity data based on a log file. The horizontal axis represents the time axis in minutes and the vertical axis represents the yaw, pitch and roll velocity data in degrees per second. This figure shows a span of twenty minutes. From minute 380 to minute 393, the subject was using a computer. After that, the subject was eating.

Each segmented task was manually categorized based on the content in the log file into one of 23 categories, listed in Table 3.1. Although most tasks were able to be mapped to these categories, a few tasks were difficult to categorize. In some cases, a subject listed two categories at the same time, such as eating apples and working on a computer. Different subjects sometimes made different notes on the same activity in different ways; for example, one subject wrote "walk to car, stop to talk to a friend" as one log entry, while another subject broke a similar activity into two parts. Because eating activities are the primary task of interest, any manual log entry that described eating is categorized as "eating". All

Eating activity	Sedentary activity	Ambulatory activity
Eating	Using computer	Cooking
	Using phone	Walking
	Reading	Driving
	Writing	Washing dishes
	Napping	Cleaning
	Talking	Doing laundry
	Watching TV	Packing
	Changing laptop battery	Brushing
	Filing nail	Shopping
	Playing card game	
	Going to restroom	
	Being passenger in car	
	Playing video game	

Table 3.1 Activity category.

other log entries were categorized to the best of the author's ability.

Since eating is the primary task of interest, the total set of tasks were condensed into three categories: eating, sedentary, and ambulatory. An eating activity was considered any long entry related to eating food or drinking liquid. A sedentary activity is a task (except eating) which involves sitting down, not moving or not exercising. All tasks in the middle column of Table 3.1 belong to this category. An ambulatory activity is a task which is related to walking, moving or exercising. All tasks in the right column of Table 3.1 belong to this category. It is well known in the activity recognition community that sedentary and ambulatory tasks are easily discernible, due to high accelerometer readings during ambulatory tasks and low accelerometer readings during sedentary tasks. Therefore, we considered primarily the difficulty of classifying eating activities versus other sedentary activities.

To classify the segmented tasks, five features were calculated for each task:

1. Variance of yaw velocity (Y_VAR)

2. Variance of pitch velocity (P_VAR)

3. Variance of roll velocity (R_VAR)

4. Bites per minute (BPM).

5. Periods of not eating (NOT_EAT).

All features were calculated using all the data in each segment. Bites per minute was calculated using the bite counter method. Periods of not eating was calculated as the number of occurrences when the bite detection method did not detect a bite over a span of at least one minute.

Using these features, each task was classified as follows. A task was classified as an ambulatory activity if any of the following conditions were met:

1. Y_VAR + P_VAR + R_VAR > T1
2. Y_VAR > T2
3. P_VAR > T3
4. R_VAR > T4

All remaining tasks were assumed to be sedentary, either eating or non-eating. A task was classified as an eating activity if all of the following conditions were met:

1. Y_VAR < T5 and Y_VAR > T6
2. P_VAR < T7 and P_VAR > T8
3. R_VAR < T9 and R_VAR > T10
4. BPM > T11
5. NOT_EAT < T12

Otherwise a task was classified as a non-eating sedentary activity.

Due to the low number of subjects and small amount of tasks, thresholds were determined using the full data set that could provide the best classification. The best thresholds {T1, T2, ... T12} were {8500, 5000, 1000, 5000, 3000, 200, 900, 150, 5000, 600, 2, 3}. If the variance of the task's velocity data was large, it was considered as an ambulatory task. If this criterion was not met, the task was considered as either an eating task or a sedentary task. An eating activity required that the variance of pitch, yaw and roll should be within a moderate range. In addition, an eating activity should have reached certain bite counts per minute and should not include a long period where no bite is detected.

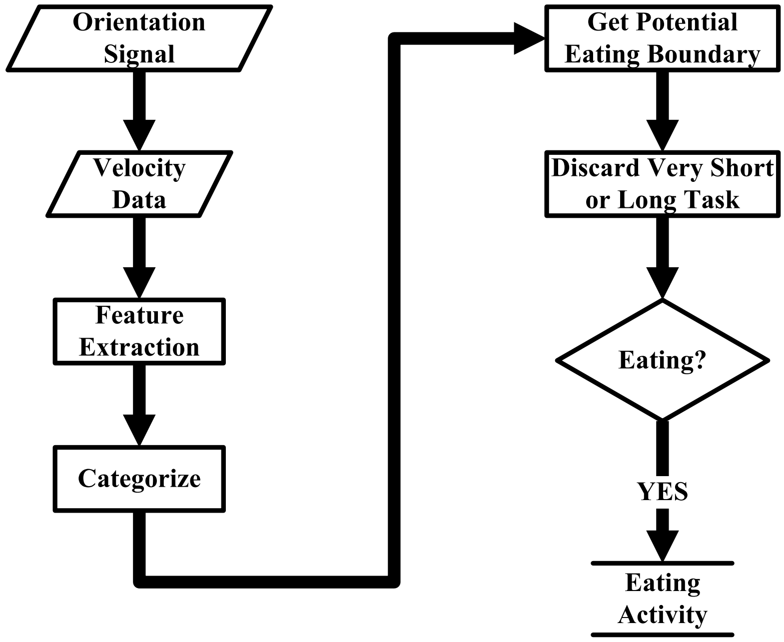

Figure 3.3 Diagram of real time detection.

3.1.1.2 Real time eating detection

The second portion of the backpack experiment considered the problem of detecting eating activities without knowing the start time of each task in the log file. This method has the potential to detect eating activities in real time. The outline of the method is shown in Figure 3.3. In this algorithm, only the roll orientation data is used.

The roll velocity data from the orientation data is calculated, the same as in section . A sliding window is then used to extract motion features. The window size is set to 10 minutes and each motion feature is updated every 1 minute. For each 10 minute window, the data is segmented into 2 parts, one from $t-10$ to $t-5$ and one from $t-5$ to t. Each of these two parts is classified using the methods outlined in section . Based on these classifications, the point at time $t-5$ is categorized as one of 4 categories:

1. category 1: possible start boundary for an eating task

2. category 2: possible end boundary for an eating task

3. category 3: this point cannot be inside an eating task

4. category 4: this point may be inside or outside an eating task

Figure 3.4 illustrates a state machine that shows the method. Initially it is in the state "not eating". After that, the transition condition (category from the previous list) is updated every 1 minute. If the transition condition is category 1, the state transits to "possibly eating", at the same time, the potential start time of an eating session is updated. While in the state "possibly eating", if the transition condition is category 1, the start time is updated; if the transition condition is category 3, it goes back to state "not eating"; if the transition condition is category 2, a potential eating session has been detected. The start time and the end time of the potential eating session are output and the state goes back to "not eating".

After a potential eating session was detected, several criteria were tested. First, the duration was examined, and if it was too short or too long, it was not considered as an eating activity. Second, the features and algorithm described in section were used to classify all the data within the entire segment. If all criteria are met, an eating session is detected.

3.1.2 Data collection

A wired InertiaCube3 sensor produced by InterSense Corporation was used to record the wrist motion data. The sensor was connected to an external 9V battery as a power source and a laptop with a running program to store collected data through an RS232 interface. Both the external battery and the laptop were carried by the subject in a backpack. The adjustable wire connecting the two parts was long enough to make sure the subject's normal behaviors were not being affected, as much as possible.

Subjects were asked to wear the sensor and carry the backpack to record their wrist motion data when they got up in the morning, and to stop recording the data when they went to bed at night. As shown in Figure 3.5, the subject placed the sensor on the dominant eating hand, and then wrapped the band tightly around the forearm to ensure it would not slide around the arm. The program running on the laptop in the backpack (Figure 3.6) was set up to collect the orientation data from the sensor and store it continuously.

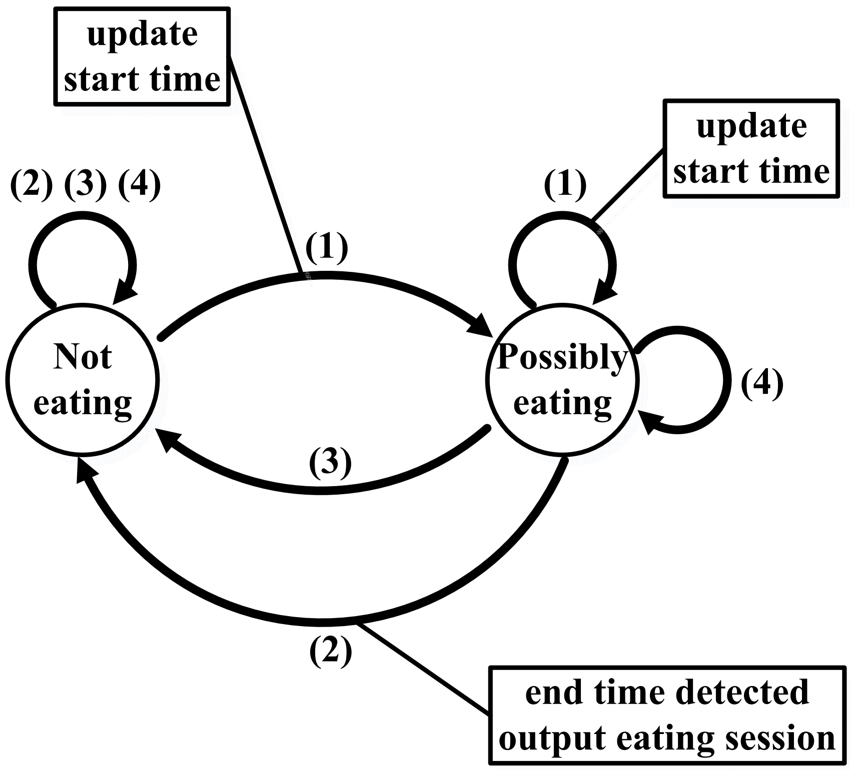

Figure 3.4 State machine of potential eating session detection.

Figure 3.5 Data collection for the backpack experiment.

Figure 3.6 Backpack instrumentation.

Using the recording program on the laptop was straightforward. Double clicking the program icon on the desktop would automatically start it to record the pitch, yaw and roll orientation at a rate of 60Hz. Due to the fact that the battery in the laptop could only last for about four hours, the program generated continuous beeping for 3 minutes when the battery level of the laptop dropped to 10%. The subject was asked to close the program and replace the battery (an extra was provided in the backpack) when he or she heard the beeping reminder. He or she was asked to restart the program afterward to continue recording.

During recording, subjects were asked to conduct daily activities as naturally as possible. The subject was asked to remove the device when engaging in activities which would damage the device, such as taking a shower or playing contact sports. The subject was asked to record activity behaviors in a written log book. The subject was asked to record the start time and the name of the activity for each new task. For example, 08:02:04 eating; 13:24:58 walking. A task was defined as a piece of work or activity to be finished. The log information written by the subject was used for segmenting the ground truth tasks from the wrist motion data later.

A total of 4 subjects participated in this experiment. Two were male and two were female. All the data was collected in a completely free living condition, with no supervision.

3.1.3 Results

Table 3.2 shows the duration statistics of all the tasks for each subject. The total time recorded for the four subjects ranged from 9.4 hours to 13.4 hours. The total number of tasks for each subject was between 23 and 39. Table 3.2 also shows the shortest task duration, longest task duration, average task duration, and standard deviation of task duration for each subject. In addition, the most frequent task for different subjects varied.

Statistics concerning the eating tasks for each subject are shown in Table 3.3. The total eating time of each subject was from 0.7 hour to 1 hour. This was consistent with the "American Time Use Survey" from the United States Bureau of Labor Statistics [12] which reported an average of 1.18 hours for eating and drinking per weekday. The total number of eating tasks was within a range from 4 to 6 times. Table 3.3 also shows the shortest eating

	Subject 1	**Subject 2**	**Subject 3**	**Subject 4**
total time of all tasks (h)	13.4	9.8	10.1	9.4
total number of tasks	39	36	23	27
shortest task (min)	3	1.2	3.3	3.5
longest task (min)	93.3	90.7	97.5	78.7
average task (min)	20.6	16.3	26.3	20.9
standard deviation (min)	20.6	19.1	27.4	21.7
most frequent task	Using computer	Driving	Eating	Using computer

Table 3.2 Durations of all the tasks for each subject.

	Subject 1	**Subject 2**	**Subject 3**	**Subject 4**
total time of eating (h)	0.8	0.7	1	0.8
total number of eating sessions	5	5	6	4
shortest session (min)	5.8	1.2	3.3	7
longest session (min)	18.6	15.3	12.3	21.7
average session (min)	10.2	7.9	10	12.6
standard deviation (min)	5.2	6	3.6	6.5

Table 3.3 Eating tasks for each subject.

	Classify: Eating	**Classify: Sedentary**	**Classify: Ambulatory**
GT: Eating	17	2	1
GT: Sedentary	4	49	1
GT: Ambulatory	2	1	48

Table 3.4 Offline classification result (GT = ground truth).

session, longest eating session, average eating session, and standard deviation of eating session for each subject.

Table 3.4 shows the results of the task classification portion of the backpack experiment, which used the log files to perfectly segment all the wrist motion data. There were 125 total tasks across all 4 subjects; 16% of the tasks were eating activities, 43% of the tasks were sedentary activities, and the rest were ambulatory activities. In this portion of the backpack experiment, the classification accuracy was 91%, and 17 of 20 actual eating tasks were correctly classified.

Table 3.5 shows the results for the second portion of the backpack experiment, real time eating activity recognition without knowing any information in the log file. In the table, the second and the third column show the ground truth time of each eating task. The second column shows the start time of the eating task and the third column shows the end time of the corresponding eating task. The fourth column and the fifth column show the computer detected boundary for each eating task. The fourth column shows the detected start time of each eating task and the fifth column shows the detected end time of the corresponding eating task. All of these numbers are in minutes. A row without any number in the fourth and fifth column indicates that there was an undetected eating task. A row without any number in the second column and third column indicates that there is a false detection of

	Ground Truth		PC Detect	
Subject	**Start time**	**End time**	**Start time**	**End time**
S1	11	17	9	17
S1	195	205	194	205
S1	393	400	393	399
S1	537	547	537	549
S1	654	673	653	674
S1			685	700
S2	78	91	78	96
S2	523	538		
S2	565	573		
S2			100	112
S2			192	201
S2			538	548
S3	85	94	85	94
S3	166	178	166	179
S3	257	269	258	272
S3	412	424	412	426
S3	603	615	601	615
S3			362	370
S4	14	27		
S4	270	277	270	276
S4	462	484	466	475
S4	518	527	515	528

Table 3.5 Real time classification result (all units are minutes).

an eating task. A row with numbers in all columns indicates that this is a detected eating task.

Although there were a total of 20 eating sessions recorded by the subjects, 3 of them lasted for less than 3 minutes so they were not included in Table 3.5. These tasks were excluded because they were so short that the feature set did not adequately describe them. For the remaining 17 eating tasks, 3 of them were not detected. There were 6 false detections. Thus the sensitivity was 82% and the positive predictive value was 70%. In addition, for the 14 eating sessions detected, 10 of them were detected with start and end boundaries which match the log file within 2 minutes. For the other 4 sessions, the boundary errors are (0, 5), (1, 3), (4, 9), (3, 1) minutes respectively. It is likely that these boundary errors are due to timing misalignments between the user logs and wrist motion data, as well as judgment calls by the subjects as to when they actually started and stopped eating.

3.2 iPhone experiment

Although the number of subjects in the backpack experiment was very small, the results were encouraging. In order to further develop the method, it was clear that a much larger data set would be needed. This in turn required better hardware, in order to facilitate more data collection. After more data was collected, a more sophisticated algorithm was developed. This section describes an experiment using an Apple iPhone 4 that builds upon the backpack experiment.

3.2.1 Methods

Similar to the method developed for the backpack experiment, the improved algorithm consists of four parts: pre-processing, hypothesized eating detection, feature extraction, and final classification. The approach uses a simple set of features to detect a hypothesized eating activity, identifying the start and stop time. A richer set of features (mean absolute deviation, regularity of motion, entropy, etc.) is then calculated on all the data between these boundaries. Final classification to determine whether or not the detected activity was an eating activity is done using a Naive Bayes classifier [55] on the rich feature set.

A motivating question in the study is to determine the usefulness of rotational versus linear wrist motion. Features derived from gyroscopes were compared versus those derived from accelerometers. This is important for two reasons. First, gyroscopes typically consume about ten times more power than accelerometers [85, 86]; for continuous daily use it would therefore be preferable to use linear motion features in order to conserve battery life. Second, the previous work on the bite counter showed that rotational wrist motion was related to the taking of a bite of food; this study seeks to determine if rotational motion features can differentiate eating from other activities.

3.2.1.1 Preprocessing

Figure 3.7 shows an example of raw data recorded using the iPhone. The x axis is the time in minutes, the y axis shows the 6 axes of motion data: rotation motion along yaw, pitch and roll axes, and acceleration motion along x, y and z axes.

Equation 3.2 was used to smooth the raw data for each axis

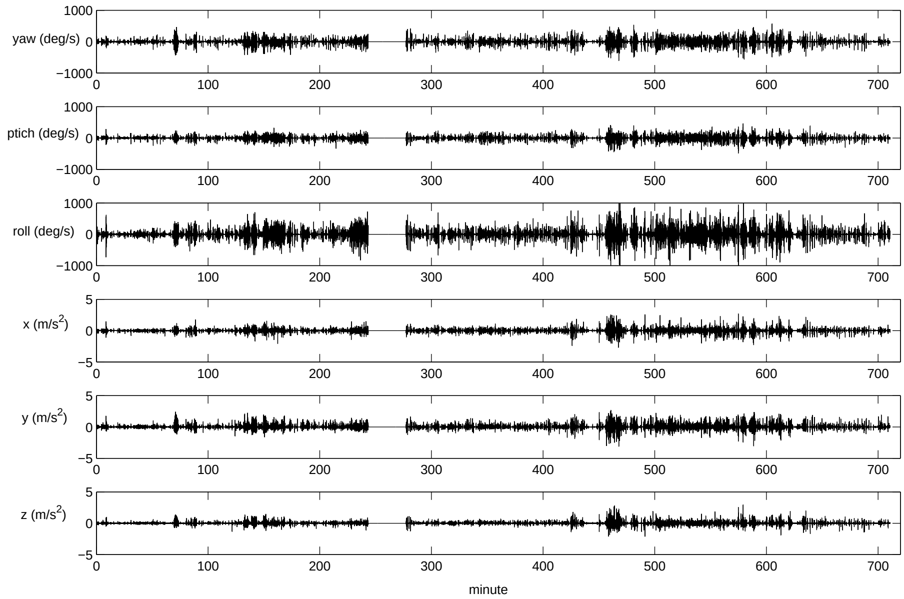

Figure 3.7 Example of raw iPhone data.

$$S_t = \sum_{i=-N}^{0} R_{t+i} \frac{e^{\frac{-t^2}{2R^2}}}{\sum_{x=0}^{N} e^{\frac{-(x-N)^2}{2R^2}}} \tag{3.2}$$

where R_t is the raw data and S_t is the smoothed data at time t. Smoothing is performed using a Gaussian-weighted window. The midpoint of the window corresponding to the peak of the Gaussian is centered on the current measurement, so that only half of a Gaussian distribution is used for smoothing. The most recent N measurements are buffered and updated after each new measurement, shifting out the previously stored oldest measurement. The value R denotes the width of the Gaussian relative to the buffer size used to smooth the data. For data sampled at 60 Hz, a buffer size of 1 second (N=60) with a Gaussian sigma defined by R=40 produced good results for the sensors in the iPhone 4 device.

device	**axis**	**notation**
gyroscope	yaw	$G_{\alpha,t}$
gyroscope	pitch	$G_{\beta,t}$
gyroscope	roll	$G_{\gamma,t}$
gyroscope	any	$G_{any,t}$
gyroscope	sum	$G_{sum,t}$
accelerometer	x	$A_{x,t}$
accelerometer	y	$A_{y,t}$
accelerometer	z	$A_{z,t}$
accelerometer	any	$A_{any,t}$
accelerometer	sum	$A_{sum,t}$

Table 3.6 Symbol notation.

Table 3.6 shows the notation used in the rest of this chapter. Some notation is commonly used for both accelerometer data and gyroscope data during their comparison, and for different axes during their comparison. For example, $G_{\alpha,t}$, $G_{\beta,t}$ $G_{\gamma,t}$ are the gyroscope data along the yaw, pitch and roll axes at time t, and $G_{any,t}$ is gyroscope data along any axis at time t. $G_{sum,t}$ is the average sum of absolute gyroscope motion data over a constant window at time t. A sliding window method is used where the window size is set to W samples and it is updated every T samples. $G_{sum,t}$ is defined in Equation 3.3.

$$G_{sum,t} = \frac{1}{W+1} \sum_{i=t-\frac{W}{2}}^{i=t+\frac{W}{2}} |G_{\alpha,i}| + |G_{\beta,i}| + |G_{\gamma,i}| \tag{3.3}$$

$A_{x,t}$, $A_{y,t}$ and $A_{z,t}$ denote the accelerometer data along the x, y and z axes at time t, and $A_{any,t}$ denotes accelerometer data along any axis at time t. $A_{sum,t}$ is the average sum of absolute accelerometer motion data over a constant window at time t. A sliding window method is used where the window size is set to W samples and it is updated every T samples. $A_{sum,t}$ is defined in Equation 3.4.

$$A_{sum,t} = \frac{1}{W+1} \sum_{i=t-\frac{W}{2}}^{i=t+\frac{W}{2}} |A_{x,i}| + |A_{x,i}| + |A_{x,i}| \tag{3.4}$$

Figure 3.8 illustrates the effect of different window sizes and different update steps. In the figure, the horizontal axis represents the time in minutes, and the vertical axis represents the feature calculated by acceleration data. The dotted vertical line is the boundary of an eating activity. The data in the left figure is too noisy and the data in the right figure is smoothed too much. The parameter chosen in the middle figure looks more appropriate, and corresponds to a window size of 3600 samples and an update step of 300 samples.

3.2.1.2 Detecting hypothesized eating activity

A general pattern of wrist motion energy related to eating activities was found. At the beginning of an eating activity, there tends to be a period of larger wrist motion energy, probably caused by things like bringing food to a table, adjusting the position of utensils, opening food containers, and unwrapping food. During eating, the total wrist motion energy is reduced. At the end of an eating activity, there tends to be another period of larger wrist motion energy, likely caused by things like putting remaining food away, washing hands, standing up, and putting dishes away.

The use of both gyroscopes and accelerometers was investigated for detecting hypothesized eating activities. $G_{sum,t}$ and $A_{sum,t}$ is used to represent the level of wrist motion energy, where a higher value indicates more energetic activity. Figure 3.9 shows an example from the collected data. The dotted lines indicate the start and stop times of the meal in the manual log. It can be seen that the wrist motion energy spikes both before and after the meal. Figure 3.10 shows a second example. In this case the spike is less pronounced at the end, indicating that the intensity of meal clean-up activities was less than during

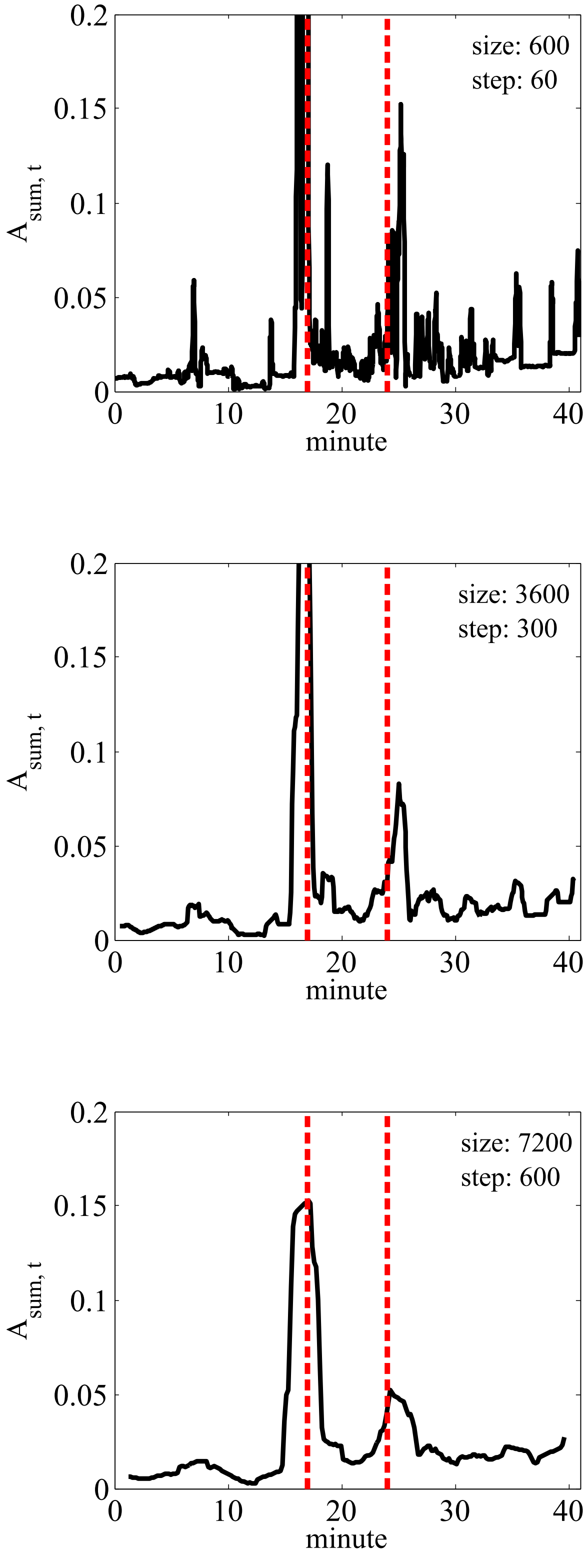

Figure 3.8 Effect of window size and update step to calculate the average sum of absolute value.

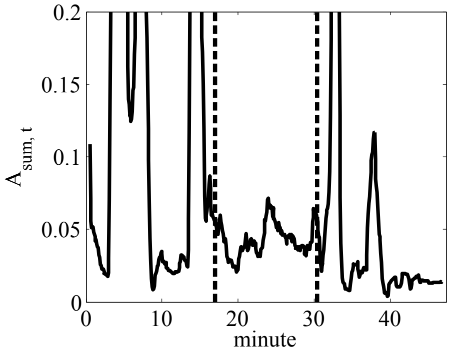

Figure 3.9 Example of wrist motion energy during an eating activity (dotted lines denote the start and stop time indicated in the manual log).

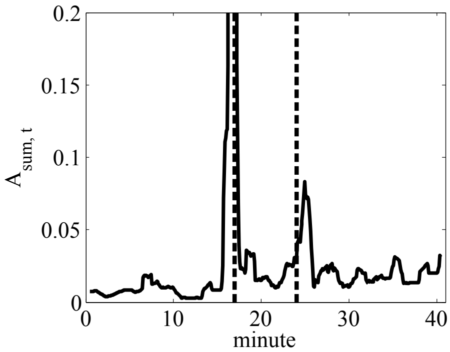

Figure 3.10 Second example.

meal preparation. This occurred frequently enough to warrant two pattern variations for detecting hypothesized eating activities.

Formally, a hypothesized eating activity is detected based upon five events as illustrated in Figure 3.11. In the figure, the horizontal axis is time and the vertical axis is the average sum of absolute motion data, either $A_{sum,t}$ or $G_{sum,t}$ (I test both independently in the experiments). The five events are:

1. At the beginning of eating, $A_{sum,t}$ (or $G_{sum,t}$) must surpass a threshold K at time a
2. The time between a and b should be no more than 10 minutes.
3. At the end of eating, $A_{sum,t}$ (or $G_{sum,t}$) must surpass the threshold K at time c.
4. The time between b and c should be at least 3 minutes and less than 30 minutes.

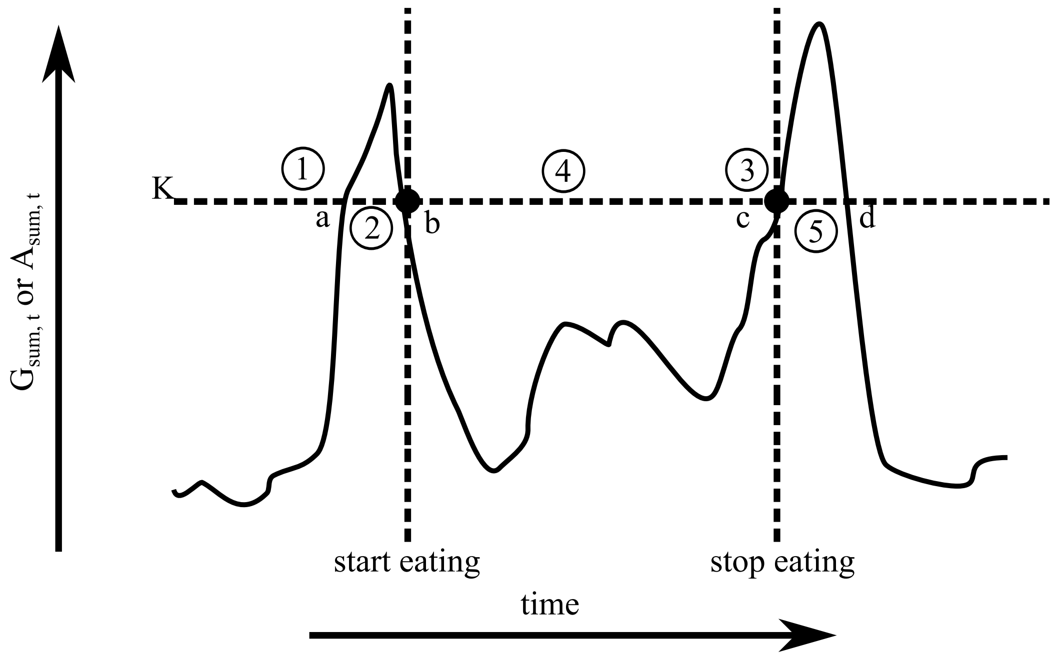

Figure 3.11 Criteria of first eating pattern.

5. The time between c and d should be no more than 10 minutes.

If those five conditions are met, then a hypothesized eating activity is detected as having occurred between time b and c.

If the first two criteria are met, but the data does not meet the third to fifth criteria, a second pattern is searched for where the wrist motion energy at the end of the eating activity is assumed to be smaller compared to the energy at the beginning of eating. This is illustrated in Figure 3.12. After the first and second criteria are found, a running average of wrist motion energy is calculated starting two minutes after b. At time c, if the following two events are met:

1. The time between b and c should be at least 3 minutes and less than 30 minutes.

2. $A_{sum,t}$ or $G_{sum,t}$ at c is more than 2.5 times the running average.

then it can be concluded that there is a hypothesized eating activity between time b and c.

For the threshold K, the range of values 0.1 to 1.5 was tested in increments of 0.1 for accelerometer data and from 10 to 100 in increments of 10 for gyroscope data. It was found

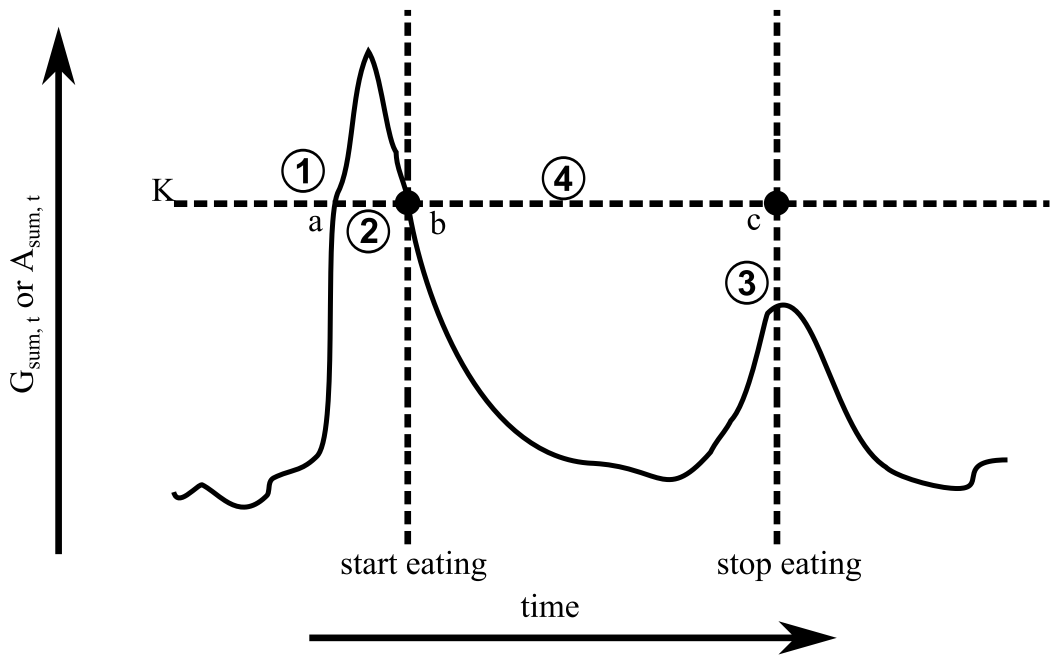

Figure 3.12 Criteria of second eating pattern.

that the methods were not overly sensitive to this parameter. The final values $K = 0.9\ m/s^2$ (accelerometer) and $K = 50\ deg/s$ (gyroscope) were selected for the experiments.

3.2.1.3 Extracting features during a hypothesized eating activity

For each hypothesized eating activity, the use of both gyroscope and accelerometer features were investigated for classification. Results are reported for four types of gyroscope-derived features. The first feature is the mean absolute deviation of yaw, pitch and roll. It is assumed that this value must be in some medium range, because the wrist motion must vary during eating, but it probably does not vary as much as during other activities. The average distance of the data set from its mean is calculated as in Equation 3.5

$$\frac{1}{N}\sum_{j=1}^{N}|G_{any,j} - \frac{1}{N}\sum_{i=1}^{N}G_{any,i}| \tag{3.5}$$

where N is the total data sample.

The second feature is the regularity of motion. It is assumed that an eating activity may have more regular cycles of rest and motion, while other activities may not follow this pattern. This is illustrated in Figure 3.13, where two hypothesized activities are shown. The x axis is the time and the y axis is $|G_{any,t}|$. The active motion time is defined as the time that rotational motion exceeds the threshold (10 deg/s), plus an additional 8 seconds, a typical time between bites that has been observed in our previous research [23]. The rectangles below each activity are the active motion time. Thus, the regularity of motion is defined as the total active motion time over the total activity time. For the top activity in Figure 3.13, it can be seen that the regularity of motion is much larger than for the bottom activity, even though the total time that motion exceeds the threshold K is the same.

The third feature is gyroscope line fit. For all $|G_{any,t}|$ in the hypothesized eating session, a line is fit and the slope is used to represent the trend of the session. If the slope is positive, it indicates that activity increased over time; if the slope is negative, it indicates that activity decreased. It is hypothesized that people may slow their activity as eating winds down.

The fourth feature is related to the bite counting method described earlier in this dissertation. This algorithm is run on the hypothesized eating activity and the number of bites is counted, along with the mean, variance and skewness of bite intervals. It is hypothesized

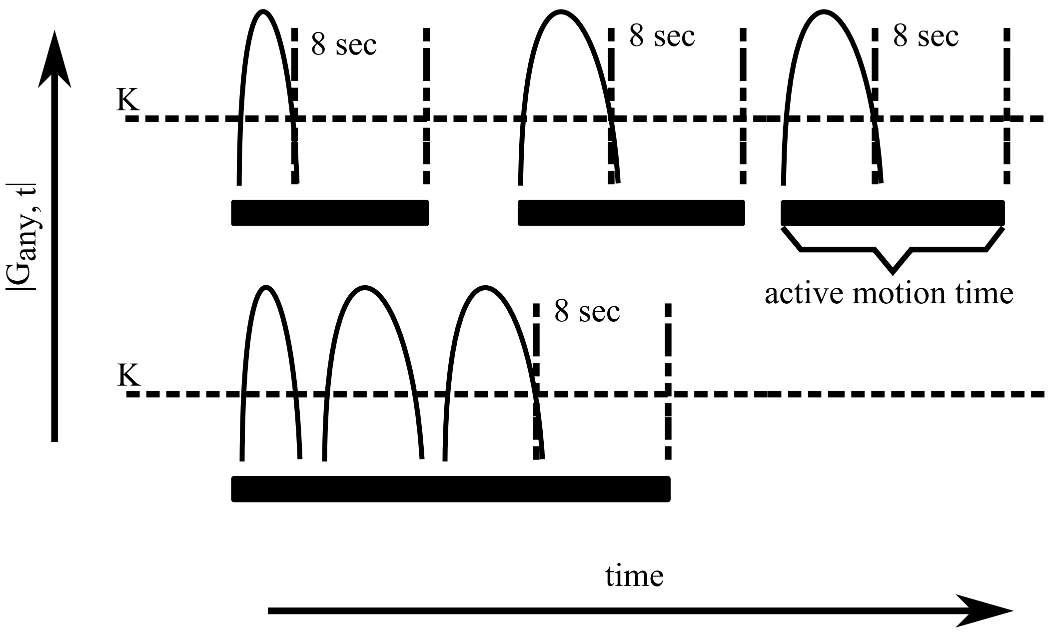

Figure 3.13 Regularity of motion.

that non-eating activities may show different ranges of values for these numbers than eating activities.

Accelerometer features were calculated in the same way as the gyroscope features, except that the bite counter algorithm is based upon wrist roll and so accelerometer features cannot be calculated. In addition to the features described here, several other features were investigated including entropy, variance, zero crossing rate, mean of minima, mean of maxima, percentile distributions and autocorrelation, etc. The variance is similar to mean absolute deviation but is second order. It can be calculated using Equation 3.6.

$$\frac{1}{N}\sum_{j=1}^{N}(G_{any,j}-\frac{1}{N}\sum_{i=1}^{N}G_{any,i})^2 \tag{3.6}$$

The entropy is a measurement of the level of disorder and can be computed using Equation 3.7, where $p(x_i)$ is the probability mass function of outcome x_i.

$$-\sum_{i=1}^{n}p(x_i)\log p(x_i) \tag{3.7}$$

The zero crossing rate is a way to represent the frequency of motion. The mean of minima and mean of maxima is a way to represent the size of motion. The percentile distribution is a way to present the range of motion. The autocorrelation is a way to represent the repetition of motion. However, none of these showed sufficient discriminatory power during classification to warrant further discussion here.

3.2.1.4 Classification

The Fisher linear discriminant (FLD) [49] was used to determine a rough measure of the discriminatory power of each feature. All the hypothesized detected eating activities were manually grouped into either actual eating activities or non-eating activities, using the manual logs provided by subjects. For each feature described in previous section, the mean μ_m and variance σ_m^2 of the feature were calculated for all eating activities, and the mean μ_n and variance σ_n^2 for all non-eating activities. The FLD was then calculated as:

$$J=\frac{|\mu_m-\mu_n|^2}{\sigma_m^2+\sigma_n^2} \tag{3.8}$$

A higher FLD indicates the feature has better discriminatory power (is better for classification). Sets of features for use in classification were selected according to those combinations having higher FLD values.

A Naive Bayes classifier [55] was used for final classification. The Bayesian approach to classification is to assign the most probable class v_{MAP}, given feature values $a_1, a_2, ..., a_N$ as shown in Equation 3.9.

$$v_{MAP} = \underset{v_j \in V}{argmax}\, P(v_j | a_1, a_2, ..., a_N) \tag{3.9}$$

V is the class space, in this case it is either eating activity or non-eating activity. Using Bayes theorem, this expression can be rewritten as

$$v_{MAP} = \underset{v_j \in V}{argmax} \frac{P(v_j) P(a_1, a_2, ..., a_N | v_j)}{P(a_1, a_2, ..., a_N)} \tag{3.10}$$

In practice only the numerator of this fraction is of interest because the denominator does not depend on v_j. The Naive Bayes classifier is based on the simplifying assumption that the attribute values are conditionally independent. Thus, the model can be expressed using Equation 3.11.

$$v_{MAP} = \underset{v_j \in V}{argmax}\, P(v_j) \prod_i P(a_i | v_j) \tag{3.11}$$

For this experiment, $P(v_j)$ for both eating activity and non-eating activities was set to 0.5. For each feature, the $P(a_i|v_j)$ was computed using Equation 3.12

$$P(a_i | v_j) = \frac{1}{\sqrt{2\pi\sigma_{a,i}^2}} e^{-\frac{(a_i - \mu_{a,i})^2}{2\sigma_{a,i}^2}} \tag{3.12}$$

where $\mu_{a,i}$ is the mean of the value in feature a_i associated with class v_i and $\sigma_{a,i}^2$ is the variance of the value in feature a_i associated with class v_i.

3.2.2 Data collection

An touchscreen slate smartphone iPhone 4 (Apple Inc., 1 Infinite Loop, Cupertino, CA 95014, http://www.apple.com/iPhone/) was used to collect data. This device was chosen because it contains 3-axis accelerometers and gyroscopes, so it can track both linear and rotational motion. It has a sufficiently large memory (16GB) to store continuous data for an entire day, and its battery is sufficiently large (1420 mAh) to power data collection for

Figure 3.14 Data collection using an iPhone 4 on the wrist.

up to 10 hours. Although the device is a little larger than I would prefer (larger than a common watch), due to large-scale manufacturing it has a relatively small footprint while still providing the necessary functions.

The iPhone 4 was fixed to a wristband, and the subject wrapped the band tightly around the forearm to ensure that it did not slide around the arm (Figure 3.14). The top of the device was aligned with the wrist joint but positioned so that it would not inhibit movement of the wrist (Figure 3.15).

A custom program was written for the iPhone to record the wrist motion data. The

Figure 3.15 Example of eating activity.

program records the raw acceleration readings along the x, y, z axes and the raw rotation readings around the pitch, yaw, and roll axes at a rate of 60Hz. The data was stored on the device and later transferred to a computer through a USB port. The program interface is shown in Figure 3.16. In the middle of the interface, it shows the status and the current time. The status will say "NOT Recording" if the device is not recording the data and the status will say "Recording" if the device is recording the data. In the lower part, the "Reset" button clears all the recorded data in the text file. The "Start" button is used to start recording and the "Stop" button is used to stop recording.

Subjects were given the device in a brief laboratory visit prior to the day of recording, and were instructed in its use. They were asked to start the custom program soon after waking in the morning, and to conduct all activities throughout the day as naturally as possible while the device continuously recorded their wrist motion. Subjects were asked to remove the device when engaging in activities that could damage it, such as taking a shower or playing contact sports. Subjects were also instructed to manually record eating activities in a provided log book (5 cm $\times$ 14 cm) using the time displayed on the device for reference. Figure 3.17 shows an example of one log entry. The following were the exact instructions for making log entries:

1. Record the start time and stop time of each eating activity using the time display on the iPhone. Record the time as precisely as possible. It is acceptable if the record is off by a few seconds.

2. Record the name of the foods and liquids taken.

3. Check the utensil used such as hand, fork, and spoon. Subjects may choose more than one utensil.

4. Only log continuous eating or drinking for longer than 3 minutes; ignore short snacks (e.g., single bite or drink).

Recording continued until the user determined end-of-day, at which time the user could press "stop" on the application. Additionally, the iPhone was programmed to vibrate and automatically stop recording if the battery dropped below 22%, in order to allow for

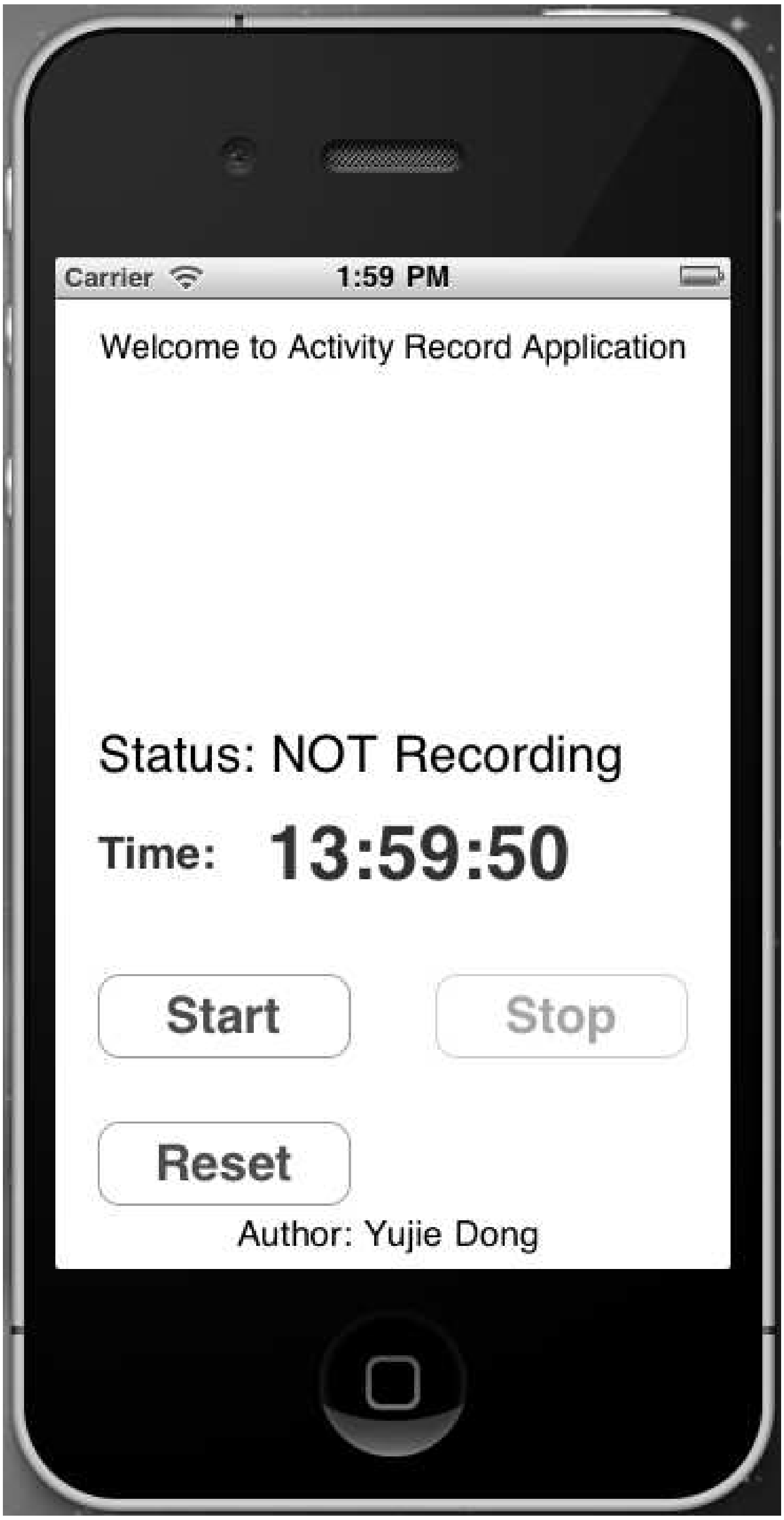

Figure 3.16 Data collection program interface.

START TIME	STOP TIME
10:09:11	10:24:35
FOOD(s) & LIQUID(s)	**UTENSIL**
Carrots Hamburger Green tea	☒ Hand ☐ Spoon ☐ Fork ☐ Other:___________

Figure 3.17 Example manual log entry.

an orderly shutdown and to avoid the default operating system behavior of stopping all applications when the battery drops below 20%. Subjects were scheduled to return the device the following day in another brief laboratory visit.

3.2.3 Evaluation

The detection and classification stages were evaluated separately. For purposes of detection, if the detected eating start time is within 15 minutes of the actual eating start time, the detected eating stop time is within 15 minutes of the actual eating stop time, and the total absolute error at both boundaries is less than 20 minutes, the activity was classified as correctly detected. Otherwise, the hypothesized detection was classified as a false positive. These values were chosen in order to allow for some error in when subjects manually logged times, as well as to allow for some ambiguity in how a subject interpreted the beginning or ending of actual consumption. All the remaining actual eating activities which are not paired with any detected eating activity were classified as undetected.

For classifying activities, the 5 folder cross validation scheme [44] was used to evaluate the accuracy. In this scheme, the detected activities are randomly partitioned into five subgroups. For each experimental run, one of the subgroups is used as the testing data set and the other four subgroups are used as the training data set. This process is repeated five times with each subgroup being used exactly once as the test data set. The classification accuracy was then averaged to produce a final result.

3.2.4 Results

A group of 30 subjects were recruited for participation. The Clemson University Institutional Review Board approved the study and each subject provided informed consent. For demographics, 12 subjects were male and 18 female; ages ranged from 18 to 32.

3.2.4.1 Usable data

A total of 78 eating activities were manually logged by all users, of which 35 were deemed usable for purposes of this study. Table 3.7 lists the reasons for exclusion. Some were excluded because the user did not log the start or stop time (highlighting the difficulty of manual self-monitoring methods), or because the subject did not leave the device on while eating. Recorded data segments that were less then 30 minutes (the user turned the device on/off for only a brief period) were excluded. One subject did not eat all day and was excluded.

Data from the American Time Use Survey [12] show that Americans spend on average 1.25 hours eating and drinking per day. Dividing this time by three meals per day, even without considering snacks, suggests an average of less than 30 minutes per meal. The purpose of this work is to detect periods of continuous eating, so that a dining experience consisting of an appetizer, main course and dessert would be detected as 3 separate eating activities. Food preparation, cleanup, or other activities outside of actual consumption are not included. I therefore set an upper bound on duration of 30 minutes for an eating activity. This caused the exclusion of 9 activities (reported lengths of 32, 36, 38, 41, 47, 54, 145, 156 and 259 minutes), some of which were likely errors and others of which were likely misinterpretations of the instructions. In order to limit the potential number of false positives I set a lower bound on duration of 3 minutes, and therefore do not consider brief periods of consumption such as a single bite of food or swallow of liquid. This caused the exclusion of 3 activities (reported lengths all less than 2 minutes).

Finally, I excluded activities where the subject turned the device on right before eating, or off right after eating. Any algorithm designed to detect eating activities could benefit unfairly from these artificial boundaries. Subjects were instructed to use this feature so as to avoid restricting daily activities, but I failed to anticipate this potential effect. Future work should plan to remove the "stop" button feature and instruct subjects to remove the device only during bathing or hard-contact athletic activities.

category	**occurrences**
total manually logged eating activities	78
usable eating activities	**35**
Subject forgot to manually log start or stop time	4
Motion data was not recorded during manually logged entry	8
Activity duration was too short (less than 3 min.)	3
Activity duration was too long (more than 30 min.)	9
Recording was started or stopped within 10 min. before or after eating	18
Logged eating activity is inside another logged eating activity	1

Table 3.7 Usability of manually logged eating activities.

Figure 3.18 shows all the usable data and manually logged usable meals (hereafter, the shorter term "meal" is used interchangeably with "eating activity"). The horizontal axis is the time in hours. The subjects started recording on average at 10 am. The vertical axis is the subject ID. For each subject, filled rectangles are usable recorded data and hollow rectangles are meals. After exclusion, 20 subjects were deemed usable, consisting of 35 usable meals.

3.2.4.2 Detection

The gyroscope and accelerometer data were processed independently to determine which was better for detecting hypothesized eating activities. Table 3.8 shows the result. Both sensor types detected the same amount of actual eating activities (31 out of 35), with slightly more false positives detected using gyroscopes.

	true detection	**false detection**	**undetected**
accelerometer	31	203	4
gyroscope	31	267	4

Table 3.8 Total detected hypothesized eating activities.

Table 3.9 shows the detailed information for each actual eating activity. The first column is the index of the eating activity (1 to 35). The second and the third columns are the actual eating start time and eating stop time from the manual logs. The fourth column has two numbers: the detected start time using accelerometers, and the offset to the actual start time

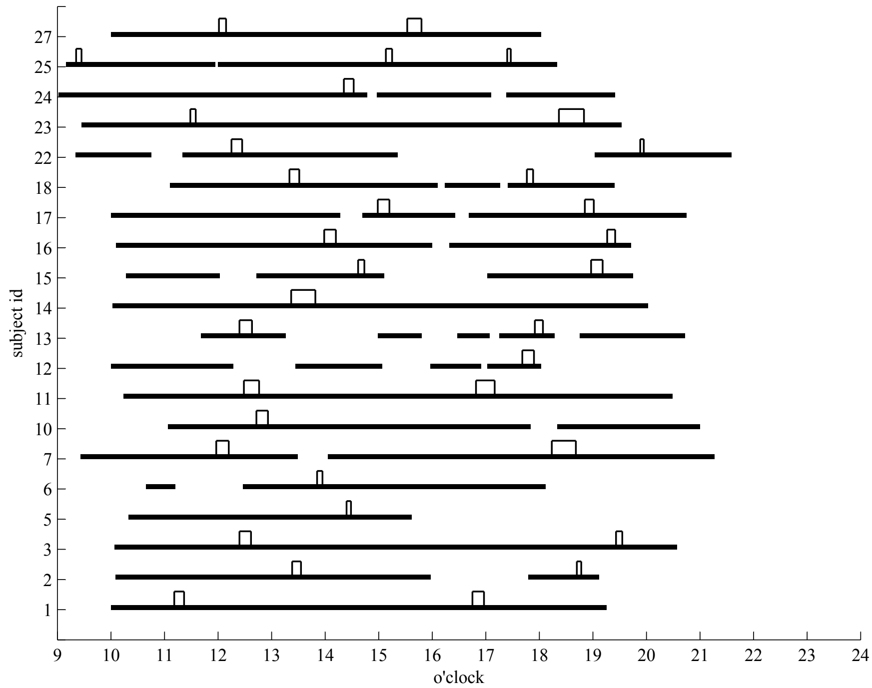

Figure 3.18 Illustration of usable data. (Filled rectangles indicate usable recorded data and hollow rectangles indicate meals).

(in parentheses). The fifth column shows the detected stop time using the accelerometers. The sixth and the seventh columns show the detected start time and stop time using the gyroscopes. The last two columns show the total error made by the accelerometers and gyroscopes respectively. (The error for the accelerometers equals the sum of the absolute value of the number in the parentheses in the third column and the absolute value of the number in the parentheses in the fourth column.) The last row shows the average of total error made by the accelerometers and gyroscopes respectively.

meal	**meal start time**	**meal stop time**	**start time detected (accel)**	**stop time detected (accel)**	**start time detected (gyro)**	**stop time detected (gyro)**	**total error (accel)**	**total error (gyro)**
1	71.1	81.8	61.0 (-10.1)	80.8 (-1.0)			11.0	
2	405.1	418.2	403.8 (-1.4)	411.0 (-7.2)	404.0 (-1.1)	411 (-7.2)	8.6	8.3
3	198.5	208.1	197.9 (-0.6)	207.9 (-0.2)	198.0 (-0.5)	208.3 (0.1)	0.8	0.6
4	53.5	58.4	53.3 (-0.2)	58.9 (0.6)	53.3 (-0.2)	58.4 (0.1)	0.7	0.3
5	139.5	152.5	135.5 (-4.0)	157.3 (4.7)	135.4 (-4.1)	157.2 (4.6)	8.7	8.7
6	561.4	568.4	558.3 (-3.1)	571.3 (2.8)	558.2 (-3.3)	571.3 (2.9)	5.9	6.2
7	244.1	249.5						
8	83.4	89.2	82.6 (-0.8)	93.0 (3.8)	82.7 (-0.8)	93.2 (4.0)	4.6	4.7
9	152.5	165.8	150.6 (-1.9)	167.1 (1.3)	151.3 (-1.2)	164.8 (-1.0)	3.2	2.2
10	251.2	278.4			262.2 (11.0)	275.6 (-2.8)		13.8
11	99.0	111.3	104.7 (5.7)	110.8 (-0.5)	104.1 (5.1)	110.9 (-0.4)	6.2	5.4
12	134.6	151.1	134.4 (-0.2)	151.0 (-0.1)	134.4 (-0.2)	150.6 (-0.5)	0.3	0.7
13	394.3	415.8	393.1 (-1.2)	415.3 (-0.5)	393.1 (-1.2)	414.8 (-1.0)	1.7	2.2
14	38.8	52.1	38.1 (-0.7)	45.6 (-6.5)	38.5 (-0.3)	45.7 (-6.5)	7.2	6.7
15	43.1	57.3	43.5 (0.4)	56.6 (-0.7)	43.5 (0.4)	56.5 (-0.8)	1.1	1.2
16	39.8	48.8	41.9 (2.2)	48.3 (-0.5)	42.0 (2.2)	48.3 (-0.5)	2.6	2.7
17	199.7	226.7	205.6 (5.9)	228.8 (-3.8)	205.3 (5.7)	222.8 (-3.8)	9.7	9.5
18	114.3	121.3	114.2 (-0.1)	121.3 (0.1)	114.1 (-0.2)	121.8 (0.5)	0.2	0.7
19	116.0	129.0	123.7 (7.7)	139.7 (10.7)	116.3 (0.3)	139.8 (10.8)	18.3	11.1
20	233.5	246.0	233.0 (-0.5)	246.8 (0.8)	233.2 (-0.3)	247.7 (1.6)	1.3	2.0
21	177.1	186.2	170.4 (-6.7)	190.6 (4.4)	170.5 (-6.6)	190.6 (4.4)	11.1	11.1
22	17.8	30.6	16.0 (-1.8)	30.3 (-0.2)	16.0 (-1.8)	26.8 (-3.8)	2.0	5.6
23	129.9	140.2	129.1 (-0.9)	139.8 (-0.4)	129.0 (-0.9)	139.9 (-0.3)	1.2	1.2
24	133.6	144.6						
25	20.6	27.7	19.3 (-1.3)	34.9 (7.2)	19.7 (-0.9)	34.8 (7.2)	8.5	8.0
26	54.5	66.9	54.1 (-0.4)	66.5 (-0.4)	54.0 (-0.5)	66.4 (-0.4)	0.8	1.0
27	50.3	54.3	49.8 (-0.6)	54.3 (0.1)	49.8 (-0.6)	54.3 (0.0)	0.7	0.6
28	121.2	127.4	115.0 (-6.2)	126.3 (-1.1)			7.2	
29	534.3	562.6	537.5 (3.2)	548.9 (-13.7)	535.9 (1.6)	551.8 (-10.9)	16.9	12.5
30	319.5	330.4	317.8 (-1.6)	331.6 (1.2)	317.8 (-1.6)	331.6 (1.2)	2.9	2.9
31	10.4	17.1	9.0 (-1.4)	24.4 (7.3)	7.3 (-3.2)	24.4 (7.3)	8.7	10.5
32	187.7	194.7	184.9 (-2.8)	197.8 (3.2)	193.2 (5.5)	197.8 (3.1)	5.9	8.6
33	323.7	327.7	326 (2.3)	330.2 (2.5)	326.1 (2.4)	330.3 (2.7)	4.8	5.1
34	121.3	129.4	121.8 (0.5)	136.8 (7.4)	122.4 (1.1)	136.8 (7.4)	17.0	8.5
35	332.5	348.8			338.7 (6.2)	343.3 (-5.5)		11.7
avg.							5.5	5.6

Table 3.9 Detections of actual eating activities (all units are minutes).

From this table, it can be concluded that for most of the actual meals, the time boundaries detected by both sensors are very close, and that the pattern of wrist energy motion used for detection can be seen in both accelerometer and gyroscope sensor data. Both sensor types have the same number of undetected activities, but the accelerometers had fewer false detections. In addition, because accelerometers use less power than gyroscopes, it can be concluded that accelerometers should be used to detect hypothesized eating activities.

3.2.4.3 Classification

Table 3.10 shows the FLD of all the gyroscope features for the detected activities. The true positive and false positive rates are shown for classification using the Bayesian method from the single feature.

gyroscope feature	**FLD**	**TP**	**FP**
mean absolute deviation of yaw	0.44	22	63
mean absolute deviation of pitch	0.43	23	61
mean absolute deviation of roll	0.78	22	43
regularity of yaw motion	1.04	26	53
regularity of pitch motion	0.80	25	52
regularity of roll motion	1.08	24	55
gyroscope line fit.	0.00	18	80
bite count	0.74	25	58
mean of bite interval	0.16	23	74
variance of bite interval	0.01	24	93
skewness of bite interval	0.32	16	50

Table 3.10 Fisher linear discriminant of gyroscope features.

Table 3.11 shows the FLD of all the accelerometer features for the detected activities. This table also shows the true positive and false positive rates if each feature is used individually for classification.

Comparing Table 3.10 and Table 3.11 shows that the FLD values for the gyroscope features are in general much higher than for the accelerometer features. As a result, the gyroscope features have higher true positive rates and much smaller false positive rates than the accelerometer features. In addition, the roll axis shows much higher FLD values than the other axes.

For each number of features N, all combinations with the highest N+2 FLD values were tested. Table 3.12 shows the result of classification of some of the best of these combinations.

accelerometer feature	**FLD**	**TP**	**FP**
mean absolute deviation of x	0.05	21	111
mean absolute deviation of y	0.00	26	133
mean absolute deviation of z	0.00	24	117
regularity of x motion	0.26	28	124
regularity of y motion	0.26	28	112
regularity of z motion	0.28	27	109
accelerometer line fit.	0.01	13	86
bite count x	0.12	13	38
bite count y	0.23	19	48
bite count z	0.10	13	48
mean of bite interval x	0.00	17	84
variance of bite interval x	0.02	11	74
skewness of bite interval x	0.03	21	100
mean of bite interval y	0.09	16	127
variance of bite interval y	0.14	24	134
skewness of bite interval y	0.00	25	122
mean of bite interval z	0.03	21	135
variance of bite interval z	0.03	22	154
skewness of bite interval z	0.01	13	76

Table 3.11 Fisher linear discriminant of accelerometer features.

From this table, it can be seen that an increase beyond 2 features does not improve the result. It can also be concluded that using only the data along the roll axis shows the best result. Specifically, using only mean absolute deviation of roll and regularity of roll yields 26 true detections and 46 false detections. Classification using other combinations of accelerometer features yielded consistently lower true detections and higher false positives. Similarly, combinations of accelerometer and gyroscope features yielded no improvements over gyroscope features alone.

gyroscope feature	**total features**	**true detection**	**false detection**	**undetected**
reg yaw, reg roll	2	25	54	6
mad roll, reg roll	**2**	**26**	**46**	**5**
reg yaw, reg pitch, reg roll	3	27	54	4
mad roll, reg roll, bite count	3	27	47	4
mad roll, reg yaw, reg pitch, reg roll	4	27	51	4
mad roll, var roll, reg roll, bc	4	24	43	7
mad roll, reg yaw, reg pitch, reg roll, bc	5	27	49	4
mad roll, var roll, reg roll, line fit, bc	5	23	43	8

Table 3.12 Result of classification using gyroscope feature sets (mad: mean absolute deviation; var: variance; reg: regularity of motion; bc: bite counter).

3.3 Conclusions and future work

This chapter has described a new method to automatically detect the eating activities of a free living human using wrist-mounted gyroscopes and accelerometers. The backpack experiment first explored whether or not the concept was feasible. A subsequent experiment using an iPhone allowed for more data collection and the development of a more sophisticated algorithm. The final algorithm searches for a general pattern of wrist motion that was found to appear consistently during eating activities. The pattern consists of a burst of activity at the beginning and end, with a period of lesser motion in-between. Wrist motion for detecting a hypothesized eating activity was best accomplished using accelerometers, which is ideal because they use less power than gyroscopes. It was also found that wrist roll tends to be higher during eating as compared to other activities.

One limitation to the work reported herein is that the method does not directly measure consumption, it only detects the times of eating activities. To address this limitation, the method could be used as a prompt for additional methods. For example, upon detecting an eating activity the device could vibrate or otherwise remind the user to write down what was just eaten in a food diary. Future work could pursue combining this approach with the previously developed method for automatically counting bites of food during eating [21, 23]. Even without a measure of consumption, there are many epidemiological and behavioral questions that could be explored using a calendar of eating activities, for example in a study of when or how frequently different demographics eat throughout a week. It could also be useful as a general measure for health monitoring.

Another limitation of the work described herein was the large amount of collected data that had to be discarded before analysis. It was somewhat difficult for participants because the device was a phone rather than a watch. Future work should seek to construct a custom watch-like package for additional experiments. It was also difficult for subjects to remember to write down all meals, and they unexpectedly used the "stop" button in ways that affected the data collection. Future work should plan to remove the "stop" button and instruct subjects only to remove the device when absolutely necessary. It is important to note that the study is the first to try to automatically detect eating activities during normal free living. An interesting follow-on study would use this method to prompt the user at the time of detection of an eating activity, and study how this affects both the compliance and accuracy of a food diary.

As a secondary point of interest, the work also compares the detection of eating activities using accelerometers versus using gyroscopes. This is important because a MEMS accelerometer uses approximately 10% of the power of a MEMS gyroscope [85, 86]; a typical coin-sized battery can power a single MEMS gyroscope for part of one day, while it can power an accelerometer for over one week. All commercial activity monitoring devices use accelerometers, and the majority of research papers exploring other types of activity recognition use accelerometers [6, 25, 40, 41, 46, 52, 65, 68, 71, 80, 96, 102] while only a few utilize gyroscopes [31, 70]. It may be that other types of activities could be more reliably recognized if rotational motion was more commonly analyzed. The results suggest a method where accelerometers are powered continuously to detect the activity of interest, with gyroscopes powered only during the detected periods in order to increase classification accuracy.

CHAPTER 4

OTHER WORK

This chapter briefly describes two additional efforts in which this author has been involved. The first is an ongoing NIH funded study. The second is a demonstration of the utility of the bite counter method for research in slowing eating rate.

4.1 An instrumented cafeteria table

The goal of this project is to systematically test the accuracy of the bite counter across a wide variety of foods, utensils, containers and people. The experiment takes place in the Clemson University Harcombe Dining Hall, in order to provide a wide range of food choices. The Dining Hall operates like a cafeteria, allowing eaters to build a variety of meals. Food choices include omelets, sandwiches, pizza, pasta, fruits and vegetables, meat cuts, deserts, juices, milk, sodas, teas and coffee. The foods are served on a wide variety of containers, including plates, bowls, wraps, pouches, trays, cartons, cups and glasses, and are eaten using different utensils including forks, knives, spoons, straws, and fingers. While not necessarily representative of all possible eating situations, the cafeteria provides the opportunity to observe a wide variety of eating situations in a fixed setting.

The Clemson University Dining Services agreed to allow our research team to use a fixed space within the Harcombe Dining Hall, in order to provide as normal a space as possible for communal eating, while enabling as much data collection as possible. Figure 4.1 shows a diagram of how the experimental area is arranged. We instrumented a table that can simultaneously seat up to 4 eaters. The table looks like a standard cafeteria table. In the ceiling (approximately 16 feet high), four digital video recorders are positioned, each one recording one of the user eating areas. The cameras are equipped with zoom lenses so that each participant's mouth, torso, and tray can be recorded in detail. In the dining table, scales are hidden such that each can continuously measure grams of food consumed over time. Wrist-worn packages, similar to bite counters, are tethered to laptop computers in a nearby cabinet so that raw gyroscope and accelerometer data can be recorded. All the instrumentation is hardwired to computers so that the data can be synchronized during

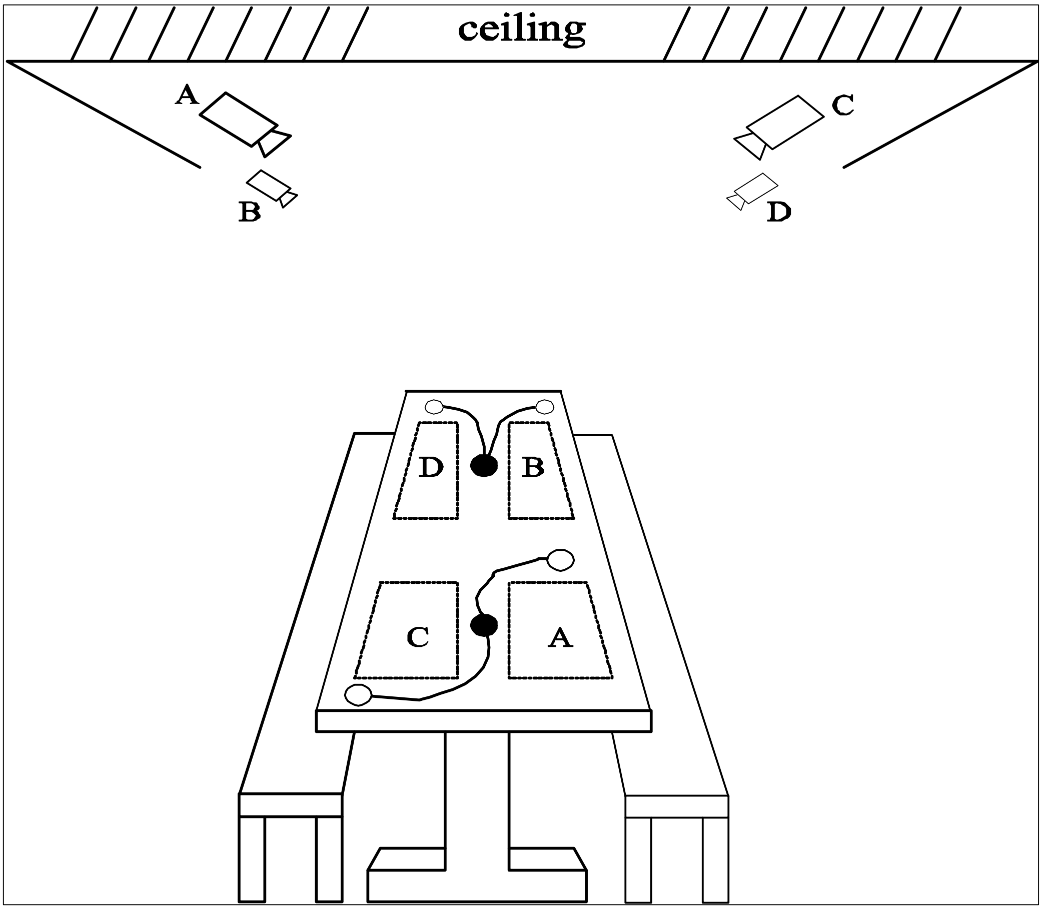

Figure 4.1 Diagram of eating area.

recording using a custom written recording program (Figure 4.2). The data is stored on the computer for later review and post-analysis. Figure 4.3 shows a picture of the dining table while four subjects were eating.

During eating, the following specific quantities are measured:

1. Automated bite count. This is measured using the bite counter method.

2. Actual bite count. By post-reviewing the video of the recorded meal, an experimenter manually indicates times at which each bite is taken.

3. Food consumption. In order to measure total grams of food consumed over time, the scale samples the weight of the meal every second.

In addition, meal-level data is collected regarding the caloric and nutritional content of the

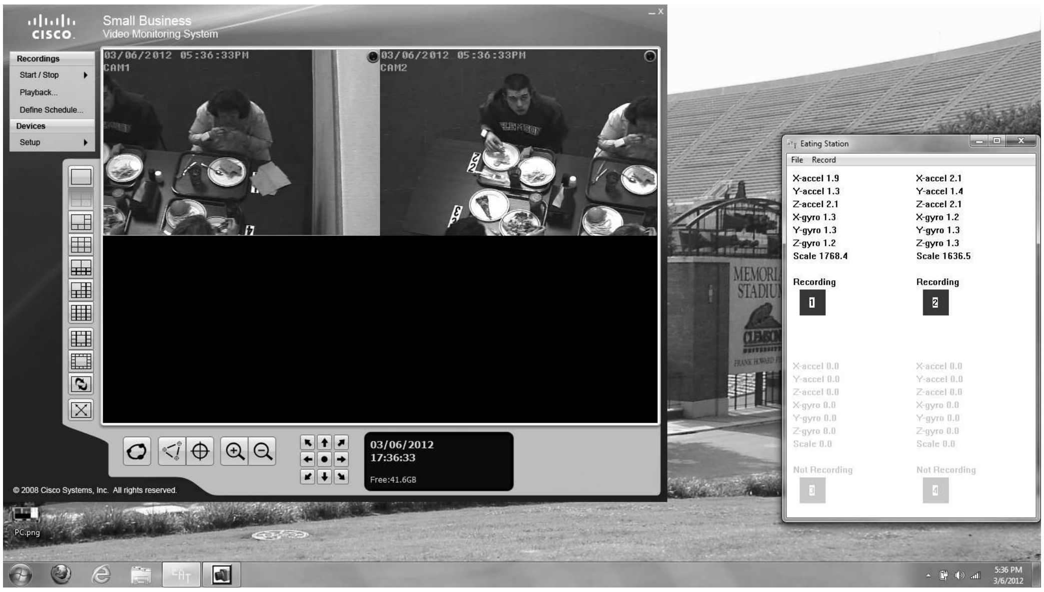

Figure 4.2 Recording software for the cafeteria research.

Figure 4.3 A dining table for measuring eating.

food eaten. This is estimated for each food serving using the Clemson University Dining Service nutrient analysis and the USDA nutrient data base [95]. Finally, data is collected concerning the participant. Individual characteristics, such as handedness, food and utensil selection may show correlations to bite count accuracy. These data will afford opportunities to examine participant-to-meal correlations with respect to total bite count. Specifically, the heights and weights of participants are measured and BMI calculated using the Tanita WB-3000 Digital Beam Scale. Body fat percentage is measured using the Omrom Body Logic Body Fat Analyzer.

After recruitment, participants report to the research laboratory for a pre-meal session. At this session they complete a brief demographics questionnaire, and have their height, weight and body fat measured. They are then given instructions on their "cafeteria day". On the cafeteria day, participants arrive, walk through the cafeteria and select their food. The experimenter records the foods selected based on the cafeteria menu for later cross-referencing with the video recordings. Any behaviors, such as the mixing together of individual foods, which could confuse the analysis of the video recordings, is also recorded. During the meal, participants are free to talk with friends, read, watch nearby televisions, or engage in any other normal communal eating activities.

Custom software tools (see Figure 4.4) have been developed to facilitate post review of the recordings. The primary tool allows the user to review video streams correlated with the device data. VCR-like controls enable rewinding, fast-forwarding, pausing, etc. of the playback. Simple mouse clicks enable the user to mark the ground truth times for when bites occur. Pull-down menus enable the user to indicate the type of food eaten, the utensil used, the container from which the food was eaten and possibly other information.

The goal of this work is to build a "bite database" that can be used to systematically test the accuracy of the bite counter method across a wide variety of foods, utensils, containers and people. The database will consist of three parts. The first part relies primarily upon data entered by the researcher reviewing the recording. It looks like the data shown in Table 4.1. The ID is unique to each bite in the database. The utensil is one of fork, finger, spoon, chopsticks, knife, and straw. The food label is taken directly from the cafeteria nutrition menu by Dining Services. The container is one of plate, tray, glass, bowl, pouch, and

Figure 4.4 Review software for the cafeteria research.

possibly others. All of the proper values for these fields will be visually identified through observation of the correlated video. This database will allow for the analysis of groups of bites according to their bite pattern: utensil, food type, and container. It will allow for the examination of correlations of bite patterns with bite count accuracy. For example, bites of French fries eaten with fingers from a pouch may show a high accuracy, while bites of soda taken through a straw from a Styrofoam cup may show a low accuracy. The database will allow for the systematic examination of bite patterns exhibiting the lowest accuracy in order to focus new efforts for refining the bite counter algorithm.

ID	**Utensil**	**Food**	**Container**	**Eating or drinking**	**Detected?**	**Subject**	**Raw data**
1	hands	fries	tray	eating	yes	S1	[...]
2	straw	cola	glass	drinking	no	S1	[...]
...							

Table 4.1 Bite database for all bites taken.

The second piece of the bite database concerns false positives. It will look like the data shown in Table 4.2. For each instance where the device triggers a bite detection for an event that was not an actual bite, the reviewer will select an event type from a list including napkin, glasses, stirring food, gesturing, and possibly other choices. The raw sensor data surrounding the event will be automatically classified into a number of wrist motion patterns, providing a high-level description.

False detection ID	**Reason**	**Subject**	**Raw data**
1	napkin	S1	[...]
2	stirring food	S1	[...]
3	gesture	S2	[...]
4	glasses	S2	[...]
5	others	S2	[...]
...			

Table 4.2 Bite database for false positive.

The third piece of the bite database concerns meal-level data. It will look like the data shown in Table 4.3. Each entry in this database will have a meal-level bite count and meal-level calorie count. In addition, the gender, age, ethnicity, and BMI of the person eating the meal will be recorded. The measure of calories will offer opportunities to examine participant-to-meal correlations with respect to total bite count.

Meal ID	Bite	Calorie	Gender	Age	Ethnicity	BMI	Subject
1	25	600	male	25	Asian	35	S1
2	20	400	female	20	Caucasian	19	S1
3	30	819	female	31	Caucasian	24	S2
...							

Table 4.3 Bite database for meal-level data.

At the time of this writing (April, 2012), this experiment is ongoing. Approximately 200 participants have been recorded, and another 100 are planned. Post review and creation of the bite database is planned for the summer of 2012. This data should provide many opportunities for future work to improve the bite counter method described in this dissertation.

4.2 Slowing bite rate reduces energy intake

This section provides an example of how the work in this dissertation can be used. The experiment summarized here explored the bite counter's potential application for slowing bite-rate and reducing energy intake. The study was a within-participants design with three conditions. University students (N=30) ate three meals in the laboratory: a baseline meal without feedback (Baseline), a meal during which participants received bite-rate feedback (Feedback), and a meal during which participants followed a 50% slower bite-rate target (Slow Bite- Rate). Kilocalories of food consumed, ratings of satiation and food-liking, and milliliters of water consumed were statistically compared across conditions using repeated measures analyses of variance. Overall, participants ate 70 kcal fewer during the Slow Bite-Rate condition compared with the Feedback condition. In addition, when baseline energy consumption was added post hoc as a grouping variable, participants who ate more than 400 kcal at baseline (n=11) ate 164 kcal fewer during the Slow Bite-Rate condition compared to Baseline, and 142 kcal fewer in the Feedback condition compared with Baseline. However, the Slow Bite-Rate condition did not significantly affect participants who ate fewer than 400 kcal at baseline (n=19). Therefore, it seems that slowing bite-rate with the bite counter may be most effective for individuals who consume larger amounts of food. A deeper discussion of this experiment can be found in [78, 79].

CHAPTER 5
DISCUSSION

Obesity has become one of the largest avoidable causes of death [29, 56]. Over 500 million people worldwide are obese, and the number is growing [101]. There are over 2,000 researchers in the U.S. Obesity Society and over 10,000 researchers in the International Obesity Society, yet almost none are engineers. The need for new tools to measure eating intake is recognized by leading researchers in the field [54, 92], and was widely discussed at a joint U.S. NSF/NIH workshop on the topic [26]. This work is motivated by this need.

This dissertation describes the development of two novel tools, one for measuring consumption and one for detecting eating activities. The bite counter can automatically measure meal-level intake using wrist motion tracking. It detects a pattern of wrist roll motion that correlates highly with the action of taking of a bite. For most eating situations, regardless of the type of food or liquid, and regardless of the utensil (or fingers) used, a roll of the wrist must occur. The progression of experiments described in this dissertation has shown that (1) this method works across a reasonably large number of subjects (94% sensitivity and 80% positive predictive value), (2) it works across a reasonably large variety of foods 86% sensitivity and 81% positive predictive value), and (3) there is some correlation with kilocalories on a per-meal level (0.6 linear correlation).

The second part of this dissertation describes a new method to automatically detect eating activities throughout natural daily living with minimum non-invasive instrumentation. A general pattern of wrist motion energy was found that correlates highly with eating activities. At the beginning of an eating activity, there tends to be a period of larger wrist motion energy, caused by things like bringing food to a table, adjusting the position of utensils, opening food containers, or unwrapping food. During eating, the total wrist motion energy is reduced. At the end of an eating activity, there tends to be another period of larger wrist motion energy, caused by things like putting remaining food away, washing hands, standing up, or putting dishes away. Wrist motion for detecting a hypothesized eating activity is best accomplished by accelerometers. Wrist roll is usually higher during eating activities as compared to other normal daily activities. An experimental test of the new method found that it correctly identified 74% of eating activities with approximately 1.3 false positives per actual eating activity.

Future work should focus on trying to reduce the false positive rates for both new tools. An ongoing cafeteria research project is collecting data across 300 subjects eating a large variety of foods with different utensils and containers. It is possible that additional pattern recognition techniques could be applied to the eating detection method based upon time of day. For example, a person may eat at a certain period time of in a day; after eating a meal, a person may not eat again until after a certain amount of time, etc. Adding this type of feature could help reduce the false positive rate of hypothesized eating activities.

It is the hope of this author that this work will motivate other engineers to tackle instrumentation problems related to obesity. It is also the hope of this author that the tools developed in this dissertation find use by the obesity research community. Finally, ultimately, these tools may find their way to the individual user who is trying to lose weight or maintain weight loss.

APPENDIX

LIST OF PUBLICATIONS

1. Y. Dong, A. Hoover, J. Scisco, and E. Muth. “Detecting the eating activities of a free living human using wrist-worn accelerometers and gyroscopes”. *IEEE Transactions on Biomedical Engineering*, 2012, (under review).

2. Y. Dong, A. Hoover, J. Scisco, and E. Muth. “Monitoring eating consumption via wrist motion tracking”. *Applied Psychophysiology and Biofeedback*, 2011, (accepted).

3. W. Wu, Y. Dong, and A. Hoover. “Measuring digital system latency from sensing to actuation at continuous 1 ms resolution”. *Presence: Teleoperators and Virtual Environments*, 2011, (under revision).

4. J. Scisco, E. Muth, Y. Dong, A. Hoover. “Slowing bite-rate reduces caloric consumption: an application of the bite counter device”. *Journal of the American Dietetic Association*, vol. 111, 2011, pp. 1231-1235.

5. Y. Dong, A. Hoover, J. Scisco, and E. Muth. “Detecting eating using a wrist mounted device during normal daily activities”. *Proceedings of the 9th International Conference on Embedded Systems and Applications*, 2011.

6. J. Scisco, E. Muth, Y. Dong, A. Hoover, P. O’Neil, and S. Fishel-Brown. “Usability and acceptability of the bite counter device”. *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, 2011.

7. W. Wu, Y. Dong, and A. Hoover. “Measuring digital system latency from sensing to actuation at continuous 1 ms resolution (abstract)”. *The 3rd International Symposium on Visual Image Safety*, 2011.

8. J. Scisco, E. Muth, A. Hoover, Y. Dong, L. Hill, M. Wiles, and S. Harris. “An environmental cue to eat slowly reduces food consumption (abstract)”. *Proceedings of the 55th Annual Meeting of the Human Factors and Ergonomics Society*, 2010.

9. Y. Dong, A. Hoover and E. Muth. "A device for detecting and counting bites of food taken by a person during eating". *Proceedings of IEEE Conference on Bioinformatics and Biomedicine*, 2009, pp. 265-268.

10. A. Hoover, E. Muth, Y. Dong and J. Scisco. "Eating Activity Detection Device". *Disclosed to Clemson University for Patent Application*, March, 2012.

11. A. Hoover, E. Muth and Y. Dong. "Weight control device". *US Provisional Patent Application*, Serial No. 61/144.203, Filed January 13, 2009.

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