Measuring the consumption of individual solid and liquid bites using a table embedded scale during unrestricted eating

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Abstract—**The universal eating monitor (UEM) is a table-embedded scale used to measure grams consumed over time while a person eats. It has been used in laboratory settings to test the effects of anorectic drugs and behavior manipulations such as slowing eating, and to study relationships between demographics and body weight. However, its use requires restricted conditions on the foods consumed and behaviors allowed during eating in order to simplify analysis of the scale data. Individual bites can be only measured when the only interaction with the scale is to carefully remove a single bite of food, consume it fully, and wait a minimum amount of time before the next bite. Other interactions are prohibited such as stirring and manipulating foods, retrieving or placing napkins or utensils on the scale, and in general anything that would change the scale weight that was not related to the consumption of an individual bite. This paper describes a new algorithm that can detect and measure the weight consumed of individual bites during unrestricted eating. The algorithm works by identifying periods of time in which the scale weight is stable and then analyzing the surrounding weight changes. The series of preceding and succeeding weight changes is compared against patterns for single food bites, food mass bites and drink bites to determine if a scale interaction is due to a bite or some other activity. The method was tested on 271 subjects, each eating a single meal in a cafeteria setting. A total of 24,101 bites were manually annotated in synchronized videos to establish ground truth as to the true, false and missed detections of bites. Our algorithm correctly detected and weighed approximately 39% of bites with approximately 1 false positive per 10 actual bites. The improvement compared to the UEM is approximately three times the number of true detections and a 90% reduction in the number of false positives. Finally, an analysis of bites that could not be weighed compared to those that could be weighed revealed no statistically significant difference. These results suggest that our algorithm could be used to conduct studies using a table scale outside of laboratory or clinical settings and with unrestricted eating behaviors.**

I. Introduction

The prevalence of obesity has doubled since 1980 and currently afflicts 13% of the world population [1]. Obesity is associated with increased risks for cardiovascular disease, diabetes, and certain forms of cancer [16], and has become a leading preventable cause of death [19]. The study and treatment of obesity is aided by tools that measure phenomena associated with the amount and rate of food and beverage consumption during a meal. The universal eating monitor (UEM) is a table-embedded scale that measures grams consumed per unit time [13]. It has been used in clinical and laboratory settings to test the effects of anorectic drugs [14], behavior modifications on eating rate and total consumption [10], [15], [28], [29]. It has also been used to measure variations in eating rate between the beginning and end of a meal to categorize subjects as typical (slowing down as a meal progresses), linear, or binging (speeding up as a meal progresses) [7]. However, the UEM requires carefully restricted eating conditions in order to detect and measure individual bites, and the generalization of laboratory results to natural eating during free-living have been questioned [4], [23]. This paper describes a new algorithm that improves on the UEM by allowing a table-embedded scale to be used to measure individual bites during unrestricted eating.

Eating behaviors are generally restricted to simplify interactions with the scale and thus simplify data analysis. Restrictions are applied to both consumption and non-consumption activities. Consumption restrictions include requiring a specific utensil, disallowing drinks and limiting food choices. For example, food masses such as a sandwich or piece of pizza are typically avoided because they are picked up and consumed in multiple bites without being returned to the scale, preventing the weight measurement of each bite individually. Drinks cause a similar problem. Typical non-consumption activity limitations include disallowing manipulation of dishes on the scale, requiring the utensil to be left off of the scale, leaving the participant alone in the room, and disallowing mixing of foods. These activities can cause interaction with the scale without consumption occurring, triggering false positives. Some studies report that multiple participants were excluded from analysis due to manipulation of dishes on the scale [10], [29]. While such controlled conditions may be necessary for experiments involving administration of drugs, other experiments involving the manipulation of behaviors would benefit from less restricted conditions.

Given the difficulty of detecting individual bites in scale data, one approach to analysis is to calculate a cumulative intake curve that blurs bites over time by fitting a linear or curvilinear function [7]. However, analysis of individual bites provides more information about the microstructure of ingestive behavior such as time between bites (eating rate), total bites and average bite size [3], [12]. Some UEM studies rely upon review of synchronized videos to manually mark when bites were consumed [13], [14]. Other studies use direct observation to manually count bites [28]. For studies using automation to count bites, details can be lacking [15] (in this case a footnote in an earlier study from the same group states that every decrease in weight is counted as a bite [10]). Another study reports automatically detecting scale stability at a 2 sec interval but the software was outsourced and is not described [30]. The original UEM [13] sampled weight at

3 sec intervals providing an inherent type of smoothing that supports the detection of weight decreases as individual bites.

While existing methods for studying consumption through use of UEM based methods have provided valuable insights through cumulative intake curves, no methods currently exist to automatically detect and measure bites using a table embedded scale in unrestricted eating. If this type of automation were possible, it could provide opportunities for unobtrusively studying the microstructure of eating and behavior change paradigms in naturalistic settings. This paper describes a new algorithm which demonstrates improvement for bite identification and measurement in a natural eating environment.

II. Methods

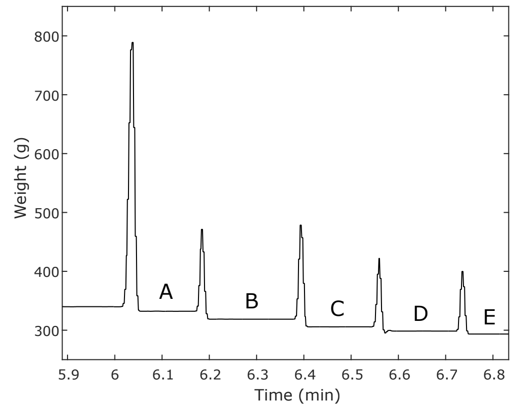
This section first describes the limitations of the UEM when attempting to measure unrestricted eating. It then describes our algorithm that improves upon the UEM, the data collected, and our evaluation metrics.

A. Challenges in Unrestricted Eating

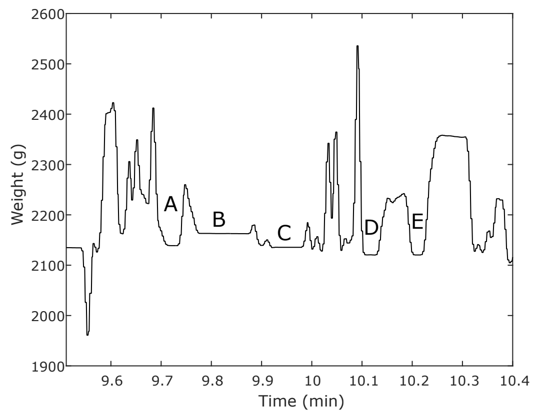
Figure 1a shows an example of scale data where the x-axis is time and the y-axis is grams. When a bite is taken, there is a temporary spike in weight as the person presses down on the plate to pick up a bite of food. The change in weight from before to after the spike yields the bite weight. The stable periods between these spikes correspond to the time when food is being consumed and the plate is not being touched. This is an example from restricted eating. Figure 1b shows unrestricted eating in a naturalistic environment. In addition to having multiple spikes as participants cut, stir, or otherwise prepare food, not every stable period corresponds to a bite. In fact, only labels A, C, and D correspond to a bite. During labels B and E, the participant is talking with friends after preparing food, rather than consuming the food. These activities are common and expected in a naturalistic eating environment, causing the difficulty in identifying bite times and bite weights.

A second challenge is the accurate measurement of weight. The UEM measures consumption by down-sampling the scale data in order to minimize noise caused when the scale is interacted with as shown in Figure 2. By down-sampling at .33 Hz, each weight decrease corresponds to a bite. However, there are three problems with this method when applied to unrestricted eating. First, any scale interaction lasting longer than 3 seconds will likely produce false positives, as multiple weight decreases may be associated with a single bite. Second, any bites taken within 3 seconds of each other would produce at least one false negative. Finally, only two of the bites in Figure 2 would yield correct weights (labels A and D). Labels B, C, and E would be incorrect weights, as the change in weight recorded would be the result of a sample being taken during a spike as the participant presses down on the scale to pick up food. Any bite weight measured could potentially be accurate or inaccurate based on the time the sample happens to be taken.

A third challenge is the existence of food mass bites and drink bites. Under laboratory conditions, foods are typically limited to those which can be consumed in individual bites without returning food to the scale. In naturalistic eating, food mass bites can occur when a participant picks up a food mass (such as a sandwich or a piece of pizza), takes a bite, and returns the remainder of the food mass to the scale. Drink bites



(a) Restricted eating in a laboratory setting.



(b) Unrestricted eating in a cafeteria environment.

Fig. 1: Restricted eating compared to unrestricted eating. All labels in (a) correspond to bites while only labels A, C, and D in (b) are bites.

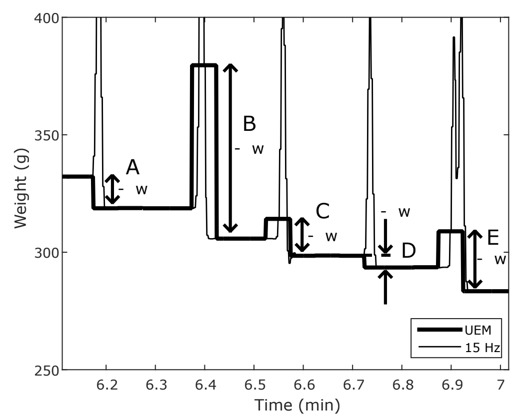


Fig. 2: The effect of down-sampling at .33 Hz to measure bite weights.

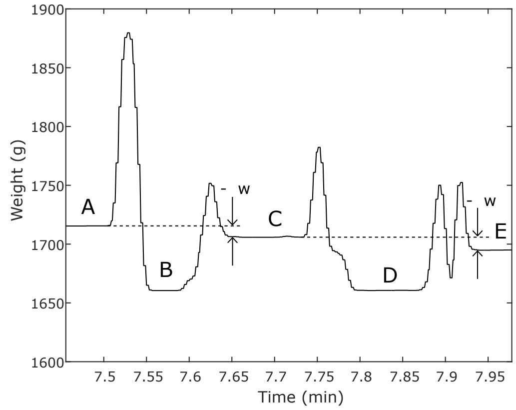


Fig. 3: Scale data generated while a sandwich is picked up and returned to the scale twice. The weight of food consumed can be found based on the change in weight values identified in the figure.

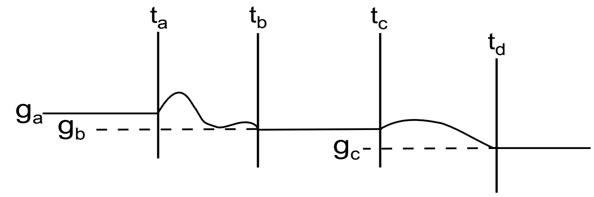


Fig. 4: A hand drawn depiction of a typical single bite.

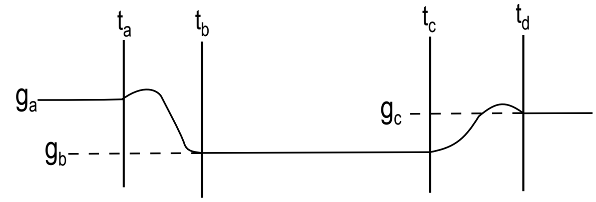


Fig. 5: A hand drawn depiction of a typical food mass bite.

can occur when a participants picks up their drink, consumes some liquid, and returns the remainder of their drink to the scale. These two activities appear very different from single bites and must be treated differently when considering bite weight. Figure 5 shows an example of two consecutive food mass bites. Between labels A and B, the sandwich is picked up, during the stable period at label B, a bite is taken, and between labels B and C, the sandwich is returned to the tray. In order to calculate the weight of the food consumed, the difference between the weight shown in labels A and C is required. Similarly, for the second food mass bite shown, the weight consumed can be calculated as the difference between labels C and E. When the UEM algorithm is applied to this data, the first weight decrease seen is the change from label A and label B. If this change in weight were considered to be the weight of a bite, then the algorithm would mistakenly indicate that the entire sandwich was consumed in a single bite.

B. Algorithm

Our method works by segmenting periods of time in which the scale weight is stable or unstable. The weight of a bite is determined by the difference in scale weight during stable periods surrounding the bite. Further contextual analysis is required based upon the type of bite and is discussed more below.

Scale stability is determined using a 1 second sliding window. If all data within that window are within $\pm 3\sigma_{noise}$ of the mean, where σ_{noise} is the measurement error of the scale, then the window of data is considered stable. The total extent of a stable period is the contiguous sequence of data points passing this test. All remaining data are considered unstable.

Once stability has been established, the algorithm examines each stable period to determine if it fits one of three patterns: a single food bite, a food mass bite or a drink bite. A single food bite is an bite during which the participant picks up food and consumes it fully, returning nothing to the scale. A food mass bite is an bite in which the participant picks up a mass of food, consumes some, then returns the remainder of the food mass to the scale. A drink bite is a bite in which the participant consumes liquid. Each type of bite differs in expected ranges of weight changes before and after consumption.

Figure 4 shows the variables of interest for a single food bite. The stable period being analyzed spans time t_b to t_c. Equations 1-2 define the expected weight changes. There must be a decrease in weight during the preceding unstable period, as the food to be consumed is picked up. In order to eliminate scale noise from being identified as a bite, a minimum weight change equal to $3\sigma_{noise}$ is required. The bounds on the bite size are controlled by the range $3\sigma_{noise} - T_1$. Actual values for all parameters used in our experiments are provided in section II-E. Following the bite, there must not be an increase in scale weight beyond scale noise (Equation 2). If weight is returned to the scale during the next unstable period, it may indicate that a utensil or food item was returned to the tray, which biases the weight determination from the previous two stable periods.

$$3\sigma_{noise} \leq g_a - g_b \leq T_1 \tag{1}$$

$$g_b - g_c \leq 3\sigma_{noise} \tag{2}$$

If the requirements for a single bite are not met, the requirements for a food mass bite are tested. Figure 5 shows the variables of interest. There must be a decrease in weight during the preceding unstable period and an increase in weight during the following unstable period as food is returned to the scale. Equations 3 defines the range of weight $T_2 - T_3$ for a food mass to be picked up from the scale, and equation 4 defines the bounds $3\sigma_{noise} - T_1$ on the amount consumed.

$$T_2 \leq g_a - g_b \leq T_3 \tag{3}$$

$$3\sigma_{noise} \leq g_a - g_c \leq T_1 \tag{4}$$

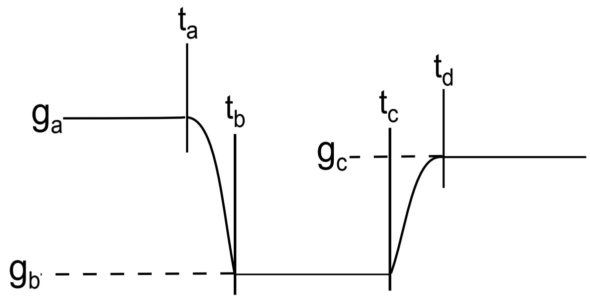


Fig. 6: A hand drawn depiction of a typical drink bite.

Lastly, if the previous patterns did not match then the pattern for a drink bite is tested. Figure 6 shows the variables of interest. There must be a decrease in weight during the preceding unstable period as the liquid container is removed from the scale, and an increase in weight during the following unstable period as the liquid container is returned to the scale. Equation 5 defines the expected weight range $T_4 - T_5$ of the weight of a container plus the maximum amount of liquid it can hold. Equation 6 defines the bounds $3\sigma_{noise} - T_6$ on the expected range of consumption of liquid.

$$T_4 \leq g_a - g_b \leq T_5 \tag{5}$$

$$3\sigma_{noise} \leq g_a - g_c \leq T_6 \tag{6}$$

C. Examples

The following two examples demonstrate the preceding algorithm and the difficulties that can be encountered in measuring bite weights. Figure 7 shows scale data collected during a meal that includes several individually detectable bites. Unstable scale periods are identified by labels A through M. In the example shown, label A indicates the time when the participant picks up a glass. Between labels A and B, the participant takes a drink from their beverage, and at label B, the participant returns the glass to the tray. The stable weight before label A and after label B indicate the weight of drink consumed. At label C, the participant picks up a piece of pizza. Between labels C and D, she takes a bite of pizza, and at label D, she returns it to the tray. Weights before C and after D indicate the weight of the food consumed. The same pattern as shown for labels C and D is shown again at labels E and F. At labels G, L, and M, the participant picks up a piece of salad and consumes it. In these scenarios, the bite weight can be found by taking the difference between the weights before and after the label. At labels H, I, J, and K, the participant is eating salad, but the scale does not have time to stabilize and allow the bite weights to be individually determined.

Figure 8 shows an example containing more challenging data. In this example, label A is an unstable region in which the participant picks up a French fry from their tray. This is the only individually detectable bite in the example. At label B, a large piece of pita bread is picked up but not immediately consumed. At labels C and D, bread is dipped in hummus and consumed in multiple bites while never being returned

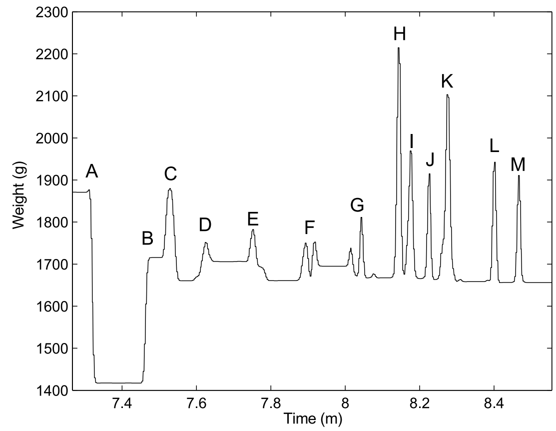


Fig. 7: Example of scale data showing individually detectable bites of each of the three types.

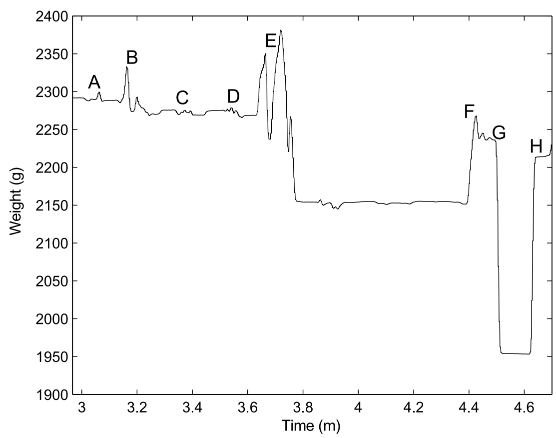


Fig. 8: Example of scale data in which the only individually detectable bite occurs at label A.

to the scale. Labels C and D only correspond to the amount of hummus added to the bread when it is dipped, not the weight of the bite including bread and hummus. At label E, the participant picks up a sandwich and takes multiple bites before returning the sandwich to the tray at label F. None of the individual bites from the sandwich can be measured because the sandwich does not make contact with the scale during this time. A drink is picked up at label G, some is consumed, and the glass is returned at label H. This bite weight is not detectable because the scale is not able to stabilize between labels F and G.

D. Data

The data used in this study was recorded in the Harcombe Dining Hall of Clemson University. The facility seats up to 800 guests and provides hundreds of different foods and beverages, allowing people to build their own meal. A total of 271 subjects (130 male, 141 female; age 18-75; BMI 17-46 kg/m^2; ethnicity 189 Caucasian, 27 African-American, 2 American

Fig. 9: The instrumented table used for data collection.

Fig. 10: A scale was mounted beneath each participant's tray.

Indian or Alaska Native, 29 Asian or Pacific Islander, 11 Hispanic, and 13 Other) participated in the study. Each subject provided informed consent. The study was approved by the Clemson University institution for the protection of human subjects review board.

An instrumented table was prepared to record data from up to four participants simultaneously. Figure 9 shows the table. Digital cameras in the ceiling were positioned to record each participant, including the tray, upper torso and head. A scale was located under the tray of each subject to continuously record food weight during eating, as shown in Figure 10. The scale and video data for each meal was synchronized at 15 Hz during recording.

Each recording was manually reviewed and each bite was marked. Reviewers watched the synchronized video of the participants eating and marked the times at which food or drink was consumed (identified as the time when placed into the mouth). For each bite, the reviewer annotated the container used, hand used, type of food/beverage consumed, and utensil used. Food and drink bites were differentiated by the container used; drinks were consumed from either mugs or cups, while food was consumed from either plates or bowls. Across all 271 subjects, a total of 24,101 bites were annotated as ground truth. Across all bites, 380 different types of food were consumed using 4 different utensils from 4 different containers [9].

E. Parameters

The scale used in our experiments was an OHAUS Scout Pro SP4001. The SP4001 is readable to 0.1 grams. It supports a maximum capacity of 4 kg. To determine the scale measurement noise, different amounts of weight were placed on the scale and repeated measurements were taken to experimentally determine $\sigma_{noise} = 0.29$ g.

For the algorithm parameters $T_1 - T_6$, previous work provides some guidance. One study [13] found that an average spoonful of a yogurt blend was 13.3 ± 4.1 g when participants were deprived of food for 6 hours before eating, suggesting a 99.7% confidence range of 1.0 - 25.6 g. Another study [20] found a range of bite size for boiled rice of 4 to 23 g and a range of bite weights for apples of 2 to 18 g. These sources were based upon a limited selection of foods. To investigate further, we selected 20 meals randomly from our data set and looked at the distribution of bite weights. Approximately 97% of bites were less than 30 g, with the remaining 3% residing in a long tail of the distribution. Based on this evidence, we selected $T_1 = 30$ g.

Using the same analysis of 20 meals, we found that the range of weight decrease for picking up a food mass bite ranged between 100 g and 300 g. It did not exhibit long tails; thus, we selected $T_2 = 100$ g and $T_3 = 300$ g. Similarly, we found that the range of weight decrease for picking up a liquid container was between 80 g and 550 g, and that the maximum consumption during a single liquid bite was 79 g. We therefore selected $T_4 = 80$ g, $T_5 = 550$ g and $T_6 = 80$ g. Note that the parameters T_4 and T_5 are tuned to the characteristics of liquid containers within our experimental environment (their weight plus the maximum weight of liquid they can hold), and would need to be adjusted if different containers were used.

F. UEM Algorithm

As mentioned in the introduction, studies using the UEM either manually detects bites through video or direct observation or treat each weight decrease as a bite. To represent this class of methods, we downsample our data to .33 Hz, as described in the original UEM [13], and count every weight decrease as a bite as described in [10].

G. Evaluation metrics

Figure 11 illustrates our evaluation process. Our algorithm produces two times used to determine a bite weight, between which the bite must occur. This span of time is depicted by thick horizontal bars under the scale data, and thin vertical bars indicate ground truth marked times of actual bites. The algorithm detections cover a time span from the beginning of an unstable period to the end of the following stable period for a single food bite or the beginning of an unstable period to the end of the following unstable period for a food mass or drink bite. The figure depicts five scenarios for evaluation. An actual bite that occurred within an algorithm detection of consumption was considered a true positive (TP). A TP is shown for a single food bite and for a food mass bite. Multiple bites occurring within a single algorithm detection

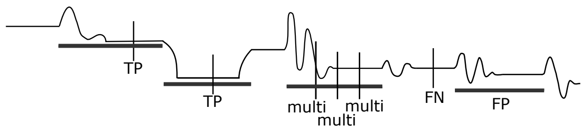


Fig. 11: Examples of classification results. Thick horizontal bars are algorithm detections, thin vertical lines are ground truth times of bites.

are not considered TPs because they cannot be measured independently. Instead, these are labeled as multi bites. If an actual bite occurs outside any algorithm detections of consumption, it is considered a false negative (FN). If an algorithm detection of consumption occurs but there is no actual bite, it is considered a false positive (FP).

To evaluate the UEM method, we searched a span equal to the sample rate used for each bite detected. At the .33 Hz sample rate used, each weight decrease detected would trigger a search for ground truth bites across a span of one and one half seconds before and after the weight decrease detection. These time spans are evaluated in the same way as the time spans identified by our algorithm.

Finally, for both algorithms, any time spans which begin or end in unstable scale data were labeled as invalid weights. This metric is applied because any weight measurement taken during instability in scale data cannot be relied upon for an accurate weight.

III. Results

A. Algorithm performance

Table I shows a comparison between the results of our proposed algorithm and the UEM algorithm. Of the 24,101 ground truth bites, our algorithm correctly detected and measured 39% of bites and missed 47%. An additional 14% of bites were multi-bites, in which our algorithm detected that at least one bite occurs, but cannot provide accurate weights because multiple bites were taken without scale interaction. Compared to the UEM method, our algorithm provides roughly three times the number of true detections and a 90% reduction in the number of false positives.

Table II shows our algorithm's performance on food vs drink bites. Both types of bite were equally detected (39%). The mean drink bite weight was larger than the mean food bite weight, with the average food bite being 8.9 grams with a 3.3 gram standard deviation and the average drink bite being 30.7 grams with a 13.7 gram standard deviation.

B. Analysis of unmeasurable bites

In this section we evaluate if the bites that were individually detected and measured differed statistically from the bites that were undetected and thus unmeasurable. The average unmeasurable bite weight was found through the following steps. First, the starting and ending weights for each meal were found by identifying the stable scale weight immediately before the first actual bite and immediately following the last actual bite. The measurable bite weights were subtracted from this total, giving the total weight of the unmeasurable bites. The following formula was then applied:

$$W_{\text{unmeasurable}} = N_{\text{ud}} \frac{W_{\text{md}}}{W_{\text{mf}}} x + N_{\text{uf}} x \tag{7}$$

where $W_{\text{unmeasurable}}$ is the total weight of unmeasurable bites, N_{ud} and N_{uf} are the number of unmeasurable drink and food bites, and W_{md} and W_{mf} are the average weights of the measurable drink and food bites. Recall that all bites were manually annotated using synchronized video so their count could be identified. As shown in Table II, drink bites were found to be heavier than food bites, so that their relative contribution must be weighted differently. The value x calculated in equation 7 is the average weight of an unmeasurable food bite, and the value $\frac{W_{\text{md}}}{W_{\text{mf}}} x$ is the average weight of an unmeasurable drink bite. To apply this formula, a subject must have at least 1 of each type of bite (measurable and unmeasurable, food and drink). Of 271 participants, 37 did not meet this criteria. An additional 5 participants removed entire containers from the scale preventing the calculation of total weight consumed. For the remaining 229 participants, the mean weight of the measured food bites (8.9 +/- 0.22 gms) did not differ significantly from the mean weight of the unmeasured food bites (8.6 +/- 0.31 gms) (t[229] = 0.967, p = 0.34), and the weights of the measured drink bites (30.7 +/- 0.91 gms) did not differ significantly from the weights of the unmeasured drink bites (30.6 +/- 1.37 gms) (t[229] = 0.153, p = 0.879). This suggests that while our method is only capable of measuring 39% of bites, on average, they are representative of the whole distribution.

IV. Discussion

Up to now, scale methods for analyzing eating behaviors have been limited to clinical and laboratory settings. We envision a table capable of discreetly and unobtrusively monitoring eating behaviors. Such behaviors could include eating rate, bite size, ration of food to drink bites, and distribution of bite weights. It is possible that these statistics could be used in behavior change paradigms. While this system places no burden on the user, it requires an algorithm which can be applied to unrestricted eating, which we seek to provide.

During restricted eating, the UEM method can approach 100% bite detection accuracy. When applied to unrestricted eating, as in our dataset, the UEM method provides true positives for 2991 bites and 26630 false positives, while our algorithm provides three times the number of true detections and a 90% reduction in the number of false positives. Major factors preventing our method from achieving higher accuracy include multiple bites taken without scale interaction, actions taken too quickly the scale to stabilize, and interactions with non-food items (such as a utensil, napkin, or dish). Given these limitations, however, the bites detected by our algorithm were found to be representative of all bites taken by each subject.

Our study has some limitations. The meals were all consumed in a cafeteria setting and subjects always ate in groups. There were a large variety of foods and beverages, so T_1, T_2, T_3, and T_6 are fairly generic, but containers of liquid were limited to two types of plastic container available in the

TABLE I: Comparison between prior bite detection methods and proposed method

Method	TP (valid weight)	TP (invalid weight)	Multi (combined weight)	FN	FP
UEM Method	2991 (12.4%)	10438 (43.3%)	68 (0.3%)	10604 (44.0%)	26630
Our Method	9318 (38.7%)	0	3433 (14.2%)	11350 (47.1%)	2840

TABLE II: Food vs drink bites.

	Total	Individually Detected	Average weight
Food	20542	7940 (39%)	8.9 ± 3.3 g
Drink	3559	1378 (39%)	30.7 ± 13.7 g

cafeteria, causing T_4 and T_5 to be specific to the containers used in the study.

Using a table embedded scale to monitor eating behaviors has the advantage of being discrete and does not rely upon the user to do anything. Alternatives being researched include wearable sensors on the head or neck to detect chewing or swallowing [2], [21], [22], [25]–[27] and sensors worn on the wrist to detect when bites are taken [5], [6], [11]. These have the advantage of being with the user at all locations but require compliance with wearing and operating the devices. Similarly, image based approaches to measuring consumption [8], [18], [24], [32] provide more accurate kilocalorie estimation, but require pictures to be taken of each meal. Future work could explore the their combination. For example, one study performed two experiments integrating several sensors, including a multi-touch tabletop computer, infrared camera, a kinect camera, a Myo armband, a green wristband, and tags. These sensors were used to track plate location, detect bites, and identify the plate from which the bite was taken [17]. Another study used a cloth equipped with a fine grained pressure textile matrix and a weight sensitive tablet to recognize food intake actions (such as cutting, scooping, stirring, etc) and identify the plate on which an action is executed, but the method must be combined with a scale in order to accurately measure weight [31]. The inclusion of additional sensors could provide additional context for our algorithm, perhaps allowing for improved bite detection or direct weight to kilocalorie estimations.

Acknowledgments

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