

A Comparison of Finger and Wrist Motion Tracking to Detect Bites during Food Consumption

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Abstract—This paper evaluates the use of a sensor mounted on a finger to detect bites during food consumption. Previous works have demonstrated the capability to detect bites by tracking wrist motion. The key motion is the roll of the wrist that occurs between picking up food and delivering it to the mouth. We hypothesize that the roll axes of the wrist, hand, and finger are congruent, and that therefore the roll motion measured at the wrist can be similarly measured at the finger. We collected data for 10 meals of subjects wearing sensors on both the wrist and finger. Results indicate that the bite counting algorithm obtains similar accuracy at both locations. The practical implication is that an eating activity monitor could be embedded in the form of a ring worn on the finger, and that this form factor could work as well as a watch-like device.

I. INTRODUCTION

This paper considers the problem of detecting bites by tracking finger motion during a meal. A bite refers to the process of picking up a morsel of food and placing it into the mouth for consumption [2]. Automated bite counting has recently emerged as an alternative method to self-reporting of energy intake [6], [8], [13]. Although bites do not provide indicators of nutrition (what types of foods were consumed), they can be automatically and objectively counted [7]. When aggregated at the meal level they can provide unbiased approximations of energy intake [14]. A study of 271 people in a cafeteria setting, using video to identify the ground truth of 24,088 bites of 374 different food and beverage items, found that wrist tracking could detect bites with a sensitivity of 75% and a positive predictive value of 89% during natural, unrestricted eating [16]. Another study of 77 people compared automatic bite count versus kilocalories measured using 24-hour recall over a 2 week period (2,975 meals/snacks) and found a per-individual correlation of 0.53 [15]. Inspired by the Mifflin-St. Jeor formula, this data was used to derive a kilocalories per bite (KPB) formula based upon gender, age, height and weight [14]. The formula was fit to the 2 week data set and tested on the cafeteria data set, finding that a bite-based estimate of energy intake was more accurate than participant self-estimates of energy intake during the cafeteria meal [14].

Wearable sensors are receiving growing interest for their potential for automated dietary monitoring [11]. Approaches that have been investigated include acoustic sensing in the ear and neck areas of the body [4], [10]. Swallowing sounds

can be detected and associated with consumption, but the presence of background noise presents a significant challenge. Another approach is the detection of jaw and throat motion caused by mastication and swallowing [3]. However, face and throat mounted wearable devices are likely to present challenges in terms of social acceptability. A recent approach is the detection of chewing motions via sensors mounted in eyeglasses [1], [12], [20]. While eyeglasses have widespread social acceptance, not everyone wears them, and it is not clear how someone without a vision problem could be motivated to wear them solely for tracking energy intake.

This paper is motivated by the detection of bites by tracking wrist motion [2], [16], [8], [18]. The wrist can be instrumented with a device that looks like a watch. Wristwatches have widespread social acceptance, so that someone wearing a watch for the purpose of tracking energy intake is unlikely to be stigmatized. However, not everyone likes to wear a watch, especially now that smartphones provide a comparable measure of time of day. In this paper we investigate the possibility of counting bites by tracking finger motion instead. We hypothesize that a device in the shape of a common ring could be worn on the finger and that it could track motion comparable to what is tracked by wrist-mounted sensors to detect bites.

The novelty of this paper is as follows. First, we collected a data set of 10 meals with a person wearing sensors on both the wrist and middle finger. Second, we compare the accuracy of a classic algorithm for detecting and counting bites using wrist motion [2] versus the exact same algorithm using finger motion. The primary objective is to determine if finger tracking could serve as a substitute for wrist tracking. If it can be made viable, then people could be given an option to wear either a watch or ring depending on their comfort level with body-worn sensors at different positions on the hand and wrist.

II. METHODS

During eating, our group discovered that the wrist of a person undergoes a characteristic rolling motion that is indicative of the person taking a bite of food [2]. The concept is demonstrated in Figure 1. As food is picked up and brought towards the mouth, the wrist rotates. The rolling part of the motion is independent of whatever else the arm does. It can therefore be tracked using a wrist-mounted gyroscope. Using appropriate filtering and heuristics, features based upon wrist-roll motions can be reliably associated with eating and drinking. Although the wrist-roll shown in Figure 1 is

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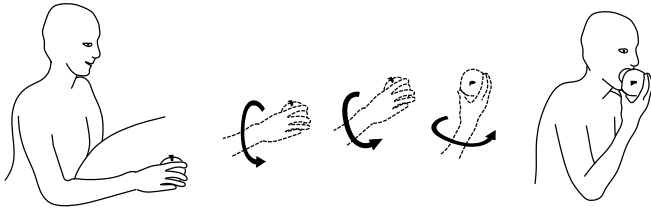


Fig. 1: Wrist roll motion that occurs during eating.

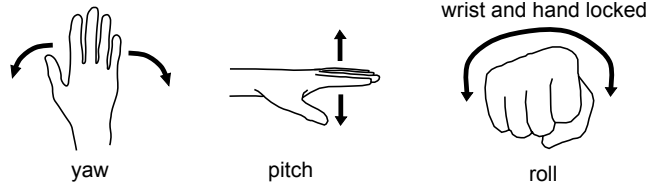


Fig. 2: Although the hand and fingers can yaw and pitch independent of the wrist, the roll motion of the hand and fingers is locked to the roll motion of the wrist.

emphasized for illustrative effect, a slight-to-moderate wrist roll occurs very consistently in practice [2], [16].

For this paper, our hypothesis is that it is possible to track a finger instead of the wrist. Figure 2 illustrates the relevant anatomy. The hand can yaw and pitch relative to the wrist, but the roll axis of the hand is locked to the roll axis of the wrist. The only way to rotate the hand along the roll axis is to rotate the wrist. Similarly, a finger can yaw and pitch relative to the hand, but its roll axis is locked to the roll axis of the hand and thus to the wrist. Therefore, we hypothesize that it is possible to operate our bite counting method by tracking finger motion instead of wrist motion. The motion may be easier to track given that the finger is further from the fulcrum of the rotation (the elbow) which means that the radial motion at the finger is slightly larger than the radial motion at the wrist.

A. Data collection

To collect our data, two Shimmer3 devices were used to record wrist and finger motion, as shown in figure 3. A Samsung Galaxy S8+ was positioned on a tripod to simultaneously record video of subject actions during the meals, in order to determine the ground truth times of bites. Two subjects were recorded eating a total of 10 meals. Utensils and foods were varied and are reported in the results. Collectively the data spans approximately 170 minutes.

Figure 4 shows a custom program developed by our group that was used to identify the ground truth times of bites. The six graphed lines plot the values of accelerometer x, y, z and gyroscope yaw, pitch, roll over an approximately 1 minute window. The green vertical bar indicates the time index currently displayed in the synchronized video. Bite times are marked when the subject is observed to place food into the mouth. The hand that was used for the bite, the utensil used (if any), the type of dishware containing the food, and the food item itself are also specified.



Fig. 3: Photo of both the finger mounted and wrist mounted sensors

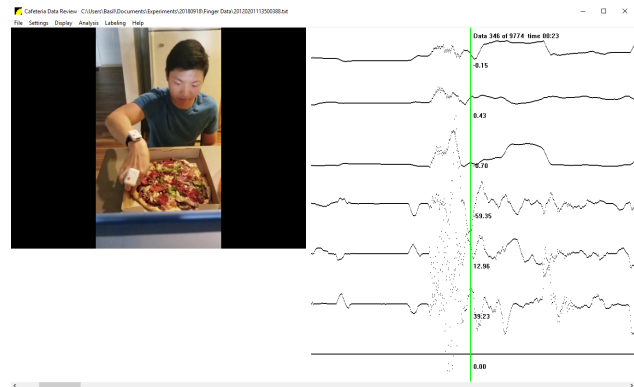


Fig. 4: Screenshot of our ground truthing CafeView program.

B. Algorithm

The algorithm used to detect and count bites is taken from [2] and uses the following pseudocode:

```

Let EVENT = 0
Loop
  Let Vt = roll velocity 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
End Loop

```

Roll velocity is measured using the appropriate gyroscope axis as depicted in figures 1 and 2. The threshold T1 and T2 are used to define the roll velocities that must be surpassed to identify roll motions associated with a single bite. The threshold T3 defines the amount of time that must pass between the positive and negative roll motions. The threshold T4 defines the amount of time that must pass before the algorithm can reset to detect another bite.

The original experiments with this algorithm identified the following optimal values for the four thresholds: $T1 = T2 = 10$ degrees per second, $T3 = 2$ seconds, and $T4 = 8$ seconds [2].

As illustrated in figure 2, we hypothesize that the same roll motion measured at the wrist can be measured at the finger. We therefore operate the exact same algorithm, including threshold values, for both the wrist and finger sensors.

C. Evaluation

For evaluation of bite detection accuracy we follow the same procedure described previously in [2], [16]. Briefly, time indices identified as bites by the algorithm are compared to time indices manually identified as bites in the ground truth. The comparison matches indices using a greedy approach matching the closest ground truth bite to each algorithm-detected bite, while also requiring that matches occur within a window. The match process identifies a total count of true positive detections (TP), false positive detections (FP), and actual bites that were undetected (U). The true positive rate is calculated as $TP/(TP+U)$ and the positive predictive value is calculated as $TP/(TP+FP)$.

To compare the accuracy of wrist vs finger tracking for counting bites, we compare the amount of bites detected, TP, FP and U values across our set of 10 meals. We also report the per meal average true positive rate and positive predictive value. Finally, we conducted t-tests to compare the distributions of both TP and FP values to determine statistical significance.

III. RESULTS

Table I lists the results for each of the 10 meals. Foods and utensils for each meal are listed, along with the ground truth number of actual bites determined via video. The detected, TP, FP and missed columns show the results from the finger sensor vs the wrist sensor. The per-meal average true positive rate and positive predictive value for the finger sensor were 77.9% and 95.8%. The per-meal average true positive rate and positive predictive value for the wrist sensor were 74.5% and 95.8%.

The bottom row of the table shows that the finger sensor detected 13 more true positives and 2 less false positives than the wrist sensor. A t-test comparison between the distributions of true positives revealed no significant difference between the finger ($M=27.3$, $SD=7.8$) and wrist ($M=26$, $SD=7.3$); $t(9)=2.1$, $p=0.7$. A t-test comparison between the distributions of false positives also revealed no significant difference between the finger ($M=1.2$, $SD=1.8$) and wrist ($M=1.4$, $SD=2.2$); $t(9)=2.1$, $p=0.8$. Collectively these tests indicate that the finger sensor performed similar to the wrist sensor. They also show that the finger sensor showed slightly better performance in detecting bites, but on this limited dataset the performance difference was not statistically significant.

Figure 5 shows some example data from the finger and wrist sensors across the same approximately 10 second window. During the center of that window, a bite was taken. It



Fig. 5: Comparison of raw sensor data during a bite of the finger mounted sensor (left) and the wrist mounted sensor (right).

can be seen that amount of motion at the finger is marginally larger than the amount of motion at the wrist. We believe this is in part because the finger is further from the fulcrum of rotation (the elbow) than the wrist, so that slightly larger rotational motions occur at the finger than at the wrist. This probably explains at least some of the performance difference between the finger and wrist sensors.

IV. DISCUSSION

This study tested the ability of a finger mounted sensor to detect bites compared to a wrist mounted sensor. Across 10 meals of varying foods, eaten with varying utensils, the sensors performed similarly. The algorithm that was tested was designed to measure the roll of the wrist that occurs during eating. The results suggest that the roll that occurs at the wrist is similarly measurable on the middle finger and thus a finger location can be used to detect and count bites with similar accuracy to a wrist location.

The implication of this result is that it should be possible to build a new device in the shape of a ring that could be used to automatically measure bite count during a meal. An important advance for mobile health applications has been the continuing decrease in power and size of accelerometer and gyroscope sensors. In the past 5 years, these sensors have become ubiquitous in smartwatches, and smartwatches have become commonplace. Smart rings are the current frontier. At the time of this writing, a few smart rings are being manufactured that contain accelerometers, but to our knowledge there are no smart rings that include gyroscopes or IMU sensors. Our tests therefore used laboratory devices (Shimmer3 devices), much like our group originally used laboratory devices for testing wrist motion tracking over 10 years ago. However, we are optimistic that smart rings may be manufactured in the near future that include the necessary sensors to operate this algorithm.

It is interesting that the results for the finger sensor were slightly better than the results for the wrist sensor. We believe this is in part because the rotational motion associated with consumption is more pronounced at the finger than the wrist, because it is further from the elbow. Although the difference in results reported in this paper did

TABLE I: Finger vs wrist results for bite counting algorithm

Meal	Food(s)	Utensil	Actual Bites	Finger vs Wrist							
				Detected		TP		FP		Missed	
1	Dim Sum	chopsticks	23	20	19	19	19	1	0	4	4
2	Spaghetti	fork	29	34	34	28	28	6	6	1	1
3	Ramen	chopsticks	38	30	30	29	29	1	1	9	9
4	Fries	hand	56	32	29	32	29	0	0	24	27
5	Dumplings	chopsticks / spoon	44	37	40	37	35	0	5	7	9
6	Rice Porridge	chopsticks / spoon	51	42	39	41	38	1	1	10	13
7	Sausage & Eggs	fork	28	22	19	22	19	0	0	6	9
8	Sausage & Eggs	fork	19	19	17	17	16	2	1	2	3
9	Dumplings	fork	34	28	27	27	27	1	0	7	7
10	Quesidilla & Vegetables	hand / fork	38	21	20	21	20	0	0	17	18
Totals				285	274	273	260	12	14	87	100

not reach statistical significance, we suspect that if the test was conducted on a suitably large dataset, a significant effect would be found. It should also be noted that we did not retrain the algorithm parameters for the finger, and instead used the same algorithm parameters for the wrist and finger. It may be that different parameter values for the finger could improve the performance of the algorithm. A larger dataset is needed to perform this training and evaluation.

Several approaches to body worn sensors for measuring energy intake are actively being researched [11]. These include devices worn on the ear and throat to measure sounds associated with consumption [4], [10], devices worn on the neck and face to detect facial motions associated with consumption [3], and devices worn on the wrist to detect hand-to-mouth gestures [8], [16]. Recent experiments have shown that facial motions associated with chewing can be detected using load cells mounted in eyeglasses [1], [12], [20], removing the need to place sensors at uncommon positions on the face. Similarly, the experiment in this paper shows that wrist motions associated with consumption can be detected at the finger, allowing the sensors to be repositioned to the finger. It is important that the research community continue to investigate methods to place sensors at locations where people are likely to wear them. The measurement of energy intake needs to be done daily over long periods of time in order to have an effect on weight change. Comfort and social acceptance require as much consideration as measurement accuracy if these tools are to achieve widespread use.

REFERENCES

- [1] J. Chung, et al. "A glasses-type wearable device for monitoring the patterns of food intake and facial activity", in *Scientific Reports*, vol. 7 no. 41690, 2017.
- [2] Y. Dong, A. Hoover, J. Scisco and E. Muth, "A new method for measuring meal intake in humans via automated wrist motion tracking", in *Applied Psychophysiol Biofeedback*, vol. 37 no. 3, pp. 205-215, 2012.
- [3] M. Farooq and E. Sazonov, "A novel wearable device for food intake and physical activity recognition", in *Sensors*, vol. 16 no. 7, p. 1067, 2016.
- [4] Y. Gao, et al. "iHear food: eating detection using commodity bluetooth headsets", in *IEEE Int'l Conf on Connected Health: Applications, Systems and Engineering Technologies*, pp. 163-172, 2016.
- [5] J. Hill, H. Wyatt, G. Reed, J. Peters, "Obesity and the environment: where do we go from here?", in *Science*, vol. 299 no. 5608, pp. 853-855, 2003.
- [6] A. Hoover and E. Sazonov, "Measuring Human Energy Intake and Ingestive Behavior: Challenges and Opportunities", in *IEEE Pulse*, vol. 7 no. 6, pp. 6-7, 2016.
- [7] A. Hoover, R. Mattfeld and E. Muth, "Bites as a Unit of Measurement", chapter 8 in eds. Dale A. Schoeller M. Westerterp, "Advances in the Assessment of Dietary Intake", CRC Press, August 2017, pp. 149-161.
- [8] K. Kyritsis, C. Diou and A. Delopoulos, "Modeling Wrist Micromovements to Measure In-Meal Eating Behavior from Inertial Sensor Data", in *IEEE J. of Biomedical and Health Informatics*, preprint (2019).
- [9] C. Martin, H. Han, S. Coulon, H. Allen, C. Champagne and S. Anton, "A novel method to remotely measure food intake of free-living individuals in real time: the remote food photography method", in *British Journal of Nutrition*, vol. 101 no. 3, pp. 446-456, 2008.
- [10] S. Passler and W. Fischer, "Food intake monitoring: Automated chew event detection in chewing sounds", in *IEEE J. of Biomedical and Health Informatics*, vol. 18 no. 1, pp. 278-289, 2014.
- [11] T. Prioleau, E. Moore II and M. Ghovanloo, "Unobtrusive and wearable systems for automatic dietary monitoring", in *IEEE Trans. on Biomedical Engineering*, vol. 64 no. 9, pp. 2075-2089, 2017.
- [12] S. Rahman, C. Merck, Y. Huang and S. Kleinberg, "Unintrusive eating recognition using Google Glass", in *Int'l Conf on Pervasive Computing Technologies for Healthcare*, pp. 108-111, 2015.
- [13] J. Rehg, S. Murphy and S. Kumar, eds., "Mobile Health: Sensors, Analytic Methods, and Applications", Springer, 2017.
- [14] J. Salley, E. Muth, M. Wilson and A. Hoover, "A Comparison Between Human and Bite-Based Methods of Estimating Caloric Intake", in *Journal of the Academy of Nutrition and Dietetics*, vol. 116 no. 10, pp. 1568-1577, Oct 2016.
- [15] J. Scisco, E. Muth and A. Hoover, "Examining the utility of a bite-count based measure of eating activity in free-living human beings", in *Journal of the Academy of Nutrition and Dietetic*, vol. 114 no. 3, pp. 464-469, 2014.
- [16] Y. Shen, J. Salley, E. Muth and A. Hoover, "Assessing the Accuracy of a Wrist Motion Tracking Method for Counting Bites across Demographic and Food Variables", in *IEEE Journal of Biomedical and Health Informatics*, vol. 21 no. 3, pp. 599-606, March 2017.
- [17] D. Thomas, C. Martin, S. Lettieri, C. Bredlau, K. Kaiser, T. Church and S. Heymsfield, "Can a weight loss of one pound a week be achieved with a 3500-kcal deficit? Commentary on a commonly accepted rule.", in *International Journal of Obesity*, vol. 37 no. 12, pp. 1611-1613, 2013.
- [18] E. Thomaz, I. Essa and G. Abowd, "A practical approach for recognizing eating moments with wrist-mounted inertial sensing", in *ACM Int'l Conf on Pervasive and Ubiquitous Computing*, pp. 1029-1040, 2015.
- [19] G. Turner-McGrievy, S. Wilcox, A. Boutt  , B. Hutto, C. Singletary, E. Muth and A. Hoover, "The Dietary Intervention to Enhance Tracking with mobile (DIET Mobile) study: A six-month randomized weight loss trial", in *Obesity*, vol. 25 no. 8, pp. 1336-1342, 2017.
- [20] R. Zhang and O. Amft. "Monitoring chewing and eating in free-living using smart eyeglasses", in *IEEE J. of Biomedical and Health Informatics*, vol. 22 no. 1, pp. 23-32, 2018.