A Smart Utensil for Detecting Food Pick-Up Gesture and Amount While Eating

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ABSTRACT

Higher food intake rates (i.e., eating too fast) are linked to several health concerns such as an elevated risk of obesity or gastritis. Raising awareness of one's eating habits can regulate one's pace of food intake. In this paper, we propose a novel smart-eating utensil that can potentially increase the users' awareness of their eating rate by detecting their food pick-up gesture as well as the weight upon each bite. We design and implement a proof-of-concept prototype fork with multiple embedded sensors and processor to collect the eating data. After that, we propose a solution for food pick-up gesture detection and food amount estimation in each food pick-up. We assess the accuracy of our solution through ten successful data collection sessions with participants. We demonstrate that our method has strong potential to accurately detect the food pick-up gesture and estimate the amount of food on each pick-up.

CCS CONCEPTS

• **Human-centered computing → Ubiquitous and mobile devices**; **Ubiquitous and mobile computing design and evaluation methods**; **Empirical studies in ubiquitous and mobile computing**; • **Hardware → Sensor devices and platforms**; • **Applied computing → Health informatics**.

KEYWORDS

Food pick-up gesture detection, food amount estimation, smart utensil, eating rate, automatic dietary monitoring, load cell, IMU

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1 INTRODUCTION

Eating rates influence the health and well-being of individuals. Researchers have linked eating rate, or how much food people eat within a short interval, to obesity [24]. For instance, Ohkuma *et al.* [24] conducted a systematic review of studies focusing on the relationship between eating rate and obesity. They concluded that a fast eating rate is positively correlated with one's Body Mass Index (BMI) and how obese they are. Understandably, studies showed that a reduced eating rate is associated with a reduction in energy intake [28] and hence, minimizes the risk of obesity [24], a serious issue in North America [1, 22]. Further, Kim *et al.* found that a high eating rate is associated with an increased risk of endoscopic erosive gastritis in Korean adults [15]. Reducing one's eating rate is also a fundamental principle of mindful eating in order to avoid being overweight [23]. Moreover, eating slowly could help individuals have earlier satiety in their meals [16]. These studies show that decreasing the eating rate is vital for improving health.

Having good eating habits, especially an appropriate eating rate, is important. Numerous interventions have been applied in various settings to improve eating habits [36]. Prior studies have manipulated the eating rate [28], while others have leveraged digital interventions to help modify people's eating behaviour [29]. One critical feature to provide such intervention is detecting eating behaviour accurately, especially eating rate. However, many of these interventions are relatively difficult to apply in everyday life. For example, some require setting up extra devices and equipment such as a Mandometer[1] or a Smartplate[2]. Such burdensome tools and settings might discourage adoption of the tools. Thus, we propose the development of a smart and easy to carry eating utensil that can monitor food pick-up gestures and food weight on the utensil.

We identified critical capabilities and essential functions to design a device to detect eating rate. The device or system must be able to detect the movement of delivering food for consumption, and how much food is consumed by the user in weight or energy. Thus, we focused on proposing a self-contained solution to detect the food pick-up gesture on its rotational movement and food weight in a fork. An Inertial Measurement Unit (IMU) was used to detect the eating gesture based on prior projects which examined various

[1] https://mando.se/en/
[2] https://www.getsmartplate.com/index.html

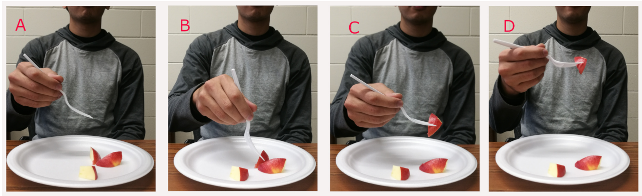

Figure 1: The rotational movement while eating use a fork

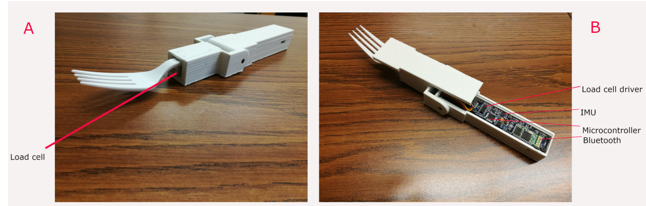

Figure 2: The current prototype we built for the data collection sessions and the current prototype circuit structure

modalities to detect eating moments [33]. As for the food amount estimation, we applied a load cell to predict the weight on the fork.

After we investigated the load cell and the IMU sensor data, we proposed to apply a regression model to the load cell data to estimate the weight of the food. After we developed a prototype using a fork as a base, we conducted a study with twelve participants to collect sensor data on the prototype. We evaluated the method on the dataset and found it is efficient to detect the food pick-up gesture and estimate the food weight.

This work stands to make three main contributions, specifically, in the area of digital monitoring for eating behaviour. First, we provide a prototype eating utensil that has variable sensors to collect data for the development of methods to detect a food pick-up gesture and food amount in weight. Second, we produce a method to detect eating gesture and food weight based on the sensor data. Lastly, we provide an evaluation to study the accuracy of our proposed method with eating data collected with participants.

2 RELATED WORK

2.1 Eating Detection Techniques

Researchers first found using the Inertial Measurement Unit (IMU) on the smart watch could help to detect the eating movement [32]. Thomaz *et al.* [32] presented a practical approach that leveraged an inertial sensor from a smartwatch to identify eating moment. They conducted a semi-controlled lab study to train an eating moment classifier based on inertial sensor data, and then they validated the classifier in two in-the-wild studies. Compared with other modalities such as first-person images captured by a camera and acoustic data captured by earbuds, inertial sensing is beneficial because it does not interfere with user privacy [33]. Maintaining user privacy also makes motion tracking more appropriate when applying this modality to detect intake behaviour in research studies. Mirtchouk *et al.* [20] concluded that the combination of multiple sensing modalities and personal free-living data could improve accuracy of eating detection. Furthermore, Dong *et al.* affixed a smartphone on a user's wrist to collect accelerometer and gyroscope data to detect whether or not a user was eating based on the data collected [6].

2.2 Detect Eating Gesture and Bite

Various solutions have been raised to track the eating gesture. Kim *et al.* [14] designed Slowee, which is equipped with elaborate sensors on headphones and a necklace to detect the eating action, which are potentially intrusive to users. The Slowee system applies Electromyography(EMG) and piezo sensors to detect chewing and swallowing, in order to provide eating speed guidance. Kadomura *et al.* [12] designed and implemented a smart fork called Sensing Fork to recognize eating behaviour for children and the fork can detect the eating gesture as well as the food color.

Dong *et al.* proposed a method to detect the bites gesture by monitoring the variation of the roll value caused by rotational movement of the wrist from the inertial sensor worn on the wrist [4]. Dong *et al.* introduced an algorithm that applied the roll velocity of the inertial sensor to track the eating wrist motion [5]. Their method is simple enough to be implemented into micro processor chips. Following this method [5] Shen *et al.* applied a wrist motion tracker to detect and count bites for eaters in a cafeteria [30].

Zhang *et al.* [35] developed a machine learning model on the IMU sensor data from the wrist band to detect the feeding gesture and recognize bites. They conducted the data preprocessing and model training while comparing various algorithms and parameters for the development of the machine learning model. Zhang *et al.* used a wrist-worn sensor to detect eating episodes on eight participants in the wild and found high false alarms were detected caused by hand movements such as texting on the phone [34].

Kyristis *et al.* [19] generated a dataset from an IMU sensor on a wrist band from Microsoft and annotated the data using video data captured by a Gopro. Kyristis *et al.* used Supported Vector Machine(SVM) and Hidden Markov Models(HMM) to train their models to detect the five eating micro-movements including: picking up food, upwards, downwards, feeding food to mouth,and no movement. Kyristis *et al.* present a solution that combines the SVM with Long Short Term Memory(LSTM) network to improve the gesture detection on the dataset collected with 10 participants using a smartwatch [17].Papadopoulos also applied the SVM and LSTM to a semi-supervised machine learning method on the eating gesture detection [25]. In the recent project, Kyristis *et al.* proposed an algorithm combining the Convolutional Neural Network(CNN) and LSTM to detect the food intake cycles on a dataset of twenty-one meals with twelve participants [18]. The evaluations of the method showed their proposed method has sufficient performance [18]. These machine learning based gesture pattern models are accurate but complex with heavy models. It is hard to deploy such a model in an embedded device (e.g. Arduino board microcontroller with ATmega328P (32 KB memory and 2KB RAM)).

2.3 Food Weight Detection

To detect the eating rate, the system needs to accurately detect the food weight/ energy intake. Amft *et al.* [2] investigated applying chewing sound to predict the weight of each bite through linear regression and they verified their approach with three selected foods across eight participants. Mitchouk *et al.* [21] proposed to

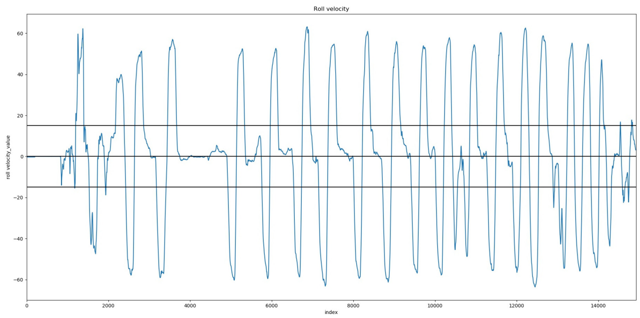

Figure 3: The roll velocity data plot from the session data (S1) collected from Participant 1 (P1).

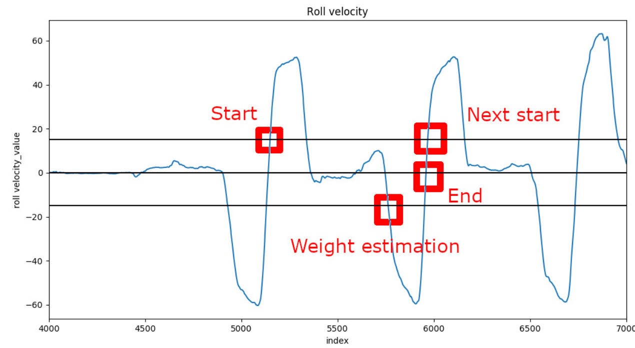

Figure 4: The chunk of roll velocity data plot for the cycle of the rotational motion corresponding to a series of pick-up gestures. The data collected from the session data (S1) collected from Participant 1 (P1).

use in-ear audio and motion sensor on the head and wrist to detect the food type and estimate the food amount in weight consumed by people. Besides, the food weight, Hamatani *et al.* [11] designed FluidMeter which leverages the IMU sensor data from a smartwatch to detect the human drink activity and estimate the amount of fluid intake in weight by analyzing the motion sensor data.

Several other devices have been used to measure food consumption in weight. One such device, the MandoMeter, leverages a smart device with a scale that put under the food to track food consumption through tracking the weight change of the meal and provides visual feedback on a smartphone application. Another device, SmartPlate, includes a weight tracking plate embed with a scale to track weight and a smartphone application that could take pictures of the food on the plate to provide visual analysis data on the meal. Both the MandoMeter and the SmartPlate require additional equipment in the form of a plate size weight scale.

3 DESIGN AND IMPLEMENTATION

3.1 Prototype Design

Our prototype of the smart fork utensil is shown in Figure 2. It is a self-contained device with a controller section for the data collection. The current prototype contains a customized Printed Circuit Board(PCB) with an ATmega328P micro-controller on it, and a Bluetooth module to support information transmission. A load cell with a capacity of 780g was attached to the prototype and its corresponding driver was embedded on the PCB to extract the load cell sensor data. The load cell could detect the force on the top of the fork (i.e., the weight of the food). There is an Inertial Measurement Unit(IMU; MPU6050 module) on the board to detect the motion of the utensil. Finally, the prototype is powered by a 3.7V 400 mAh Li-po battery. The current prototype is around 23 cm long, 4 cm wide and 1.7 cm high. The fork tip is a one-time use plastic addition, which is replaceable for hygiene purpose.

3.2 Food Pick-up Detection Implementation

Kadomura *et al.* [13] categorized the eating motion into four stages: at rest, holding, poking and biting. In another project, the food intake cycle could be categorized into five different micro-movements including picking up food, moving the device upwards and downwards, delivering the food to one's mouth, as well as no movement [19]. To make it simple, we first aimed to detect the eating movement in a less complex stage structures. Using Dong's algorithm [5], we found that there is a rotational movement while eating with a utensil, especially when picking up the food and then angling the fork to deliver it to the mouth (see Figure 1).

The IMU sensor provides the orientation data of the angular roll, pitch and yaw values. We leverage the IMU sensor data to track the movement of the fork by computing the roll velocity to detect the rotational gesture. Following Dong's approach [4] we compute the derivative of the roll data as the roll velocity to show the changes of the roll (the roll velocity results from data collection session 1 (S1) with Participant 1 (P1) are shown in Figure 3).

Algorithm 1: Food Pick-up Gesture Detection

Data: rv as the roll velocity at the current time;
Result: Food Pick-Up Detection
bitestart is false;
pickup is false;
while *not at end of the dataset* **do**
  if *rv is larger than thresholdvalue1 and bitestart is false* **then**
    bitestart is true;
  end
  if *rv is less than thresholdvalue2 and bitestart is true* **then**
    pickup is true;
    bitestart is false;
  end
  if *rv is larger than thresholdvalue3 and pickup is true* **then**
    pickup is false;
    bite detected;
  end
end

We modified Dong's algorithm [4] and developed a threshold value based algorithm, which are show in Algorithm 1. We added

Figure 5: Food provided for the study

one more threshold value in our algorithm compared with Dong's algorithm. In Dong's algorithm [4], aside from the threshold value on the roll velocity, there is also a time interval threshold value to count the bites and eating gesture. In contrast, we only focus on the food pick-up gesture and we infer bites upon the pick-up. Thus, we did not set a time interval threshold value for pick-up detection since we believe the pick-up gesture is solely related with the movement rather than the time duration (see Figure 4).

3.3 Food Weight Estimation Implementation

We leveraged the load cell to detect the weight of the food on the fork. As we learned by a previous design, the load cell could be used to develop a scale, especially a spoon-sized scale used to get the weight of food ingredients in the kitchen [31]. One challenge with the spoon scale is that the scale requires users to pick up food and wait for a certain amount of time for the spoon to stabilize before obtaining the weight value. Since eating behavior is a series of actions that are connected (picking up food, and then biting, etc.), the time required to pick up the food and wait for the load cell to compute the result are not reasonable in a real eating scenario.

We computed the food amount value by taking the load cell force value's average (lc) in a time span. Since the sensor data gathered in movement varies at each time, we computed the average of the load cell value to reduce this variability. We then applied a linear regression to compute the Weight (W) with the linear regression parameters (p and I) to compensate for the noise caused by the mechanical structure and the sensor itself.

$$W = lc * p + I \tag{1}$$

3.4 Issues in the Implementation

3.4.1 Potential Left Hand Issues. Since our algorithm leverages the rotational movement induced by picking up food, the approach (Algorithm 1) is, theoretically, applicable to either left or right hand users as the rotational movement is similar in both. Furthermore, food weight estimation computation is unaffected by handedness.

3.4.2 Noise in Data. Compared with the previous work [35], we did not apply a smoothing techniques to the raw data since we aim to keep the system simple to deploy on the fork itself. A preliminary study shows that the noise is within control. Small effects of the noise caused by the sensor will not significantly affect the results.

4 STUDY METHODOLOGY

4.1 Participants

Twelve participants (Females = 3) were recruited from a local university. The participants were required to be 18 years of age or older, and have no food allergies or food restrictions to the fruit

Figure 6: Participant 5 (P5) in the data collection session. (left) the participant's fork is leaning toward the food. (right) the participant picks up food. Both of these states are distinctly recognized by our method.

cups we provided for the experiment (see figure 5). Data from two participants were excluded due to mechanical errors. Thus, for analysis, we used the remaining ten participants (Females = 2) from this study. All participants were right handed.

4.2 Study Procedure

The studies were conducted in a lab. Each participant was asked to eat using the prototype, which would send real-time data to computer via Bluetooth. Two types of fruit cups were provided; the first half of the participants had mandarins slices while the rest were asked to eat peach slices (see Figure 5). The ingredients of the food were shown to participants before they started eating for health purposes and we put the fruit into a one-time use bowl for each participant. The fork prototype was put horizontally, facing upward to initialize the load cell and IMU. During each session, we used a scale under the bowl of the fruit to track the weight in the bowl, and a GoPro camera was placed in front of the participants to capture the ground truth of the eating gesture and the food weight showing on the scale screen (see Figure 6). The sensor on the fork collected the data and transmitted it to the computer with a frequency at approximately 100 Hz. First, the instruction of the study was provided by the on site researcher. After they agreed and signed the consent form, the eating activity started: Each session took up to 30 minutes. The participants were asked to eat at their own speed.

Following previous studies [21, 25], we asked participants to perform a quick vertical movement with the fork at the beginning and the end of the session. The purpose of the gesture was to generate a high peak in the data to support the synchronization of the sensor data and the ground truth (see Figure 7).

4.3 Ground Truth Annotation

After the study, the Boris software[9] was used to annotate the video for the ground truth of the gesture and weight on the scale in time span. We chose to use Boris over other softwares (e.g., ChronoViz[8]) or the software developed by researchers for the eating gesture annotation [27] because Boris is convenient to annotate behavior in a more detailed way for video with corresponding timestamps.

We first plotted the raw data at the Z axis of the acceleration in IMU (e.g. Figure 7). We found the high peak gesture in the figure and then we found the corresponding data point. We synchronized the moment of high peak in the video with the corresponding moment in the sensor data. We then annotated the start and the end high peak movements and the pick-up gesture. The pick-up gesture started from the moment the fork started approaching the fruit target, and it ended when the food was picked up. During the annotation, we found some events such as food falling down from the fork and the user poking the food multiple times to pick up the food. These actions are natural and happen regularly in real life. We further annotated the weight values on the scale in grams.

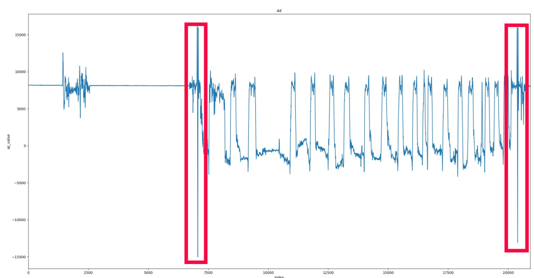

Figure 7: The plot of the Z axis of the accelerator sensor data from participants 1 (P1). The red rectangle was labelled to show the high peak movement sensed by the sensor.

Additionally, we processed the annotation data by extracting the weight value and the gesture annotation with the corresponding time and removed the irrelevant observation data created by the Boris software. Then we matched the annotated start and the end time points with the sensor data. After this, we computed the food weight based on the weight scale data recorded. The food weight per pick-up was computed by the weight changes between two consecutive time points on the scale (i.e., before picking up food and after picking up food).

Next, we labelled the raw sensor data with the corresponding synced ground truth data (including start, end, and pick-up food) and the weight record. After we finished processing data for all of the ten participants, we manually cleaned the data to run the algorithm for the detection. The data sets required extra cleaning due to some broken data points caused by Bluetooth. The final dataset was then used to build the detection algorithm to detect the pick-up gesture and weight.

5 EVALUATION

We applied our algorithm 1 to perform the gesture detection and compute the accuracy on the pick-up gesture detection. We used the ground truth data with the sensor data to train a linear regression model to predict the food weight estimation. The evaluation of the utensil design was based on the analysis of the study data

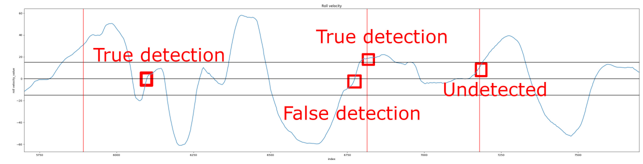

Figure 8: The classification of the gesture detection results in the cycles of the gestures. The red lines are the ground truth gestures. The chunk of the data from Participant 3 (P3) in Session 3 (S3).

collected with the prototype. We analyzed the results from both of the detection of the pick-up gesture and the estimation of the food weight. Following the previous paper [4], we first computed the sensitivity of the food pick-up gesture detection. Then we computed the accuracy of the food weight estimation.

5.1 Gesture Detection Sensitivity

Based on Dong's method [4], we computed the sensitivity to evaluate the detection of the pick-up gesture. We first computed the frequency of true detections, undetected, and false detections. Following Dong's definition [4], true detections are pick up gestures that are within the cycle of the pick-up gesture defined by the method. Additional detections within same cycle were identified as undetected. A pick-up cycle detected with no true pick-up gesture occurring within the cycle are false detection.(See Figure 8).

The sensitivity is computed following Dong's method [4]:

$$sensitivity = \frac{true\ detections}{true\ detections + undetected\ gestures} \times 100\%$$

5.2 Gesture Detection Results

The algorithm for gesture detection was tested based on our data, and the accuracy of the eating detection is computed. We conducted trials to tune the parameters of the algorithm and evaluate the accuracy of our method of detecting the food pick-up gesture.

After the trials of tuning the parameters of the algorithm, we found that if we set the *thresholdvalue1* as 15 and *thresholdvalue2* as -15 and the *thresholdvalue3* as 0 for the cycle of the gesture, we could compute the higher accuracy result. After investigating, we detected 202 pick-up gestures out of 226 food pick-up gestures seen in the video. The sensitivity was computed as mentioned above. The resulting sensitivity of the device and the method is 89.38%. The results are summarized in Table 1.

5.3 Weight Estimation Results

We examined the load cell data of the all the 202 true detected pick-up gestures. We found that Participants 3 and 4 's load cell data were outliers caused by improper calibration and initialization of the load cell (the results are negative in load cell sensor data), hence, we excluded data from those two sessions. We then calculated the load cell data from the true detected cycles. The sum of the positive load cell data was calculated once the second If condition (roll velocity is less than thresholdvalue2) is satisfied in the algorithm 1 and the roll angle data is less than the threshold value T and larger than the threshold value -T (i.e., the fork is horizontally facing upward). After

Table 1: Performance of the pick-up detection on 10 participants

Participants	True detect	Undetected	False detect
1	18	1	1
2	16	4	2
3	11	6	7
4	21	0	1
5	24	3	0
6	21	2	2
7	40	3	4
8	14	1	4
9	16	3	4
10	21	1	1

investigating the sensor data, here we set the threshold value as 15. Then we compute the average load cell value (Loadcell). Inspired by FluidMeter project [11], we computed the Pearson correlation coefficients of the load cell value and the ground truth weight data. After further excluded 4 outliers from the dataset (i.e., the load cell value are negative values), the Pearson correlation coefficient value was (r = 0.878) among 166 true detected pick-ups.

5.4 Weight Estimation Accuracy

We calculated the weight estimation accuracy by training a linear regression model based on the true detect gesture cycles. The model was trained based on the dataset using a Leave-one-intake-out cross-validation following previous work [21]. The data was split into N-folds where N is the 166 true detected gestures (see Figure 9).

We followed previous work [11] to calculate the weight estimation accuracy by computing the Mean Absolute Percentage Error (MAPE) as the metric to evaluate the result of the estimation. We calculated the MAPE for the pick-ups that have food on it. In the data set, four pick-ups are further excluded since the weight ground truth is 0 caused by food falling down after the pick-up gestures. The MAPE focuses on the absolute error caused by the estimation for each pick-up food weight. The MAPE was calculated to be 26.297%, which is relatively lower compared with previous work[21] and the mean absolute error was calculated to be 1.357g.

6 DISCUSSION

To further understand the reason for the false and undetected gestures, we plotted and investigated the data. We discovered that undetected gestures occur when participants try to pick up food too quickly: This is not detected by our method since the method monitors the roll velocity in a longer time span.

The weight estimation resulted in an error rate of 26.297% in MAPE. We investigated the dataset to explore the cause of this error rate. Negative values were found in the load cell data, which may have been caused by the feeding gesture or the food poking gesture. Since the feeding gesture is connected to the food pocking gesture, a latency issue may have affected the result of weight estimation. The angle of the load cell on the fork may have also influenced the sensor data since the force values from the load cell are influenced by the angle between the fork and the gravity direction. Users

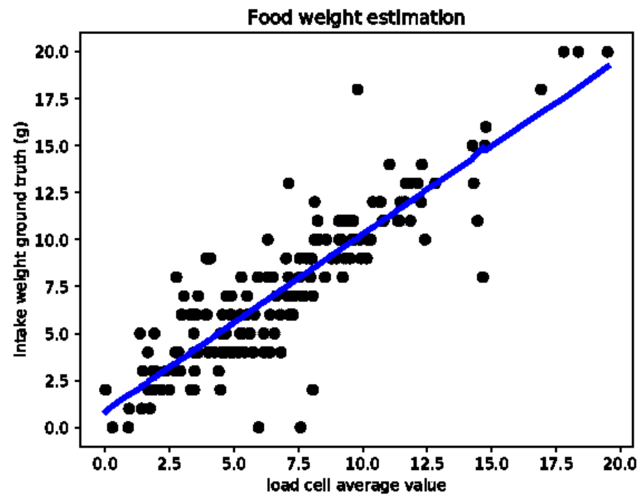

Figure 9: The scatter plot of the food weight amount in gram (i.e.,the ground truth amount)and the average value of the load cell value of 166 points

may potentially use this fork at an angle, which will cause the force value to be lower than the ground truth. In future work, we intend to leverage the MPU6050 sensor's vertical acceleration data to counter-balance the angle problem generated by the load cell.

7 LIMITATIONS

7.1 Prototype Size and Utensil Variety

Our prototype is still bulky for most users due to the size of the control board. Currently, the device is approximately twice as large as a normal eating utensil, which could influence the user's eating gestures. A study is needed to investigate whether the prototype size could influence the user's eating gesture and the detection accuracy. While we were able to develop a successful prototype, further iteration of the prototype is needed to deliver a more acceptable, simple, and robust smart utensil. Specifically, we plan to iterate future prototype designs to reduce their size and match that of traditional eating utensils, while also working on improving the eating behavior recognition function. One of the challenges associated with these improvements will be the simplification of its set-up process as our smart utensil should be used frequently.

There may potentially be different eating patterns while using a variety of different utensils such as a spoon; this question remains unexplored. For future iterations, the utensil may be designed with an interchangeable part at the tip of the tool to switch from a fork end to a spoon end. This change would allow us to investigate the eating detection with other types of utensils as well as food types.

7.2 Eating Activity and Eating Setting

Our study did not consider potentially distracting events such as sharing a meal with other people and multi-tasking while eating. These occur regularly in real-life situations and might influence the detection algorithm. [34].

Water was not provided during the session since there was already syrup from the fruit cup we provided, and we were not concerned about choking. Additionally, a drinking gesture could have disrupted the data as well as the overall flow of the study. Thus, we opted to control this aspect of the experiment. In future studies, we may look into providing liquids. We are interested in investigating the effect of drinking gestures and how it may influence the gesture detection. For the sake of simplicity, the food provided was also limited to two different types of fruit. In the future, we may look into expanding the types of food to test how it may affect the gesture detection. For the food weight estimation, the calories of each bite of food and the total amount of the energy of the consumption at the detection procedure was not considered.

7.3 Eating Behaviour and Eating Patterns

While everyone has their own unique eating patterns, our method is not able to distinguish such unique patterns yet. To effectively develop an individualized method, much more data need to be collected in real world setting. Note data collection in real-world setting will be particularly important as noise could also be an contributing factor to errors. Another limitation is that our method detects food pick-up gestures rather than the actual bite itself [18]. To monitor the eating rate, bite detection is needed in real-world setting such as a user picking up food without feeding themselves. However, our current method can not detect such behaviour.

7.4 Longitudinal and In-the-field study

The experiment was conducted only one session per participant. We are interested in the results of a longitudinal study to validate our method in a longer period of time. Besides, the current data collection sessions are conducted in the lab. The in-the-field study [32] such as data collection with the eaters in a university cafeteria [5] will be fruitful to generalize the method in a larger scope.

8 FUTURE WORK

8.1 Real time intervention on eating rate

After we detect the food pick-up gesture and the food weight on the utensil, we could then potentially compute the eating rate by dividing the food weight by the time interval between two consecutive food pick-up gestures. With a device that could provide eating rate detection, researchers could design various feedback mechanism to intervene users' eating rate during a meal. Such real-time feedback intervention (i.e., vibration on 10s fork [3]) could provide an in-situ effect on the eating regulation [3]. When such solutions is ready, we hope the device will be useful in the future so the users' awareness about their eating behaviours can be enhanced [37].

8.2 Improving the Detection Method

Patil *et al.* applied the ProtoNN algorithm [10] to train their model and applied the predictor into an Arduino to conduct the gesture recognition. Inspired by Patil *et al.* [26], we aim to look for other methods to detect the eating gesture with the capacity to deploy on the prototype itself and then compare different methods. Moreover, the lower accuracy rate will need to be improved to promote acceptance.

8.3 Deploying the Algorithm

Currently, we are working on deploying the algorithm to the prototype itself. We wish the method could work in a good performance in order to work in real life setting as a standalone prototype [7]. In addition, recruiting left handed users would allow us to explore the generalizability of our results. We will also investigate the users' subjective experiences about using our utensil, since it is a new design.

9 CONCLUSION

Inappropriate eating behavior could trigger various health issues. Based on previous studies, we know that fast eating rates could lead to obesity [24], while slow eating rates could lower calorie intake [28]. Researchers further find a high eating rate to be linked to an increased risk of gastritis [15]. Indeed, reducing the eating rate is the first fundamental principle of mindful eating, which focuses on the enjoyment of food without judgement of sensations [23]. This paper proposed a solution to help eaters monitor their eating rate by detecting their food pick-up gesture and calculate the food weight on each pick-up. From this idea, we built a proof-of-concept prototype fork with various sensors. To the extent of our knowledge, this is the first solution to both calculate the food weight and detect food pick-up gestures with data collected from a fork.

The primary goal of the solution was to detect both food pick-up gesture and food weight estimation. We conducted an in-lab study that assessed the efficiency of the method by examining the detection of pick-up gestures and the weight of the food per pick-up. The ground truth data of the study was recorded to annotate the sensor data and compute the accuracy. We used a weight scale to track the weight change of the fruit in the bowl and placed a camera in front of the participant to track their hand movement. The data collected from the sensors attached to our prototype was used to develop a food pick-up gesture detection and weight estimation method. We evaluated both features using the data collected from the experiments and found that both models performed well. In the future, we hope to leverage our findings by deploying these features onto the next iteration of our prototype such that the next smart utensil is able to detect food-pick up gestures and calculate the weight of each bite alone. By warning users that they are eating too fast, this solution will be a beneficial asset in healthier eating habits.

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