Computers in Biology and Medicine 58 (2015) 46–55

Contents lists available at ScienceDirect

Computers in Biology and Medicine

journal homepage: www.elsevier.com/locate/cbm

Monitoring eating habits using a piezoelectric sensor-based necklace

Haik Kalantarian*, Nabil Alshurafa, Tuan Le, Majid Sarrafzadeh

University of California, Los Angeles, United States

ARTICLE INFO

Article history:
Received 29 October 2014
Accepted 1 January 2015

Keywords:
Piezoelectric sensor
Wireless Health
Nutrition
Necklace

ABSTRACT

Maintaining appropriate levels of food intake and developing regularity in eating habits is crucial to weight loss and the preservation of a healthy lifestyle. Moreover, awareness of eating habits is an important step towards portion control and weight loss. In this paper, we introduce a novel food-intake monitoring system based around a wearable wireless-enabled necklace.

The proposed necklace includes an embedded piezoelectric sensor, small Arduino-compatible microcontroller, Bluetooth LE transceiver, and Lithium-Polymer battery. Motion in the throat is captured and transmitted to a mobile application for processing and user guidance. Results from data collected from 30 subjects indicate that it is possible to detect solid and liquid foods, with an *F*-measure of 0.837 and 0.864, respectively, using a naive Bayes classifier. Furthermore, identification of extraneous motions such as head turns and walking are shown to significantly reduce the false positive rate of swallow detection.

1. Motivation

In 2008, medical costs associated with obesity were estimated to be over $147 billion [1], and over one-third of adults in the United States are considered obese. The average BMI (body mass index) has consistently increased over the last two decades, which has been shown to be a contributor to risk of stroke, diabetes, certain cancers, heart disease, and other conditions [1]. Though many activity-monitoring systems have been proposed [2–4], little research has been conducted on quantifying the volume of food consumption, which has been shown to correlate with weight gain [5]. Though countless manual data collections have been proposed such as food records and 24-h recall, these approaches suffer from poor accuracy, high user burden, and low compliance. Wireless health-monitoring technologies have the potential to promote healthy lifestyle behavior and address the ultimate goal of enabling better lifestyle choices. In this paper, we describe a wearable nutrition-monitoring system in the form of a necklace, which is capable of identifying swallows, performing basic classification, and providing user guidance through a mobile application.

2. Background

Our work on nutrition monitoring pertains to the development and test of an nutrition-monitoring necklace with an embedded piezoelectric (vibration) sensor. Piezoelectric sensors are capable of producing a voltage at their terminals in response to mechanical stress. Thus, the system is capable of detecting swallows based on skin movement in the lower trachea during ingestion. Vibration-sensor data was transmitted to a mobile application using a low-powered Bluetooth LE transceiver built into the processing board mounted upon the necklace. The application included algorithms for identifying swallows, performing basic classification between solid and liquid foods, and providing recommendations to the user with respect to the timing, volume, and composition of their meals. An overview of the hardware architecture is provided in Fig. 6. The system includes a piezoelectric strip, Bluetooth-compatible microcontroller board, and a small lithium-polymer or cell battery for powering the system.

Though the system provides high accuracy in laboratory-based testing environments, accuracy is compromised in certain use-cases such as walking, running, and head motions in both horizontal and vertical directions. Often, these motions are detected as swallows, which significantly reduced the accuracy and practicality of the system. Therefore, we propose different classification techniques to distinguish these motions from those associated with eating using both the piezoelectric sensor, and a small accelerometer.

Fig. 7 shows how the addition of a new sensor could be used to assist in activity classification to improve system accuracy. Prior to

---

* Corresponding author.
E-mail addresses: kalantarian@cs.ucla.edu (H. Kalantarian), nabil@cs.ucla.edu (N. Alshurafa), tuanle@cs.ucla.edu (T. Le), majid@cs.ucla.edu (M. Sarrafzadeh).

http://dx.doi.org/10.1016/j.compbiomed.2015.01.005
0010-4825/

swallow detection, which in the previous system was based on vibration sensor data alone, activity recognition is computed from a necklace-mounted tri-axial accelerometer. This accelerometer data is intended to detect motion of the necklace itself caused by head motions or movement, rather than the skin in the lower throat as in the case of the piezoelectric sensor.

This paper is organized as follows. Section 3 presents an overview of prior art in the field of food intake monitoring. Section 4 describes the algorithms used to detect swallows, followed by the experimental procedure in 5. The evaluation is presented in Section 6, followed by the conclusion in Section 7.

3. Related works

3.1. Manual methods

Food records generally are not impacted by the accuracy of a subject's memory; they typically require individual to make note of their eating habits during or immediately after a meal [6]. However, there are several problems with this approach. In cases where assessment of a typical diet is the goal, this technique is not feasible because it has been found that the necessity of completing a food record affects dietary choices. Other concerns include patient compliance, and the difficulty that untrained individuals face when accurately assessing portion size.

One of the most simple and yet pervasive methods of monitoring dietary intake is the multi-pass 24-h dietary recall method, based on the data patients provide at the end of a randomly selected day. This approach measures food intake in a reasonably quantitative manner but with significant error because people do not recall the exact amount of food they have eaten [7]. Experimental data shows that food intake is usually reported with error and measurement variance also depends on the patient's experience with this system [8].

A third method for manually assessing dietary intake is to use a food frequency questionnaire (FFQ), in which individuals specify their rate of consumption for various food items. Nutritional intake can subsequently be assessed by summing various food types provided within the list [6]. Though this technique is inexpensive to administer and insensitive to recent changes in diet, FFQs are typically inaccurate in comparison with other techniques. This is often a result of several factors including incomplete lists of food, poor user compliance, errors in recording frequency, and errors in recording serving size [9].

3.2. Automated methods

Recent research has been developed that use a watch-like configuration of sensors to track wrist motion throughout the day to automatically detect periods of eating [10]. While this work shows promise, it does not capture people that eat and drink with two hands (92% of food bites with the dominant hand but only 57% of liquid bites), and also has a high false positive rate (one per five bites).

Swallows could also be detected as a sign of food intake. However, current systems detecting swallowing maintain a dependency on bulky and potentially unsafe equipment (video fluoroscopy) and invasiveness (subcutaneous EMG) [11]. Some recent works suggest the use of throat microphones as a means of acquiring audio signals from throat and extracting swallowing sounds afterwards [12,13]. In a promising work by Amft et al. [14], authors analyze bite weight and classify food acoustically from an earpad-mounted sensor. However, as other acoustic methods, this system may not be practical in environments with high ambient noise. Analyzing wave shape in time domain [12] or feature extraction and machine learning [15] has resulted in an 86% swallow detection accuracy in an in-lab controlled environment. Some studies have reached accuracy rates of 91.7% in an in-lab controlled environment using neural networks with false positives of 9.5%. A more recent study using support vector machines have been able to reach swallow detections of up to 96.7% in an in-lab setting [11]. However, these devices are mounted very high up in the top part of the trachea, near the larynx. Such positioning of a device is quite uncomfortable to wear throughout the day.

Many prior works have attempted to detect swallow disorders using inertial sensors. The work by Toyosato et al. in [16] used a piezoelectric pulse transducer to detect food bolus passage through the esophagus. In [17], Ertekin et al. used piezoelectric sensors to evaluate dysphagia symptoms in a study with thirty normal subjects and 66 dysphagia patients. The authors concluded that piezoelectric sensors can be applied successfully towards objective evaluation of oropharyngeal dysphagia. Another example is our prior work in nutrition monitoring in [18], in which we propose monitoring eating habits by placing a piezoelectricc sensor in the lower trachea. In [19], Miyaoka et al. used piezolectric sensor signals were able to detect the volume of tea swallowed based on the waveforms acquired from the sensor, after GLM-ANOVA analysis. Though the application did not relate to nutrition monitoring, this work is significant because it shows that food volume can be inferred from a piezoelectric sensor.

4. Hardware and sensors

In this section, we describe the hardware and software components of our system.

4.1. Piezoelectric sensor

A piezoelectric sensor, sometimes known as a vibration sensor, produces a voltage when subjected to physical strain. By placing a piezoelectric sensor against the throat, the motion of the skin during a swallow is represented in the output of the sensor, when sampled at frequencies as low as 5 Hz. During a swallow event, muscular contractions result in motion of the skin, which pushes the vibration sensor away from the body and towards the inside of the necklace, generating a unique output voltage pattern, as shown in Fig. 1. The piezoelectric sensor was integrated into our system by connecting the positive terminal to the microcontroller board's GPIO pin, which is internally connected to a 12-bit analog/digital converter. The other terminal of the sensor is connected directly to ground on the microcontroller board. Amplification of the piezoelectric signal was not required due to the relatively high voltages produced by the sensor.

The piezoelectric sensor used is the LDT0-028 K, which consists of a 28 μm PDVDF polymer film laminated to a 0.125 mm substrate, which produces voltages within standard CMOS input voltage ranges when deflected directly. The necklace can operate under conditions ranging from 0 to 85 °C. The LDT0 is available with added masses at the tip, which reduce the resonant frequency but can greatly increase the sensitivity of the device. In the configuration without an added mass at the tip, the baseline sensitivity is approximately 50 mV/g, with sensitivity at resonance of 1.4 V/g [20].

4.2. Necklace

Our necklace features a thin, lightweight piezoelectric vibration sensor attached to the inside of the necklace, along with a small microcontroller board capable of sampling the sensor and transmitting the data to a mobile phone via Bluetooth. The hardware is