

# A Device for Detecting and Counting Bites of Food Taken by a Person During Eating

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**Abstract**—We introduce methods for detecting in real-time information concerning bites taken during a meal. Our methods use an orientation sensor placed on the wrist of a user, and analyze the rolling motion of the wrist in order to detect a pattern related to biting behavior. We have built a prototype bite detector device based upon our methods. The device can count the total number of bites the user has taken, and provide the bites-taken rate (bites per minute) of the user. Experiments have been conducted to determine its accuracy. Ten subjects ate a meal of their choice, using utensils (or fingers) of their choice. Video was recorded of subjects eating, and synchronized with our device, in order to evaluate its performance. The sensitivity of the device was found to be 91%. Our methods could find use in a number of applications, including helping a user with obesity, eating disorders or eating rate problems.

**Index Terms**—Eating monitor, orientation sensor, bite detector

## I. INTRODUCTION

This paper introduces a wrist-worn device capable of detecting in real-time information with regards to bites taken during a meal. Eating occurs in a variety of environments, including homes, restaurants, places of business, and other social gathering spots. It is very difficult to monitor food intake at all these locations using manual methods. Furthermore, while people eat, they may simultaneously engage in a variety of other activities, including talking, reading, watching television, and working. These activities distract from efforts meant to monitor food intake. For example, when 105 participants were asked to manually count the number of bites taken during each meal in a 24-hour period by using an index card and slash system, 43 participants lost count during the meal or forgot to count the number of bites entirely [1].

One method to measure the amount of food intake is to weigh the amount of food before and after eating [2]. However, this method can only monitor people when they eat at an instrumented table, and for example can not be used to monitor people when they dine at a restaurant or at a friend's house.

A second approach to monitor food intake is to take photos of the food before and after eating. Image processing can be used to analyze the images and determine the amount eaten [3]. However, this sort of system requires carefully constructed environments similar to the dining tables with built-in scales. The food measured must also be restricted due to the difficulty of using image processing techniques to detect pre and post-eaten differences.

Wrist-worn devices have been used for a variety of applications unrelated to eating. Sharples and Beale [4] reviewed a variety of monitoring devices. Such devices have been proposed or built to measure environment and health properties [5], including temperature, barometric pressure, altitude, and heart rate. Wrist-worn devices have also been used in non-health-monitoring applications [6]. Wrist-worn devices can be used to study hand motion and gesture recognition in various domains [7] [8]. Amft et al. [9] used wrist-worn sensors in combination with sensors on the upper arms, head, and ears, to classify an eating action taken by a person. Their methods searched for pre-defined patterns in the signals conveyed by all the sensors in order to classify a motion pattern as one of drinking, using a spoon, using cutlery, or using fingers to eat. In contrast, we are interested in a simpler problem. We use a single wrist-worn sensor to detect a bite taken by a person regardless of the type of food or motion involved in the bite.

Considering all the above, what is needed is a non-invasive, inexpensive, easy to operate, and discreet device that can measure food intake. Thus, we envision a bite detector device that is worn like a watch and can detect individual bites and count them while the person wearing it eats. In this paper we describe our methods for detecting bites, as well as a prototype built using these methods. The device is placed on the person's wrist and connected to an external computer. During use, the device can gather and interpret information with regard to the motion of the user's wrist during a meal, with particular emphasis given to the rolling motion of the user's wrist. Information gathered can be utilized to provide real-time feedback to the user. Information can also be stored to maintain a long term record of eating, so as to better examine the user's eating habits over time. The following sections will introduce the bite detector device, the bite detection algorithm, the experiments conducted and the performance of the bite detector in detail.

## II. METHODS

This section describes the implementation of our bite detector device. First, we describe the sensor used. Second, we introduce our algorithm for bite detection. It includes collecting the orientation data, controlling the recording frequency, dealing with the bound problem, smoothing the signal, calculating the derivative, defining the coordinate system of wrist motion, and defining the bite period. Third, we describe the

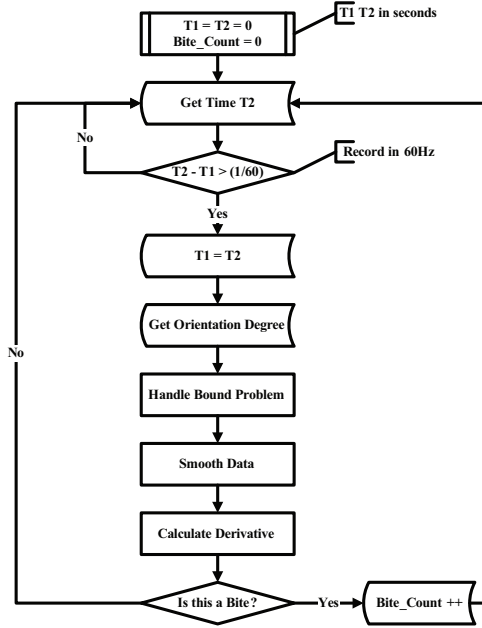


Fig. 1. Flow diagram of bite detection algorithm.

experimental environment we used, including video capture and a graphical user interfaces (GUI). Finally, we discuss the evaluation of our bite detector.

#### A. Sensor

We used a wired InertiaCube3 sensor produced by InterSense Corporation (InterSense, Inc., 36 Crosby Drive, Suite 150, Bedford, MA 01730, www.isense.com). The sensor is used to calculate the motion of the user's wrist in order to identify individual bites during a meal. It can sense the relative (to startup) orientation of angular roll, pitch and yaw.

#### B. Bite detection algorithm

Figure 1 shows the flow diagram of our bite detection algorithm. The sensor data collection frequency is 60 Hz. Before the loop, we initialize *Bite\_Count* as 0 and two time parameters, *T1* and *T2*, also as 0 where *T1* is the old time and *T2* is the current time. When we update the time from the system, if the current time is more than  $\frac{1}{60}$  second plus the old time, we replace the old time with the current time and get one sensor orientation data from the sensor. The next steps deal with the bound problem, smooth the data, calculate the derivative data, and judge if a bite has happened at this specific time. If so, the parameter *Bite\_Count* is increased by 1. Finally, the time is polled and the process repeats.

1) *Bound problem*: When the sensor records the orientation data, the orientation range is from  $-180^\circ$  to  $180^\circ$ . If the data goes past  $180^\circ$ , it will suddenly change to  $-180^\circ$ , and vice versa. Because of this, the signal may be discontinuous. In order to smooth the data signal in the next step, we have to transform this discontinuous signal to a continuous signal. We use a common approach (for example, [10]). Considering that a person cannot rotate his or her hand  $180^\circ$  in a very short time

(less than 0.1 second), a simple and effective way is shown below:

```

if (R_t - R_(t-1) > 180)
    R_t = R_t - 360;
else if (R_t - R_(t-1) < -180)
    R_t = R_t + 360;
else
    R_t = R_t;
  
```

where  $R_t$  is the roll data at time  $t$  and  $R_{(t-1)}$  is the roll data at time  $t-1$ .

2) *Smoothing*: The raw sensor data is noisy. To smooth the noise, we apply a Gaussian-weighted window. The midpoint of the window corresponds to the peak of a Gaussian centered on the current measurement, so that only one half of a Gaussian distribution is used for smoothing. Equation 1 shows how we compute the smoothed roll data. In this equation,  $O_t$  is the original roll orientation measured at time  $t$  and  $S_t$  is smoothed data at time  $t$ ,  $N$  is the Gaussian-weighted window size and  $R$  is the Gaussian standard deviation. In our implementation, the default values of  $N$  and  $R$  are 120 and 20 respectively.

$$S_t = \sum_{i=-N}^0 O_{t+i} \times \frac{e^{-\frac{(t-N)^2}{2R^2}}}{\sum_{x=0}^N e^{-\frac{(x-N)^2}{2R^2}}} \quad (1)$$

3) *Derivative*: Different people may wear the sensor at different angles. If we use the absolute value of the roll data, it is difficult to define a bite period. Therefore, we compute the derivative of the smoothed roll data. Using the derivative data, the behavior of rotation by different people will be the same.

The derivative is computed simply as the difference between smoothed measurements:

$$d_t = s_t - s_{t-Q} \quad (2)$$

The default value of  $Q$  is 120. To calculate the derivative data, we use Equation 2 where  $d_t$  is the derivative data and  $s_t$  is the smoothed data at time  $t$ . because the default  $Q$  is 120 and our data collection frequency is 60 Hz, the value for  $d_t/2$  is the roll velocity (degrees/second). In order to smooth the original roll data and compute the derivative of the smoothed roll data, the computer must buffer the most recent  $Q$  measurements. The contents of the buffer are updated after each new measurement, shifting out the previously stored oldest measurement.

4) *Bite detection*: We have discovered that while eating, the wrist of a person undergoes a characteristic rolling motion that is indicative of the person taking a bite of food [11]. The roll motion takes place about the axis extending from the elbow to the hand. We define a positive roll as clockwise direction motion if viewed from the elbow looking towards the hand, and negative roll as a counterclockwise motion. The characteristic motion involves a cycle of the roll motion that contains an interval of positive roll followed by an interval of negative roll. Figure 2 shows the characteristics of the motion.

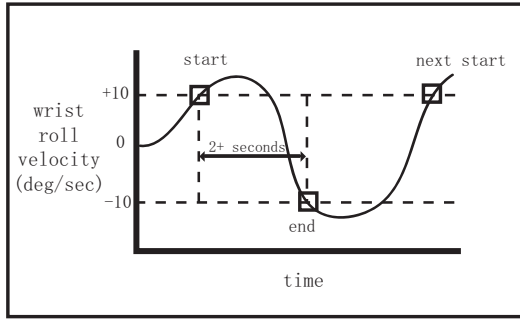


Fig. 2. Roll motion corresponding to a bite.

If the velocity of the roll is measured over time, then three events define the motion that corresponds to a bite. First, the velocity must surpass a positive threshold (10 degrees/second in our figure). Second, a specified period of time must elapse (2 seconds in our figure). Third, the velocity must surpass a negative threshold (-10 degrees/second in our figure). The detection of these three events provides strong evidence that a person has taken a bite of food.

This characteristic roll is important because it differentiates wrist or arm motions caused by a variety of activities, such as moving food around a plate or engaging in non-eating-related activities, from a motion that can be directly associated with taking a bite of food. The detection of this characteristic roll is indifferent to the time taken between bites. Thus, we have discovered methods to build an actual bite detector.

An algorithm for implementing the detection of a bite via the characteristic wrist roll can be implemented as follows:

```
bite_start = 0
loop:
  Let v_t = roll velocity at time t
  If v_t > T1 and bite_start = 0 then
    bite_start = 1
    Let s = t
  If v_t < T2 and t-s > T3 then
    Bite detected
    bite_start = 0
```

The variable *bite\_start* notes the first event of the cycle of roll motion. The thresholds  $T1$  and  $T2$  define the roll velocities that must be exceeded to trigger detection of the first and second events of the roll motion. The threshold  $T3$  defines the interval of time that must elapse between the first and second events of the roll motion. In our default setting,  $T1$  is 10 (degrees/second),  $T2$  is -10 (degrees/second) and  $T3$  is 2 seconds.

For a typical person, the positive roll happens when a person is raising food from an eating surface (such as a table or plate) towards the mouth. The negative roll happens when the hand is being lowered, or when food is being picked up by fingers or placed on a utensil. The actual placing of food into the mouth usually occurs between the positive and negative rolls. However, even when a person does not follow this particular



Fig. 3. Images of a subject demonstrating the wrist roll events that correspond to eating a bite.

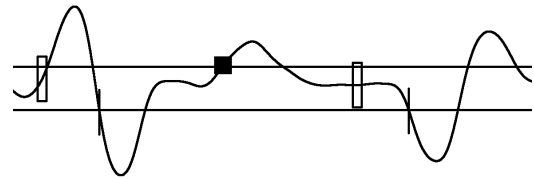


Fig. 4. Wrist roll velocity over time, showing the events that correspond to eating a bite.

pattern, the cycle of motion (positive to negative roll) is almost always witnessed during the taking of a bite of food. We present data to support this conclusion later.

Figure 3 shows three images demonstrating the two events defining the roll motion corresponding to a bite. In the first image, the subject's wrist has exceeded the threshold for positive roll velocity; in the third image, the subject's wrist has exceeded the threshold for negative roll velocity; the second image shows the bite of food taken in between.

Figure 4 shows the wrist roll data that was recorded simultaneously to the images shown in Figure 3. The square shows when the positive roll velocity threshold is first exceeded, and corresponds to the image on the left. The right-most line shows when the negative roll velocity threshold is first exceeded, and corresponds to the image on the right. The rectangle in between those marks corresponds to when the subject first placed food into his mouth, as shown in the middle image in Figure 3.

### C. Video capture

A Canon HG10 video camcorder was used to record the meal. This enabled the experimenter to review the video with the synchronized sensor data after the meal. The camcorder was placed in front of each subject in order to capture the subject and the food he or she was eating. The camcorder was started before the subject began to eat, and stopped after the subject finished eating. The video was saved in a MTS file format and transferred to a personal computer through a USB port.

### D. Graphical user interfaces

A user interface was developed for this project using the Win32 API in Microsoft Visual C++ 6.0. It has three main functions. First, it can review the sensor data with the synchronized video. Second, it can detect the bites offline. Third,

it can be used to mark the ground truth bites (based upon observation of the video) and thereby evaluate the performance of the bite detector device.

#### E. Evaluation of methods

We have developed methods to assess our bite detector. Ground truth bites were marked using the tool just described. This allows us to calculate the correspondences of computer-detected wrist motion cycles to manually marked bites taken. For each wrist motion cycle detected, a single bite taken within its cycle was classified as a true detection. Any additional bites taken within that cycle were classified as undetected bites. A wrist motion cycle detected in which no bites occurred was classified as a false detection. Sensitivity of the device was calculated for each subject as follows:

$$\text{sensitivity} = \frac{\text{true detections}}{\text{true detections} + \text{undetected bites}} \times 100\% \quad (3)$$

### III. RESULTS

We have conducted trials to determine the accuracy of our invention. In our experiments there were 10 subjects. They used different hands and different utensils. Eight of them used their right hand to eat, and two of them used their left hand to eat. Five of them used a fork to eat, three of them used a spoon to eat, and two of them used their fingers to eat.

The performance of our bite detector was evaluated according to methods described in Section II-E. Table I summarizes the performance of our bite detector using these classifications on the 10 subjects. The sensitivity of the device was 91% and only 9% of the actual bites were undetected. In its current state, the device is sensitive, erring on the side of over-detection.

Person	True detected	False detected	Undetected	Sensitivity
1	54	12	11	83%
2	20	8	1	95%
3	49	13	11	82%
4	35	12	0	100%
5	37	15	0	100%
6	20	6	6	77%
7	23	22	0	100%
8	27	20	3	90%
9	19	1	0	100%
10	27	12	4	87%

TABLE I  
PERFORMANCE OF OUR BITE DETECTOR ON 10 SUBJECTS.

In order to understand the reasons for false detections and undetected bites, we reviewed the video and analyzed each bite of these 10 subjects. We found that there are three main reasons for false detections. First, the subject grabs food, but does not eat it and puts the food back on the plate or container. Second, the subject uses a napkin while eating. Third, after taking a bite, the subject tends to rest for a while before the next bite; however, he or she keeps rotating his or her wrist during this period. All these three behaviors will seem like

taking a bite to the bite detector so they will result in false detections. For undetected bites, we found two main causes. First, a subject does not roll enough degrees during a bite. Second, after the subject puts food on a utensil, he or she does not eat all the food in one bite. Instead, he or she bites the food on the utensil several times until it is finished. As a result, the bite detector thinks the subject has only taken one bite during the whole period.

Due to space constraints, further experiments and results can be found in [12].

### IV. CONCLUSIONS

In this paper, we have introduced a methods for detecting and counting bites of food taken by a person during eating. We have built a prototype based on the wired InertiaCube3 sensor. Several experiments were conducted in order to evaluate our methods. For ten subjects, eating the meal of their choice and with the utensil (or fingers) of their choice, the sensitivity of our methods was 91%. Our methods could help people who are overweight or obese to manage their body weight, by providing bite count targets over an extended period of time. They could also be used to help people control eating rate, or to help people with other eating disorders.

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