Intelligent Food Intake Monitoring System

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Abstract— **In this project, we propose a low cost, an open source wearable earmuff based device built using off the shelf piezoelectric sensors that captures chewing sounds and muscle contractions. The captured data is transferred to a hardware platform running a custom developed software to classify and monitor eating habits of the user. The lightweight level quantization algorithm accurately distinguishes between various food types such as hard, soft, extremely hard and extremely soft foods. Further, a web application developed aggregates the food intake recognition results in a user-friendly way and provides feedback reports on healthier eating, such as better eating habits or nutrition balance. We validate our solution with experiments conducted on two subjects consuming a variety of foods and experimental results demonstrate good classification accuracy of the proposed system.**

Index Terms—**Health, Food intake monitoring, chewing sound detection, smart wearable device.**

I. Introduction

Healthy eating is associated with reduced risk for many diseases, including several of the leading causes of death: heart disease, some cancers, stroke, and diabetes. Several activity recognition devices available in the market focuses primarily on exercise and physical activity. In this project we propose a novel system that attempts to classify food types from a device in the form of an earmuff.

A key factor in maintaining healthy life is balancing energy intake and expenditure. Abnormalities in this balance can lead to diseases, such as obesity, anorexia, and other eating disorders, which may furthermore deteriorate into chronic diseases if not seriously treated. A crucial step to solve the problems is to continuously measure daily calorie balance. There are many off-the-shelf solutions to measure calorie expenditure, such as Fitbit, Philips Direct Life, etc. However, continuously and non-invasively monitoring calorie intake remains a challenge. Currently, the common solutions rely on users' self-reports, which are neither convenient nor precise since food intakes are versatile and energy contained in different food may vary significantly. It is highly desirable to develop accurate and easy-to-use methods to monitor the food eaten and predict energy intake. Although some food intake monitoring methods exist, they are either inaccurate or involve complex sensor systems, which limits their adoption in daily life.

Accurate detection of chewing and swallowing activity in a non-intrusive manner is still an unaddressed challenge. To empower people to effectively manage their diet, many Automated Dietary Monitoring (ADM) approaches have been developed. While not focusing on nutritional food analysis, ADM can be used to better understand users' eating habits and to lay the foundation of just-in-time intervention for lifestyle change. For example, an ADM system detecting the eating episodes may trigger a reminder for the user to log the food or even automatically take a photo of what the user is eating to assist dietary recall and assessment. More advanced ADM systems could estimate the consumed calorie based on number of detected bites, or may simply alert the user if eating too fast.

Current technologies for eating pattern detection are either inaccurate or exhibit low rates of adherence to using the technology, due to one or more of these shortcomings:

i) They infer eating indirectly from, for example, hand movements or capturing food images

ii) They are non-pervasive requiring manual data entry or user involvement in capturing data

iii) They are non-wearable, bulky, invasive, or semi-invasive

iv) They exhibit low accuracy in detecting swallows and distinguishing food types.

In this project we focus on automatically detecting eating episodes using wearable sensors, as non-intrusive monitoring approaches. We focus on classifying food types using a novel piezoelectric-based design of an earmuff that is worn around the head. The Sensed data is transferred to a hardware platform running a custom developed software to classify and monitor eating habits of the user. A lightweight level quantization algorithm runs on the hardware device which accurately distinguishes between various food types such as hard, soft, extremely hard and extremely soft foods. Further, a web application developed aggregates the food intake recognition results in a user-friendly way and provides feedback reports on healthier eating, such as better eating habits or nutrition balance. To evaluate our system, experiments are conducted involving 2 subjects to eat several different types of food and data was recorded and evaluated

This report is organized as follows: Section 2 details the proposed system, data collection methods and a concept for food intake recognition suitable for real-time monitoring. Section 3 discusses the classification algorithm developed to recognize eating activity. In Section 4, experimental and evaluation results are discussed followed by the conclusion.

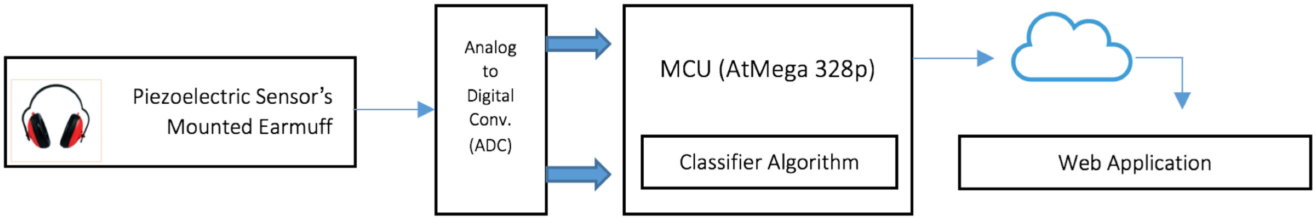

Fig. 1. System Block Diagram

II. System Design

The proposed system consists of a two modules, the sensing module and hardware module which work in tandem to monitor eating habits of an individual. An online web application performs user gives the user feedback and guidance. The system hardware performs eating detection, feature extraction and classification to detect food hardness level and chew rates. This section describes the sensor technology, hardware design and classification algorithms implemented.

A. Sensing Module

The sensing module consists of a pair of piezoelectric sensor, also known as a vibration sensor affixed to an earmuff. The sensors produce a voltage when subjected to physical strain and contact vibrations. The sensor is positioned firmly on the user's cheeks which captures the muscle contraction and motion of the skin during a chewing action performed. in the output voltage of the sensor, when sampled at frequencies at 9 GHz. Figure 1 shows the system block diagram.

B. Hardware Module

The data from sensing module passed to a AtMega328 microcontroller unit which is used for decoding, pre-processing of the sensed data. The sensed data is passed through a 8-bit Analog to Digital Converter present in the MCU at a sampling at 9 GHz. This data is used for detection and classifying the user's eating gestures. This hardware module also consists of ESP8266 Wi-Fi module which establishes a wireless network connection and transfers processed binary data to a cloud platform for further processing.

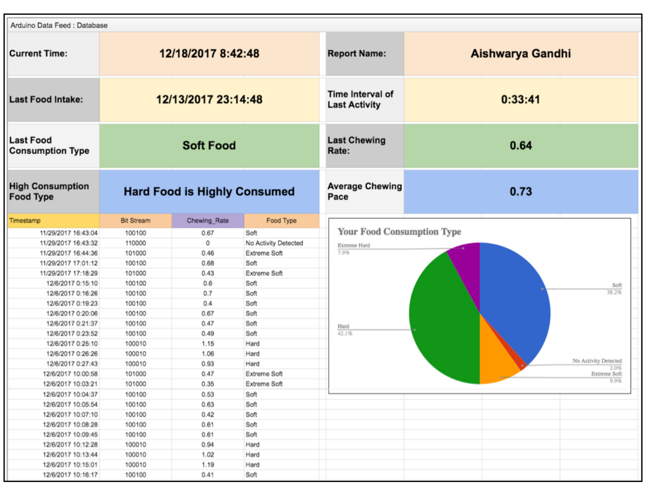

Fig. 2. Web Application Screenshot

C. Web Application

An online application is developed to perform two major roles. First, it receives processed bit-stream sent by the hardware module and stores them to a database. This serves as a data manager and provides an interface to the user. The application extracts the activity type from the bit-steam received and appends a timestamp to it. This acts as the user's record displaying food intake activity database. Second, the application not only provides detailed records (as shown in Figure 2), but also few suggestions on healthier eating habits which are obtained by analyzing the data.

Currently the user feedback includes:

i) Type of food consumed

ii) Chewing frequency

iii) Excessive snacking alert

iv) Interval of food intake

v) Last food intake time

The food type recognition by implementing the main algorithms is detailed in the next section. Figure 2 gives some screenshots of the web application.

III. Food Type Recognition

In this project, food type is categorized into 4 types based on the hardness levels, as shown in Table 1. Food type recognition takes the continuous detection of peaks through a sliding window (every window is 0.5s and the overlap is 0.05s) applied to the waveform captured during the process of eating. Using a level quantization approach, food type and category is recognized for each identified chewing or swallowing event, which is realized by two consecutive steps as explained below.

TABLE 1. FOOD CLASSIFICATION

Category	**Food Subset**
Extremely Soft	Yogurt, Pudding and Soup
Soft	Rice, Bread, Corn Flakes
Hard	Tortilla, Biscuits and Orange Fruit
Extremely Hard	Potato Chips, Tortilla Chips, Walnuts, Peanuts

A. Peak Detection using Sliding Window

The sensed data is buffered locally until a sufficient number of samples have been acquired. Subsequently, a sliding window is applied to generate a new waveform representing the standard

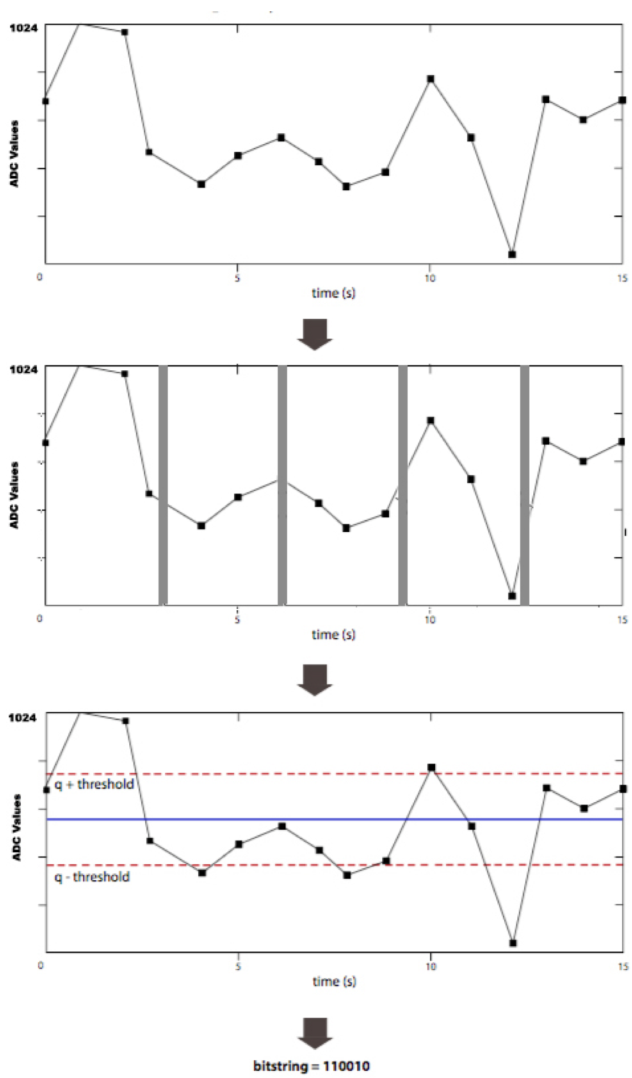

Fig. 1. peak detection from sliding window

deviation of the original data. The swallows are represented in the resulting waveform as peaks, while they may correspond to either peaks in the original data.

The algorithm then proceeds to smooth the waveform by applying a convolution filter, which yields clearly visible peaks representative of each chewing action, while removing noise from the signal. This is represented by the waveform in Figure 3. Consequently, the number of chews is identified by counting the number of peaks, provided there is sufficient spacing between chews.

B. Level Crossing Quantization

Level quantization is a signal processing technique that can efficiently distil the raw peak data to a much smaller and manageable size. For each window the number of peaks that crosses each of the threshold q+ and q- are detected. These values are then used for food type and hardness classification. Graph 3 in Figure 2 illustrates this quantization levels fixed.

C. Food Classification

Food type is classified based on the number of hard chews and soft chews the user makes within a time frame. This is monitored constantly when a eating activity is detected. The peak crossing values from the level quantization is used to classify the hardness of food by referencing a look-up-table. This data is then places in a bit-stream, which is used for uploading data to the cloud server. The bit-stream table is shown in Table 2.

TABLE 2. BIT STREAM

Handshake (MSB)	**No Activity**	**Ext. Soft**	**Soft**	**Hard**	**Ext. Soft** (LSB)
↓	↓	↓	↓	↓	↓
B[0]	**B[1]**	**B[2]**	**B[3]**	**B[4]**	**B[5]**

D. Chewing Frequency Detection

The user's chewing frequency is calculated based on the number of chews per sliding window for a fixed period is calculated. This is the chewing frequency of the user for the particular food being consumed. This data is appended to the bit-stream and upload to the cloud database.

IV. Experimental Results

The system was tested and data are collected from 2 different subjects. The sensor affixed earmuffs were positioned on the subjects loosely touching their cheeks. The system was trained over 10 minutes to fix the threshold values for quantization during which the subjects were asked to push a button every time before they begin their food intake process. This helped us further annotate the data in order to provide truth labels for the user. Each subject consumed four types of food: hard, extremely hard, soft and extremely soft food. Over 10 different types of food, including oranges, potato chips, walnuts, peanuts were used to evaluate our system. The subjects are suggested to reduce the movement of head, speaking, coughing and other activities during the experiments. Note that liquid food activity was not attempted in this project as the system was designed to detect solid foods alone. Future work would include classifying solid food from liquid food with no addition of resources. Our findings currently show that it is challenging to distinguish between solid food types.

V. Conclusion

The goal of this work is to develop a practical solution for automatic detection of eating episodes and also distinguishing various solid food types. We chose a piezoelectric sensor based approach as it achieves a good tradeoff between accuracy and intrusiveness. We developed an embedded hardware to collect food intake sensor data, which is highlighted by a earmuff worn worn by the subject to precisely record muscular contractions during eating in a non-invasive manner. Our results show promise using level quantization algorithm in combination with piezoelectric sensors. We have developed and tested a prototype which has shown the ability to successfully distinguish between 4 different types of solid foods. We show methods of distinguish between hot and cold drinks with an F-measure of 90%. We also show potential for distinguishing between solid food types. As a future work, we intend to expand classification to more food types and liquid foods, while testing in a more free-living environment.

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