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Automatic Detection of Periods of Eating using Wrist Motion Tracking

Surya Sharma[1], Phillip Jasper[2], Eric Muth[2], Adam Hoover[1]

***Abstract*—More than one third of adults in the United States are now classified as obese. Self monitoring of energy intake has been shown to have a positive impact on weight loss, but existing tools for logging eating activities are tedious to use and prone to bias which leads to noncompliance and underestimation. In this paper we describe preliminary results from our ongoing data collection from 500 free living participants, in an effort to improve our previous algorithm that detects periods of eating. We see a 75% accuracy in our data collected to date.**

***Index Terms*—wearable sensors, activity recognition, obesity, energy intake**

I. Introduction

We consider the problem of monitoring energy intake in this paper. The problem is motivated by the fact that obesity is increasing, and nearly 1 in 5 deaths are linked to it [1]. Tracking dietary intake of calories has been shown to be an important component for effective weight loss [2], however, numerous studies have shown that self reported estimates of calorie intake suffer from underestimation bias [3]. There have been multiple attempts to engineer solutions for tracking energy intake using wearable sensors placed at various body positions [4], [5], [6]. Our group has been investigating the use of wrist motion tracking to automatically monitor energy intake [7], [8]. In [7] we describe an algorithm to detect patterns of wrist motion indicative of the hand to mouth gestures seen during eating, and count their occurrence, a technique we call bite counting. To further automate the process, we developed an algorithm to automatically detect entire periods of eating (a complete meal or snack) by tracking wrist motion [8]. Preliminary tests yielded an accuracy of 81%. We require more data from more free-living participants to improve this algorithm. We have collected new data from 104 participants and plan to reach 500 participants by June 2016. This paper describes the ongoing data collection, lessons learned so far, and some preliminary results.

II. Methods

Our method for detecting eating activities uses acceleration and angular velocity data from a wrist mounted configuration of accelerometers and gyroscopes as seen in Figure 1. In previous work we discovered that a participant shows a large movement in wrist motion before and after a meal [8]. Vigorous wrist motions at the boundaries of an eating activity can be attributed to actions like washing hands, collecting meal items or utensils before a meal, standing up, cleaning items or putting utensils away after a meal. An algorithm to detect eating was created based on this event time line, where a continuous estimate of wrist motion energy is processed by a hysteresis based peak detector. Inter-peak segments are tested against features calculated for eating and non-eating activities, which allow the algorithm to classify a segment of time as an eating activity or a non-eating activity. We first describe how this data was collected, and then describe the details of this algorithm and its results on a larger set of participants using new hardware.

[1]Electrical and Computer Engineering Department [2]Psychology Department Clemson University, Clemson, USA. email: spsharm@clemson.edu

Fig. 1. Photo of Shimmer3 showing position on wrist and relative size of device

A. Data Collection

In early work we constructed a custom wrist-worn device that can record 3-axis accelerometer and gyroscope data for a full day [9]. The present study uses the Shimmer3 sensor platform.

The Clemson University Institutional Review Board approved data collection and each participant provided informed consent. On day 1, participants were trained to use the Shimmer3 and the purpose of the data collection was explained. Participants used the device on day 2, and returned the device back to us on day 3. Participants were instructed with the following rules when logging data for our work: 1) Wear the device and turn it on after waking up in the morning. 2) Wait at least 10 minutes before consuming the first meal. 3) Mark the start and end of each meal. 4) Wait at least 10 minutes after the last meal. 5) Turn the device off before going to bed.

B. Algorithm

1) Pre-Processing: The algorithm first smooths sensor data using a Gaussian window. Wrist motion energy is then characterized as the total amount of acceleration experienced by the wrist. Figure 2 shows an example of change in wrist motion energy over time. A custom hysteresis threshold based peak detector [8] was used to identify peaks in the data which were used for segmentation.

2) Classification: Four features from our previous work [8], [10] were calculated for segments between peaks. Each segment was then classified into eating or non-eating based on the value of the feature using a naive Bayes classifier. Figure 2

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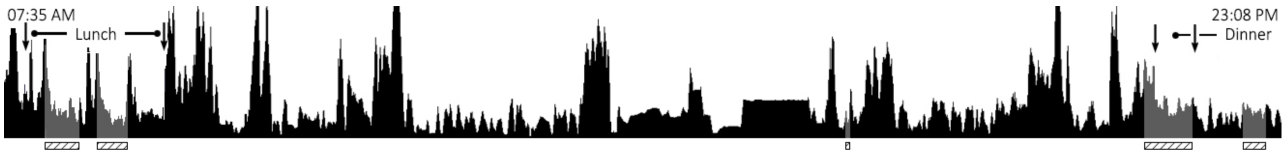

Fig. 2. Visualization of wrist motion energy versus time with manually marked eating activities (ground truth) labeled. Automatically detected eating activities are colored gray and marked underneath.

TABLE I. PRELIMINARY RESULTS IN ONGOING DATA COLLECTION COMPARED TO PREVIOUS RESULTS

Study	Subjects	Hours	Accuracy	Specificity	Sensitivity
Previous study	44	449	81%	82%	81%
Current study	104	1413	75%	80%	69%

shows an example of detected eating activities from a selected participant.

C. Evaluation

We split the data into two equal sets of 52 participants each, one set was used for training the classifier, the other for testing. We measured how well all the data was classified, calculating this for each second in the test set. Accuracy was calculated as:

$$accuracy = \frac{TP \times 20 + TN}{(TP + FN) \times 20 + (TN + FP)} \quad (1)$$

Since eating activities occur much less frequently than non-eating activities, we use a factor of 20:1. In a previous study, weighting 1:1 was shown to result in a 95% accuracy at a sensitivity of 0% [8]. Put simply, blindly labeling all data as non-eating activity results in a high accuracy because eating activities consume very little of a person's time during a day. The ratio 20:1 more accurately balances the weights of eating and non-eating activities based on how often they occur.

III. Results

In the test set, accuracy per person ranged from 48% to 93% while the median accuracy was 76%. The classifier correctly detected 155 eating activities, missed 13 and had 821 false detections. Dong et al. suggested that this detection method may not work for certain participants [8]. We see a similar pattern, in which 49 of 52 participants in the test data (94%) reported an accuracy above 70%, and three participants showed lower accuracy.

IV. Discussion

During our analysis, we ignored data from participants who did not fully comply with the given instructions. 10% of our total participants did not wait 10 minutes between wearing the device and their first meal. 30% of the participants removed the device during the day. We expect to see similar behavior in the future, and plan to create alternate algorithms that use this knowledge.

Table I compares the results from our previous study to the preliminary results of our new data collection. To date we have seen a 6% decrease in accuracy. We hypothesize that this may be due to the larger number of participants being modeled by our classifier. In the future we plan to explore contextual variables such as the day of week, time of day, time since last meal was eaten, and place of eating (home vs. other) to determine if they can be used to improve recognition accuracy. In order to evaluate these contextual variables we need a large amount of data, hence our goal of recording 500 participants. The high accuracy seen in this data collection gives us reason to believe that the algorithm is fairly independent of hardware differences and encourages us to test our algorithm on other wrist based devices which fit our required sensor criteria.

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