Appl Psychophysiol Biofeedback (2012) 37:205–215
DOI 10.1007/s10484-012-9194-1

A New Method for Measuring Meal Intake in Humans via Automated Wrist Motion Tracking

Yujie Dong · Adam Hoover · Jenna Scisco · Eric Muth

Received: 29 July 2011 / Accepted: 28 March 2012 / Published online: 10 April 2012

Abstract Measuring the energy intake (kcal) of a person in day-to-day life is difficult. The best laboratory tool achieves 95 % accuracy on average, while tools used in daily living typically achieve 60–80 % accuracy. This paper describes a new method for measuring intake via automated tracking of wrist motion. Our method uses a watch-like device with a micro-electro-mechanical gyroscope to detect and record when an individual has taken a bite of food. Two tests of the accuracy of our device in counting bites found that our method has 94 % sensitivity in a controlled meal setting and 86 % sensitivity in an uncontrolled meal setting, with one false positive per every 5 bites in both settings. Preliminary data from daily living indicates that bites measured by the device are positively related to caloric intake illustrating the potential of the device to monitor energy intake. Future research should seek to further explore the relationship between bites taken and kilocalories consumed to validate the device as an automated measure of energy intake.

Keywords Energy intake · Eating · Activity recognition · MEMS sensors

Introduction

This work is motivated by the growing obesity problem. In order to lose weight, the common strategy is to measure, track and reduce intake. However, measuring energy intake (kcal) in day-to-day life is tedious and prone to error. For the individual trying to count kilocalories on their own, the methods of using calorie labels, interpreting serving sizes, or plain guessing commonly causes errors of 50 % or more (Roberto et al. 2010). Put simply, the calorimeter is a laboratory tool, producing a measure that was never intended for daily human use in measuring energy intake (Hargrove 2007). Recent position papers within the dietetics research community emphasize the need for new tools (McCabe-Sellers 2010; Thompson et al. 2010). In this paper we describe a new method and tool for measuring intake using automated wrist motion tracking. We describe a progression of experiments 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. While more studies need to be undertaken to more thoroughly evaluate our method, the work presented herein shows its promising potential.

Y. Dong · A. Hoover (✉)
Department of Electrical and Computer Engineering, Clemson University, Clemson, SC, USA
e-mail: ahoover@clemson.edu

J. Scisco · E. Muth
Department of Psychology, Clemson University, Clemson, SC, USA

Review of Tools for Measuring Intake

Table 1 lists methods for measuring energy intake. Doubly labeled water (DLW), considered the gold standard for measuring energy expenditure (Speakman 1997), 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 ± stored

Table 1 Comparison of methods for monitoring intake

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
Bite counter	Bites	Discrete live measurement during each meal

energy change due to weight gain/loss) was shown to be 2–8 % error per day (Schoeller 1988). A meta-analysis (Black and Cole 2000) 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-h recalls, and food frequency questionnaires (Thompson and Subar 2008). 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 (Champagne et al. 2002; Glanz et al. 1997; Jonnalagadda et al. 2000; Lichtman et al. 1992; Muhlheim et al. 1998; Tooze et al. 2004). Estimates of underreporting range from 10 to 30 % for normal weight subjects to 20–50 % for obese adults and children (Champagne et al. 2002). A meta-analysis (Burrows et al. 2010) 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 (Brunner et al. 2001) and blood nutrient analysis (Day et al. 2001).

Several uses of technology to improve food record methods have been explored, such as using the internet for dietary recalls (Arab et al. 2010) and using a personal digital assistant to record an eating diary (Yon et al. 2006). 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 (Beasley et al. 2005; Yon et al. 2006).

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 (Plasque and Westerterp 2007) 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 (Kissileff et al. 1980); tables can be configured to measure gram changes in different areas (Chang et al. 2006). 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 (Williamson et al. 2003; Martin et al. 2007). A similar accuracy has also been shown when subjects take the pictures themselves (Martin et al. 2009), 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 (Saeik and Takeda 2005; Takeda et al. 2003; Zhu et al. 2008). This has been demonstrated on a small set of foods (Zhu et al. 2010), 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 (Boushey et al. 2009; Six et al. 2010).

In this paper, we propose a new method that has the potential to automate intake monitoring. Our "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 micro-electro-mechanical (MEMS) 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. It is appreciated that our method will not exceed the accuracy of the best laboratory tools. However, we believe our method has the potential to improve compliance and accuracy under conditions where a person is unlikely to use other methods because of their cost, manual effort required, or inconvenience.

Methods

Algorithm

In preliminary studies, we examined data from all three linear and rotational axes of the wrist during eating (Dong 2009; Drennan 2010). We found a high correlation between a simple pattern of wrist roll and the taking of a bite

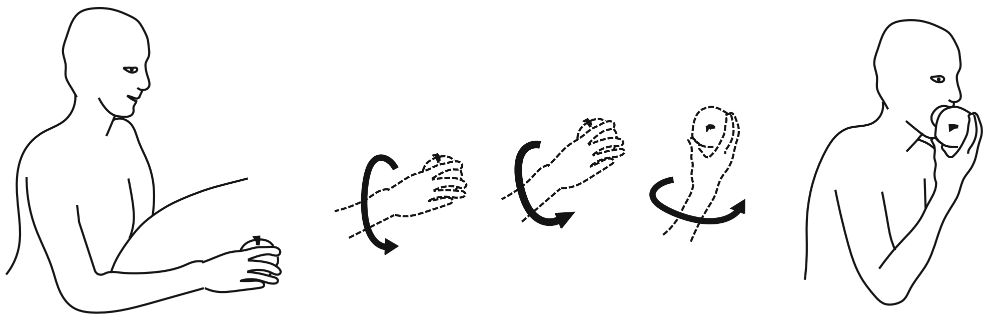

Fig. 1 Wrist roll during taking a bite

(we follow the common language definition, where a bite is generally referred to as the placing of food into the mouth). Figure 1 emphasizes the key motion. Compared to body sensing approaches (Amft et al. 2005; Amft and Troster 2008, 2009; Junker et al. 2008), which use additional sensors on other parts of the body, our approach requires only one wrist-mounted sensor. Instead of trying to classify different types of eating activities, we have discovered that a simple pattern of wrist roll occurs during any bite. We believe 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, we can describe a pattern 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 of the specific configuration of the wrist relative to the rest of the arm. We define a wrist roll motion pattern for eating as having four events. 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. Our 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 *T*1 and *T*2 define the roll velocities that must be exceeded to trigger detection of the roll events. The threshold *T*3 defines the interval of time that must elapse between the first and second events of the roll motion, while the threshold *T*4 defines the interval of time that must elapse between the end of one bite and the beginning of another bite.

Although our 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 we used for thresholds are described below.

Hardware and Prototype

In our preliminary studies (Dong et al. 2009) we used an InertiaCube3 sensor manufactured by InterSense. Figure 2 shows a picture of the relatively expensive ($2,000 US) 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. Our first laboratory experiment makes use of this sensor; it was wired to a nearby computer for processing of the data.

While such a sensor may be practical for laboratory use, its cost and size raise questions as to its applicability for general public use. In this work, we tested a much less expensive sensor ($5 US), that is also much smaller (see Fig. 3). The STMicroelectronics LPR530al is a MEMS gyroscope that directly measures radial velocity. In our second laboratory experiment we compared both sensors in terms of their accuracy for executing our algorithm. Both sensors were mounted to a single wrist-worn package so that the motions observed by both sensors were identical.

Fig. 2 Larger, more expensive sensor used in earlier work

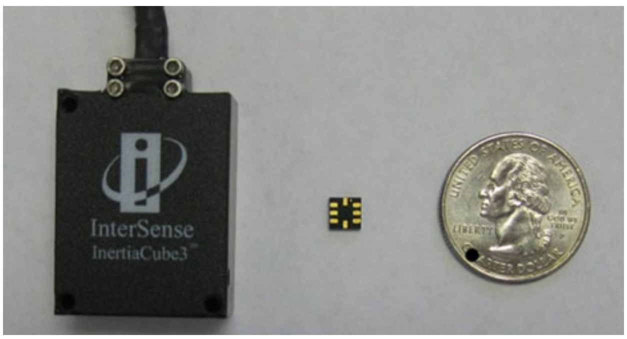

Fig. 3 MEMS sensor (*middle*) used in this work

The wrist-worn package was wired to a nearby computer for processing of the data. A video of this hardware being used during eating can be seen at http://www.parl.clemson.edu/~ahoover/bite-counter/BiteCounter.wmv.

For our third experiment, we built a self-contained prototype device using the MEMS gyroscope. Figure 4 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 times of recording sessions and the number of bites detected. 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.

Fig. 4 Prototype device using MEMS gyroscope

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. Two experiments were performed in a laboratory setting, in order to evaluate the accuracy of the device to detect bites. A third experiment was performed in unrestricted settings, in order to examine the correlation of device detected bites to kilocalories per meal.

In the laboratory experiments, 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 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 5 shows a picture of the environment in which subjects ate, with the video synchronized to the sensor data.

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 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

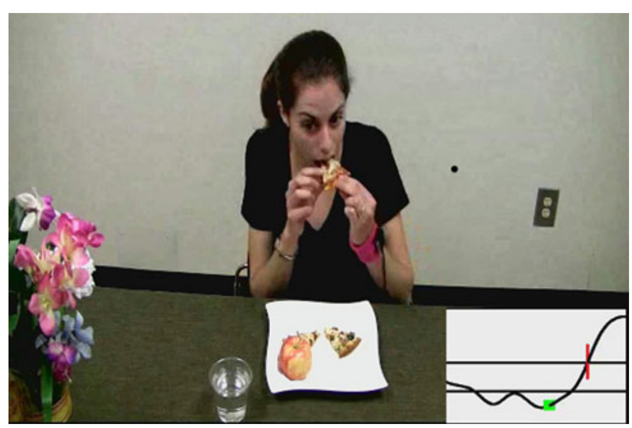

Fig. 5 Synchronized video and sensor data (used with permission)

our goal was to determine an accuracy for our 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.”

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.

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 our 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.

Evaluation

In order to evaluate the performance of our bite detector in the laboratory, we calculated the correspondences of computer-detected bites to manually marked bites. Figure 6 illustrates how detections were classified. For each computer detected bite (small square in the figure), we consider the interval of time from the previous detection to the following detection. 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 we use this approach is because we want 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 our methods do not allow for the definition of a true negative, we cannot calculate specificity (false detection rate). We therefore calculate the positive predictive value as a measure of the performance of our device regarding false positives. The positive predictive value (PPV) of the device was calculated as (total Ts)/(total Ts + total Fs).

Parameter Tuning

In order to select values for the thresholds in our algorithm, we considered the following ranges for each: $T_1 = T_2 = \{5, 10, 15, 20, 25\}$ degrees/s, $T_3 = \{1, 2, 3\}$ s, and $T_4 =$

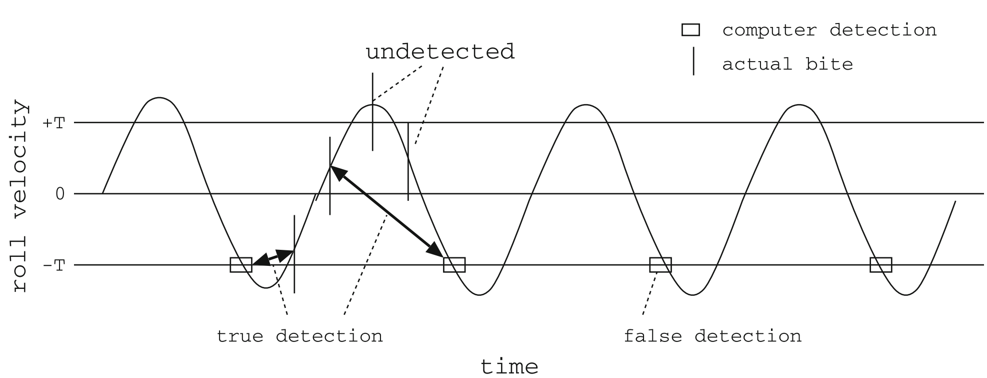

Fig. 6 Classification of results

{2, 4, 6, 8, 10} s. We tested every combination of values from these sets, running our 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 from 38 to 93 %. A wide range of combinations performed well, with over half giving a sensitivity and PPV above 70 %, showing that our method is not overly sensitive to the values chosen. We scored each set according to the formula $\frac{3 \cdot PPV}{7} + \frac{4 \cdot \text{sensitivity}}{7}$, placing slightly more importance on the sensitivity. The parameter set with the highest score was $T_1 = T_2 = 10$, $T_3 = 2$, $T_4 = 8$.

Results

Experiment #1

Across the 139 meals, the subjects ate a range of 8–72 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). While the conditions in this test were restrictive in terms of food type eaten and utensil used, it showed that our technique works across a large number of subjects.

Experiment #2

As we placed no restrictions on foods or utensils, subjects brought their own foods and liquids and consumed them however they wanted. Table 2 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 3 shows the manual classification of the 1,675 total bites taken across

Table 3 Breakdown of bites taken during 49 uncontrolled meals

	Dominant hand	Non-dominant hand
Food	1281	105
Liquid	165	124

Table 2 Meals consumed by subjects

Sub.	Meal	Utensil	Sub.	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			

all 49 meals. A range of 12–72 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, 1,281/(1,281 + 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 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 our 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 %. Thus, our 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 that we are tracking. 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 we operationally defined a bite 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 min, with a range of 4.6–25.2 min. 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, we reviewed the videos and noted activities occurring that involve arm motions. Table 4 summarizes our findings. For each type of activity, we counted the number of times that it happened between bites. The first two entries, both involving conversation, are exclusive of each other; the remaining entries 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 1,675 = 67 %). Amidst all these natural activities, our methods accurately and reliably detected bites across a large number of subjects and meals.

Table 4 Other actions during eating

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

Experiment #3

Figure 7 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 our 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.

Discussion

Obesity is a growing problem. In the United States, the National Health and Nutrition Examination Survey in 2007–2008 found that 33.9 % of Americans were obese

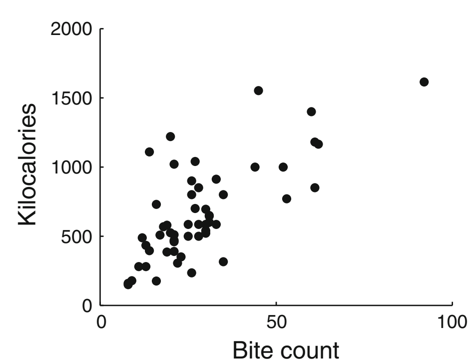

Fig. 7 Bite count as measured by our tool, versus kilocalories, for 54 meals eaten in unrestricted conditions

and 68.3 % of Americans were overweight (Flegal et al. 2010). The most recent assessment of global obesity (World Health Organization 2010) revealed that 1.6 billion adults (ages 15+ years) are overweight and 400 million adults are obese. A number of health problems have been linked to this rise in body weight, including diabetes, gallbladder disease, dyslipidemia (abnormal blood lipid levels), insulin resistance, and sleep apnea risk (Antipatis and Gill 2001). In the United States, the medical costs of obesity were estimated to be $147 billion per year in 2008, doubling from $78.5 billion in 1998 (Finkelstein et al. 2009).

The obesity epidemic is "undoubtedly attributable to dietary and behavioral causes" (Muller et al. 2010) coupled with an "obesogenic environment" that promotes energy overconsumption and under-expenditure (Kirk et al. 2010). 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 (Wing and Hill 2001; Wing and Phelan 2005). A recent meta-review found that in all 15 studies reviewed, there was a significant relationship between self-monitoring dietary intake and weight loss (Burke et al. 2011). 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 (Amft and Troster 2009; Sazonov and Schuckers 2010). 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 (Junker et al. 2008), and how ear and neck mounted sensors could be used to detect chewing sounds and swallowing motions (Amft and Troster 2008, 2009). Another group used neck- and ear-worn sensors to detect and classify swallowing activities (Lopez-Meyer et al. 2010; Sazonov et al. 2008, 2009, 2010). 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 they 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 futher validate the relationship between bites taken and kilocalories consumed before the bite counter can be used as a proxy for energy intake.

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 kilocalorie goals depend to some degree on the individual. Although our unit of measurement is a single bite, we believe its utility for correlating to kilocalories should be evaluated at a daily or weekly period, customized to the individual, 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 paper. 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.

Future Work

There are several aspects of our method not pursued in this paper 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 h on a coin-sized (appx 120 mAh) battery (STMicroelectronics 2011). 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 (Dong et al. 2011), 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 × 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.

References

Amft, O., Junker, H., & Troster, G. (2005). Detection of eating and drinking arm gestures using inertial body-worn sensors. *Proceedings of international symposium on wearable computers*, (pp. 160–163).

Amft, O., & Troster, G. (2008). Recognition of dietary activity events using on-body sensors. *Artificial Intelligence in Medicine, 42*, 121–136.

Amft, O., & Troster, G. (2009). On-body sensing solutions for automatic dietary monitoring. *Pervasive Computing*, 62–70.

Antipatis, V., & Gill, T. (2001). Obesity as a global problem. In P. Bjorntorp (Eds.), *International textbook of obesity* (pp. 3–22). London: Wiley.

Arab, L., Wesseling-Pery, K., Jardack, P., Henry, J., & Winter, A. (2010). Eight self-administered 24-hour dietary recalls using the internet are feasible in African Americans and Whites. *Journal of the American Dietetics Association, 110*(6), 857–864.

Beasley, J., Riley, W., & Jean-Mary, J. (2005). Accuracy of a PDA-based dietary assessment program. *Nutrition, 21*, 672–677.

Black, A., & Cole, T. (2000). Within- and between-subject variation in energy expenditure measured by the doubly-labelled water technique: Implications for validating reported dietary energy intake. *European Journal of Clinical Nutrition, 54*, 386–394.

Boushey, C., Kerr, D., Wright, J., Lutes, K., Ebert, D., & Delp, E. (2009). Use of technology in children's dietary assessment. *European Journal of Clinical Nutrition, 63*, S50–S57.

Brunner, E., Stallone, D., Maneesh, J., Bingham, S., & Marmot, M. (2001). Dietary assessment in whitehall II: Comparison of 7d diet diary and food-frequency questionnaire and validity against biomarkers. *British Journal of Nutrition, 86*, 405–414.

Burke, L., Wang, J., & Sevick, M. (2011). Self-monitoring in weight loss: A systematic review of the literature. *Journal of the American Dietetic Association, 111*(1), 92–102.

Burrows, T., Martin, R., & Collins, C. (2010). A systematic review of the validity of dietary assessment methods in children when compared with the method of doubly labeled water. *Journal of the American Dietetic Association, 110*(10), 1501–1510.

Champagne, C., Bray, G., Kurtz, A., Monteiro, J., Tucker, E., Volaufovaand, J., et al. (2002). Energy intake and energy expenditure: A controlled study comparing dietitians and non-dietitians. *Journal of the American Dietetic Association, 102*(10), 1428–1432.

Chang, K., Liu, S., Chu, H., Hsu, J., Chen, C., Lin, T., et al. (2006). The diet-aware dining table: Observing dietary behaviors over a tabletop surface. *Proceedings of 4th international conference on pervasive computing* (Vol. 3968, pp. 366–382).

Day, N., McKeown, N., Wong, M., Welch, A., & Bingham, S. (2001). Epidemiological assessment of diet: A comparison of 7-day diary with a food frequency questionnaire using urinary markers of nitrogen, potassium and sodium. *International Journal of Epidemiology, 30*, 309–317.

Dong, Y. (2009). *A device for detecting and counting bites of food taken by a person during eating*. Master's Thesis, Electrical & Computer Engineering Dept., Clemson University.

Dong, Y., Hoover, A., & Muth, E. (2009). A device for detecting and counting bites of food taken by a person during eating. *IEEE conference on bioinformatics and biomedicine*, 265–268.

Dong, Y., Hoover, A., Scisco, J., & Muth, E. (2011). Detecting eating using a wrist mounted device during normal daily activities. *International conference on embedded systems and applications*.

Drennan, M. (2010). *An assessment of linear wrist motion during the taking of a bite of food*. Master's Thesis, Electrical & Computer Engineering Dept., Clemson University.

Finkelstein, E., Trogdon, J., Cohen, J., & Dietz, W. (2009). Annual medical spending attributable to obesity: Payer- and service-specific estimates. *Health Affairs, 28*, w822–w831.

Flegal, K., Carroll, M., Ogden, C., & Curtin, L. (2010). Prevalence and trends in obesity among us adults, 1999–2008. *Journal of the American Medical Association, 303*, 235–241.

Glanz, K., Brug, J., & Assema, P. van (1997). Are awareness of dietary food intake and actual fat consumption associated? A Dutch–American comparison. *European Journal of Clinical Nutrition, 51*, 542–547.

Hargrove, J. (2007). Does the history of food energy units suggest a solution to calorie confusion. *Nutrition Journal, 6*(44).

Jonnalagadda, S., Mitchell, D., Smiciklas-Wright, H., Meaker, K., Heel, N., Karmally, W., et al. (2000). Accuracy of energy intake data estimated by a multiple-pass, 24-hour dietary recall technique. *Journal of the American Dietetic Association, 100*(3), 303–311.

Junker, H., Amft, O., Lukowicz, P., & Troster, G. (2008). Gesture spotting with body-worn inertial sensors to detect user activities. *Pattern Recognition, 41*(6), 2010–2024.

Kirk, S., Penney, T., & McHugh, T. (2010). Characterizing the obesogenic environment: The state of the evidence with directions for future research. *Obesity Reviews, 11*, 109–117.

Kissileff, H., Klingsberg, G., & Itallie, T. V. (1980). Universal eating monitor for continuous recording of solid or liquid consumption in man. *American Journal of Physiology, 238*(1), R14–R22.

Lichtman, S., Pisarska, K., Berman, E., Pestone, M., Dowling, H., Offenbacher, E., et al. (1992). Discrepancy between self-reported and actual caloric intake and exercise in obese subjects. *The New England Journal of Medicine, 327*(27), 1894–1898.

Lopez-Meyer, P., Makeyev, O., Schuckers, S., Melanson, E., Neuman, M., & Sazonov, E. (2010). Detection of food intake from swallowing sequences by supervised and unsupervised methods. *Annals of Biomedical Engineering, 38*(8), 2766–2774.

Martin, C., Anton, S., York-Crowe, E., Heilbronn, L., VanSkiver, C., Redman, L., et al. (2007). Empirical evaluation of the ability to learn a calorie counting system and estimate portion size and food intake. *British Journal of Nutrition, 98*, 439–444.

Martin, C., Han, H., Coulon, S., Allen, H., Champagne, C., & Anton, S. (2009). A novel method to remotely measure food intake of free-living people in real-time: The remote food photography method (rfpm). *British Journal of Nutrition, 101*(3), 446–456.

McCabe-Sellers, B. (2010). Advancing the art and science of dietary assessment through technology. *Journal of the American Dietetic Association, 110*(1), 52–54.

Muhlheim, L., Allison, D., Heshka, S., & Heymsfield, S. (1998). Do unsuccessful dieters intentionally underreport food intake?. *International Journal of Eating Disorders, 24*, 259–266.

Muller, M., Bosy-Westphal, A., & Krawczak, M. (2010). Genetic studies of common types of obesity: A critique of the current use of phenotypes. *Obesity Reviews, 11*, 612–618.

Plasque, G., & Westerterp, K. (2007). Physical activity assessment with accelerometers: An evaluation against doubly labeled water. *Obesity, 15*(10), 2371–2379.

Roberto, C., Larsen, P., Agnew, A., Balk, J., & Brownell, K. (2010). Evaluating the impact of menu labeling on food choices and intake. *American Journal of Public Health, 100*, 312–318.

Saeik, Y., & Takeda, F. (2005). Proposal of food intake measurement system in medical use and its discussion of practical capability. *Lecture Notes in Computer Science, 3683*, 1266–1273.

Sazonov, E., Makeyev, O., Schuckers, S., Lopez-Meyer, P., Melanson, E., & Neuman, M. (2010). Automatic detection of swallowing events by acoustical means for applications of monitoring of ingestive behavior. *IEEE Transactions on Biomedical Engineering, 57*(3), 626–633.

Sazonov, E., & Schuckers, S. (2010). The energetics of obesity: A review: Monitoring energy intake and energy expenditure in humans. *IEEE Engineering in Medicine and Biology Magazine, 29*(1), 31–35.

Sazonov, E., Schuckers, S., Lopez-Meyer, P., Makeyev, O., Melanson, E., Neuman, M., et al. (2009). Toward objective monitoring of ingestive behavior in free-living population. *Obesity, 17*(10), 1971–1975.

Sazonov, E., Schuckers, S., Lopez-Meyer, P., Makeyev, O., Sazonova, N., Melanson, E., et al. (2008). Non-invasive monitoring of chewing and swallowing for objective quantification of ingestive behavior. *Physiological Measurement, 29*(5), 525–541.

Schoeller, D. (1988). Measurement of energy expenditure in free-living humans by using doubly labeled water. *Journal of Nutrition, 118*, 1278–1289.

Six, B., Schap, T., Zhu, F., Mariappan, A., Bosch, M., Delp, F., et al. (2010). Evidence-based development of a mobile telephone food record. *Journal of the American Dietetic Association, 110*(1), 74–79.

Speakman, J. (1997). *Doubly labelled water—theory and practice (1 ed.)*. Berlin: Springer.

STMicroelectronics. (2011, December 5). Mems inertial sensor, LPR410AL gyroscope.

Takeda, F., Kumada, K., & Takara, M. (2003). Dish extraction method with neural network for food intake measuring system on medical use. *Proceedings of IEEE international symposium on computational intelligence for measurement system and applications*, (pp. 56–59).

Thompson, F., & Subar, A. (2008). Dietary assessment methodology. In A. Coulston & C. Boushey (Eds.), *Nutrition in the prevention and treatment of disease (2 ed.)*. New York: Academic Press.

Thompson, F., Subar, A., Loria, C., Reedy, J., & Baranowski, T. (2010). Need for technological innovation in dietary assessment. *Journal of American Dietetic Association, 110*(1), 48–51.

Tooze, J., Subar, A., Thompson, F., Troiano, R., Schatzkin, A., & Kipnis, V. (2004). Psychosocial predictors of energy underreporting in a large doubly labeled water study. *American Journal of Clinical Nutrition, 79*, 795–804.

Williamson, D., Allen, H., Martin, P., Alfonso, A., Gerald, B., & Hunt, A. (2003). Comparison of digital photography to weighed and visual estimation of portion sizes. *Journal of the American Dietetic Association, 103*(9), 1139–1145.

Wing, R., & Hill, J. (2001). Successful weight loss maintenance. *Annual Review of Nutrition, 21*, 323–341.

Wing, R., & Phelan, S. (2005). Long-term weight loss maintenance. *American Journal of Clinical Nutrition, 82*, 222S–225S.

World Health Organization (2010, April 19). *Obesity and overweight*.

Yon, B., Johnson, R., Harvey-Berino, J., & Gold, J. (2006). The use of a personal digital assistant for dietary self-monitoring does not improve the validity of self-reports of energy intake. *Journal of the American Dietetics Association, 106*(8), 1256–1259.

Zhu, F., Bosch, M., Woo, I., Kim, S., Boushey, C., Ebert, D., et al. (2010). The use of mobile devices in aiding dietary assessment and evaluation. *IEEE Journal of Selected Topics in Signal Processing, 4*(4), 756–766.

Zhu, F., Mariappan, A., Boushey, C., Kerr, D., Lutes, K., Ebert, D., et al. (2008). Technology-assisted dietary assessment. *Proceedings of SPIE: Computational Imaging VI* (Vol. 6814, pp. 1–10).