A Mobile Food Intake Monitoring System based on Breathing Signal Analysis

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ABSTRACT
This paper presents a mobile food intake monitoring system. The system works based on a key observation that a person's otherwise continuous breathing signal is interrupted by a short apnea during swallowing. The breathing signal is collected using two Respiratory Inductance Plethysmography (RIP) belts on the chest and abdomen, and wirelessly transmitted to an Android smart phone via Bluetooth. Support Vector Machine estimating the posterior probability is applied on the extracted features. Through experiments on six healthy subjects, the system is demonstrated to be an effective way of monitoring food and drink intake. The key novelty of this paper includes 1) a non-invasive RIP belt system for swallow detection without any cosmetic and wearing discomfort issues, and 2) a smart phone to collect data wirelessly and execute swallow detection algorithms before uploading the results to the cloud for enabling remote health monitoring.

Keywords
Wearable Sensors; Swallow Detection; Food Intake Monitoring; Breathing Pattern Analysis; Android; Smart Phone

1. INTRODUCTION
This paper presents a novel food intake monitoring system based on two non-invasive Respiratory Inductance Plethysmography [1] belts and a smart phone. Such a system can be useful for analyzing ingestive behaviors associated with different diet disorders and providing clinical suggestions accordingly. Based on the data from World Health Organization, worldwide obesity increased over 200% since 1980, and 1.4 billion adults were overweight in 2008 [2]. It has been proven that obesity can cause various health issues, such as coronary heart disease, type-2 diabetes, and different types of cancers [3]. Traditionally, self-reported questionnaires were widely used by researchers to estimate food intake for high-risk population. An instrumented system can thus reduce the subjectivity and bias [4] associated with questionnaire based self-reporting systems. The proposed system can detect each instance of food/drink intake, and can have enormous significance for obesity control and health monitoring. Together with self-reporting at the high level of overall dietary habits, the system can aid the obesity and health management practices by estimating the trends of quantifiable calorie intake for its users. Moreover, the connection of the smart phone to the cloud via WiFi or cellular network can facilitate remote diet monitoring by healthcare providers and possible feedback to the subject who is wearing the system.

Swallow detection and analysis methods can be categorized as invasive and noninvasive. One of the invasive methods is Videofluoroscopy, which uses X-ray to analyze swallowing process in order to evaluate neurological conditions affecting swallowing [5]. Although it provides detailed information about the swallowing process, these methods are too involved and not applicable for everyday monitoring. On the other hand, non-invasive methods use sensors to capture various biological signals such as sound, electromyography, and movement to detect swallows. In [6][7][8], microphones are attached to the skin in the neck area near laryngopharynx to capture the sound of swallowing. The microphones are placed either by a stretchy band or elastic structure. It has been demonstrated that these methods provide promising results. But according to our previous experiments [9], where a microphone and elastic band are placed in the neck region as control, subjects suggested that equipments on the neck are not comfortable and impact their swallowing habit. In [10], sound and surface electromyography (SEMG) signals are used to capture the sound associated with the swallowing process and the activation of muscles involved. The SEMG electrodes are attached to the skin in the neck region, which may raise user acceptability issues for prolonged usage due to cosmetic and safety reasons. A dual-microphone system is developed in [11] to record chewing and swallowing sound through the ear canal as well as externally through the air. Placing such microphones has similar cosmetic issues and therefore its suitability for prolonged usage is questionable. Damouras [12] used a dual axis accelerometer affixed to the thyroid notch for swallow detection in strictly controlled settings. Kandori [13] proposed a novel magnetic swallow detection system using a magnetic field generating coil and a detection coil installed on a elastic holding structure and placed on left and right sides of thyroid cartilage. RIP is used for liquid intake detection in [14], but the experiment is done in a strictly controlled environment and the proposed algorithm is carried out on a limited data set.

The concept of swallow apnea is the key for swallow detection through breathing signal in this paper. Anatomically, breathing is inhibited in part of the swallowing process, thus causing a short apnea. According to [10], the swallowing process has three consecutive phases: 1) the oral preparation phase, 2) the pharyngeal phase, and 3) the esophageal phase. In the oral phase, a piece of food is chewed into a viscous bolus and the pharyngeal phase is initiated. The viscosity and size of bolus is also sensed, such that the swallowing apparatus can adapt to the bolus. In the pharyngeal phase, the bolus is pushed through the pharynx and passes the upper esophageal sphincter. A set of muscles are activated to propel the bolus and the epiglottis moves downward to protect the trachea from contamination. Therefore, breathing is concomitantly inhibited. Finally, the bolus moves towards the stomach in the esophageal phase.

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In this paper, we present a mobile food intake monitoring system. We derive the breathing signal using two RIP belts on the chest and abdomen. Since the belts do not need direct skin contact and they can be worn inside, outside, or between garments, they do not raise any cosmetic issue. Moreover, the belts are also comfortable to wear even for a long period of time. After the swallow sequence is recorded, swallow pattern analysis can potentially be used for identifying non-intake swallows (or empty swallows), solid intake swallows, and drinking swallows.

2. SYSTEM COMPONENTS

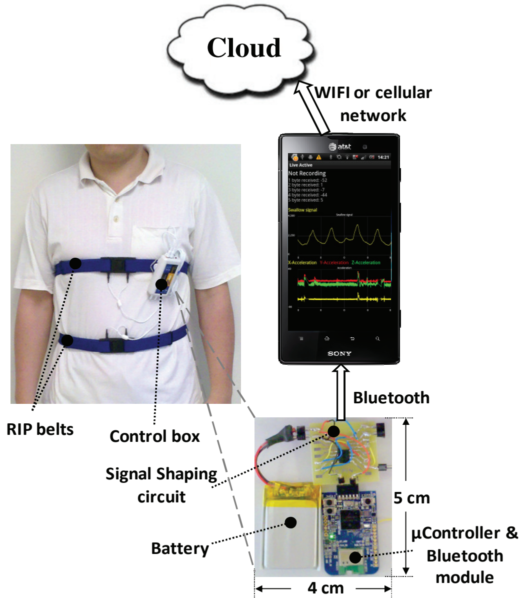

Figure 1: The mobile food intake monitoring system

As shown in Figure 1, a wearable sensor system is worn on the torso to collect breathing signal. The breathing signal is then wirelessly transmitted to an Android smart phone over Bluetooth. The wearable sensor system includes: 1) a pair of RIP belts for collecting breathing signal, 2) a signal shaping circuit for amplifying and filtering the raw signal from the sensor to cater the requirement of ADC stage, 3) a processor and Bluetooth subsystem (TI EZ430-RF256x), which is able to sample the signal at 100Hz and transmit it over Bluetooth to the external smart phone, and 4) a 3.7V 300mAh polymer rechargeable battery. The whole packet weighs approximately 45 grams. The 300mAh polymer battery is able to support the system for around 20 hours.

2.1 RIP belts

Respiratory Inductance Plethysmography (RIP) belts work based on Faraday's Law that a current through a loop of wire generates a magnetic field perpendicular to the plane of the loop, and according to Lenz's Law, a change in the area enclosed by the loop creates an opposing potential in the loop proportional to the change of area in a unit time [15]. It can be expressed as:

$$\varepsilon = -\frac{d\Phi_B}{dt} \text{ and } \Phi_B = \int_A B \cdot d\Delta$$

Where ε is the induced electromotive force (emf) in volts, and Φ_B is the magnetic flux, B is the magnetic field and A is the area enclosed by the RIP belt. Observe that a change in area A would cause the emf ε opposing to the current inducing the magnetic field.

In a RIP belt, a conductive wire is sewn in a zigzag manner, and an alternating current is injected to create a magnetic field. Two RIP belts are worn by the subject on the chest and abdomen. Breathe changes the cross-sectional area enclosed by the belts, and induces an opposing emf, which actually impacts the frequency of the injected current. The alternating current is injected by a driving module, and the frequency change of the current is sensed by a sensing module. Both the driving module and the sensing module are enclosed in an external control box, connected to the RIP belts through wires.

In this paper, we derive the breathing signal by summing up the signals from the two belts on the chest and abdomen. It should also be noted that in order to save energy, the current in the RIP belts and output signal amplitude is very small. Therefore, a signal shaping circuit is needed.

2.2 Signal Shaping Circuit

Since the output signal strength of the RIP sensing module is very small (around 20μV peak-to-peak for normal breathing), high amplification ratio is necessary for the signal shaping circuit. Figure 2 shows the schematic of the circuit. The first op amp (i.e., MAX412 (1) in the figure) is to provide a stable 1.5V reference to the input and the amplifier on the right. The second op amp (i.e., MAX412 (2) in the figure) forms the amplifier with an amplification ratio of 10,000. The low pass filter accompanying the amplifier has a cutoff frequency of 28Hz. After the amplification, the breathing signal has a peak-to-peak value around 200mV.

To accommodate the high amplification ratio, MAX412 (MAX412BCSA+) is chosen because of its low offset voltage and noise voltage density.

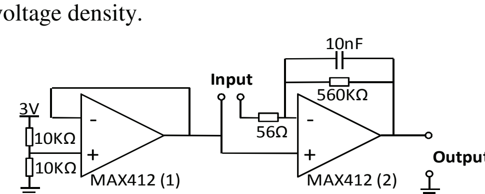

Figure 2: Schematic of signal shaping circuit

2.3 μController and Bluetooth Module

The processed signal from the amplification module is fed into an ADC channel of a μController and Bluetooth module (EZ430-RF256x). The ADC converter has an accuracy of 14 bits, and a sampling rate at 100Hz. Considering the 200mV peak-to-peak value of the breathing signal, the SNR regarding the quantization noise is 60dB.

The sampled data is then sent via Bluetooth to the Android smart phone for food intake monitoring application.

2.4 Food Intake Monitoring App on Smart Phone

An Android app, named LiveActive, is developed on the smart phone to perform food intake detection based on breathing signal received from Bluetooth.

Figure 3 demonstrates the logic layering of the LiveActive. The LiveActive activity coordinates the other modules. Bluetooth connection module receives breathing signal from Bluetooth API provided by Android. Graphic User Interface (GUI) plots the breathing signal on the screen. Food intake detection module runs in background to perform the detection algorithm illustrated in Section 3. Webservice module updates the detection results to the server using either WIFI or cellular network.

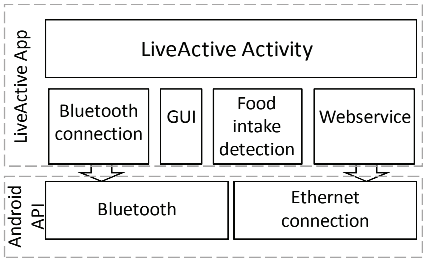

Figure 3 Logic layering of LiveActive

3. FOOD INTAKE DETECTION METHOD

Figure 4 demonstrates the processing scheme for food intake detection. The breathing signal amplified and filtered by the signal shaping circuit depicted in Section 2.2 is sampled by ADC of the µController and Bluetooth Module at 100Hz, and then fed into a low pass filter for removing quantization noise caused by ADC conversion. The sampling rate of 100Hz is sufficient for capturing the apnea signature in the breathing signal, since the power spectrum of breathing signal is mainly below 2.5Hz. In the second step, a peak and valley detection algorithm is applied to extract individual breathing cycles. In order to perform real time swallow detection, the data stream is divided into 30% overlapping 10-second windows, and the threshold based algorithm proposed in [16] is applied, where the threshold equals to 30% of amplitude span in the window. The normalization module normalizes the extracted breathing cycles in both time and amplitude dimensions. Each breathing cycle is normalized to be between 0 and 100 vertically, and interpolated to 128 points. Considering the average length of a breathing cycle is 3.77 seconds in our experiments, the effective sampling rate after interpolation is 34Hz. The purpose of normalization is to get rid of the variance in duration and amplitude of breathing cycles.

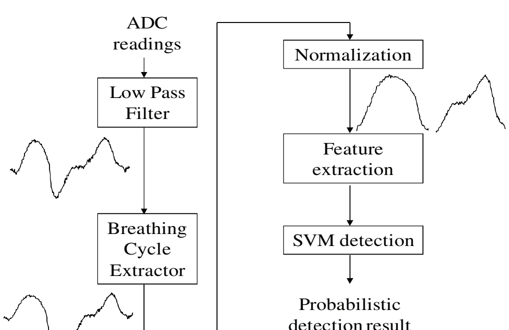

Figure 4 Food intake detection scheme

The feature extraction module extracts features from both segmented and normalized breathing cycles. The features are breathing cycle length, inhalation duration and depth, exhalation duration and depth, ±10 crossing count, and FFT coefficients of normalized breathing cycles. ±10 crossing count is defined as the number of sample points whose first derivatives are +10 or -10.

Support Vector Machine (SVM) [17] detection module is then applied for probabilistic swallow detection. Different from SVM classifiers for discrete classification, the SVM classifier used in this project outputs the posterior probability indicating the likelihood of being in one of the classes given the provided features. The classifier works based on the idea that an instance's probability of being in one class is lower if the instance is closer to the decision boundary than other samples in that class. The advantages of using SVM with posterior probability output are: 1) detection threshold can be adjusted according to the preference of application, and 2) other algorithms, such as Hidden Markov Model, can be applied to improve the accuracy using temporal patterns.

4. PERFORMANCE EVALUATION

The proposed system shown in Figure 1 was used in the experiments and the algorithm proposed in Figure 4 is evaluated in this section.

To evaluate the performance of detection, the metrics of *Precision* and *Recall* are adopted and they are defined as:

$$Precision = \frac{TP}{TP + FP} = \frac{Recognized\ swallows}{Retrieved\ swallows}$$

$$Recall = \frac{TP}{P} = \frac{Recognized\ swallows}{Relevant\ swallows}$$

The number of correctly detected swallows is expressed as *recognized swallows* (true positives, TP). *Retrieved swallows* corresponds to the number of swallows detected by the proposed algorithm, which includes both TP and incorrectly detected swallows (false positives, FP). *Relevant swallows* (positive, P) refers to the number of swallows annotated by a breathing analyzing expert, which is also known as ground truth.

4.1 Experiments

The experiments were carried out on 6 subjects (2 females and 4 males) without any known breathing or swallow disorders. Each subject was instructed to wear the instrumented RIP belts, and had lunch at his or her own pace. The food includes vegetarian food, meat and mixed.

In the process of experiment, the subject was instructed to press a button whenever she or he swallows, and the breathing signal was recorded on the smart phone for later processing. A video camera was deployed to record the movement of mouth and laryngopharynx for verification. A session of the experiment lasted between 10 to 20 minutes. In each session, the number of breathing cycles that the subject executed spans from 111 to 274, and total number of swallows varies from 44 to 92. The number of breathing cycles depends on the duration of the experiment, and the number of swallows is highly correlated to the amount of food consumed.

4.2 Results and Discussion

The food intake detection method mentioned in Section 3 was carried out on the data collected during the experiment. In order to prove the generalizability of the proposed method, the classifier was trained with the data collected in our previous work [18] in a subject independent manner. Specifically, a subject's data would not be used as the testing data set if her or his data (in any experiment) is included in the training data set.

The detection performance is shown in detail in Table 1. Please note that the detection metric is

$$\begin{cases} \boldsymbol{Swallow}, if\ P(swallow|features) > P(non\text{-}swallow|features) \\ \boldsymbol{Non\text{-}swallow}, if\ P(swallow|features) < P(non-swallow|feature) \end{cases}$$

where

$$P(swallow|features) + P(non\text{-}swallow|features) = 1,$$

therefore,

$$\begin{cases} \boldsymbol{Swallow}, if\ P(swallow|features) > 0.5 \\ \boldsymbol{Non\text{-}swallow}, if\ P(swallow|features) < 0.5 \end{cases}$$

and $P(swallow|features)$ is the output of the SVM detection module in Figure 4, representing of the posterior probability of detecting a swallow. By varying the threshold in the detection metric above, a balance between precision and recall can be achieved.

Subject	Precision (%)	Recall (%)
Subject 1	59.0	87.3
Subject 2	72.1	73.8
Subject 3	62.8	89.4
Subject 4	60.0	94.9
Subject 5	72.9	53.1
Subject 6	70.4	89.3

Table 1 Detection performance of the proposed method with fixed threshold

Figure 5 shows the precision and recall for all 6 subjects when threshold is varied from 0.05 to 0.95. Observe that the curve of subject 5 is the lowest, and the curve for subject 6 is the highest, indicating the worst and best scenarios respectively. Lower threshold values in the figure correspond to higher recall and lower precision, and vice versa. Depending on the application requirements, if high recall is preferred, a low threshold can be adopted, while if high precision is emphasized, a high threshold can be used. Appropriate threshold for each subject can be dimensioned based on a curve in the figure corresponding to the specific subject. Note that the precision and recall values for each subject in Table 1 correspond to a point (i.e., for threshold 0.5) along the curve of that subject in Figure 5.

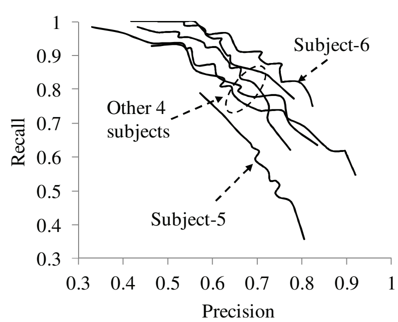

Figure 5 Classifier performance on precision-recall plane by varying detection threshold

5. CONCLUSION

This paper presents a mobile food intake monitoring system. The system is able to detect food intake by monitoring the breathing signal using two RIP belts on the chest and abdomen. SVM with the capability of outputting posterior probability is applied and evaluated. The ongoing work includes: 1) using temporal swallowing event information to improve the accuracy, such as Hidden Markov Model, and 2) investigating the relation between apnea and the viscosity and volume of the bolus.

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