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Recognition of Nutrition Intake using MEAS Piezoelectric Sensor

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Abstract*—Food intake levels, hydration, ingestion rate, and dietary choices are all factors known to impact the risk of obesity. This paper presents a novel wearable system in the form of a necklace, which aggregates data from an embedded piezoelectric sensor capable of detecting skin motion in the lower trachea during ingestion. The skin motion produces an output voltage with varying frequencies over time. As a result we propose an algorithm based on time-frequency decomposition, spectrogram analysis of piezoelectric sensor signals, to accurately distinguish between food types such as liquid and solid, hard and soft foods. The necklace transmits data to a smartphone, which performs the processing of the signals, classifies the food type, and provides visual feedback to the user to assist the user in monitoring their eating habits over time.

***Keywords*— Nutrition Monitoring; Wearable Necklace; Spec-trogram Analysis; Piezoelectric Sensor.**

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 [1]. The development and the incorporation of wireless technologies has the potential to address our ultimate goal of enabling healthier lifestyle choices and behavior modification needed to prevent obesity and obesity-related diseases. Much of the wireless technology developed and used in the market, howev-er, focuses primarily on exercise and physical activity [7], [3], [4], [6], [15], [32]. In this paper, we describe a novel system that attempts to infer eating patterns from a device disguised as a necklace.

Automatically and accurately recognizing the type of food in a non-intrusive manner has been for the most part an unaddressed challenge. Most of the 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: 1) they infer eating indirectly from, for example, hand movements or food images [10], [37]; 2) they require manual data entry or user involvement in capturing data [19]; or 3) they are non-wearable, bulky, invasive, or semi-invasive [11]. There is a need for a system that is non-invasive and detects individual's eating patterns, and provides necessary guidance and feedback to the user (see Figure 1). Such a system represents a significant advance in researchers' ability to evaluate the combined impact of adherence to dietary guidelines.

Fig1. . Monitoring eating habits is essential to promoting healthy lifestyle behavior

Current systems either have low accuracy in detecting swallows and distinguishing food types, or must be uncomfortably worn around the neck, which renders continuous use impractical [8]. In this paper, we focus on a piezoelectric based design of a necklace that is not worn tightly around the neck, but rather hangs loosely and falls more naturally right above the sternum [24], [5], [20], [21], [23].

Equally critical to detecting eating episodes is determining whether calories are consumed in solid or liquid form. Studies show reduced ability of the body to compensate properly when calories are consumed in liquid form compared to solid form [30], with the result that some health recommendations now explicitly recommend restrictions on liquid calories consumed (e.g., 2007 report by the World Cancer Research Fund [16]. The proposed system will enable individuals to track the amount of solid vs. liquid consumed throughout the day.

II. RELATED WORK

Various sensors have been employed to identify the volume of food being consumed, and among the most popular methods is acoustic detection [22]. Several systems have identified chewing and swallowing acoustically by placing a microphone near the throat, and using signal processing techniques for classification. For example, Sazanov et al. [35] uses acoustic data acquired from a small microphone placed near the bottom of the throat. However, their system is coupled with a strain gauge placed near the ear which is not practical for daily use. Similarly, Nagae et al. [33] attempts to distinguish be-tween swallowing, coughing, and vocalization using wavelet-transform analysis of audio data. Though results are promising, this technology is targeted towards those who suffer from dysphagia, and identifying the volume or characteristic of food intake is not the focus of their work.

Aboofazeli et al. [2] present another approach to acous-tic swallow detection, achieving basic classification between swallows and breath sounds using a feedforward neural net-work classifier. A manual inspection of their classification results is performed using a spectrogram, which is a basis for the feature extraction technique for food classification used in our work. Makayev et al. apply spectrograms for swallow detection using machine learning algorithms [27], though once again, no classification is performed, and their analysis is limited to identifying swallows. Ultimately, acoustic detection of food intake is promising, but suffers from several serious drawbacks including the interference of background noise, a lack of uniformity between individual eating styles, and no prior work validating the feasibility of classification between different types of food.

Several other methods for detecting swallows have been explored. Amft et al. [9] performs detection of eating and drinking by identifying associated arm gestures using ac-celerometers and gyroscopes. For example, the use of cutlery, spoon, hand, and cup can be identified based on the gestures associated with food intake using these objects. However, the

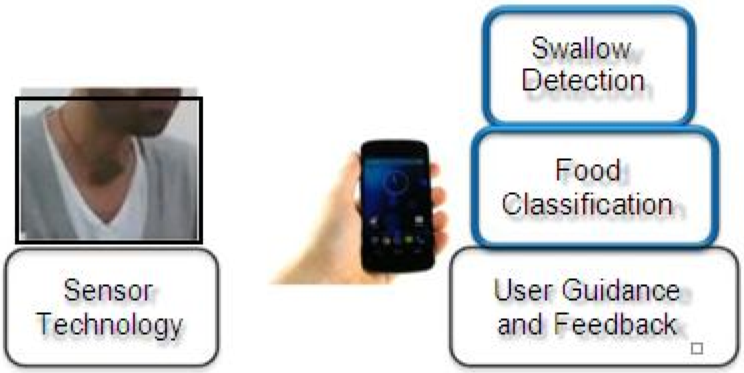

Fig2. The essential components of the system

eating style does not necessarily reveal the volume of food the intake, which severely limits usefulness of this approach. the system is limited to a clinical environment [26]. Piezoelectric sensors, which produce an output voltage

corresponding with the mechanical stress applied to the body of the sensor, are used in countless applications. Recently, they have been applied to problems in the medical domain, such as identifying individual heart beats and respiration [25]. Very few works describe attempts to use piezoelectric sensors for monitoring food ingestion, with several exceptions [13], though evaluation of dysphagia symptoms is the primary objective of their work.

In this paper, we compare the accuracy of classification techniques from a piezoelectric sensor worn around the neck using statistical features extracted in the time domain to a novel spectrogram-based approach which considers time and frequency-based components in tandem. A spectrogram, often used for speech recognition and other countless applications, is a visual representation of the frequency spectrum over time generated using a short-time Fourier transform (STFT) with a fixed window size, the squared magnitude of which yields the spectrogram.

Spectrograms are used to visually represent changes in the frequency spectrum over time, have been applied to countless research problems pertaining to the analysis of acoustic signals. Examples include speech recognition, the identification of animal sounds such as whale vocalizations, and pattern recognition in genome sequences [31], [36], [12]. However, their utility in analyzing piezoelec-tric sensor data has not been adequately explored. The primary novelty of our work is the application of spectrograms for analysis of piezoelectric sensor data in the realm of detection and classification of food ingestion. In this paper we collect statistical features on a spectrogram of swallows to distinguish between solid and liquid foods.

III.NUTRITION MONITORING NECKLACE DESIGN

Our nutrition monitoring system comprises two main components: piezoelectric-based sensor technology, and a smart-phone application that performs data processing, user guidance, and feedback. The smart phone application performs swallow detection, feature extraction and classification to detect swallows. This section describes the sensor technology and user guidance and feedback (See Figure 5). Section IV will further discuss the classification algorithms implemented on the smart phone. Figure 2 provides a component overview of the system.

A. Sensor Technology

A piezoelectric sensor, also known as a vibration sensor, produces a voltage when subjected to physical strain. By placing a piezoelectric sensor against the throat, the muscle contraction and motion of the skin during a swallow is represented in the output voltage of the sensor, when sampled at frequencies as low as 5 Hz. 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 powered by a lightweight lithium-polymer battery. Figure 4 depicts a subject wearing the necklace, and further illustrates each component.

Figure 3 models the piezoelectric sensor as a nonlinear voltage source when subject to mechanical excitation. The data is smoothed using a 90nF filtering capacitor, and a small resistor brings voltage levels to the valid input range of the Analog/Digital converter unit (ADC). After sampling is complete, the data is buffered into SRAM memory, processed, and transmitted. The on-board ADC has a resolution of 10 bits and can convert data at a rate of up to 257 kHz. The offset error, gain error, and absolute error ratings are 1, 3, and 3 LSB volts, respectively. The resolution of the ADC was therefore approximately 15 mV, based on the supported input voltage range. This was sufficient for the purposes of a nutrition monitoring application, as swallows were typically associated with a voltage spike of 50 mV or more. The hardware platform supports an input voltage range of 1.8-3.6 volts. The lithium-polymer battery used to power the device is a 3.7 volt unregulated voltage source with a capacity of 170 mAh and a maximum discharge current of 1 Ampere at room temperature.

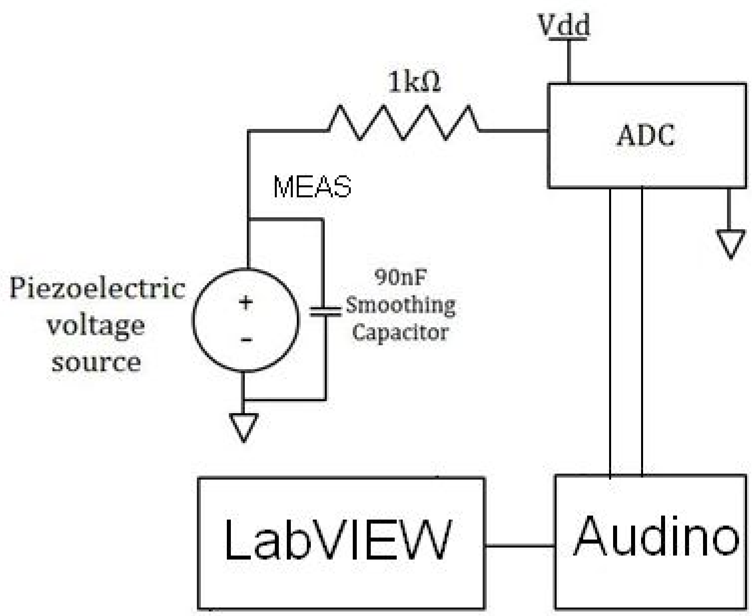

Fig3. Block Diagram- Diet Pattern analyser

The necklace is available in several varieties including a sportsband suitable for athletes and other active individuals, and another targeted towards a more fashion-conscious audi-ence. Because the hardware components of the necklace are very small and lightweight, they can be embedded in several different form factors.

The microcontroller board samples the voltage of the vi-bration sensor at a rate of 20Hz, converting the voltage to a digital signal using the on-chip A/D converter. The data is then buffered and transmitted to a mobile phone. This Arduino-compatible board features a Bluetooth 4.0 LE transceiver on-board, based on the RFD22301 SMT module. The embedded processor is an ARM Cortex M0 with 256kB of flash memory and 16kB of RAM.

B. Device Battery Lifetime

The device battery lifetime depends on many parameters including sample rate, battery capacity, Bluetooth connection interval, and various algorithm parameters such as window size and sample rate. A CR2032 coin-cell battery typically has a capacity of approximately 235mAh. Our experimental simulations reveal that a window size of 10 and a sample rate of 20Hz results in a power consumption of .07 mW, using the Nordic nRF simulation software and a low-power MSP430 microcontroller. This would correspond with a device lifetime of over 6 months. However, the hardware platform used in this paper is not optimized for energy-efficient applications, as the focus is aggregating data for offline processing to evaluate our algorithms.

C. User Guidance and Feedback

This system includes a mobile phone application for data reporting and visualization (see Figure 5). The application displays the estimated liquid and solid volume of the current meal, as well as the daily and monthly total. A reporting tool displays alerts to the user.The mobile application uses the Bluetooth 4.0 LE protocol to receive data from the necklace while maximizing battery life. The data is then processed for swallow identification, classification, and analytics.

IV. ALGORITHM

On data acquired from the vibration sensor and received via Bluetooth. The data is buffered locally until suffient number of samples have been taken. Subsequently, a sliding window is applied to generate a new waveform representing the standard deviation of original data. The swallows are represented in the resulting wave form as peaks, while they may correspond to either peaks or troughs in the original data. The algorithm then proceeds to smooth the waveform by applying a Savitzky-golay convolution filter to increase the signal-to-noise ratio.

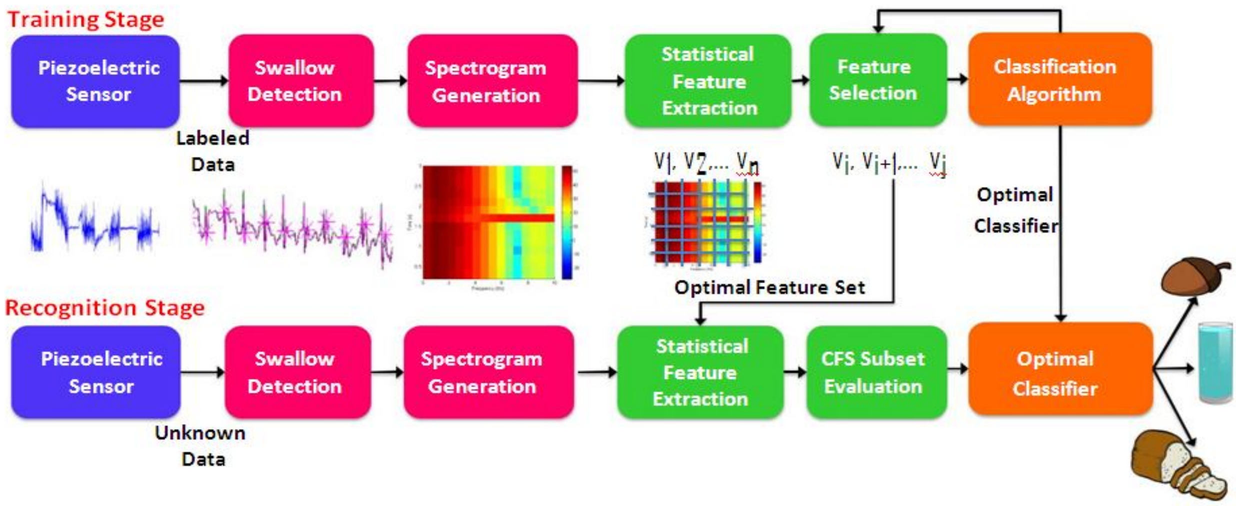

Fig4.system architecture

A.Feature Selection and Classification

The conventional feature selection algorithms usually focus on specific metrics to quantify the relevance and/or redun-dancy to find the smallest subset of features that provides the maximum amount of useful information for prediction. Thus, the main goal of feature selection algorithms is to eliminate redundant or irrelevant features in a given feature set. Applying an effective feature selection algorithm not only decreases the computational complexity of the system by reducing the dimensionality and eliminating the redundancy, but also increases the performance of the classifier by deleting irrelevant and confusing information.

The two well-known feature selection categories are the filter and wrapper methods. Filter methods use a specific metric to score each individual feature (or a subset of features together), and are usually fast and much less computationally intensive. Wrapper methods usually utilize a classifier to evaluate feature subsets in an iterative manner according to their predictive power [17]. We applied the wrapper method, testing on multiple combinations of feature subsets and classi-fiers including: kNN, Bayesian Network, Random Forest. We reduce the dimensionality of the features from $s = 360$ to l, where l depends on the feature selection algorithm used.

V.SIMULATION RESULTS

The piezo electric sensor is placed in the throat region and connected to the audino uno board. The LabVIEW code is written for interfacing the sensor and LabVIEW software. The food pattern for 100 min is taken the biscuit are used as solid diet and water is taken for liquid diet. The graph below clearly indicating the differences in voltage level of the sensor output for different food pattern. For solid food the output is around 15-25 mV and for liquid food it is 5-15mV.

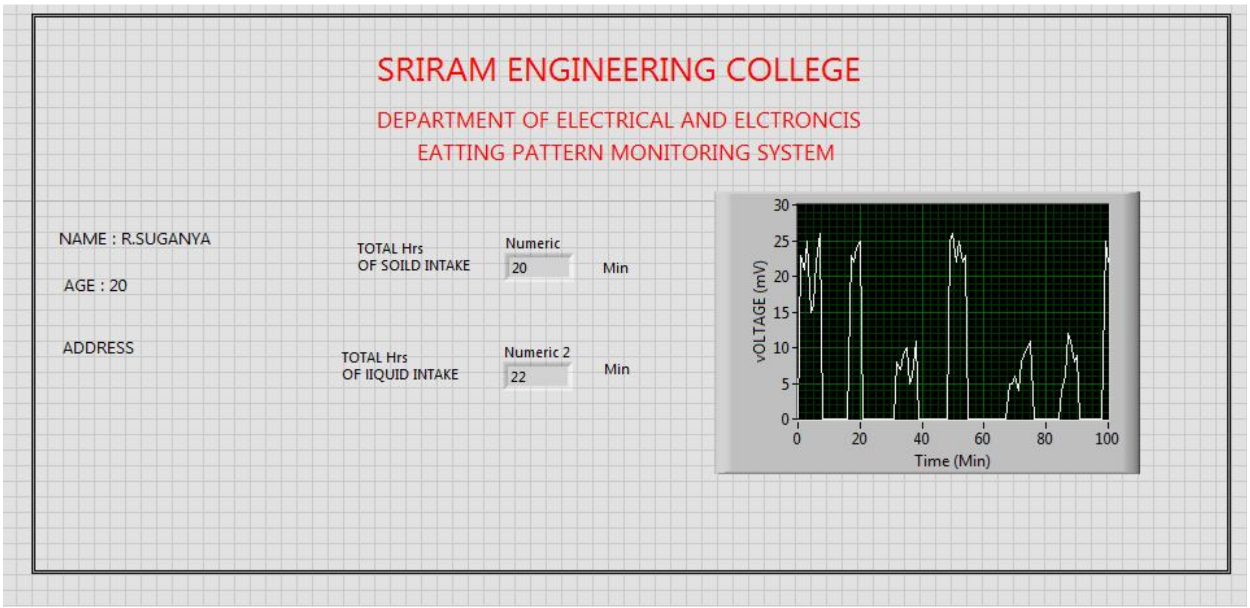

Fig 5 : LabVIEW VI output of the diet pattern analysis system

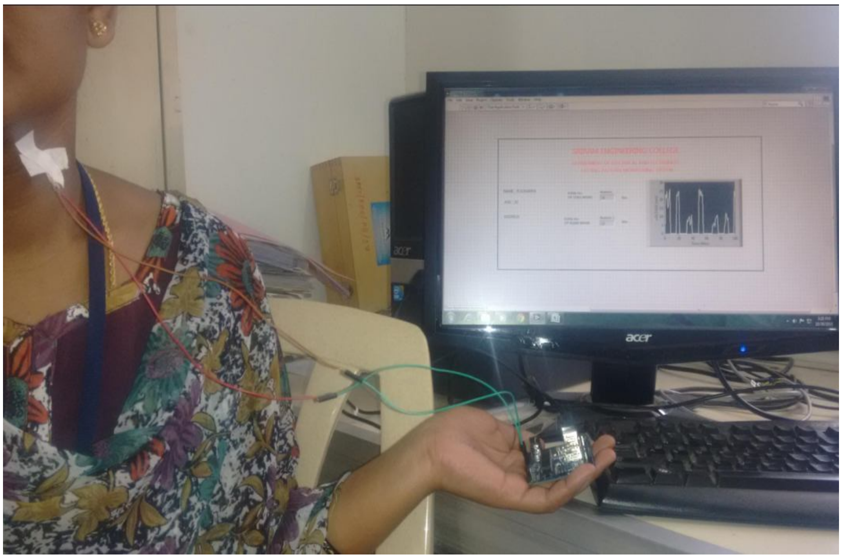

Fig6: Hardware setup for the diet pattern analysis system

VI. CONCLUSION

In this paper we performed classification of swallows using statistical features collected from spectrograms generated from piezoelectric sensor signals. Our results show promise in using spectrogram analysis in combination with piezoelectric sensors as opposed to audio sensors. We have developed and tested a necklace prototype which has shown the ability to successfully distinguish between liquids and solids in two experiments using Random Forest Classifier with 100 trees resulting in an F-measure above 90%. We show a system and framework capable of distinguishing between hot and cold drinks with an F-measure of 90%. We also show potential for distinguishing between solid food types with an F-measure of about 80%. Our future work intends to expand classification to different types of foods, and test in more natural living environments.

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