SmartNecklace: Designing a Wearable Multi-sensor System for Smart Eating Detection

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ABSTRACT

Characterizing eating behaviors to inform and prevent obesity requires nutritionists, behaviorists and interventionists to disrupt subjects' routine with questionnaires and unfamiliar eating environments. Such a disruption may be necessary as a means of self-reflection, however, prevents researchers from capturing problematic eating behaviors in a free-living environment. An automated system alleviates many of these disruptions; however, success in automating sensing of eating habits has proven to be a challenge due to high within-subject variability in people's eating habits. Given a positive correlation between eating duration and caloric intake, along with the fact that many problematic eaters spend time alone, this paper presents a passive sensing system designed with the following three goals: detecting eating episodes through data analytics of passive sensors, detecting time spent alone while eating, and designing a passive sensing system that people will adhere to wearing in the field, without disrupting regular activity or behavior. A real-time coarse multi-layered classification approach is proposed to detect challenging eating episodes with confounding factors using data from piezoelectric, audio, and inertial sensors. The system was tested on 7 participants with 14 eating episodes, resulting in an 80.8%, and 91.3% average F-measure for detection of eating and alone time, respectively. Additionally, results of a survey highlights the importance of user-customization to increase adherence to neck-worn sensors.

CCS Concepts

•Applied computing → Consumer health; Health informatics; •Hardware → Wireless devices;

BODYNETS 2016, December 15-16, Turin, Italy

Keywords

wearables, passive sensing, eating detection, alone, piezoelectric sensor, audio, accelerometer, wireless

1. INTRODUCTION

The American Medical Association now considers obesity a disease that increases the risk of other chronic diseases [1]. A major contributing factor to obesity is excess caloric intake, the imbalance between calories consumed and calories burned. Steps toward automated ingestion detection are being made to detect eating episodes in hopes of defining problematic eating, identifying its antecedents and ultimately predicting and preventing problematic eating episodes and habits. In the 21st century, the traditional family sit-down dinner setting is rapidly giving way to people eating alone while performing other activities, such as making/accepting phone calls, watching television, or responding to email on a laptop. It has been observed that people who exhibit problematic eating may show patterns of long meals and time alone [7]. In this study participants exhibited a significant linear correlation (Figure 1) between eating duration and caloric intake. Steps toward automated ingestion detection are being made in hopes of defining problematic eating and ultimately predicting and preventing problematic eating episodes.

When people eat, the skin surrounding the neck vibrates and moves in unique ways as a result of chewing and activity within the mouth, and during swallowing, food is moved through the pharynx and into the esophagus, during which the larynx rises to guard food from going into our lungs [9]. In this work a customized (using a 3-D printed casing) neck-worn sensor system is presented and shown in Figure 2 to detect such unique motion to identify eating episodes in company and alone.

In prior work [2], spectrogram-based features were used to detect swallows from a piezoelectric vibration sensor around the neck. One of the major challenges was removing artifacts due to non-eating motion (activity such as walking) and audio (conversation and talking); this design attempts to solve these problems (see Figure 2). The neck-worn device comprises a tri-axial accelerometer to remove motion artifacts, a microphone to remove talking and conversation effects and to determine whether or not the participant is alone, and a piezoelectric vibration sensor to detect neck-motion.

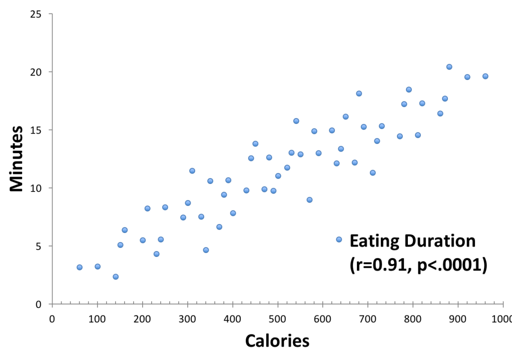

Figure 1: Correlation between eating duration and Calories

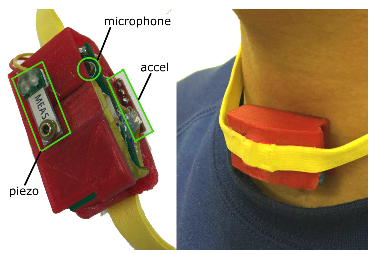

Figure 2: A microcontroller, inside a customizeable 3D-printed case, streams sensor data via Bluetooth

2. RELATED WORKS

Traditional diet assessment methods such as diaries, ecological momentary assessments (EMAs), and interviewer-assisted recalls have been used retrospectively to assess eating via self-report [8], but these self-reported methods often suffer from fatigue, non-adherence, social desirability bias, and recall failure [14]. To overcome these issues, research groups around the world have been focusing on developing automated methods to observe ingestive behavior in free living populations.

Many researchers have resorted to using audio [15, 3, 5] as the sensing mechanism, mounted either in the ear or on the throat to detect sounds produced by chewing and swallowing. Others have employed strain gauges [16], and piezoelectric [10, 2] and inertial [4] sensors to detect the unique motions made by the neck during eating sessions. Researchers have also assessed the feasibility of using proximity sensors in or around the ear to identify chews by the deformation of ear canal walls [6], or camera-based configurations to capture food through imaging [13].

This study aims to build on this related work with the following contributions:

- A neck-worn sensor system to detect activity, eating, and time alone.
- A personalized and generalized multi-layer classification model to detect eating episodes.
- A survey presenting the acceptability of personalized wearable devices.

3. EXPERIMENTAL SETUP

3.1 Sensor System

This system was designed to best emulate conditions in the wild. To reduce all obstacles for the user, the system is powered by a 250mAh lithium coin cell for extended battery life, and it transmits data wirelessly to a companion Android application. Additionally, the size of the device was carefully taken into account during the design process, so as to reduce obstruction of normal eating habits and decrease conspicuousness and discomfort caused by the device. To gather features for our multi-layer classifier, a microphone and piezoelectric sensor were integrated into a custom PCB board. The piezoelectric sensor was mounted with the end opposite the terminals resting just above the sternum, such that the unique motions of the neck while swallowing could be captured. The microphone was directly embedded into the board and the audio signal pre-processed with an on-board amplifying circuit before being recorded and transmitted. The tri-axial accelerometer embedded in the 3D-printed case outputs the orientation and acceleration in the x, y, and z directions, using a serial protocol instead of an analog voltage to communicate with a Bluetooth Low-Energy (BLE)-enabled RFduino microncontroller.

Data was collected by establishing a BLE connection with the mobile app and sampling the analog (piezo, audio) and digital (inertial) values at 100Hz, before transmitting and logging the data in CSV format to the smartphone's local storage. The system was tested for battery life and lasted more than 24 hours while streaming data, far longer than a standard smartphone's battery life; this prevents disruption in the most common charging cycle for users of mobile phones, which is to charge the devices overnight.

3.2 Eating Study

Seven participants (3 male and 4 female, with a mean age of 33 years) of varying BMIs were recruited to be the subjects of the in-lab study. Each participant attended two meal sessions on separate days, the first being a lunch session, and the second a breakfast session. In each session, the neck-worn device was placed around their necks, and they were instructed to follow a standardized protocol. The classification of the activities into Alone/Not Alone and Eating/Non-Eating are shown in Table 1. For the breakfast session participants drank tea and water and ate a cup of fruit, pancakes, and yogurt, interspersed with activities where they wore and adjusted their glasses, made a phone call, and had a conversation with someone in the room. During the lunch session they drank sparkling water and ate a sandwich, soup, and chips, and for non-eating activities typed on a keyboard and got up for a two-minute walk.

The entire meal was recorded using a Logitech C615 HD webcam, and the subjects were allowed to eat their fill. The caloric intake for each food item was known in advance based on food labels and was weighed after each meal to approximate caloric intake. Ground truth was labeled as eating (E), not-eating (NE), activity (A), not-activity (NA), alone (A) and not-alone (NA) time segments using Chronoviz [11]. Eating is defined as the time spent consuming food. When the participant speaks with someone, or when someone else is speaking with them, we identify that time as a not-alone segment. Finally, activity is defined by whether or not the participant is walking.

	Eating	Not Eating
Alone	Tea Water Fruit Pancakes Yogurt Sparkling Water Sandwich Soup Chips	Adjusted glasses Typing Walk
Not Alone		Phone call Conversation

Table 1: Classification of each activity into Alone/Not Alone and Eating/Non-Eating.

4. METHODS

4.1 Analysis

Prior to performing any machine learning analysis, a Savitzky-Golay convolution filter is applied to smooth each signal, and the data is normalized within each sensor to remove scale and translation effects (we subtract the signal by its mean and divide by standard deviation).

Samples are generated using a fixed-time subdivision of the data using a sliding window of 5, 10, and 30 seconds, with a 50% sliding window shift and a 60% overlap threshold; if greater than 60% of the window overlaps with ground truth of a certain class, then the whole window is labeled as that class.

Several statistical features shown in Table 2 are extracted from the windows generating a total of 70 features. Correlation based Feature Subset (CFS) selection was then applied to all features to select the optimal features. CFS determines the information gain of each subset of attributes by calculating the predictive power of each feature, subtracting its degree of redundancy [12]. Features that were highly correlated with the class label but have low inter-correlation were selected.

The following classifiers were chosen because they are known to be beneficial in detecting eating and talking and result in both generative and discriminative models: kNN, BayesNet, Random Forest (n=100 trees), C4.5 Decision Tree (DT), Logistic Regression(LR), and Adaptive Boosting (Adaboost).

Type	Feature
Average	Mean Median Root Mean Square
Quartiles	1st and 3rd Quartile Interquartile Range
Shape of distribution	Skew Kurtosis Standard Deviation
Extremes	Minimum Maximum Zero-crossing Rate

Table 2: Statistical features gathered from each sensor, for each window.

Because people can perform several types of activities at the same time, like walking, talking and eating, a multi-layer classification scheme (Figure 3) is tested to avoid the problem of non-eating activities interfering with eating detection. Activity is first filtered through RF1, then a separate eating/non-eating classifier (RF2) is applied when the participants are inactive, and an alone/not-alone detection classifier (RF3) is run independent of whether the subject is active or not. Since physical activity detection is shown to be reliable in detecting when participants are active vs. inactive, results focus on eating (RF2) and alone or not (RF3).

4.2 Evaluation

The classification algorithms were evaluated against ground truth from the recorded video of the subjects using Leave One Subject Out Cross Validation (LOSOCV), and a user-dependent model, where for each participant, the algorithms were trained on data from the lunch session and tested on data from the breakfast session. The metrics used include precision (positive predictive value), recall (sensitivity), and F-measure, which is the harmonic mean of precision and recall.

5. RESULTS

The results for testing multiple window sizes to detect eating and alone time are provided in Table 3. Based on these results, the window size of 30 seconds was selected for analysis.

Window (sec)	Eating (F-measure)	Alone (F-measure)
5	78.6%	63%
10	78%	58%
30	78.3%	75%

Table 3: LOSOCV Random Forest results for varying window sizes.

5.1 User-Independent Model

The results for the various user-independent classifiers used for alone/not-alone are shown in Figure 5 and for eating/not-eating are shown in Figure 4. The optimal classifier for detecting eating was the Random Forest (n=100 trees), yielding a 78.3% average F-measure, while Naive Bayes provided optimal results for detecting alone time, with a 77.7% average F-measure.

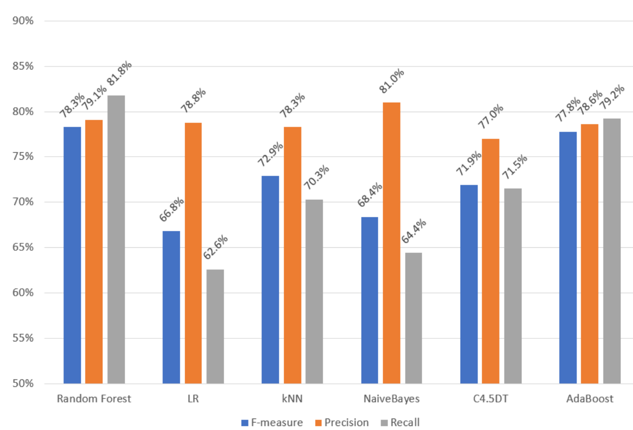

Figure 4: LOSOCV (User-independent) Results for Eating/Not Eating.

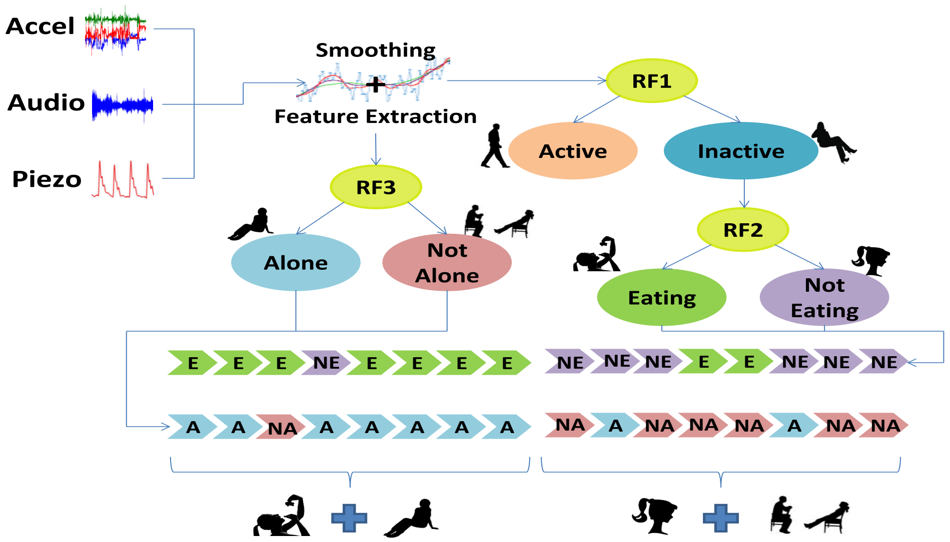

Figure 3: A multi-layer framework for detecting eating and alone time.

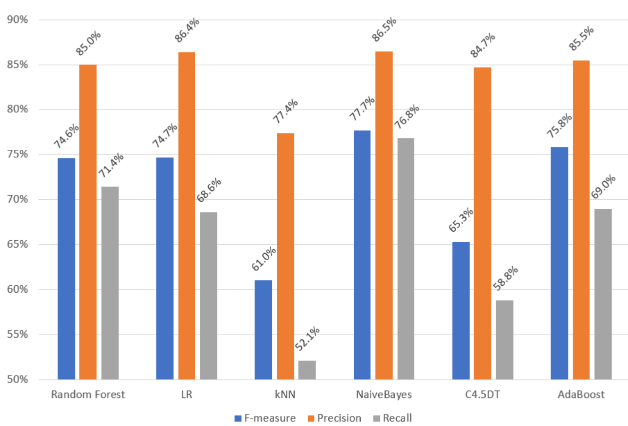

Figure 5: LOSOCV (User-independent) Results for Alone/Not Alone.

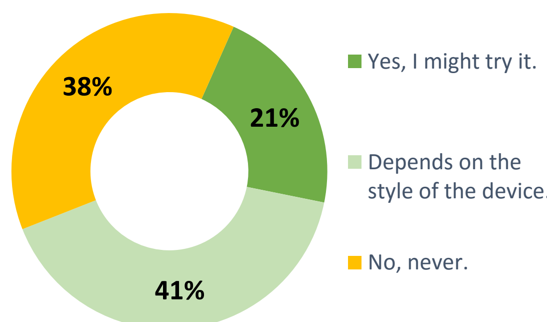

Figure 6: University students' responses to a survey about desirability of the neck-worn device

Random Forest	Eating	Alone
F-measure	80.8%	91.3%
Precision	79%	93.8%
Recall	86.5%	90.2%

Table 4: User-dependent Model Results

5.2 User-Dependent Model

The user-dependent model was developed by training on lunch and testing on breakfast. The optimal window size was 30 seconds, resulting in an optimal average F-measure of 80.8% and 91.3% for both eating and alone-time detection respectively using the Random Forest (n=100 trees) classifier.

5.3 Survey and Wearability

Unlike a smartphone or a smart watch, a neck-worn device will be extremely visible with almost any outfit. Therefore, one that will be simultaneously attractive as well as relatively inconspicuous has the greatest appeal for potential users, and will be the most usable in the wild.

To gauge the general desirability of the device, 93 college undergraduate and graduate students were asked to answer a short 5-minute survey about the device. The survey included two simple yes-or-no questions: whether or not they would be willing to wear such a device during daily activity, and whether their willingness to do so would be affected by a one-time user customization of the device.

While the number of answers in favor of wearing and using the device regularly was relatively low at 21.5%, this amount reached 62.5% upon offering the possibility for a one-time user customization of the device. This agrees with existing trends, as user customization and personalization of technology-based products is rapidly becoming mainstream. For example, Motorola allows users to combine different materials and colors, and even add custom engravings before purchasing a smartphone, and Apple allows purchasers of an Apple Watch to choose their preferred casing size and material, as well as the material and color of the watch band.

6. CONCLUSION

A neck-worn passive sensing system was designed to gather data from multiple sensors with the ultimate goal of detecting periods of eating and alone-time, and a secondary goal of developing a low-distraction, inconspicuous device that users could adhere to in the wild. This system performed well when using a generalized model, trained across all subjects, to detect eating and alone-time with average F-measures of 78.3% and 77.7%, respectively.

The system actually improved when using a personalized model, trained and evaluated within a single subject, with an average F-measure of 80.8% and 91.3% in detecting eating and alone-time respectively. The potential for such a system to aid in detecting and characterizing problematic episodes can prove to be reliable if participants feel the device can be customized or fashionable, and as a result future efforts will look into enabling 3D-printing customization of the neck-worn sensor. In the future, this system will be evaluated across obese and overweight subjects, with a diverse range of activities, in a free-living environment.

7. REFERENCES

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