A WEARABLE SENSOR SYSTEM FOR AUTOMATIC DETECTION, CHARACTERIZATION AND MODIFICATION OF EATING BEHAVIOR

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ABSTRACT

Food intake is the main source of energy and nutrients required to maintain life. The study of food intake patterns and ingestive behavior is critical to human health, as inadequate or excessive energy intake may result in medical conditions such as a decrease in weight or malnutrition, or increase in weight and obesity respectively. Monitoring of ingestive behavior is also important in understanding food intake patterns which contribute to the development of eating disorders such as anorexia nervosa, bulimia, and binge eating. Traditionally, ingestive behavior is assessed and monitored through self-reporting methods such as dietary records, 24hrs recall, and food frequency questionnaire, etc. However, these methods suffer severely from underreporting which may be as high as 50%. Thus, there is a need for the development of solutions for objective, accurate and automatic monitoring of the ingestive behavior of individuals, especially under free-living conditions.

This work investigates the use of wearable sensor system for automatic detection, characterization and modification of the eating behavior of individuals with minimal or no conscious effort from the individuals. Automatic detection of food intake is proposed via monitoring of chewing and swallowing associated with food intake. Chewing monitoring is performed by using a piezoelectric strain sensor. A study was performed for food intake detection via chewing monitoring in free-living conditions for 24 hrs where chewing was captured with a piezoelectric strain sensor. Swallowing was monitored by using Electroglottography (EGG) measurement for monitoring of ingestive behavior during ad-libitum food intake in a controlled setting. This work also presents a new sensor system for which can accurately detect eating episodes in the presence of excessive ambulation.

Research suggests that modifying the chewing behavior might be helpful in reducing the energy intake. This work further explores the potential use of the presented wearable sensor system to provide just-in-time feedback on the progression (based on total chew counts) of a meal and test its ability to reduce the total mass intake.

DEDICATION

This work is dedicated to my beloved family (Daji ao Bebe) and friends.

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CHAPTER 1 INTRODUCTION

1.1 MOTIVATION

The balance between the Energy Intake (EI) and Energy Expenditure (EE) is critical in maintaining weight and healthy lifestyle. Dietary intake in the form of food and beverages is the main source of EI. Energy expenditure comprises of the energy burnt by the body in part for homeostasis (maintaining body functions, basal metabolic rate (BMR)) and the energy required for performing daily activities i.e. EI is a function of dietary intake (both solid food and beverages), whereas EE is a function of resting metabolic rate, the thermic effect of food, and the thermic effect of physical activity. The imbalance between energy intake and energy expenditure can result in the storage of the excessive energy in the body in the form of fats. This energy storage can contribute towards the development of obesity and increase in weight [1]. Thus, it is critical to objectively monitor the EI and EE patterns for better understanding the patterns that might contribute to the development of obesity and increase in weight.

Energy intake monitoring is mainly concerned with eating patterns of individuals and calculating the energy intake of individuals. Classical methods mainly rely on paper-based tracking of the eating behavior of individuals through self-report. These methods include food frequency questionnaires and 24-hrs food recall [2]–[4]. Methods like 24hrs recall rely on the subject's memory where they have to go through personal interviews to quantify their eating episodes; both solid food items and liquids (beverages). Other methods such as the diet records rely on the subject’s ability to keep a record of the time, type and amount of the food consumed over an extended period of time; normally week long [5]. Some methods of self-report include use of electronic record keeping such as phone or PDA [6]–[8]. Research suggests that during self-report; subjects tend to underestimate their intake where the underestimation varies between 10% to 50% of the food consumed [1]. There are a number of factors which contributes toward this inaccurate estimation reporting [9]–[13]. Some of these methods rely on subject's memory, and people tend to forget to report certain items or deliberately do not report certain items. For experiments with extended periods of time e.g. week-long reporting, the procedure is time-consuming and tedious, and people tend to overlook. Self-reporting often requires subjects to visualize and report their portion size. Subjects often make errors in the estimation of portion sizes i.e. they tend to overestimate larger portions and underestimate smaller portions. Therefore, there is a need for more objective and accurate methods for detection and estimation of the eating patterns and behavior of individuals. These methods need to be automatic to reduce participant burden and need to be non-obtrusive and non-invasive. These methods also need to be usable under free-living conditions and need not to obstruct the daily routine of the individuals using them [14], [15].

Our previous research suggests that wearable sensors can be used for automatic detection of eating episodes both by monitoring chewing as well as swallowing [16]. Author suggested a system in [22] to recognize the swallowing sounds captured through a miniature microphone at the throat level. The system was able to detect food related swallows with an accuracy of 84.7% using subject-dependent l models. In [17] the use of a piezoelectric strain gauge sensor was proposed for automatic detection of chewing episodes during experiments performed in controlled laboratory conditions. Twenty subjects were recruited for performing a number of activities including eating. Twenty fold cross validation scheme was used to train support vector machine models and obtained an average accuracy of 80.98%.

1.2 THE BIG PICTURE

Wearable sensor systems can be used for encouraging healthy eating habits by changing the eating behavior of individuals to reduce their energy intake. Most of the work in literature is concerned with the automatic detection of eating episodes. However, for these systems to be usable in free-living conditions there is a need for not only automatic detection of eating behavior but also methods which can modify the eating behavior of individuals. Automatic detection of food intake can be achieved by monitoring chewing and swallowing during food intake. This work suggests use of piezoelectric strain sensor for detection of chewing and Electroglottography (EGG) for swallowing detection. Classification models are proposed to classify segments of the sensor signals either as eating or non-eating. For modifying the eating behavior, we propose using chew count and chewing rate as parameters for quantifying chewing/eating behavior. Research suggests that changing chewing behavior (chewing rate or intake rate) may be helpful in improving the mastication performance and help in controlling the energy intake [18], [19]. Studies have also shown that increased mastication (number of chews) before swallowing of the food might be helpful in reducing the total energy intake during a meal [20]–[22]. It has also been shown that the total number of chews per meal may be used in estimating the energy intake; given the energy density of the food is known [23]. These studies rely on manual counting of chews and chewing rate by either subjects or investigators. We propose using signals from the piezoelectric sensor for automatic chew counting which is preceded by automatic detection of chewing episodes. With automatic detection and quantification of chewing, we propose to provide subject with feedback on their chewing towards a goal. The idea is that with just-in-time feedback, subjects will be provided with clues on how to change their eating, following which they might be able to reduce their final energy intake. Figure 1-1 shows an overview of the proposed system.

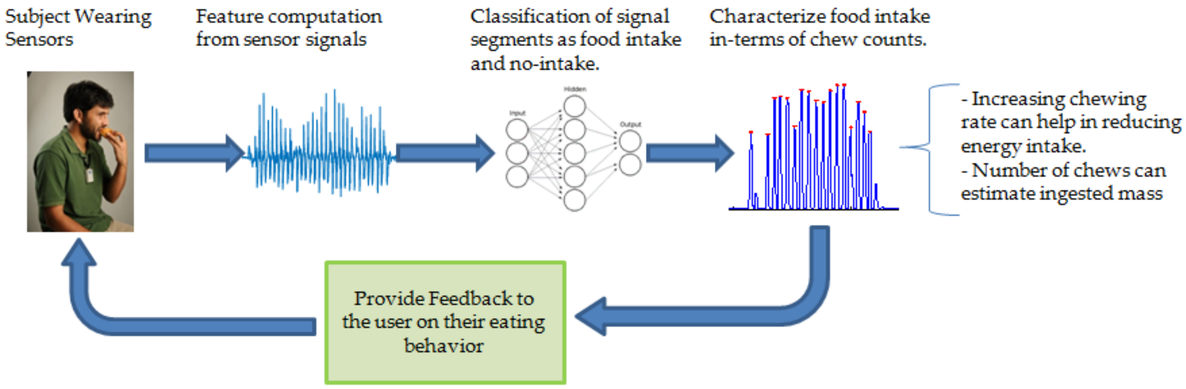

Figure 1-1 Overview of the proposed system. Wearable sensors are used to monitoring the ingestive behavior of the subject. Features computed from the sensor signals are used to train classifiers to differentiate between segments as food intake or non-intake. An algorithm is used to characterize the eating behavior in terms of chew counts which are used to provide feedback to the user on their eating.

CHAPTER 2 BACKGROUND

2.1 EATING DISORDERS AND OBESITY

Food intake patterns and eating behavior are the main contributors that maintain body weight and determine total energy consumption. Excess energy intake can cause an increase in weight. Therefore it is critically important to study the eating behavior of individuals to understand obesity and eating disorders. People suffering from eating disorders experience changes from their normal eating patterns, causing individuals to either have excess or insufficient energy intake compared to their body energy requirements. Some of the common eating disorders are bulimia nervosa, anorexia nervosa and binge eating disorder [27]. Bulimia nervosa is characterized by excessive eating over a period which is usually followed by a period of starvation or other compensatory action [27]. People suffering from anorexia nervosa tend to think they are overweight although in reality they are under-weight and tend to consume food not sufficient for their body needs. Research shows that people suffering from anorexia nervosa have a shorter life expectancy (about 18th times) in comparison to the people who are not suffering from this condition [28]. Excessively large eating episodes characterize binge-eating disorder without any control. People suffering from binge-eating are at higher risk of cardiovascular diseases and higher blood pressure [29].

One of the main cause of obesity is the energy imbalance between the energy intake and energy expenditure i.e. when the energy intake exceeds energy expenditure; the residual energy is stored in the body in the form of fats. Obesity or the level of adiposity is crudely but most commonly measured in terms of the body mass index (BMI) of the individuals and is dependent on the weight and the height of the individuals. Obesity is considered to be an epidemic now and is affecting population all over the world. Its considered to be the 5th largest cause of preventable deaths worldwide [22],[23]. According to WHO, a sharp increase has been seen in people suffering from obesity in last few decades (it has doubled since 1980) and its impact population in both developed and under-developing countries [30]. Obesity can results in other medical conditions such as type 2 diabetes mellitus, heart disease, high blood pressure, cardiovascular disease, different types of cancer, , asthma, infertility, and depression [12], [21]–[23]. Like other developed and under-developed countries, USA is also suffering from obesity epidemic where all age groups (children, adolescents and adults) are suffering from higher level of adiposity. According to National Health and Nutrition Examination Survey (NHANES), 69% of Americans are either overweight or obese. In the adult population, the prevalence of obesity is about 35% whereas in children it's about 17% i.e. about 78 million and 12.5 million adults and children and adolescents, respectively are obese [35], [36].

Traditionally three different methods are employed for treatment of increase in weight and obesity i.e. surgery, pharmacology, and behavioral change. Surgical procedures such as gastric bypass, gastric banding, and laparoscopic cholecystectomy have shown promising results [37], [38] but are used as last resort in patients where other methods have failed, and subjects are extremely obese (BMI of 40 or higher or having BMI of over 35 and at least two obesity related health conditions). Pharmacology based methods rely on the use of medication to reduce appetite, decrease nutrient absorption, or increase thermogenesis [39]. Medication along with lifestyle changes can be helpful for individuals who have been unsuccessful in reducing weight with exercise and diet alone. Some of these medications have shown negative side effects on the human body (e.g. cardiovascular heart disease, cataracts, and hemorrhagic strokes). Behavioral weight loss methods involve increasing EE, decreasing EI, and altering behavior [12], [40]. These methods rely on the ability of users to accurately track the energy intake and energy expenditure. Commonly used for dietary monitoring are food frequency questionnaires, and 24-hour dietary recalls. A limitation is the burden posed to the participants as their active involvement is required in reporting their daily intake [10], [41]. These methods are subjective and usually results in erroneous estimations of portion sizes [42]. Women and overweight and obese individuals are more prone to under reporting compared to other demographics and is also associated with other factors such as education level, social class, physical activity level and dietary restraint [43].

With the recent developments in the wearable technologies, there has been increased interest in developing sensor systems and pattern recognition algorithms for automatically detecting and quantification of eating behavior [14]. The rest of this chapter provides a summary of the methods relying on sensor system for automatic detection of food intake.

2.2 AUTOMATIC MONITORING OF INGESTION BEHAVIOR

We define the Monitoring of Ingestive Behavior (MIB) as the use of sensor systems which are either worn by the users or are present in the environment around the users, to automatically detect the eating episodes and to collect information about the eating behavior of the individuals. In order to assess the eating behavior of individuals, a number of parameters need to be considered; such as the type of food, energy content of the food, time of the eating episode, duration of the meal, volume and meal size as well as the microstructure of the meal e.g. chewing, oral bolus formation, tongue activity and swallowing etc [44]. Currently, there is not a single system which can track all these aspects of the meal. Most of the recent works have been limited to the development of sensor systems and related algorithms for automatic, accurate and objective detection of eating episodes. Consumption of food usually involves a bite, followed by some chews and ends with one or more swallows. On-body sensor systems utilize one of the stages of eating for recognition purposes such as for detection of bites, hand gestures are used whereas for chewing; jaw movements are utilized and for swallowing, the swallowing sound or the movements of the larynx are used as indicators of eating. Sensor systems which are placed in the surroundings of the users, rather than on-body mostly utilize camera systems.

2.2.1 CAMERA-BASED SYSTEM

With current advancements in image processing and computer vision techniques, some researchers have used these algorithms for MIB by using Smartphone cameras and related algorithms. Chen et al. [45] proposed an image-based dietary assessment system where 3D/2D model for image registration was used to estimate food volume from a single-view 2D image containing a reference object. Segmentation of the food from the background images was achieved by using Otsu's threshold and morphological operations. Food volume was estimated from user selected 3D shape models. In [46], [47], researchers presented a system of food recognition system coupled with nutrition information to estimate energy intake. A Smartphone application was used to compute the volume of food to estimate caloric intake. Wu and Yang [48], proposed a system where food type was recognized from a web camera and calories were estimated based on the nutritional information of the recognized food. Some of the other systems which rely on computer vision techniques to recognize food content and estimate portion size and meal contents are given in [38]–[41]. These systems still rely on users for taking pictures and inputting all the related information.

2.2.2 GESTURE-BASED SYSTEM

The first stage of food intake involves taking bites of food. Some hand/wrist-worn wearable sensors have been proposed for monitoring food intake; including accelerometer, gyroscopes, and smart watches. Dong et al. [28]–[30] proposed the use of a wrist-worn device (in the form of a watch) to track wrist movements associated with food intake and were able to detect and counts bites taken during a meal. They were also able to differentiate between meals and snacking in free-living conditions [55]. Amft et al. [56], [57] used a wrist-based acceleration sensor for detecting drinking activities, the type of container used and the fluid level. Fetch and sips motions based on the acceleration were studied. In [58], a wearable sensor system with five inertial sensors located on the wrists, upper arms and upper torso was proposed. Their research describes motion gestures based on the particular utensil used, establishing four gestures (cutlery, drink, spoon, and hands). They proposed the use of two-stage approach; where in the first stage they preselected signal sections that are likely to contain specific motion events. In the second stage, preselected signal sections were classified using Hidden Markov Models. In [59], researchers used a 3D accelerometer on an off-the-shelf Smart-watch. They used Random Forest for classification of hand gesture movements into eating and the non-eating episode in two free-living studies with F1 scores of 76.1% and F1-score of 71.3%. A similar system was used in [60]. Some researchers have suggested wearing audio recording devices on the wrists to record audio and use machine learning and pattern recognition algorithms to detect eating episodes [61], [62]. Wrist based wearable sensor systems are the most natural option, but they are relatively inaccurate compared to the other food intake monitoring systems. These rely on specific wrist movements and, therefore, are prone to false positives.

2.2.3 SWALLOW-BASED SYSTEM

In food intake, a chewing sequence is usually followed by one or more swallows. Therefore, swallowing can also be used as an indicator of food intake. During food intake, the swallowing process involves the passage of a bolus of food or liquid from the mouth to the stomach and involves contraction and relaxation of muscles of the tongue (oral preparation), pharynx (the pharyngeal) and esophagus (esophageal phase) [63]. The first phase is mainly associated with the chewing whereas the other two stages involve muscle contraction and relaxation which takes food from mouth to the stomach. The wearable sensor can be employed to monitor these muscle contractions and relaxations for detection of food intake. A number of sensor modalities such as microphones placed in the ear (to capture swallowing sounds) or on throat or surface electromyography (to capture variations in the muscles patterns) have been proposed for detecting swallowing in food intake.

Speech based approaches can be used to capture swallowing sounds produced when a bolus of food (both solid and liquid) in the pharyngeal phase passes through the pharynx. A number of different locations can be used to capture this sound such as a miniature microphone placed in the ear, on the mastoid bone, or over the laryngopharynx. In [64], researchers used two microphones embedded in an elastic band which was placed over the throat. Use of wavelet decomposition and high-pass filter were explored for analysis of swallowing sounds. Other researchers have proposed similar system [16], [65]–[67] where miniature microphones were placed on the laryngopharynx for automatically differentiating between swallowing sounds from other activities. They showed that such a system could be used for differentiating between different food types solid and liquids and estimate the ingested mass. Other researchers have [68] used an in-ear microphone along with a reference microphone to capture swallowing sound and environmental noise. They used the system to differentiate between seven different solid foods and two different beverages using a finite-state grammar decoder based on the Viterbi algorithm. In a similar study [69], subjects wore a high-fidelity microphone around the neck to record acoustic signals. Hidden Markov Models were used to detect chewing and swallowing events, next a set of time and frequency domain features along with nonlinear features was computed. Acoustic based approaches for detection of swallowing usually require a reference microphone to differentiate between sound originating from swallowing and other acoustic artifacts such as environmental noise.

The passage of a food bolus through the pharynx can be used as another indicator for the detection of swallowing. One approach is to use Electroglottography device (EGG) [70] which measures the variation in the transverse electrical impedance across the neck at the larynx level. Speech and swallowing disorders have been studied using EGG [63],[64]. The assumption is that the passage of the bolus will cause significant variation in the transverse impedance compared to the baseline and those variations can be captured through an EGG device and can be used as an indicator for food intake monitoring. A similar approach is to use EMG and bio-impedance signals [73] for detection and evaluation of swallowing. A piezoelectric sensor placed on the throat can also be used for this purpose. A piezoelectric strain sensor placed against the throat will be subjected to physical strain during muscle contraction and relaxation caused by swallows. A system using this approach in the form of a necklace has been proposed [74], [75]. These systems are virtually insensitive to the environmental noise. But these systems are not able to reliably distinguish swallows from similar head and neck movements and, therefore, cannot be used in free-living conditions [76].

2.2.4 CHEWING-BASED SYSTEM

Chewing is one of the most prominent parameters for eating solid food. A number of sensor modalities and locations have been proposed automatic and objective monitoring of chewing. These include conduction microphone to capture chewing sounds where the microphone are placed in the outer ear or on the throat, or piezoelectric sensors placed either on the throat or on the jaw to capture chewing vibrations caused at the skin surface during food intake, or the accelerometer sensors placed on the jaw to capture jaw motions during chewing.

Amft et al. used a conduction microphone placed in the outer ear canal to capture sounds produce during chewing of the food and used those signals to classify four different food types using decision trees [77]. In an extended work by the same authors; the conduction microphone was incorporated into an ear-pad. An acoustic transducer was used to capture vibrations caused by chewing of food [78]. Spectral analysis was used in combination with food texture clustering to classify 19 foods. Researchers in [79], presented the prototype of a Bluetooth in-ear conduction microphone to capture chewing sounds. In the proposed method a two stage recognition algorithm was used for chewing recognition; the first stage used log energy of 20ms frames of the signal combined with a threshold, to separate chew-like signals. The second stage is the chewing sound verification stage where (Linde-Buzo-Gray) LBG codebook [80] training algorithm with Marginalized Corrupted Features (MCF) was used to classify the chewing sounds. Researchers in [81] proposed a portable, wearable sensor system where they used a conduction microphone (Vibraudio EM20 from TEMCO corp.) placed in the user's ear for capturing internal body sounds (chewing sounds during food intake) and a condenser microphone (WM-E13U from Panasonic corp.) for monitoring of surrounding sounds. A portable IC recorder was used to sample both sensors at 48 kHz. They used k-th Nearest Neighbor algorithm (KNN) to classify activities such as eating, drinking and speech. In [82], [83], a similar two microphone system was used where the first microphone (in-ear) is used to capture chewing sounds whereas the second microphone was used to capture environment sounds. In this work, automatic food intake recognition was achieved through the use of adaptive sound models of chewing using the maximum a posterior estimation algorithm (MAP). One potential limitation of the use of microphones for chewing sound detection is that these systems are impacted by the presence of environment sound artifacts. Therefore, they usually use two microphones where one is used for capturing environment noise whereas the second is for monitoring chewing. This poses a serious limitation as it hinders the usability of such systems in free-living conditions. As a result, most of these experiments are performed in controlled laboratory conditions.

Activation of the mastication muscles during chewing can be measured by using surface electromyography (sEMG) [84]. Multi-point sheet type sensors [85] and strain abutments [86] have been proposed for measuring the chewing and bite forces. However, these sensors are likely to produce variations in individuals' normal mastication patterns because they are placed between the teeth. Another possibility is to measure the deformation in the ear canal walls due to chewing activities during food intake. In [57], a wearable sensor system in the form of an earpiece was proposed which included three infrared proximity sensors placed orthogonally with respect to each other to allow for a wider coverage of the ear canal. The system was called Outer Ear Interface (OEI) which was used to measure the magnitude of deformations in the ear canal during speech and mastication activities with an accuracy of 95.3% using subject dependent HMM models. These experiments were performed in laboratory settings. In an extended work [87] by the same authors, subjects used the system in free-living conditions with 6 subjects for 6 hours performing normal daily activities. OEI classified five-minute segments of time as eating or non-eating with 93% accuracy using subject dependent models. Other systems have been proposed which rely on the movements of the jaw muscles during mastication. In [88], the use of a single axis accelerometer placed on the temporalis was proposed to monitor chewing during eating episodes in a laboratory experiments. Six different classification techniques were compared where weighted SVM achieved the highest accuracy of about 96% for detection of eating episodes.

Another possibility is the integration of a camera system which is triggered by one of the approaches mentioned above to take pictures of the food consumed by the subject [89]. This will provide extra information about the meal content without putting an extra burden on the user in terms of user input to start the camera like cell phone cameras [90]. One example of such a system is presented in [91], where a Bluetooth headset consisted of a microphone for capturing chewing sounds and a camera which was triggered/activated when the presence of chewing was detected. The camera was triggered to log the food intake activities.

Recent advancements in the computer vision and image processing systems have encouraged researcher for using image recognition algorithm for chewing monitoring. In [92], researchers presented a computer vision system where the proposed algorithms automatically detect chewing behavior from surveillance videos of people eating. They proposed a multi-stage algorithm where first mouth region is detected, which is followed by computation of spatiotemporal frequency spectrum of the small perioral region and spectral data is then analyzed for the presence of periodic motion (to characterize chewing). A similar system is proposed in [93], where chewing events are automatically detected from the surveillance videos of the subjects. They used Active Appearance Model (AAM) to track participant's face from the video sequence , and the observed variations in the AAM parameters were used to detect chewing. Binary Support Vector Machines were used to differentiate between chewing and other activities. On a dataset consisting of 37 subjects, the proposed system was able to get an agreement of 93% for automated chewing detection. The use of computer vision techniques combined with surveillance videos presents a system which poses the least amount of burden to the user. Users are not required to wear any sensors and are not required to record their eating patterns. The main limitation of such a system is that users are restricted to specially equipped spaces where they need to be constantly in the view of the camera. Such a system will fail if the user is out of the view of the camera. Another limitation is that these systems cannot be used in free-living conditions. Also, computer vision and image processing algorithms are highly sensitive to the quality of images captured e.g. such a system may fail in low lighting conditions.

Mastication of the food produces vibration at the skin surface which can be captured by a piezoelectric strain sensor placed on the jaw below the ear [94]. During food intake, mastication produces rhythmic up-and-down and side-to-side jaw movements which produce strong signals in the frequency range of 1.25 to 2.5 Hz. Characteristic jaw movements seen during chewing are not prominent during other activities such as walking, talking or inactivity. Therefore, these movements can be captured by using piezoelectric strain sensors to differentiate between chewing and other activities. Features computed from piezoelectric strain sensor signals were used to train subject independent SVM models to differentiate between episodes of chewing and non-chewing with an accuracy of 81% with a time resolution of 30 seconds. This work was extended to monitor food intake in free-living conditions for 24 hrs on a population of 12 subjects where subjects were asked to perform daily activities including sleeping [95]. Signals were collected from 3 different sensors; including a piezoelectric strain sensor. Subject independent ANN models were able to differentiate between eating and other activities such as walking, talking, inactivity and other daily activities with an average accuracy of 89%. The proposed system has been used in other studies to evaluate the feasibility of the system in multi day experiments as well as for selection of optimal feature set [17], [96], [97].

This work proposes a framework of using a wearable sensor system for modification of the eating behavior of individuals by feedback from the sensor system on their eating patterns. The first step in the proposed method is to detect eating episodes; which is achieved through monitoring of chewing and swallowing. Use of chewing has been explored by using a piezoelectric strain sensor for capturing the jaw movements associated with food intake [95]. In this work, the use of Electroglottography (EGG) is proposed for monitoring of swallowing by measuring the changes in the electrical impedance across the larynx. Chapter 3 presents work published on the use of Electroglottography for monitoring of swallowing. This work was published in Physiological Measurement by IOPScience. Once eating episodes are identified, next step is the characterization of those eating episodes. We propose to characterize eating behavior in terms of chewing as previous research suggests that chewing can be used as an indicator for estimation of mass ingested by individuals [23]. Chapter 4 presents a semi-automatic approach for the use of a piezoelectric sensor for quantification of sucking behavior infants. This work was published in Journal of Healthcare Engineering, Multi-Science Publishing. Chapter 5, presents a method for automatic detection and characterization of chewing. This work was submitted to Journal of Biomedical Signal Processing and Control. Chapter 6 presents a new wearable sensor system, signal processing and pattern recognition which has the ability of detecting food intake in the presence of motion artifact such as walking and can accurately quantify chewing segments. This work is under review in Journal of Biomedical Health Informatics. Chapter 7 represents a multiple activity recognition system which can recognize eating episodes and physical activity and has been submitted to Sensor's Journal. Chapter 8, explores the use of just-in-time feedback from the sensor system towards a target and explores the feasibility of using the sensor system as an interventional device that could potentially be utilized in a just-in-time adaptive intervention for reducing the energy intake. This work is under review in Journal of Obesity.

CHAPTER 3 A NOVEL APPROACH FOR FOOD INTAKE DETECTION USING ELECTROGLOTTOGRAPHY

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Automatic detection of eating episodes is the first step in systems designed for monitoring of the eating behavior of individuals. This work proposes to use swallowing as an indicator for food intake detection. This chapter introduces the use of Electroglottography for swallowing detection by measuring the impedance across the larynx.

3.1 INTRODUCTION

An accurate and objective monitoring of ingestive behavior is particularly important for research in populations suffering from eating disorders and obesity. An eating disorder is a medical condition that causes a serious disruption in a person’s diet. People suffering from eating disorders have abnormal eating behaviors due to the consumption of either insufficient or excessive amounts of food. Common eating disorders include anorexia nervosa, bulimia nervosa and binge-eating disorders [1]. People suffering from anorexia nervosa are 18 times more likely to have nearly death than the general population [2]. People with binge-eating disorders tend to develop severe medical conditions such as cardiovascular disease and high blood pressure [3]. Obesity is a condition of having excess body fat and is considered to be one of the major contributors towards the decrease in life expectancy in the USA [4]. According to the World Health Organization (WHO), overweight and obesity are the 5th major cause of death worldwide with 2.8 million people dying each year [5]. The study of ingestive behavior is particularly important to identify and diagnose food intake patterns associated with eating disorders and obesity. However, an accurate dietary assessment has been difficult to achieve due to the reliance on self-reporting and the lack of tools for objective monitoring of eating in free living conditions.

Food frequency questionnaires, food records and random 24-hour dietary recalls are commonly used methods for dietary monitoring that require active participation of the subjects in reporting their daily intake [6], [7]. These methods are subjective and inaccurate mainly due to incorrect reporting of foods consumed, erroneous estimations of portion sizes and failure to report certain foods [6], [8]. A potential solution based on electronic devices was presented to overcome self-reporting problems. Some of the techniques developed were based on the use of a mobile phone equipped with a digital camera [9]–[11]. Subjects took pictures of the meal before and after eating while a computer algorithm was developed to determine the volume of food consumed using those pictures. These techniques may improve the accuracy of food intake monitoring, but they still require active participation of the subjects.

Automatic methods for recognition of food intake were developed based on the identification of important features related to a particular stage of the food consumption process: hand gestures, bites, chewing and/or swallowing [12]–[19]. In most of the proposed methods, minimal participation of the subjects is required, thus reducing the recording burden, however, accuracy of food intake detection is still far from desired. A possible reason is that many methods of food intake detection are based on acoustic signals [19]–[21] that suffer from sensitivity from external noise, which can hamper the performance in realistic environments outside of quiet laboratories. For example, [20] used recognition of swallowing sounds recorded at the throat level using a miniature microphone. Individual swallows related to food intake were detected with an accuracy of 84.7% using individual models, with the experimental conditions including simulated noises of urban environment. An attempt to use noise cancellation techniques to improve the accuracy of food intake detection [19] used sounds recorded by a microphone located in the outer ear canal and a reference microphone to cancel out external noise. This method was able to detect food intake with an accuracy of 83% and to classify among 8 different food items with an accuracy of 79%. The relatively low accuracy of acoustical methods suggests that a methodology tolerant to significant levels of external noise would be of great interest for practical applications of food intake monitoring.

This paper presents a novel approach for food intake detection based on Electroglottography. An Electroglottography (EGG) device is impervious to external noise and operates by measuring the transverse electrical impedance across the neck at the larynx level. An EGG signal is recorded by sending and receiving a high frequency signal through guard-ring electrodes placed at the larynx level. For that reason, EGG has been widely used for speech and swallowing analysis [22]–[25]. Excitation frequencies ranging from 300 kHz to 5 MHz are generally used, so that the current avoids the less conductive skin layer without the use of an additional conductive paste [26]. Typical use of guard-ring electrodes provides a reference for noise reduction without the need of an extra electrode. In speech studies, EGG is used to monitor changes in the electrical impedance across the larynx due to the changes in the contacts in the vocal folds which are separated by glottis. During phonation the impedance across the larynx increases as the vocal folds move apart and decreases when the vocal folds come closer. In swallowing studies, EGG is used to monitor submental muscle activity and laryngeal elevation as suggested by [27]. Similar action of laryngeal elevation and submental muscle activity takes place when a bolus of food passes through larynx during food swallowing, thus, EGG can potentially be used for food intake detection by measuring changes in the neck impedance. According to authors' knowledge, no one has reported the use of EGG for food intake detection. As a side note, Electroglottography should not be confused with Electro-gastrography (measurement of electrical and magnetic fields of stomach muscle) that has the same acronym (EGG) and was suggested but not studied for monitoring of food intake in [28].

The goal of this study was to evaluate the feasibility of using an EGG device and the related pattern-recognition methodology to detect periods of food intake by comparing the performance of the proposed method with the acoustical method in a controlled lab environment. The subsequent sections of the paper are organized as follows: The methods section provides a detailed description of data collection protocol and both signal processing and pattern-recognition algorithms. Results of the food intake detection by EGG and acoustical methods are presented in Section 3. Section 4 gives a detailed discussion of the results and compares the performance of the proposed system with other food intake monitoring systems found in the literature, which included different sensor modalities for detection of food consumption. Finally, Section 5 concludes the paper.

3.2 METHODS

3.2.1 DATA COLLECTION

Data from a group of 30 healthy subjects were collected for this study. Data from 5 subjects were later discarded due to equipment failure (i.e., electrode detachment) and operator's error during experiments (i.e., failure to center the video camera for subject observation). The remaining population consisted of 13 females and 12 males (average age of 29 ± 12 y, range: 19-58 y). The average body mass index (BMI) of the population (in kg/m^2) was 27.47 ± 5.45 (range: 20.5-41.7), which represented a range from normal weight to severely obese individuals. Subjects did not show any medical condition that affected their ability to eat. An Institutional Review Board approval for this study was obtained from Clarkson University, Potsdam, NY, and all subjects signed an informed-consent form before participation.

Each subject came to the laboratory in four separate visits, all of which occurred at the same time of day (breakfast, lunch or dinner). Each visit was divided into three parts:

a) An initial resting period of 5 min in which subjects remained seated in a relaxed position.

b) An unlimited food intake period during which subjects were asked to consume a meal.

c) A second resting period of 5 min identical to the first one.

Subjects self-selected two meals (different in content and size) from the menu of one of the food courts at Clarkson University. The first meals election was served in 3 of the visits and the second meal selection was served in the remaining visit. The consumption of the whole meal was not required, and there were no restrictions in the manner and order of food consumption. Contents of meals selected by subjects consisted of bananas, cereals, muffins, milk, coffee, toast, bacon, and different juices for breakfast. For lunch, subjects selected such foods as stir fry, chicken tenders, fries, chips, turkey sandwiches, pizza, burgers and salads with a wide variety of beverages. For dinner meals, subjects consumed items like corn, chef's salad, pizza, yogurt, spaghetti and meatballs, apples, cookies and brownies, along with soft drinks.

Subjects were allowed to talk, cough, clear throat, etc. and perform body movements while remaining seated (stretch, nod, turn head, etc.) at any time during the experiment, thus exposing the sensors to a variety of acoustical and motion artifacts not originating from food consumption.

A multimodal sensor system was used to monitor the subjects during the entire course of the experiment [29]. A commercially available portable digital Laryngograph (EGG-D200 from Laryngograph, Ltd) was used to record the EGG signal $\mathrm{EGG}(t)$. The excitation frequency was 3 Mhz and two gold-plated guard ring electrodes captured $\mathrm{EGG}(t)$ within a 1 Hz to 10 kHz frequency range, which was then amplified in the Laryngograph unit. EGG electrodes were placed in contact with skin on both sides of the larynx using a collar. This is a standard location implemented in most of the swallowing studies [22]. A miniature throat microphone (IASUS NT) placed over the laryngopharynx was used to capture swallowing sounds. This microphone and location provided higher sensitivity to swallowing sounds and a lower sensitivity to noise when compared to other microphones and locations studied for food intake detection [17]. The microphone had a dynamic range of 46 +/- 3 dB with a frequency range of 10 Hz to 8 kHz. The acoustic signal ($\mathrm{MIC}(\mathrm{t})$) was pre-amplified by a custom-designed amplifier. Figure 3-1 (left) shows the EGG electrodes and the throat microphone attached to a neoprene collar (paintball neck protector from JT Sports) for a comfortable wear and breathability. Figure 3-1 (right) show a subject wearing the collar equipped with the sensors. Both $\mathrm{EGG}(\mathrm{t})$ and $\mathrm{MIC}(\mathrm{t})$ were sampled at 44100 Hz with 16 bits of resolution using a USB-160HS-2AO data acquisition card (Measurement Computing) and stored on a computer. Figure 3-2 shows an example of $\mathrm{EGG}(\mathrm{t})$ for a whole experiment. Approximately 60 hours of EGG and acoustic data were obtained from 25 subjects. Approximately 9 hours of data belonged to food intake (bites, chews and swallows).

A digital camera (PS3Eye camera, Sony) captured video of subjects time-synchronously with the sensor signal collection. The video stream and the sensor signals were then used to annotate periods of food intake by means of custom-designed LabVIEW software [17]. In the annotation process, a class label (Ti) was assigned to each sample of the sensor signals, where $\mathrm{Ti} \in \{$"no food intake," "'food intake"$\}$. For solid food items, a period of food intake involved a sequence of events including bite, chews and one or more swallows. For liquid items, a period of food intake involved a sip from the container and one or more swallows. Sensor signal epochs were annotated based on the presence of one of these events instead of the presence of individual swallows. A trained human rater reviewed the acquired video and sensor signals to identify when those events occurred in the experiment and to manually mark them in both $\mathrm{EGG}(\mathrm{t})$ and $\mathrm{MIC}(\mathrm{t})$. Inter-rater reliability of this annotation methodology was demonstrated in a previous study [17]. The remaining parts of the signals, including spontaneous swallows (saliva swallows), were marked as "no food intake". The annotated data was used as the gold standard for the development of automatic food intake detection algorithms. Figure 3-2 shows a segment of $\mathrm{EGG}(t)$ during periods of resting and food intake along with an example of the food intake annotation. The resulting annotated data was used for training, validation and performance evaluation of the of the pattern-recognition algorithms.

Figure 3-1 Left: EGG and swallowing sensors attached to a neoprene collar. Right: Collar was fastened to the neck of the subject using flexible Velcro.

3.2.2 FEATURE EXTRACTION AND SELECTION

Since both $\mathrm{EGG}(t)$ and $\mathrm{MIC}(t)$ carry similar spectral contents (from 1 Hz to 10 kHz for EGG and 10 Hz to 8 kHz for acoustical signal), they were processed with the same preprocessing and feature-extraction algorithms, thus eliminating any variability in the recognition results that could be attributed to the difference in the processing algorithms. First, signals were normalized with respect to their medians to account for variations in the signal amplitude among visits. Signals were then divided into non-overlapped time segments of fixed-time length referred to as epochs. Selection of the epoch length is important as it controls the time resolution of the decision stream. Using short epochs leads to a fine time resolution, which can help in the detection of short periods of food intake such as snacking. On the other hand, long epochs involve more data in the decision process, which may result in models with better performance but with poorer time resolution. Since the average frequency of spontaneous swallowing during waking is approximately 2 swallows per minute [30], the food intake detection based on monitoring of swallowing pathway need to recognize an increase in swallowing rate (and corresponding changes in sensor signal) due to food consumption. Thus, the time resolution of such methodology is defined by the events with the lowest frequency (spontaneous swallowing) and an epoch length of 30 s was used as good trade-off between recognition accuracy and time resolution, capable of detecting small intake periods such as snacking. More information on epoch size selection and it relation to swallowing frequency may be found in [14], [17], [30].

The division of the signal into epochs resulted in some data samples labeled as food intake and some data samples labeled as no food intake within the same epoch. To tackle this issue, the 50% determination rule was implemented to assign a class label Tεi {'+1', ' -1'} to each 30s epoch. An epoch was labeled as “food intake” (Ti = +1) if at least 50% of the data samples within the epoch belonged to food intake; otherwise the epoch was labeled as “no food intake” (Ti = -1), which means that if in an epoch, there was food intake of 15 s or more, the epoch was labeled as food intake. This ensured the detection of short intake periods. For feature computation, each epoch $x(n)$, (where $n = 1,2, \dots, N$ is the total number of samples within the epoch), was decomposed using a discrete wavelet transform.

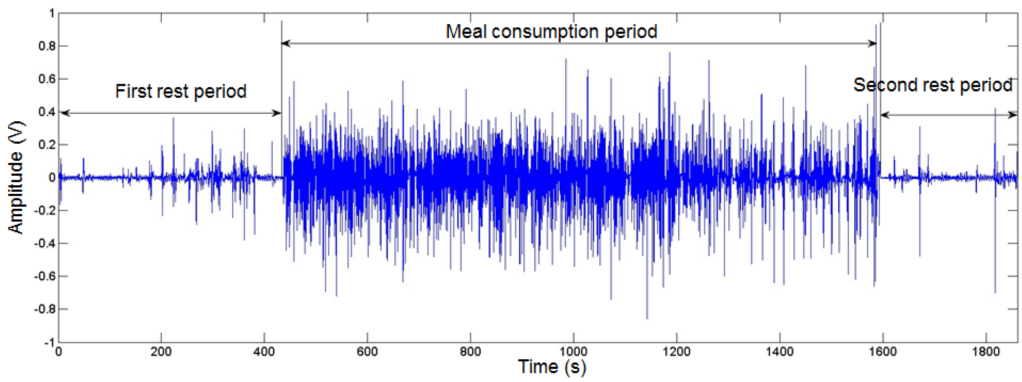

Figure 3-2 EGG signal for a complete experiment of about 30 min in duration.

The Wavelet Transform (WT) is an alternate signal analysis technique to the Short Time Fourier Transform (STFT) and provides better time and frequency resolution compared to STFT. The WT provides high frequency resolution and low time resolution at low frequencies and vice versa at high frequencies. The Discrete Wavelet Transform (DWT) is an implementation of the WT that gives a computationally efficient and compact representation of the signal in time and frequency [31]. The computational complexity of DWT is of the order of $\mathrm{O(N)}$ for an N-length data sequence compared to the Fast Fourier Transform (FFT) which has a computational complexity of $\mathrm{O(Nlog_2(N))}$. The mother wavelet and the number of decomposition levels are important parameters of the DWT, which are selected based on the application. In this study, the Coiflet mother wavelet (coif5) was chosen for feature extraction as it is able to pick up details that are missed by the simpler wavelets and may be of importance for food intake detection. For each i-th epoch of 30 s, the DWT decomposition was performed at 4 levels using Wave-kit wavelet toolbox [32], which resulted in five frequency sub-bands: D1 to D4 and A4 (detail and approximation coefficients respectively). The detail and approximation coefficients provided a compact representation of the signal's energy distribution in both time and frequency domain and were used as the features that represented the $\mathrm{EGG(t)}$ and $\mathrm{MIC(t)}$ signals. The feature vector f_i for each epoch of the signal was formed by computing various metrics over the set of the wavelet coefficients for each sub-band. As a result, each sub-band was represented by 10 features (Table 3-1), which were combined together to form f_i, consisting of 50 features (5 sub-bands with 10 features each). For each subject, features from all four visits were combined to form a combined feature vector which was used to train the food intake classification models.

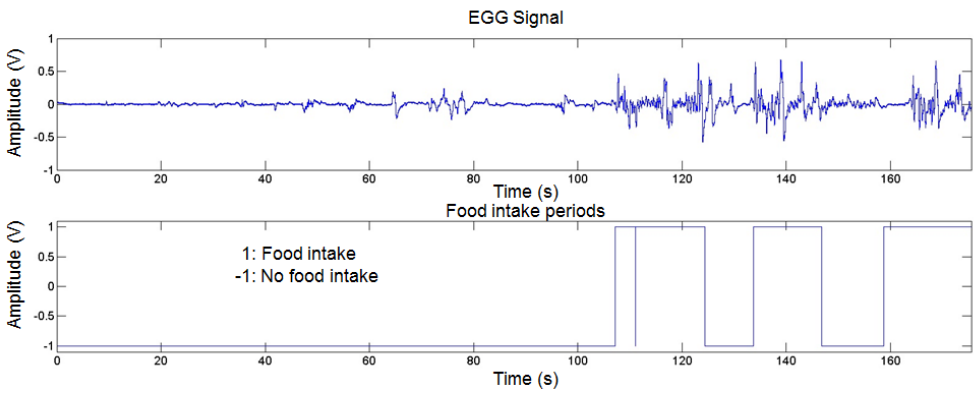

Figure 3-3 EGG signal and corresponding annotation of food intake collected during a short.

3.2.3 ARTIFICIAL NEURAL NETWORK (ANN)

Artificial neural network (ANN) is a supervised machine learning technique that has shown excellent results for a number of pattern recognition and classification problems [33]. ANN is robust, flexible and has the ability to create complex decision boundaries and handle noisy data. In this study, subject-independent models (group models) based on the ANN were trained using the wavelet features extracted from EGG(t) (EGG model) and from MIC(t)(MIC model). These models had the goal of detecting and separating food intake from other factors that resulted in changes of EGG and acoustical signals (such as intrinsic speech, head movements, bodily sounds, etc.). Subject-independent models were developed because they do not require individual calibration and ensure the applicability of the proposed technique to a wider population.

In this study, a three-layer (input layer, hidden layer and output layer) feed forward neural network trained by the back-propagation algorithm was used. In the input layer 50 predictors were used (one for each feature) whereas the hidden layer consisted of 10 neurons. The output layer consisted of only one neuron, which indicated the final output T_i ("food intake" or "no food intake") corresponding to the input feature vector f_i. The hyperbolic tangent sigmoid was the transfer function used for the hidden and output layers. Training, validation and testing of the model was done using the Neural Network toolbox available in Matlab R2011b (The Mathworks Inc).

Table 3-1 Features Computed for each sub-band

Feat #	Feature	Description
1	RMS value of $C(n)$	$RMS = \sqrt{\frac{1}{N}\sum_{n=1}^{N} C(n)^2}$
2	Entropy of $C(n)$	$H(C(n)) = (\sum p_c * log_2(p_c)$; where p_c is the histogram of $C(n)$
3	Mean of Absolute Value (MAV)	$MAV = \frac{1}{N}\sum_{n=1}^{N} \lvert C(n) \rvert$
4	Max of Abs	$MaxAbs = \max(\lvert C(n) \rvert)$
5	Ratio Max of Abs to RMS	$R_1 = MaxAbs/RMS$
6	Ratio RMS to MAV	$R_2 = RMS/MAV$
7	Standard deviation of $C(n)$	$\sigma_{X(n)} = \sqrt{\frac{1}{N}\sum_{n=1}^{N}(C(n) - \overline{C(n)})^2}$
8	Energy of $C(n)$	$E = \sum_{n=1}^{N} C(n)^2$
9	Power of $C(n)$	$P = \frac{1}{N}\sum_{n=1}^{N} C(n)^2$
10	Skew-ness $C(n)$	$\gamma = \frac{\sum_{n=1}^{N}(C(n)-\overline{C(n)})^3}{(N-1)\sigma^3}$ where σ is the standard deviation of $C(n)$

[a] $C(n) = C(1), C(2), \dots C(N)$ are the coefficients in each sub-band after DWT decomposition of each epoch.

A leave one out cross-validation procedure was used to evaluate the performance of the ANN model. Data from 24 subjects was divided into non-overlapping training (80% of the data) and validation (20% of the data) sets. Testing of the model was performed with data from the subject that was left out (25th subject). This procedure was repeated 25 times so that each subject could be used as the test subject. Since the initial weights and bias were randomly generated, the leave-one-out cross-validation procedure was performed 10 times to get generalizable results. The average of the accuracies for 10 iterations was taken to get final accuracy value for each subject. Finally, the overall result was obtained by averaging the results across all the subjects. Per-epoch classification accuracy was metric used to evaluate the performance of the classification model. It was defined as the average between Precision and Recall, to account for a high number of true negatives that are typical in the monitoring of food intake over long periods of time. These metrics measured the ability of the model to recognize food intake epochs while rejecting no food intake epochs:

$$Accuracy = (Precision + Recall) / 2 \tag{3.1}$$

$$Precison = \frac{T_+}{T_+ + F_+}; Recall = \frac{T_+}{T_+ + F_-} \tag{3.2}$$

where $T_+$was the number of food intake epochs correctly classified by the model as food intake, $F_+$was the number of no food intake epochs incorrectly classified as food intake epochs, and $F_-$was the number of food intake epochs incorrectly classified as no food intake epochs. The choice of accuracy metrics is defined by the fact that food intake constitutes only 2-3% of duration of daily activities (Fontana *et al* 2013), and a large number of true negatives (periods/epochs of no food intake) are typical for experiments in free living. Thus, precision and recall are best suited used for quantification of food intake detection accuracy as these metrics do not account for true negatives.

A statistical comparison (using t-test) was performed between EGG and MIC models for their ability to differentiate between epochs of food intake from epochs of no food intake. Both EGG and MIC models were evaluated for male and female subjects separately to determine if models were able to achieve similar accuracies for both genders and one tailed t-test (with significance level p = 0.05) was used to determine statistical significant difference between model performance. Additionally, the study's population was divided into 3 groups according to subjects' BMI (normal, overweight and obese) and a statistical analysis was performed to find significant differences among model performances for different level of adiposity (one way ANOVA with significance level $p = 0.05$).

Finally, to demonstrate the effect of background noise on the EGG and the acoustic signals, a small experiment was performed where a volunteer was asked to drink water with and without the presence of external acoustic noise originating from a laptop playing a song.

3.3 RESULTS

For food intake recognition, the results of the leave-one-out cross validation procedure showed average accuracies of 90.1% (SD +/- 8.50%) and 83.1% (SD +/-10.8%) for EGG and MIC models, respectively. The box-plot in Figure 3-4 shows the accuracy distributions for each methodology. The statistical analysis showed significant differences between model performances (p value < 0.001).

Results of evaluating the models for both genders indicated that EGG model achieved average accuracies of 89.7% (SD +/-8.35%) and 90.3% (SD +/-8.97%) for female and male subjects respectively. A statistical analysis showed no significant differences between models performances for males and females (p > 0.05). Similarly, MIC model achieved average accuracies of 85.2% (SD +/-10.3%) for male and 81.1% (SD +/-11.3%) for female subjects without significant differences between performances (p > 0.05).

Results of model performances for different levels of adiposity are presented in Figure 3-5. The EGG models achieved average accuracies of 91.8% (SD +/-9.00%), 84.17% (SD +/-9.92%) and 89.8% (SD +/-5.84%) for normal weight, overweight and obese subjects respectively. The statistical analysis showed no significant differences among model performances for all BMI groups: (p > 0.05 in all cases). Similarly, MIC models achieved average accuracies of 84.8% (SD +/-8.49%), 70.1% (SD +/-15.4%) and 86.9% (SD +/-

7.28%) for normal weight, over-weight and obese subjects respectively. There were no significance differences in the performance of both models for corresponding BMI groups.

Results of testing EGG and microphone in the presence of background noise are shown in Figure 3-6. Figure 3-6 (left) shows the power spectra of the EGG and Figure 3-6 (right) shows acoustic signals with and without the presence of external noise in the experiment. The acoustic signal was highly affected by the presence of noise whereas in the EGG signal the effect of noise was insignificant.

3.4 DISCUSSION

This study introduced a new sensor modality (EGG) for food intake detection and compared it with an acoustic based approach. In the experiment, a wide variety of food items consumed without restriction ensured that the food detection models did not over-fit to a specific food type or intake of solid or liquid foods. Sensor signals from both sensors were processed in exactly the same manner to eliminate any potential bias due to processing. Wavelet features extracted from sensor signals were used in conjunction with ANN classifiers to derive subject-independent food intake detection models that eliminated the need for individual calibration as they account for inter-subject variability.

Results suggest that the EGG models achieved a statistically-significant higher average accuracy of food intake detection than MIC models (90% vs. 83%, respectively). This showed that EGG is potentially superior for this application than the acoustic based approach with proposed signal processing and pattern-recognition techniques on this data set. The average recall of 91.8% and an average precision of 88.4% of EGG-based models suggest good overall performance of the method with just a few false negatives and false positives.

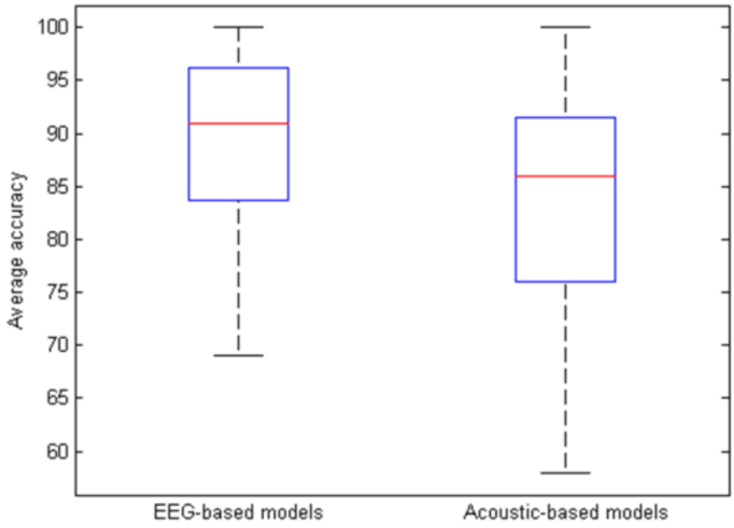

Figure 3-4 Distribution of the food intake detection accuracies obtained from both EEG-based and acoustic-based models.

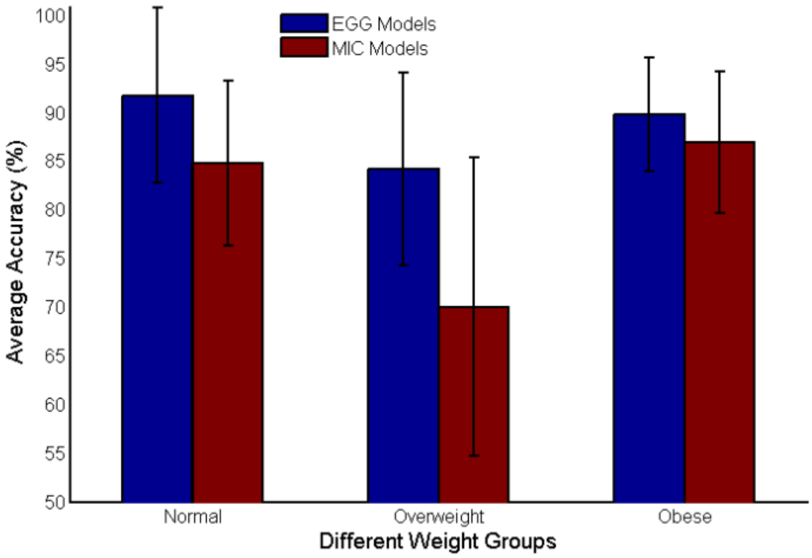

Figure 3-5 Model performance for different levels of adiposity.

An advantage of the proposed *EGG* models is their ability to detect food intake equally well for both genders and for people with different levels of adiposity with no statistically significant differences among model's performances for different genders and different BMI groups (normal, overweight and obese). This capability is critical for studying food intake in obese populations where adipose tissue may negatively impact accuracy of some sensing modalities [17].

The proposed EGG based methodology is also non-invasive and not sensitive to acoustic noise by the virtue of the physical principles used in EGG measurement. Figure 3-6 illustrates practical effects of background noise on the sensor signals with EGG clearly not being affected to the same extent as the acoustical signal. This figure reinforced the fact the EGG is immune to acoustic noise compared to acoustic signal. In most cases, acoustic based methods require a preprocessing step for noise removal to improve the results. A previous study based on the acoustic classification of sounds for food intake detection achieved an accuracy of 83% [19] using a reference microphone to remove background noise. In this work, we demonstrated that the EGG sensor can achieve a high food intake detection rate without requiring any noise cancellation procedure. However, the practical benefit of EGG's insensitivity to background noise (in terms of corresponding improvement in food intake recognition accuracy in free living environment) will need further investigation by testing the method in noisy environments that are typical in everyday living.

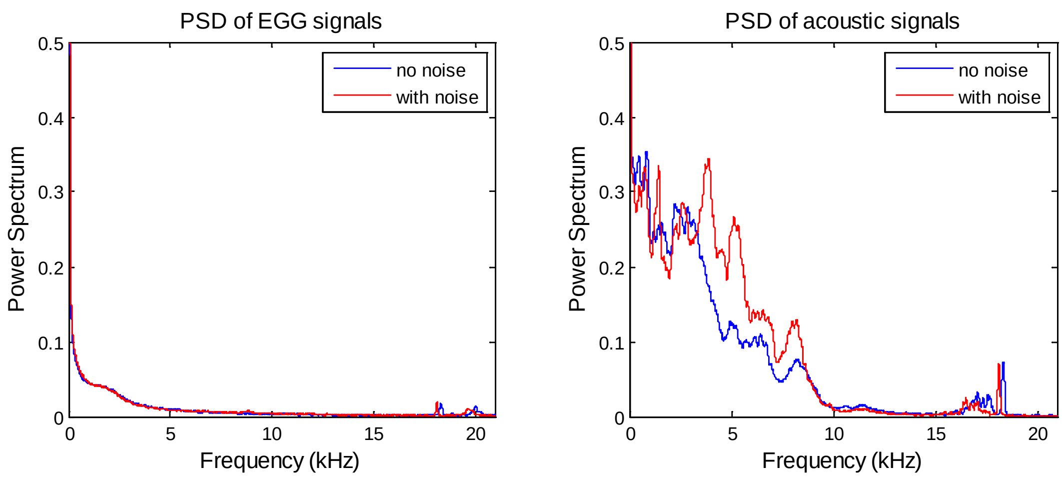

Figure 3-6. Left: Power spectral density (PSD) of EGG signal with and without noise Right: PSD of the acoustic signal for the same experiment.

The current study has established feasibility of using EGG for food intake detection, but free-living tests will be required to evaluate performance of the device over extended periods of time under realistic conditions of daily living. Impedance measurement techniques such as EGG are sensitive to motion artifacts that may negatively impact accuracy of food intake detection, but are plentiful in daily life. Similarly, acoustical sensors are prone to contamination from body motion, external noise and speech. A future study should evaluate how the proposed technique performs in free living, how motion artifacts of daily life impact the sensor signals, what electrodes and methods of attachment perform the best, what motion artifact cancellation techniques are appropriate, if and how the EGG sensor can be made into a convenient and socially acceptable device and thus more thoroughly estimate suitability of EGG-based food intake detection for long-term monitoring.

Swallowing is a complex process that involves coordinated muscle contractions, laryngeal movement and passage of the food bolus. This study used changes in EGG signal due to swallowing activity to detect food intake without evaluating relative contributions in impedance change from these processes. At this moment it is not clear that the impedance variations were caused by the passage of food bolus, the swallowing motions and muscle activity or a combination of both. Exact quantification of the contribution of these phenomena to the resulting signal is beyond the scope of this manuscript, but should be considered in the future as food impedance may carry information on food composition. Bolus impedance may potentially carry information needed to differentiate between nutritive and non-nutritive swallowing, and different food items consumed and estimate their energy density. However this hypothesis needs to be carefully tested in further studies. Another possibility to characterize ingested foods is the addition of a camera that can be automatically triggered to take a picture when the EGG methodology detect food intake. Image processing techniques would be required to estimate portion size and the type of food.

Overall, the proposed EGG-based approach showed good results for food intake detection by outperforming an acoustic-based method. While further investigation is needed to evaluate performance of EGG in free living and its potential to differentiate between different foods types, these results suggest that EGG use may potentially be a promising foundation for development of a wearable sensor system for detection of food intake under free living condition.

3.5 CONCLUSION

This paper evaluated the feasibility of using an Electroglottograph device for automatic and objective monitoring of ingestive behavior. Signals acquired by an Electroglottograph and a microphone at the larynx level were segmented into non-overlapping epochs of 30 s and a set of 50 features was computed based on DWT decomposition. These features were used to train subject-independent food intake detection models using an artificial neural network as a classifier. A leave-one-out cross validation scheme was used for training, validation and testing of the models, resulting in average food intake detection accuracy of 90.1% for EGG-based models and 83.1% for acoustical models. The difference between the average accuracies was statistically significant. The EGG models performed equally well for both genders and for people with different levels of adiposity. As a non-invasive and insensitive to background noise, the proposed EGG-based methodology justifies further investigation as a potential option for automatic and objective monitoring of ingestive behavior under free living conditions.

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CHAPTER 4 OBJECTIVE MONITORING OF INFANT FEEDING BEHAVIOR USING A JAW MOTION SENSOR

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Once the eating episodes are automatically detected, next step is the characterization of detected eating episodes. The number of chews per bite or chewing rate can be used for this purpose. This chapter introduces a semi-automatic approach for quantification of sucking behavior of infants using a piezoelectric sensor. Sucking movements in infants are similar to chewing movement of the jaw in adults. A modified form of the algorithm presented here was also used in quantification of the chewing behavior in adults [24], [25].

4.1 INTRODUCTION

Obesity is caused by excessive accumulation of body fat. Previous research suggests that infancy may be a critical period during which lifetime risk for obesity develops. Infants fed formula from bottles experience more rapid weight gain (for a systematic review see [1]) and have greater life-time risk for obesity [2-3] in comparison to breast-fed infants. In addition, bottle-fed infants have greater energy intake, and differing meal patterns and within-meal behavior as compared to breast-fed infants [4-5]. Independent of the mode of feeding, rapid weight gain in the first six months of life is also associated with subsequent life-time risk for obesity [6-14], and vigorous sucking at 3 months of age is positively associated with adiposity at 12 months of age [15]. Finally, excess energy intake during infancy is a primary determinant of rapid weight gain and subsequent body size [16]. Together, these results suggest that feeding behavior during infancy may play an important role in the development of obesity. However, methods to monitor feeding behavior and to assess energy intake among infants are limited.

This paper presents a novel approach for monitoring infant sucking count (number of sucks) during meals. If sucking count can be accurately determined, it will be possible to derive sucking vigor or rate of sucking which, as mentioned above, is associated with adiposity in early life. With further development, this tool might also facilitate efficient characterization of other feeding behaviors such as meal duration, frequency of intake, and volume consumed. Use of a jaw motion sensor was previously found to provide accurate and objective monitoring of ingestive behavior in adults [17-21]. Since infants use their jaws during sucking (both bottle-fed and breast-fed), the jaw motion sensor may be a useful tool to capture sucking count during feeding episodes. To the best of the authors' knowledge, no previous study has reported the use of a jaw sensor to monitor feeding behavior in infants.

The goal of this study was to evaluate the technical feasibility of using a non-invasive jaw motion sensor to monitor sucking count and thereby sucking frequency (number of sucks per unit time (seconds)) of infants during a meal. Data from the jaw sensor are compared to data obtained by human observation to examine the accuracy of the sensor-derived estimates of sucking count for both breast-fed and bottle-fed infants.

4.2 METHODS

4.2.1 PARTICIPANTS

Ten infants were recruited for this study. Infants were eligible for inclusion if they were healthy and between 2 and 5 months of age, with a current weight-for-length not less than the 5th percentile based on the Centers for Disease Control and Prevention (CDC) growth curves [22]. Infants were excluded if they were less than 37 weeks of gestation and/or less than 2500 g at birth. The Institutional Review Boards (IRBs) at the University of Alabama at Birmingham (UAB, site for data collection) and the University of Alabama (UA, site for data analysis) approved this study. Mothers of infants provided informed consent before data collection began. The relatively small sample size of this study is stipulated by the pilot nature of the conducted work.

4.2.2 PROTOCOL

Participants and their mothers came to the UAB Child Health Research Center (CHRU) located within the Children's of Alabama hospital facility, to complete the study protocol. Each infant came to the laboratory for one visit, which was scheduled to occur at a time when the infant was expected to be hungry, and not less than 2 hours following the previous meal. After informed consent was obtained, infant weight (without clothing) and length (supine) was measured using standard clinical procedure. Infants then underwent a weighed, timed, and videotaped meal test while wearing the jaw motion sensor. After the completion of the meal, infant body composition was assessed by air displacement plethysmography (PeaPod®; Cosmed Inc., Concord, CA).

4.2.3 MEAL TEST

All infants were weighed to the nearest 0.1 gram while wearing a clean diaper only, on the weighing scale of the PeaPod ®. For bottle-fed infants, the prepared bottle was also weighed to the nearest 0.1 gram prior to the meal test. The mother sat in an armchair to breast- or bottle-feed her infant. The mother held her infant in a side-lying position, with the infant's head supported in the crook of her bent arm. The jaw sensor (described below) was adhered directly under the ear of the infant, behind the jaw, on the side of the face that would face away from the mother during the meal. The longitudinal axis of the sensor was perpendicular to the longitudinal axis of the ear. Two video cameras (both Samsung HMX-F80) were positioned to record mouth and jaw movements prior to and during the feed; one focused from the side and the other from above the infant's head. Mothers were instructed to begin the meal once the cameras and jaw sensor were recording and to make the meal as "natural as possible". Mothers could interrupt the meal to burp the infant or to change positions, as needed, and recording continued during this time. Meals ended when the infant fell asleep, finished the bottle (if applicable), refused to consume more, and/or mothers indicated that the infant was finished feeding. Therefore, a meal was defined as the duration between the start and end of the feeding episode of the infant. After burping, infants were reweighed on the PeaPod® scale wearing the same diaper in which they were weighed prior to the meal, and bottles were also reweighed as appropriate. Any milk lost through spillage or regurgitation was captured in pre-weighed burp cloths so that milk consumption could be corrected for spillage. The total size of the recorded dataset for all 10 infants was approximately two hours.

4.2.4 BODY COMPOSITION ASSESSMENT

Body composition was measured by air displacement plethysmography (PeaPod®; Life Measurement Instruments, Concord, CA). In brief, after infant length was measured, infants were weighed on the PeaPod® scale while wearing only a tightly fitted stocking cap to compress their hair. They were then placed inside the test chamber where infant volume was assessed. Infant fat mass and fat free mass were calculated using a two compartment model [23].

4.2.5 TRAINING FOR CODING DISCRETE INFANT FEEDING BEHAVIORS: SUCKING COUNT

A researcher with expertise in coding infant behaviors trained two human raters to code the videotapes of the infant feeding sessions. Each human rater met separately with the researcher for the training. The human raters were informed that they were assisting with testing the reliability of a jaw motion sensor designed to record feeding behaviors. At the training session, video segments of infants being breast-fed and bottle-fed were played while the researcher pointed out discrete examples of infant sucks. A discrete suck was operationally defined as one complete down and up jaw movement when the infant's lips were wrapped around the nipple of the mother or the bottle. The researcher counted out loud numerous discrete sucks while watching segments of the videotapes with the rater. The rater then performed the same task, counting discrete sucks aloud during a series of breast- and bottle-fed video segments, which the researcher observed. After several trials of counting discrete sucks out loud, the researcher and the rater each viewed new video segments of breast- and bottle-fed infants with each independently and quietly counting the number of sucks and recording their total sucks on paper. The total sucks were then examined and a criterion of 90% agreement with the researcher was established for the rater to be deemed reliable in counting discrete sucks. For example, if the human rater noted that a breast feeding infant sucked 120 times in a segment of video and the expert coder counted 110 sucks for the same segment (110/120 = 91.6% agreement), then the human coder was deemed reliable for that segment.

4.2.6 JAW MOTION SENSOR

The sensor data collection system consisted of a jaw motion sensor, a data acquisition device and an Android smart phone. The sensor system was originally designed to be used in adults [17] and was used in this study without any modification. The jaw motion sensor used was a piezoelectric film element (DT2-028K; Measurement Specialties Inc. VA). Jaw movements during the sucking process bend the sensor and create an electrical signal proportional to the amount of bending. The signal from the sensor was buffered and amplified using an operational amplifier circuit and then digitized by the microcontroller of an Automatic Ingestion Monitor (AIM, [17]) at a sampling frequency of 1kHz. Digitized signals were then transmitted via Bluetooth wireless connection in real time to an Android phone that stored the signal on an SD-card for further processing. Figure 4-1 shows the jaw motion sensor (Figure

4-1 (a)) and the AIM module (Figure 4-1 (b)); the Android phone is not shown in the picture. Figure 4-1 (c) shows a bottle-fed infant wearing the sensor.

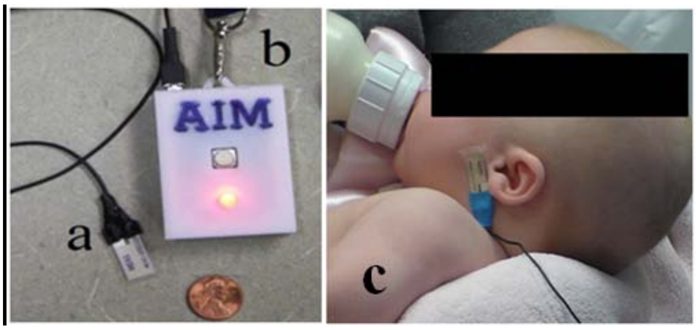

Figure 4-1 Sensor system for monitoring jaw movements: (a) jaw motion sensor, (b) wireless module, and (c) a bottle-fed infant wearing the sensor.

4.2.7 CODING OF VIDEOTAPES

After the training, video recordings and time-synchronous jaw sensor signals were annotated by the two trained raters independently using a modified version of the software introduced in [21]. To provide synchronization between the sensor signal (described below) and the video, data collection was started on the Android phone when it was in view of one of the cameras. To maintain homogeneity of the scoring process, a protocol similar to other studies [24-25] was developed to mark meal initiation and termination and sucking count. Human raters marked the start and end of the meal in the video. The period between the start and end of the meal was divided into 10 second epochs (a total of M epochs) in the scoring software and a sucking count was computed for each epoch. The 10 second interval was chosen because in the pilot coding, it was deemed a manageable period to count discrete sucks. These epochs also provided cluster data for conducting intra-class correlation (ICC) analysis between the human raters, and between the human raters and the count provided by the jaw sensor algorithm. Epochs containing partial intake (i.e. video segments where the jaw was not visible in the video) or no intake (including burping, rest period, periods where nipple was out of the mouth, etc.) were discarded. For the $n-\mathrm{th}$ epoch, the average sucking count from both human raters was used as the annotated per-epoch sucking count, denoted by $\mathrm{A_{CNT}(n)}$. On average, the raters counted 664 of sucks per meal.

4.2.8 SENSOR DATA AND SIGNAL PROCESSING

Jaw motion signals retrieved from the sensor (denoted as $\mathrm{JM(t)}$), were processed in the following manner. First, the signals were demeaned by subtracting the average computed over the duration of the experiment from each data point. This was done to account for signal variation among infants. Next, all signals were de-noised using wavelet transform. De-noising attenuates small variations in the signal due to noise on the power lines (i.e. variation in voltage due to wireless transmission that leaks into the sensor signal). A bi-orthogonal wavelet transform (with Haar mother wavelet) using a lifting scheme was used for de-noising. The lifting scheme allows custom design and fast implementation of the wavelet transform by using the similarities between low and high pass filters [26]. The sensor signal was decomposed using a Discrete Wavelet Transform (DWT) technique. The wavelet coefficients below a threshold T (described below) were discarded and the de-noised sensor signal was recovered using an Inverse Discrete Wavelet Transform. Figure 4-2 shows a segment of the jaw motion sensor signal before and after de-noising.

4.2.9 SUCKING COUNT AND ERROR COMPUTATION FOR SENSOR SIGNAL

After de-noising $JM(t)$, sensor signals were divided into M epochs of 10 second each, denoted as $x(n)$, with N samples per-epoch, where $N = L * f$, $L=10$ second or the epoch size and f= 1000 Hz or the sampling frequency. These M epochs were time-synchronous with the 10 second epochs used during the signal annotation process. For each epoch, sucking count was computed from the sensor signal by the algorithm shown in Figure 4-3. The algorithm computes per-epoch number of mean crossings $MC(n)$. For computation of mean crossing, it is assumed that the de-noised signal is smooth (Figure 4-2). Given that a suck was defined as one complete down-up jaw motion, it is assumed that the number of predicted sucks $P_{CNT}(n)$

is equal to half of the number of mean crossings of the sensor data. Per-epoch sucking frequency can be calculated by dividing number of sucks by the epoch size (10 second in this case). Since errors computed for both sucking count and sucking frequency will be the same, only results for sucking counts are reported here.

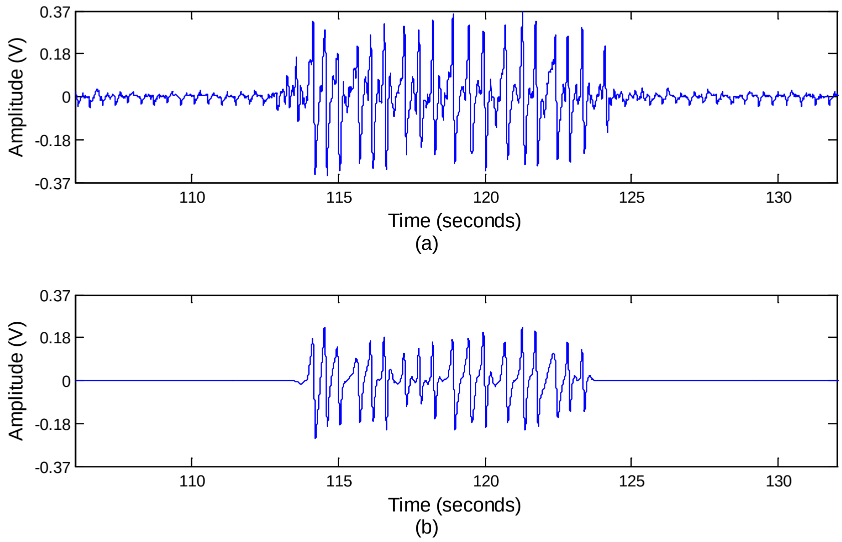

Figure 4-2 Jaw motion sensor signal before (a) and after de-noising (b) using the bi-orthogonal wavelet transform. Amplitude is in volts.

- Set the variable $MC(n)$ (number of mean crossings) to 0.
- For *i-th* sample in *n*-th epoch, increment $MC(n)$ by 1,
  if $[\boldsymbol{x}(i) > \overline{\boldsymbol{x}(n)}$ and $\boldsymbol{x}(i+1) < \overline{\boldsymbol{x}(n)}\,]$ or $[\boldsymbol{x}(i) < \overline{\boldsymbol{x}(n)}\ and\ \boldsymbol{x}(i+1) > \overline{\boldsymbol{x}(n)}]$
  where i=1,2,…,N and $\overline{\boldsymbol{x}(n)}$ is the mean amplitude of the epoch $\boldsymbol{x}(n)$.
- Compute per-epoch sucking count $P_{CNT}(n)$ as $P_{CNT}(n) = MC(n)/2$.

Figure 4-3 Algorithm for computation of sensor-predicted sucking count ($\boldsymbol{P_{CNT}(n)}$) for *n-th* epoch.

To evaluate the performance of the algorithm, the sensor-predicted counts ($P_{CNT}(n)$) were compared to human-annotated counts ($A_{CNT}(n)$), within each epoch. Two types of errors were computed for each infant. The first error characterized the per-epoch accuracy in sucking count, thus illustrating the ability of the sensor to follow temporal changes in sucking patterns.

For each infant k, per-epoch mean error (for sucking count) $E_{EPOCH}^{CNT}(k)$ was defined as

$$E_{EPOCH}^{CNT}(k) = \frac{1}{M}\sum_{n=1}^{M}\left[\frac{(A_{CNT}(n) - P_{CNT}(n)) * 100}{A_{CNT}(n)}\right] \qquad (5.1)$$

where M is the total number of epochs, $A_{CNT}(n)$ is annotated suck count for epoch n, and $P_{CNT}(n)$ is sensor-predicted suck count for epoch n.

The second type of error characterized overall accuracy across the entire feeding episode. The cumulative sucking count error over a meal for infant k was computed as the percent difference between the total counts of annotated sucks versus sensor-predicted sucks:

$$E^{CNT}(k) = \frac{[\sum_{n=1}^{M} A_{CNT}(n) - \sum_{n=1}^{M} P_{CNT}(n)] * 100}{\sum_{n=1}^{M} A_{CNT}(n)} \qquad (5.2)$$

4.2.10 PARAMETER DETERMINATION AND VALIDATION

The experimental data have shown that sensor signal amplitude is different for each infant (as it depends on the sensor location, infant's strength of sucking, etc.); therefore, the threshold value T used in the de-noising algorithm had to be individually adjusted. As a generalizable approach, the threshold used in de-noising was computed as a function of the jaw sensor signal's amplitude: $T = \alpha * \text{STD}\ (JM(t))$, where STD is the standard deviation of the signal over the meal duration. A leave one out cross validation scheme was used to find the value of the scaling factor α by withholding infant k from the dataset and performing a grid search for a value of $\alpha \in [1,10]$ on the dataset from the remaining 9 infants (training set). The value of α which resulted in the minimal absolute average E_{EPOCH}^{CNT} on the training set, was used to validate performance of the method on the withheld (validation) data from infant k by computing corresponding $E_{EPOCH}^{CNT}(k)$ and $E^{CNT}(k)$. This process was repeated such that each infant was used for the validation set only once.

For algorithm development, there were two possibilities for finding an optimum threshold and parameter selection. One possibility was to optimize per-epoch error for sucking count i.e. $E_{EPOCH}^{CNT}(k)$ and the other possibility was to optimize parameters for cumulative error for sucking count across each meal i.e. $E^{CNT}(k)$. Per-epoch sucking count provides a better estimate of the feeding behavior during a meal compared to the cumulative sucking count and therefore it was chosen for parameter optimization. Different results will be obtained if the parameters were optimized for cumulative sucking count. For de-noising, threshold T was chosen as a factor of the sensor signal's standard deviation (STD) to account for signal variation during the experiment. Other possibilities for threshold are signal’s maximum or median amplitude. Since different infants have different signal strengths, the resultant value of the threshold is unique for each infant (as shown in Table 4-1).

Measures of sample-wide performance were then computed as average values of $\mathrm{E}_{\mathrm{EPOCH}}^{\mathrm{CNT}}(\mathrm{k})$ and $\mathrm{E}^{\mathrm{CNT}}(\mathrm{k})$ over validation results from all 10 infants:

$$\overline{E_{EPOCH}^{CNT}} = \frac{1}{10}\sum_{k=1}^{10} E_{EPOCH}^{CNT}(k) \tag{5.3}$$

$$\overline{E^{CNT}} = \frac{1}{10}\sum_{k=1}^{10} E^{CNT}(k) \tag{5.4}$$

These two sample based errors give performance estimation of the proposed technique for predicting both per-epoch as well as cumulative values of sucking count across the whole sample and are used as the main metrics of performance.

4.2.11 INTRA-CLASS CORRELATION (ICC) AND STATISTICAL ANALYSIS

Intra-class correlation (ICC) analyses were conducted to examine the reliability between the two human raters, and then the reliability between the human raters (averaged together) and the sensor-predicted sucking counts. In both cases, a 2-way mixed model analysis was used with fixed observers and random subjects.

Infant weight-for-age, length-for-age, and body mass index-for-age z-scores were calculated using the World Health Organization (WHO) Anthro software (version 3.2.2, January 2011), which is based on international growth charts of healthy infants growing under optimal conditions [27]. Exploratory analyses were conducted to examine whether any other individual factors influenced the accuracy of the sensor-predicted sucking counts. Two-tailed, two-sample t-tests were used to examine the effect of feeding mode (breast versus bottle) and gender on the error in sensor-predicted sucking counts. A Passing-Bablok regression [28] was used to determine the effects of body size (i.e. BMI-for-age z-score, weight-for-age z-scores, length-for-age z-scores), age, and body composition (i.e. % body fat, total fat mass and total fat free mass) on the prediction error. Passing-Bablok regression is insensitive to outliers and assumes that measurement errors from both variables have the same distribution. All analyses were conducted using MATLAB ® (Mathworks Inc.).

4.3 RESULTS

The sample consisted of 5 male and 5 female infants with racial distribution of 6, 2, and 2 of Caucasian, African American and Other (mixed race) respectively. Age of the male and female infants did not differ (16.44 +/- 5.00 weeks for males and 16.35 +/- 2.93 weeks for females), but male infants showed a trend towards consuming more during the test meal than female infants (130.00 +/- 63.94 ml versus 58.50 +/- 30.65 ml, respectively; p = 0.10). The sample consisted of 6 breast-fed and 4 bottle-fed infants. Breast-fed infants showed a trend towards consuming less than the bottle-fed infants (74.41 +/- 28.39 ml versus 140.12 +/- 69.05 ml, respectively; p = 0.07). The average gestational age at birth was 39.9 ± 1.5 weeks and average birth weight was 3.6 ± 0.3 kg.

There were a total of 692 epochs in the data set. The ICC analysis of the sucking count between the two raters showed a correlation coefficient of 0.98 [95% CI: 0.98, 0.99]. The

ICC analysis between the raters (averaged together) and the sensor-predicted count showed a correlation coefficient of 0.86 [95% CI: 0.83, 0.88].

With respect to the accuracy of the sensor-predicted per-epoch sucking count, the sensor-based method resulted in a mean error of $\overline{\mathrm{E}_{\mathrm{EPOCH}}^{\mathrm{CNT}}} =$ -9.72 +/- 20.03%, and the cumulative sucking count error $\overline{\mathrm{E}^{\mathrm{CNT}}} =$ -2.38 +/-22.33% for the entire meal. Per-infant errors are summarized in Table 4-1. This table also provides the mean absolute errors. Figure 4-4 shows an example of the annotated and the sensor-predicted sucking count for an infant over the period of an entire experiment.

A comparison of the per-epoch mean error in sucking count was performed between bottle-fed and breast-fed infants. The results of the t-test showed that the per-epoch mean errors were greater among the bottle-fed than the breast-fed infants (-26.62 +/- 14.16% for bottle-fed infants and 1.54 +/- 14.88% for breast-fed infants; with p=0.02). A comparable analysis between male and female infants showed no difference in per-epoch mean error (-17.76 +/- 23.59% for males, -1.68 +/- 13.59% for females; with p = 0.22).

Table 4-1 Result: Comparison between annotated (human) and sensor-predicted (jaw sensor) sucking counts, including errors for breast-fed and bottle-fed infants during the epochs (10 second interval) and the course of the meal.

Infant (k)	Feeding mode	Human counted sucks*	Sensor-predicted sucks*	Human - annotated mean sucking count (per-epoch)	Sensor-predicted mean sucking count (per-epoch)	Per-epoch mean count error $E_{EPOCH}^{CNT}(k)$ (%)	Per-meal mean count error $E^{CNT}(k)$ (%)	Threshold (T) (in volts)
1	Breast-fed	354	250	7.68	5.43	8.88	29.38	3.18
2	Breast-fed	774	701	8.70	7.88	-10.07	9.43	2.65
3	Breast-fed	859	946	9.76	10.74	-9.55	-10.13	0.39
4	Breast-fed	979	748	12.39	9.47	18.53	23.60	1.69
5	Breast-fed	329	263	10.27	8.20	16.65	20.06	1.53
6	Breast-fed	641	696	7.17	9.95	-15.15	-8.58	0.68
7	Bottle-fed	416	577	10.02	12.61	-40.95	-38.70	0.24
8	Bottle-fed	662	833	13.12	14.15	-36.61	-25.83	0.13
9	Bottle-fed	1023	1104	10.57	12.17	-14.61	-7.92	0.15
10	Bottle-fed	603	694	7.28	7.90	-14.29	-15.09	0.25

	Mean:	-9.72	-2.38	1.08
	STD:	20.03	22.33	1.11
	Absolute Mean:	18.52	18.87	
	Absolute STD:	11.17	10.44	

Note: k represents infant number in the dataset; * sucks represents the frequency of infants' up and down jaw motion during the meal period as annotated by an observer (human) from videotape recordings and as predicted by the algorithm generated jaw motion sensor data; (during the epoch or over the entire meal); an epoch was defined as a 10 second interval. Per-epoch mean sucking count for infant k was computed by dividing total sucking count by number of epochs. Threshold was given in volts.

Results of Passing-Block regression analyses to examine whether the per-epoch sucking count error was independent of body size and age are shown in Figure 4-5(a) through 4-5(d). Figure 4-6(a) through 4-6(c) show the results of the Passing-Block regression analyses to examine whether the per-epoch sucking count error was independent of body composition. In all analyses, results showed that the error is independent of these individual factors.

4.4 DISCUSSION

Research shows that feeding behavior and weight gain during first 6 months of infancy are associated with risk for obesity later in life. Therefore, it is important to accurately and objectively monitor feeding behavior in infants. The assessment of infant sucking count during meals is a useful first step to develop a method to measure feeding behavior in infants because this parameter can then be used to determine sucking frequency (rate), which has previously been associated with obesity, and other feeding-related parameters such as meal duration and frequency. In this study, we introduced a new approach for objective monitoring of infant sucking count using a jaw motion sensor. The jaw sensor system was tested on a sample consisting of both breast-fed and bottle-fed infants to examine its feasibility for both feeding modes. The study compared the sucking count calculated by human raters to that predicted by the jaw sensor based algorithm. In general, these results suggest that although there was a strong correlation between the sucking count detected by human raters and that estimated by the jaw sensor algorithm, further studies are needed to examine reasons for, and methods to reduce, the error rate of this method.

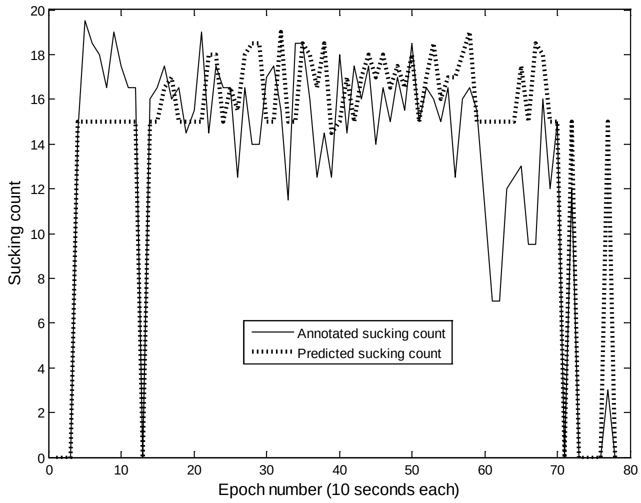

Figure 4-4 A comparison of one infant's (no. 9) annotated sucking count vs. sensor-predicted sucking count computed over 10 second epochs for the duration of the entire experiment. Epochs where both values are zeros are the epochs that involved no intake.

The method used to rate sucking count by observation (i.e. human raters) was found to be highly reliable (i.e. 0.98) across two independent raters. Although the reliability between the average of the human rater scores and the count predicted by the jaw sensor signal algorithm was a little lower, it still indicated strong agreement (0.86). Thus, based on results from this cohort, this jaw sensor protocol appears to be a reliable method to detect sucking count.

The error in sucking count predicted by the jaw sensor was approximately 10% and 3%, for per-epoch and per meal sucking counts respectively. Errors were in the negative direction, suggesting that the jaw sensor method over-estimated the sucking count. Although promising, the relatively high error, particularly for some infants, and the high standard deviation indicates variation in the performance of the algorithm among infants. Further studies are required to identify the source of these variations. Close inspection of Figure 5-4, which shows an example of the data derived from a bottle-fed infant, suggests some issues that may need to be investigated in future studies. In general, the data show that the count predicted by the jaw sensor followed the trend of the human rated count, but modestly over-estimated the sucking count in comparison to that of human raters. It is possible that the disagreement may be attributable to the presence of non-nutritive sucking periods, or to body movements (motion artifacts) that can increase the sensor-predicted sucking count. It is also possible that small sucks were detected by the sensor but not by the human raters because the chin movement generated by the suck was almost imperceptible. These potential sources of error will be the subject of further investigation. The addition of other sensor modalities such as monitoring of swallowing may help in eradicating false positives.

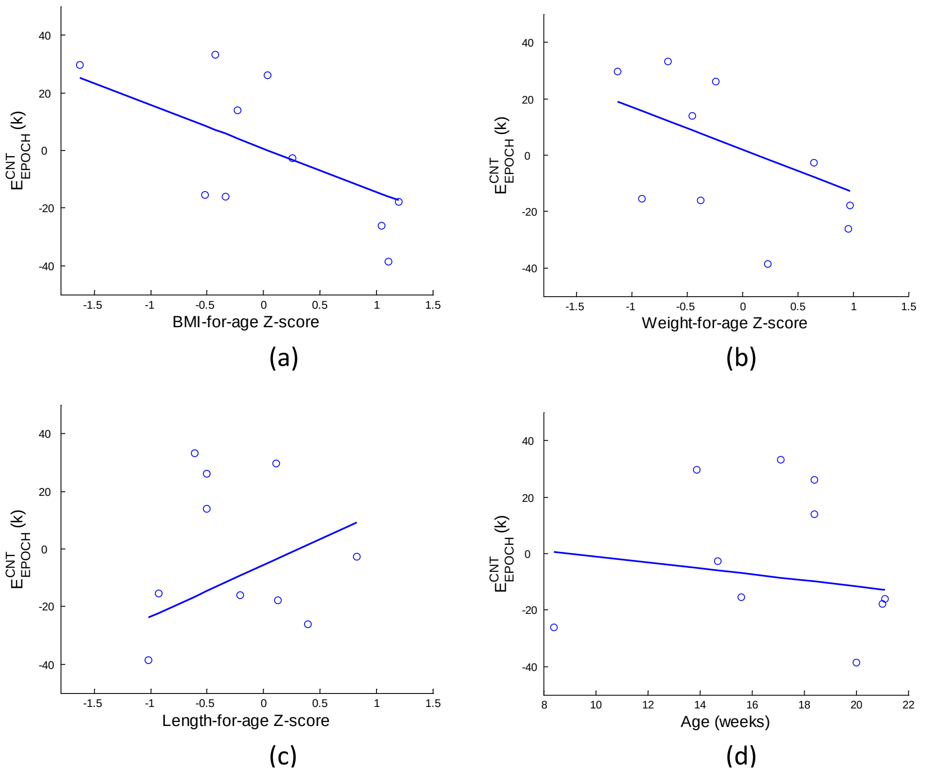

Figure 4-5 (a) Passing-Bablok regression analysis for $E^{CNT}_{EPOCH}(k)$ and BMI-for-ageZ-score. Regression line equation y = -0.01 - 0.15x; 95% CI, for intercept -0.06 to 0.06 and for slope -0.34 to 0.23. (b) Passing-Bablok regression analysis for $E^{CNT}_{EPOCH}(k)$ and Weight-for-age Z-score. Regression line equation y = 0.02 - 0.15x; 95% CI, for intercept -0.02 to 0.03 and for slope -0.32 to 0.28. (c) Passing-Bablok regression analysis for $E^{CNT}_{EPOCh}(k)$ and Length-for-age Z-score. Regression line equation y = -0.06- 0.18x; 95% CI, for intercept -0.05 to 0.46 and for slope -0.1733 to 1.25. (d) Passing-Bablok regression analysis for $E^{CNT}_{EPOCh}(k)$ and age (in weeks). Regression line equation y = 0.09 - 0.01x; 95% CI, for intercept -0.81 to 2.23 and for slope -0.12 to 0.05.

One advantage of the proposed method is its potential to predict the feeding behavior for both breast-fed and bottle-fed infants. Although other sensors that are placed on the mother or the bottle may be useful, to our knowledge, no previous study has attempted to use the same sensor to examine both feeding modes. Preliminary results from this cohort suggest that the sensor generated a higher per-epoch mean error (as well as standard deviation) for bottle-fed infants compared to breast-fed infants (i.e. the technique performed better for breast-fed infants compared to bottle-fed infants). Although not examined here, it is possible that differences in infant's movements during the meal may have contributed to greater error among bottle-fed infants, or that bottle-fed infants engage in more non-nutritive sucking during the meal in comparison to breast-fed infants. An alternate explanation may be that breastfed infants have more pronounced jaw movements since suckling from a breast requires more effort than sucking from a bottle nipple, and thus breast-fed infants' jaw movements were more perceptible by the sensor. The source of this feeding-mode variation in accuracy of the method needs further investigation in a larger sample. Another possibility may be to analyze the strength/amplitude of the sensor signal for bottle-fed and breast-fed infants and implement different processing for each group.

Other individual factors that were included in this study to examine their potential effect on the performance of the sensor were gender, age, and indices of body size and body composition. It was important to explore the influence of these variables because infant body size, composition, and therefore, function, vary a lot during the first six months of life. Results showed that there was no gender difference in the error between the sensor and human rater methods, and there was no association between the sensor performance (i.e. error) and infant age, or indices of infant size and body composition. It is important to note, however, that the small sample size may have limited the power of this study to detect any association. These results, therefore, are provided as an initial consideration of potential influences on sensor performance and would need to be replicated in a larger cohort before a conclusion could be drawn.

The small sample size is the main limitation of this study and therefore, results should be interpreted with caution until further investigation is possible. Despite this limitation, this study is an important first step in using a jaw sensor-based approach for the investigation of nutritive sucking in both breast-fed and bottle-fed infants, and results are supportive of the feasibility of this method to objectively monitor the feeding behavior of infants. Future work will involve larger cohorts to more comprehensively examine the performance of the sensor. Another possible limitation is that the sensor used in these experiments was originally designed to be used by adults and so the size may not be optimal for infants. In this cohort, however, there was no indication that the sensor size caused any discomfort for the infants or mothers, and the sensor did not impede bottle or breast feeding. Nonetheless, a smaller sensor may help to reduce over-estimation of the sucking count, and such an adaptation is technologically possible by incorporating the electronics of the sensor system into the infant's clothing. It is also important to note that there was no fixed bottle position for bottle-fed infants. Visual analysis of the videos showed that the bottles were angled somewhere between 0 (perfectly horizontal) and 90 degrees (perfectly vertical). Although no analysis was done to examine whether gravity permitted milk to drop into the infants' mouth without effort, visual inspection suggested active sucking from the infants to receive milk. It is also important to acknowledge that the experiments of this study were performed under laboratory conditions, and free-living tests will be required to evaluate performance of the proposed technique over extended periods of time under realistic conditions of daily living. An alternate approach to monitor feeding among infants is by recording pre and post meal body weights. Although well established, this method is also subject to error in the home environment and is useful only to measure overall intake, rather than within-meal feeding behavior. The jaw motion sensor may provide a complementary method to assess infant feeding behavior, or could potentially be developed further into a fully automatic version that is able to detect meal periods and energy intake, along with other useful behavioral parameters such as meal duration, and sucking count etc.

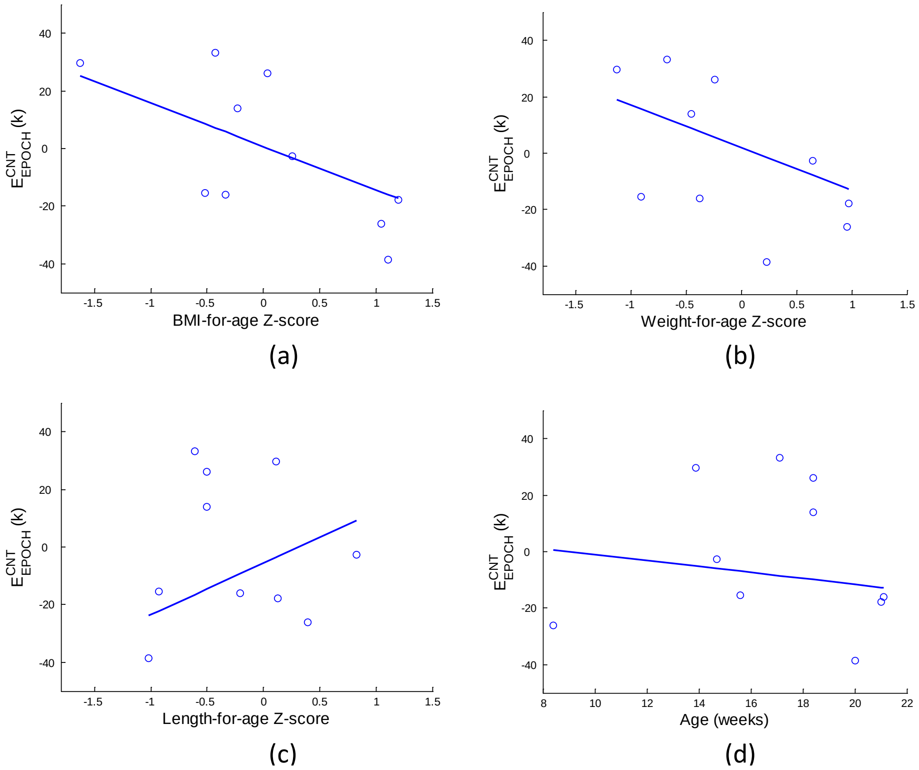

Figure 4-6 (a) Passing-Bablok regression analysis for $E^{CNT}_{EPOCH}(k)$ and % body fat. Regression line equation y = -0.03- 0.01x; 95% CI, for intercept -1.25 to 1.17 and for slope -0.05 to 0.05 (b) Passing-Bablok regression analysis for $E^{CNT}_{EPOCH}(k)$ and Total fat mass (in g). Regression line equation y = -0.65 +0.39x; 95% CI, for intercept -2.57 to 0.38 and for slope -0.23 to 1.60 (c) Passing-Bablok regression analysis for $E^{CNT}_{EPOCh}(k)$ and Total fat free mass (in g). Regression line equation y = 1.19-0.24x; 95% CI, for intercept –2.67 to 2.99 and for slope –0.61 to 0.52.

Future studies might also examine whether meal and sucking burst boundaries can be automatically recognized. In the current study, meals were marked by human raters. The relative strength of the sucking signal and swallowing rate (frequency) may provide indicators suitable for differentiation of food-related sucking with sucking on thumbs, pacifiers, and vocalizing, etc. The strength of the sucking signal may also provide another index of interest that might relate to obesity.

Overall, the results of this study suggest that monitoring of jaw motion has the potential to provide an objective measure of infant feeding behavior.

4.5 CONCLUSION

This paper evaluated the technical feasibility of using a jaw motion sensor for accurate and objective monitoring of feeding behavior among bottle-fed and breast-fed infants. The signals captured by the sensor were processed to estimate sucking counts. The computed counts were compared with results of human annotation of the same feeding episodes. The mean errors and ICC statistics showed a close, and acceptable, agreement between the human raters and the proposed sensor methodology for collecting data on infant sucking behavior during a meal. Statistical analysis of the results suggests that the performance of the proposed method is independent of factors such as gender, BMI, length, weight and age of the infants but it did differ by feeding mode. Further study with a larger sample is needed to more rigorously examine the statistical significance of these results. This would also ensure the applicability of the proposed method to a wider infant population. The preliminary findings suggest the potential of the sensor as a novel, effective and objective tool for monitoring infant feeding behavior.

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CHAPTER 5 AUTOMATIC MEASURING OF CHEW COUNT AND CHEWING RATE DURING FOOD INTAKE

Note to the reader: This work has been submitted to the Journal of Biomedical Signal Processing and Controls and is currently under review.

For modifying the eating habits of individuals such as how they chew, it is critical to automatically monitor those behaviors. This chapter introduces a fully automatic approach for detection and characterization of the chewing behavior of individuals in a controlled laboratory environment. Automatically counting chews is important for developing strategies for modifying eating patterns in individuals.

5.1 INTRODUCTION

Excessive eating can cause a drastic increase in weight, therefore, it is important to study the eating behavior of individuals to understand obesity. Similarly, people suffering from eating disorders experience changes in their normal eating patterns, causing individuals to either eat excessive or insufficient food compared to their body energy requirements. Obesity and eating disorders present a significant public health problem. Statistics from the World Health Organization (WHO) shows that worldwide, obesity is the 5th largest cause of preventable deaths [1]. People with anorexia nervosa have a shorter life expectancy (about 18th times less) in comparison to the people who are not suffering from this condition [2]. People suffering from binge-eating are at higher risk of cardiovascular diseases and high blood pressure [2]. Therefore, there is a need to study the food intake patterns and ingestive behavior of individuals; to better understand patterns and factors contributing to the obesity and eating disorders.

Traditional methods for monitoring food intake patterns such as food frequency questionnaires, food records and 24-hrs food recall, rely on self-report of the participants [3]–[5]. Research suggests that during self-report participants tend to underestimate their intake where the underestimation varies between 10% to 50% of the food consumed [6]. Apart from being inaccurate, self-reporting also puts the burden on the patients because of the need for their active involvement [8], [9]. Therefore, recent research efforts focused on the development of methods and techniques which are accurate, objective and automatic and reduces patient's burden of self-reporting their intake.

A number of wearable sensor systems and related pattern recognition algorithms have been proposed for monitoring of ingestive behavior. The systems relying on chewing as an indicator of food intake use such sensor modalities as in-ear miniature microphones [7], [8], accelerometers [9], surveillance video cameras [10], piezoelectric sensors on the throat [11] or on the jaw [12]–[14]. In [7], chewing sounds recorded with a miniature microphone in the outer-ear were used to train Hidden Markov Models (HMM) to differentiate sequences of food intake from sequences of no intake with an accuracy of 83%. In [15], an earpiece consisting of a 3D gyroscope and 3 proximity sensors was proposed which detected chewing by measuring ear canal deformations during food intake. Participant-dependent HMM achieved an average classification accuracy of 93% for food intake detection. In [9], the use of a single axis accelerometer placed on the temporalis was proposed to monitor chewing during eating episodes in laboratory experiments. Several different classification techniques (Decision Tree (DT), nearest neighbor (NN), multi-layer perceptron (MLP), support vector machine (SVM) and weighted SVM (WSVM)) were compared where WSVM achieved the highest accuracy of about 96% for detection of food intake. Our research group has been developing systems for monitoring of ingestive behavior via chewing [12]–[14], [16]. In [12], features computed from piezoelectric film sensors placed below the ear were used to train SVM and ANN models to differentiate between epochs of food intake and no intake with average accuracies of 81% and 86% respectively. In [13], this system was tested by 12 participants in free living conditions for 24-hrs each. Sensor signals were divided into 30-second epochs and for each epoch a feature vector consisting of 68 features was computed. Participant-independent ANN models differentiated between epochs of food intake and no-eating with an average accuracy of 89% using leave-one-out cross-validation.

In recent years, researchers have focused on the automatic detection of chewing but little work has been done on the quantification of chewing behavior, which may be an important factor in studying energy intake. Although no direct relationship has been established between obesity and chewing patterns, several studies have shown that increased mastication before swallowing of the food may reduce the total energy intake [17]–[21]. Results in [18] showed that obese participants had higher intake rate with the lower number of chews per 1 g of food (pork pie) compared to normal weight group. They also showed that an increase in the number of chews per bite decreased final food intake in both obese and normal weight participants. In [19], 45 participants were asked to eat pizza over four lunch sessions. Participants were asked to have 100%, 150% and 200% of the number of chews of their baseline number (first visit) of chews per bite before swallowing. According to the authors, food intake (total mass intake) reduction of 9.5% and 14.8% was observed for chewing rate of 150% and 200% respectively, compared with the 100% session. Our research demonstrated that the number of chews per meal may be used in estimating the energy intake if given the energy density of the food is known. In [22], individually calibrated models were presented to estimate the energy intake from the counts of chews and swallows.

Most of these studies relied on the manual counting of chews either by the participants or by the investigators, either from video tapes or watching participants in real time. Thus, there is a need to develop methods to provide objective and automatic estimation of chew counts and chewing rate. In recent studies, semi-automatic chew counting systems utilizing piezoelectric strain sensors have been proposed [28]–[30]. In [23], [24], a modified form of sensor system proposed in [13] was used to quantify sucking count of 10 infants by using zero crossing. In [25], an algorithm was proposed for counting chews from piezoelectric strain sensor and a printed sensor signals. A group of 5 adult participants counted the number of chews taken while eating 3 different food items and marked each chewing episode with push button signals. A peak detection algorithm was used to count chews from known chewing segments (based on push button signals) with a mean absolute error of 8% (for both sensors). An example of chewing sound use, [8] estimated the chewing rate and bite weight for 3 different food types from the sounds captured by a miniature microphone. A possible limitation of the acoustic-based approach is its sensitivity to the environmental noise, which might require a reference microphone for noise cancellation [7]. For these systems to be useful in free living conditions, fully automated solutions are needed which can not only automatically recognize chewing sequences but can also quantify the chewing behavior in terms of chew counts and chewing rates.

The goal of this paper is to present a method for automatic detection and quantification of the chew counts and chewing rate from piezoelectric film sensor signals. The proposed system is designed as means of automatic and objective quantification of the chewing behavior (chew counts and chewing rates) which can potentially be used in studying and understanding the chewing behavior of individuals and its relation to the energy intake without relying on manual chew counts. The proposed method could potentially be utilized in extending work reported in [21]–[26] to free living environment and studying the relation of chewing patterns, energy intake and obesity in community-dwelling individuals. Compared to acoustic-based approaches, the approach presented here is less sensitive to noise such as speech or environmental sounds. The system implements a fully automatic approach that first detects the intake of foods requiring chewing and then characterizes the chewing in terms of chew counts and chewing rate. The proposed approach was tested on a relatively large population and a wide variety of foods representative of the daily diet.

5.2 METHOD

5.2.1 DATA COLLECTION PROTOCOL

For this study, 30 participants were recruited. The population consisted of 15 male and 15 female participants with an average age of 29.03 ± 12.20 years and range of 19-58 years. The average body mass index (BMI) of the population (in kg/m2) was 27.87 ± 5.51 with a range of 20.5 to 41.7. Each participant came for four visits (a total of 120 experiments). Data from 16 experiments was discarded because of the equipment failure. The remaining dataset consisted of a total of 104 visits/experiments. Recruited participants did not show any medical conditions which would hinder their normal eating or chewing. An Institutional Review Board approval for this study was obtained from Clarkson University, Potsdam, NY, and all participants signed a consent form before participation.

Participants were divided into three groups based on meal type, i.e. breakfast, lunch or dinner and were asked to make two different meal selections from the food items available at one of the cafeterias at Clarkson University. The first meal selection was consumed by the participants in 3 visits whereas the second meal selection was consumed in the remaining visit. The order of visits was randomized. Overall, 110 distinct food items were selected by the participants, on average each participant consumed 1 to 3 food types and 1 or 2 different beverages. Representative food groups selected by the participants can be found in [22]. The wide spectrum of included food items ensures that the proposed algorithms behave well in the foods with varying physical properties eaten by the general population in their daily routine. The meals were consumed during a visit to a laboratory instrumented for monitoring of food intake. An accurate and objective reference (gold standard) was needed for quantification of chewing sequences. At present, obtaining an accurate reference in free living conditions is virtually impossible. Therefore, the study was conducted in the laboratory environment where close observation of the ingestion process was performed by the sensors and video recording. During each visit, participants were initially instrumented with the sensors [27]. As the first step of the protocol, the participants were asked to remain in a relaxed seated position for 5 minutes. Second, they were given an unlimited time to eat self-selected foods. Participants were allowed to talk, pause, food intake and move around (within the limitations imposed by the sensor system) during the experiment to replicate the normal eating behavior. As the final step of the protocol, participants were asked to remain in relaxed seated position for another 5 minutes.

5.2.2 SENSOR SYSTEM AND ANNOTATION

A multimodal sensor system was used to monitor participants [26]. A commercially available piezoelectric film sensor (LDT0-028K, from Measurement Specialties Inc. VA) was placed below the ear using medical adhesive for capturing motions of the lower jaw during chewing/mastication of the food. The selected sensor comprises of piezoelectric PVDF polymer film (28 µm thickness), and screen-printed Ag-ink electrodes encapsulated in a polyester substrate (0.125 mm thickness). Vibration of the surface to which the sensor is attached creates strain within the piezo-polymer which in turn generates voltage. The selected sensor has a sensitivity of 10 mV per micro-strains which have been shown to be enough to detect vibrations at the skin surface caused by chewing [26]. A custom-designed amplifier with an input impedance of about 10 MΩ was used to buffer sensor signals. Sensor signals were in the range of 0-2V which were sampled at f_s= 44,100Hz with a data acquisition device (USB-160HS-2AO from the Measurement Computing) with a resolution of 16 bits and were stored in the computer memory. This sampling frequency ensures that the sensor will be able to pick speech signals. The total duration of the sensor signal data was around 60 hours where about 26 hours of data belonged to food intake. Figure 5-1 (a, b) shows an example of the piezoelectric film sensor and its attachment to a participant. Figure 5-2 shows an example of the sensor signal captured during the experiment.

Experiments were videotaped using PS3Eye camera (Sony Corp.) and videos were time synchronized with the sensor signals. Custom-built LabVIEW software was used to annotate videos and sensor signals [27]. During the annotation process, well trained human raters marked the beginning and end of each eating event (bite, chewing and swallows) based on recorded videos. The annotation was performed by trained raters using the procedure described in [27]. Apart from marking the boundaries of eating events, human raters also recorded the number of chews for each bite. Inter-rater reliability of the annotation procedure adopted here was established in a previous study, where three raters achieved intra-class correlation coefficient of 0.988 for chew counting for a sample size of 5 participants [27]. Bites and chewing sequences were marked as food intake whereas the remaining parts of the sensor signal were marked as non-intake. For the k-th annotated chewing sequence, annotated chew counts were represented by $\mathrm{CNT(k)}$ and the corresponding chewing rate $\mathrm{CR(k)}$ was computed as

$$CR(k) = \frac{CNT(k)}{D(k)}, \tag{1}$$

where *D(k)* is the duration (in seconds) of *k*-th chewing sequence. The cumulative/ total number of annotated chews for each experiment/visit and average chewing rate were represented by $A_{CNT}(n) = \sum_{k=1}^{N} CNT(k)$, and $A_{CR}(n) = \frac{1}{N}\sum_{k=1}^{N} \mathrm{CR}(k)$ respectively, where *N* is the number of chewing sequences in the *n*-th experiment/visit. The resultant annotated data was used for the development of chew counting algorithms as well as for training and validation of the classification methods.

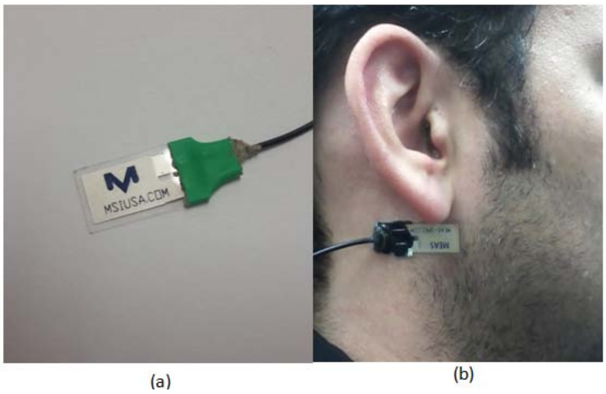

Figure 5-1 (a) Piezoelectric film sensor used in the study. (b) Sensor attached to a participant.

5.2.3 THE CHEW COUNTING ALGORITHM

To compute the chew counts, the sensor signals were processed in the following manner. All sensor signals were demeaned i.e. mean amplitude were subtracted from each signal to account for offset drift in the sensor signals. Chewing frequency is in the range of 0.94 to 2 Hz, therefore, a low-pass filter with a cutoff of 3Hz was used to remove unwanted noise [28]. Mastication/chewing of the food causes bending movements at the jaw which results in variations (peaks and valleys) in the piezoelectric sensor signal. A simple peak detection algorithm can be used to detect the presence of the peaks, the number of peaks can be used for estimation of the number of chews. To avoid peaks caused by motion artifact such as head movement, threshold-based peak detection approach was used where peaks were only considered if they were above a given threshold *T*. For selection of *T*, a histogram based approach was adopted, where signal amplitudes were considered as candidates for peaks if they were in the upper α^{th} percentile (details in section 2.4.). Figure 5-3 shows an example of histogram based peak detection algorithm where the red line indicates selected *T* value based on α^{th} percentile. This example histogram was generated using a single chewing sequence (note sampling frequency is 44100 Hz). Next, a moving average filter of 100 samples was used to smooth the resultant signal to account for small amplitude variations. The number of peaks in the resultant signal gave an estimate of the number of chews in a given segment. Figure 5-4 shows an example of the chew counting algorithm. For n^{th} experiment/visit, the cumulative estimated chew count is given by $E_{CNT}(n)$. For performance evaluation of the proposed chew counting algorithm the estimated chew counts were compared to the manually annotated chew counts and error were computed for each participant (all visits). Both mean errors and mean absolute errors were reported as:

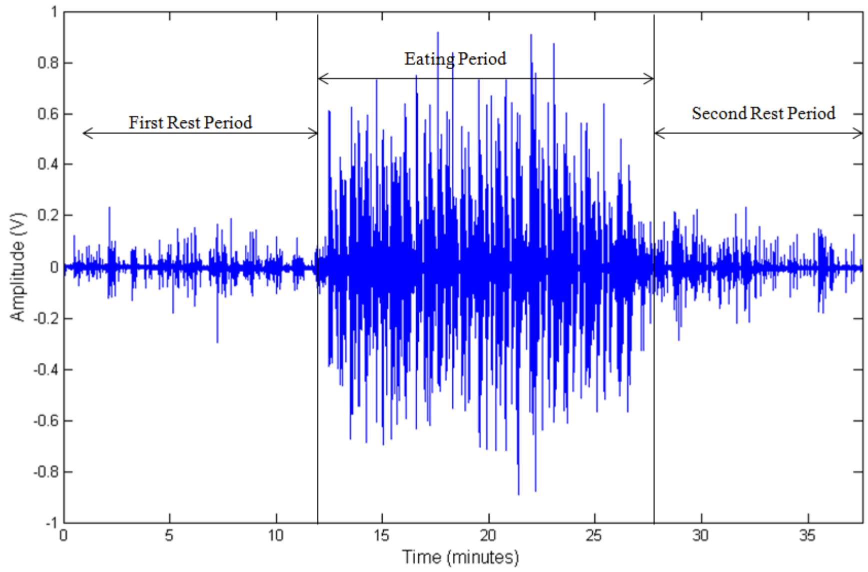

Figure 5-2. Piezoelectric Sensor (raw) Signal shows three parts of the experiment. First is a rest period, followed by an eating episode which is followed by the second rest period. Sampling frequency used was 44,100 Hz.

$$Error = \frac{1}{M}\sum_{n=1}^{M}\left[\frac{(A_{CNT}(n) - E_{CNT}(n)) * 100}{A_{CNT}(n)}\right], \quad (2)$$

$$|Error| = \frac{1}{M}\sum_{n=1}^{M}\left|\frac{(A_{CNT}(n) - E_{CNT}(n)) * 100}{A_{CNT}(n)}\right|, \quad (3)$$

where M was the total number of experiments (visits) in this case. This algorithm was used in two different approaches i.e. semi-automatic approach and fully automatic approach. In semi-automatic approach, manually annotated chewing segments from the sensor signal were considered for chew counting. In fully automatic approach, automatic recognition of food intake (chewing segments) preceded the application of the chew counting algorithm.

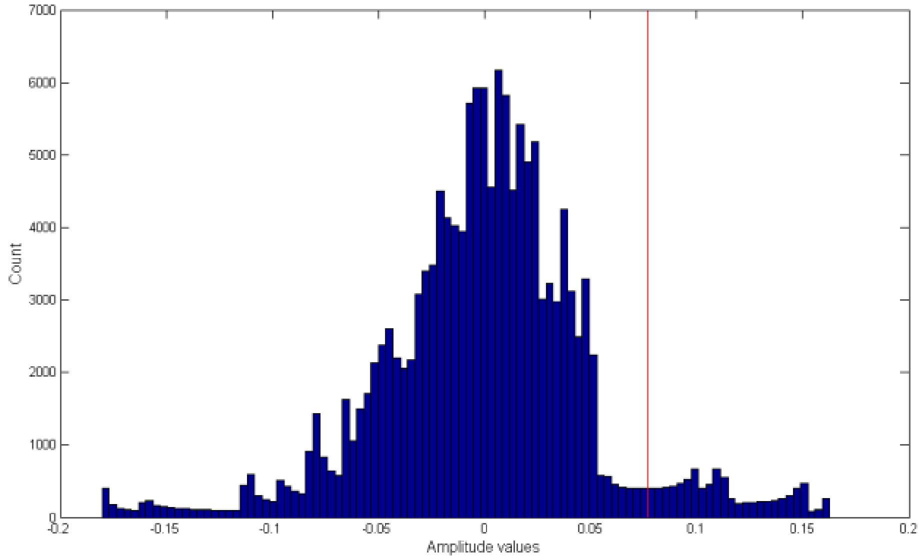

Figure 5-3. Histogram of a chewing sequence used for the selection of the threshold (*T*) for peak detection. Leave-one-out cross validation was performed for the selection of the threshold based on α-th percentile. The red line shows the selected threshold.

5.2.4 SEMI-AUTOMATIC APPROACH: PARAMETER DETERMINATION AND VALIDATION

In the semi-automatic approach, manually annotated chewing segments were used with the chew counting algorithm. Large amplitude variations were observed in the sensor signal due to different levels of adiposity in study participants, variations in the sensor placements, and variations in the physical properties of food items requiring different chewing strengths. The peak detection threshold *(T)* was adapted to the signal amplitude as *T= PERCENTILE(x(k), α),* where *x(k)* is the k^{th} manually annotated chewing sequence in the sensor signal and $\alpha \in [0.80, 0.97]$. To avoid over-fitting of the threshold, a subset of 20 randomly selected visits was used with leave-one-out cross-validation to find the value of α which gave the minimum mean absolute error (equation 3). Data from one visit were withheld, and data from the remaining visits were used to find the value of α which gave the least mean absolute error by performing a grid search on α in the given range. Selected value of α was used for computing the threshold T for the withheld visit. This process was repeated 20 times such that each visit was used for validation once, resulting in 20 different values of α. Average of these 20 different α values was calculated, and the resultant α was used for chew counting in both semi-automatic and fully automatic approaches. In the semi-automatic approach, for k^{th} chewing sequence in a visit, the estimated chew counts $CNT(k)$ were used for computing corresponding chewing rate $CR(k)$ using equation 1. For n^{th} visit for known chewing sequences, cumulative chew counts and average chewing rate were given by $E_{CNT}(n) = \sum_{k=1}^{N} CNT(k)$ and $E_{CR}(n)=\frac{1}{N}\sum_{k=1}^{N} CR(k)$ respectively. For semi-automatic approach, resultant mean error (signed) and mean absolute error (unsigned) were computed using equation 2 and 3.

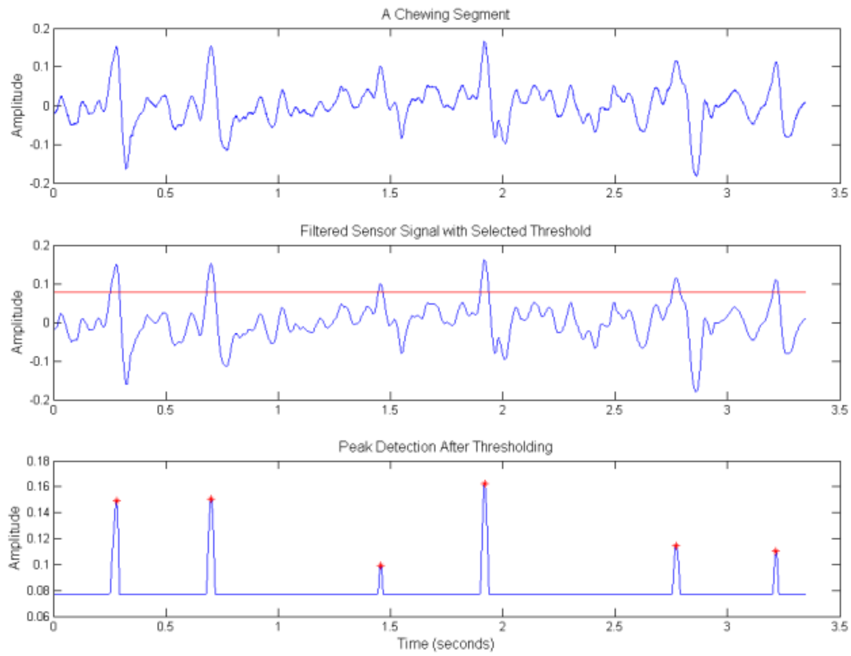

Figure 5-4. Different stages of signal processing for peak detection in chew counting algorithm. The first row shows the raw sensor signal. The second row shows filtered signal with selected threshold value (horizontal red line). The third row shows signal after thresholding and smoothing. Detected Peaks are indicated by a red ‘*’.

5.2.5 FULLY AUTOMATIC APPROACH: FEATURE COMPUTATION AND CLASSIFICATION

The fully automatic approach first recognizes periods of food intake by splitting the sensor signals into short segments called epochs and then applying the chew counting algorithm to the epochs labeled as food intake. The duration of the epochs was estimated to be 5 seconds based on the following considerations. The average length of a manually annotated chewing sequence was 7.35±5.16 seconds, therefore, 5 seconds epochs are be able to capture most of the chewing episodes. The frequency of chewing is in the range of 0.94 to 2.0 Hz, therefore, a 5-second epoch ensures that even for the lower bound of chewing frequency the epoch will contain multiple chewing events.

This approach results in epochs where some samples may belong to chewing and the rest may not belong to chewing and vice versa. Such situation will most likely occur at the start or end of chewing sequences. For this, 50% determination rule was used to assign a class label for a given epoch i.e. $C_i \in \{'-1','+1'\}$. An epoch was labeled as food intake (C_i = +1) if at least half of the samples in the epoch belong to food intake (based on human annotation) or else it was marked as non-intake epoch (C_i= -1). For i^{th} epoch $x(i)$, 38 time and frequency domain features were computed to find the corresponding feature vector f_i. The set of features used here is the same as feature extracted from piezoelectric strain sensor presented in [13]. Each feature vector f_i was associated with its corresponding class label C_i.

For classification of the epochs, a leave-one-out cross-validation scheme was used to train ANN models [13] that differentiate chewing and non-chewing. Non-chewing can be anything e.g. absence of chewing, rest, speech or motion artifacts, etc. The classification approach using Neural Networks has been demonstrated to be robust in free-living conditions in its ability to differentiate between chewing and non-chewing in the unrestricted environment [13] and shown to be superior to other methods (such as Support Vector Machines) [12]. Three layers feed-forward architecture was used for training ANN models with back-propagation training algorithm. The input layer had 38 neurons (for each feature) whereas the second layer (hidden layer) had 5 neurons and the third layer (output layer) consisted of only one output neuron to indicate the predictor output class label C_i ('-1' or '+1') for any given feature vector f_i. Both hidden and output layers used hyperbolic tangent sigmoid for transfer function. Training and validation of the models was performed with the Neural Network Toolbox available in Matlab R2013b (The Mathworks Inc.).

Classifier performance was evaluated in terms of F1 score which is defined as:

$$F1 = \frac{2 * Precision * Recall}{Precision + Recall} \quad (4)$$

$$Precision = \frac{TP}{TP + FP} \quad (5)$$

$$Recall = \frac{TP}{TP + FN} \quad (6)$$

where TP is the number of True positives, FP is the number of False Positives, and FN is the number of False Negatives. For leave-one-out cross-validation approach, data from one participant was used for validation (testing) whereas data from remaining participants was used for training. This process was repeated for each participant.

ANN models classified epochs as food intake and non-intake. Chew counting algorithm was used for epochs classified as food intake to estimate per epoch chew counts ($CNT(i)$). Forth *i-th* epoch, chewing rate ($CR(i)$) was computed using equation 1. For epoch based approach, cumulative estimated chew counts and average chewing rate for n^{th} visit were computed as $E_{CNT}(n) = \sum_{i=1}^{K} CNT(i)$ and $E_{CR}(n) = \frac{1}{K}\sum_{i=1}^{K} CR(i)$ respectively, where K represents total number of epochs in a visit. Errors (both signed and unsigned) for chew counts were computed using equations 2 and 3. For chew counting algorithms (in both semi- and fully automatic approach) 95% confidence interval was used to find the interval for the mean to check if the true mean error represents underestimation or over-estimation.

To compare the total number of chews estimated by the semi-automatic and fully automatic approaches with the manually annotated chew counts, one-way analysis of variances (ANOVA) was used. The null hypothesis in this case was that the means of chew counts estimated (for all visits) by all approaches (manual annotation, semi-automatic and fully-automatic approach) are same whereas the alternate hypothesis suggested that the means were different. ANOVA was also performed for comparing the performance of the proposed method for different meal types such as breakfast, lunch and dinner.

5.3 RESULTS

The collected dataset consisted of a total of 5467 chewing sequences marked by human raters with a total of 62001 chews (average chews per meal: 660$\pm$267 chews). Average chewing rate for all meals from human annotation was 1.53$\pm$0.22 chews per second. Table 5-1 shows meal parameters such as duration, number of bites, chews, swallows and mass ingested grouped by type of meal.

For the semi-automatic approach the algorithm estimated total chew count of ($\sum_{n=1}^{M} E_{CNT}(n)$) 58666 (average chews per meal: 624$\pm$278) with an average chewing rate of 1.44$\pm$0.24 chews per second. The chew counting algorithm was able to achieve mean absolute error (equation 3) of 10.4$\pm$ 7.0% for total number of chews compared to human annotated number of chews. The average signed error was (equation 2) 5.7$\pm$11.2%. The 95% confidence interval (CI) for mean for signed error was (3.4%, 8.0%).

In the fully automatic approach, trained ANN models were able to detect food intake with an average F1 score of 91.0 +/- 7.0% with the average precision and recall of 91.8 $\pm$ 9.0% and 91.3 $\pm$ 8.8% respectively, using leave one out cross validation. Further application of the chew counting algorithm resulted in 59862 total chews, 636$\pm$294 average chews per meal and average chewing rate of 1.76$\pm$0.31 chews per second. The mean absolute error was 15.0$\pm$11.0%. In this case the average signed error was 4.2$\pm$18.2%. The 95% confidence interval (CI) for mean for signed error was (0.05%, 8.10%). Figure 5-5 shows the distribution of both mean absolute errors for semi- and fully automatic approaches. Figure 5-6 shows the distribution of chew counts per meal for human annotated chews, estimate chew counts from the chew counting algorithm for semi- and fully automatic approaches.

Table 2 shows the results of ANOVA for comparing the mean chew counts among manual annotated, semi-automatic and fully-automatic approaches. Results of the statistical analysis showed no significant differences between the mean chew counts among different methods (p-value (0.68) > 0.05). Table 3 shows average errors in chew count estimation of both approaches for breakfast, lunch and dinner meals. Results of ANOVA show that there were no significant differences among different meal types (semi-automatic approach p-value: 0.87>0.05 and fully-automatic approach, p-value: 0.28 >0.05).

5.4 DISCUSSION

This work presented a method for automatic recognition and quantification of chewing from piezoelectric sensor signals in terms of chewing counts and chewing rate. Results of the chew counting algorithm for both semi- and fully automated approaches suggest that the method proposed can provide objective and accurate estimation of the chewing behavior. The method was tested on a comparatively large population and a wide variety of food.

In the semi-automatic approach, the algorithm was used to estimate chew counts and chewing rate in manually annotated chewing segments and was able to achieve a mean absolute error of (equation 3) $10.4\pm7.0\%$. For this approach, the mean signed error (equation 2) in comparison with human chew counts was $5.7\pm11.2\%$. A 95% CI computed for signed error (3.43%, 8.02%) did not include zero with both limits being positive, therefore, the results show a trend of under-estimation of the chew counts. A possible reason for this trend is the variability of food properties requiring different strength of chewing and variability in individual chewing patterns.

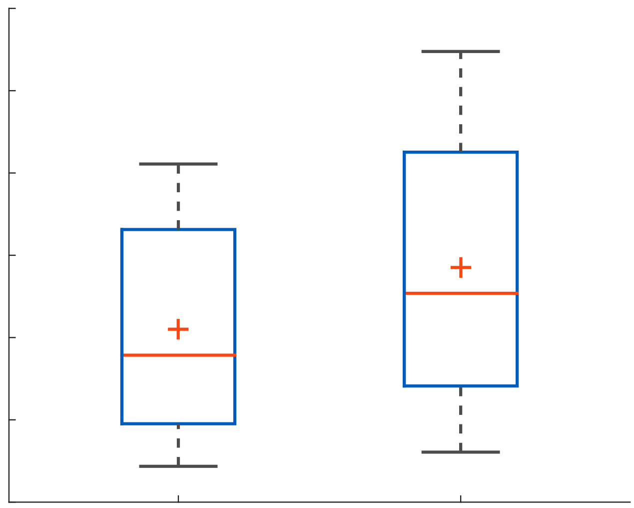

Figure 5-5. Distribution of Mean Absolute Error of chew counting algorithm for both semi- and automatic approaches.

The fully automatic approach presents a more realistic use of the proposed method for automatic detection and quantification of chewing behavior. In the proposed method ANN models for food intake detection preceded the use of chew counting algorithm for epochs classified as food intake. This two-stage process resulted in a higher mean absolute error for chew counting (15.0+/-11.0%) compared to the semi-automatic approach. The increase in error was expected as the error from both classification stage and the chew counting stage accumulate.

For cumulative chew counts, results of one-way analysis of variances (Table 2) show that the differences between the mean chew count for each visit/experiment were not statistically significant i.e. there was not enough evidence to reject the null hypothesis (all means are equal) at the given p-value of 0.68. This shows that the proposed algorithm can provide chew counts that are close to the human estimates derived from video observation. This also indicates that the trend of under-estimation of the chew counts by the algorithm is not statistically significant and can be ignored based on the strong evidence (given by p-value). Table 3 shows that the mean absolute error was also independent of the meal type i.e.

breakfast, lunch or dinner. This shows that the proposed method can be used for estimation of chew counts for foods traditionally consumed for breakfast, lunch or dinner without any sacrifice of the performance.

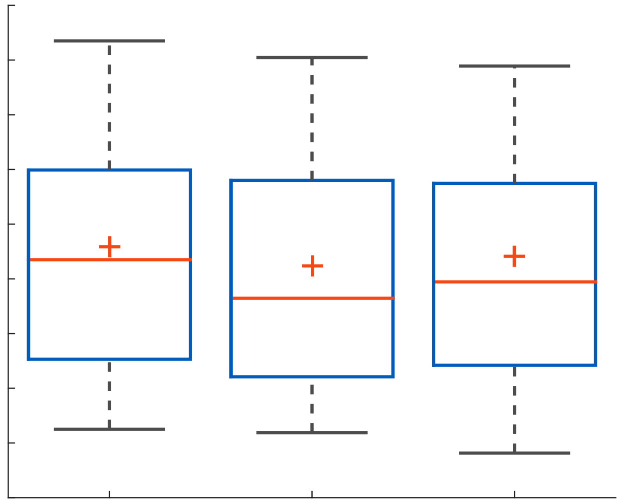

Figure 5-6. Box plots for total number per meal by human annotation, algorithm estimation with manually annotated data, semi-automatic approach and fully automatic approach.

Average chewing rate for manually annotated chewing sequences was 1.53 chews per second which is in the range of chewing frequency reported in the literature (0.94 – 2.5 chews per second) [28]. The chewing rates estimated by the chew counting algorithm were also in the range of previously reported values. Fully automatic chew counting approach resulted in the highest chewing rate of 1.76 with the standard deviation of 0.31 chews per second. A potential reason is that threshold for each epoch is a function of the signal amplitude in that particular epoch. Amplitude variations in epochs misclassified as food intake are smaller compared to actual chewing and therefore those particular epochs can result in higher chew counts. A possible improvement can be to calculate global thresholds for each participant to avoid higher chew counts in epochs incorrectly classified as food intake. This will require participant-dependent calibration of threshold computation.

In both semi- and fully automatic approaches, errors were computed for cumulative chew counts for each visit/experiment rather than the chews per known chewing segment. In the epoch based approach, one chewing sequence may be divided into multiple epochs, and there is a possibility that a part of chewing sequence may be labeled as non-chewing epochs and vice versa (because of the boundary conditions mentioned above), therefore, a direct comparison between these two approaches was not possible. To tackle this issue, the comparison was performed for the total number of chews for each visit (meal).

In this study, multi-day experiments were performed with a relatively large population to replicate daily eating behavior of people. Meals were kept as natural as possible. Participants were allowed to talk during the meals. Participants had the choice of selecting different meal times i.e. either breakfast, lunch or dinner and the choice of food items available at the cafeteria to make two different meals. While the food selection for a particular participant was somewhat limited, the study in general included a wide variety of food items with varying physical properties that may affect chewing. While not directly tested in this study, it is expected that the foods with different physical properties will have different chew estimation error, which over an extended period of time may average out across multiple food types. This hypothesis will be tested in future studies.

All presented methods were developed as participant-independent group models that do not need individual calibration. Since each participant had different meal content and the chewing patterns, therefore, use of participant dependent models (both for chew counting as well as for training classification models) may result in better accuracy and lower error but will require calibration to each participant.

Overall the presented method was able to detect and characterize the chewing behavior of a group of participants consisting of a wide range of adiposity while consuming a variety of food with wide range of physical properties. This system needs to be further explored and tested in free living conditions. One limitation of the fully automatic approach presented here is the use of fixed size epoch which contributes towards the increase in error. Rather than relying on the epoch based approach, there is a need to develop algorithms which can first separate potential chewing sequences from non-chewing sequences (without using fixed window segments) and then use classification models to identifying them as food intake or no intake sequences.

Another limitation is that the sensor system used in this study relied on an adhesive sensor and wired connections to the data acquisition system. Since the reported study the jaw sensor has been implemented as a Bluetooth-enabled wireless device that was tested in free living conditions [13]. The attachment of the sensor to the skin using medical adhesive has been shown to be simple and robust, similar to widely used adhesive bandages. In the free living study [13] the sensor did not experience any attachment issues and continuously remained on the body for approximately 24 hours. The same study demonstrated the ability of the sensor system to accurately perform in the conditions of free living, where it was subjected to uncontrolled motion artifacts such as walking, head motion and other unscripted activities of daily living. The user burden imposed by the sensor was evaluated in [29]. Results of the study suggested that participants experienced a high level of comfort while wearing the adhesive sensor and the presence of sensor did not affect their eating. For long term use (weeks and months), the sensor system may need further modifications to increase comfort and user compliance.

5.5 CONCLUSIONS

This work presented a method for automatic detection and characterization of chewing behavior in terms of chew counts and chewing rate. A histogram based peak detection algorithm was used to count chews in semi- and fully automatic approaches. For semi-automatic approach, the method was able to achieve a mean absolute error of 10.4±7.0%. In fully automatic approach, sensor signals were first divided into 5-second epochs that were classified as chewing or non-chewing by ANN. In the fully automatic approach, the classification accuracy of 91.0% and mean absolute error of 15.0$\pm$11.0% was achieved. These results suggest that the proposed method can be used to objectively characterize the chewing behavior.

Table 5-1 Details about the duration, number of bites, chews, swallow and mass in grams for different meal types.

	Breakfast					*Lunch*					*Dinner*					*All Meals (Total)*				
	Duration, s	*Mass, g*	*Bites, #*	*Chews, #*	*Swallows, #*	*Duration, s*	*Mass, g*	*Bites, #*	*Chews, #*	*Swallows, #*	*Duration, s*	*Mass, g*	*Bites, #*	*Chews, #*	*Swallows, #*	*Duration, s*	*Mass, g*	*Bites, #*	*Chews, #*	*Swallows, #*
Mean	815	618	43	508	70	1011	675	41	748	78	1281	839	52	707	107	1029	706	45	659	84
STD	349	191	10	184	27	321	160	11	253	22	645	281	19	294	39	481	228	14	266	33
Min	406	299	28	204	40	485	381	23	267	44	460	198	25	181	55	406	198	23	181	40
Max	1964	914	69	1036	154	1839	1188	65	1352	131	3052	1373	109	1441	209	3052	1373	109	1441	209
Total	24458	18565	1312	15247	2115	36398	24318	1488	26939	2827	35893	23514	1460	19815	3023	96749	66397	4260	62001	7965

Table 5-2 Results of One-way Analysis of Variance for comparison between different chew counting approaches (manually annotated, semi-automatic and fully automatic)

Source of Variation	Sum of Squares	Degrees of Freedom	Mean Square	F	P-value	F-crit
Between Groups	60737.45	2	30368.73	0.39	0.68	3.03
Within Groups	21857591.03	279	78342.62			
Total	21918328.49	281				

Table 5-3 Mean Absolute Errors for different meals for both semi- and fully automatic approaches

Meal Type	Semi-Automatic	Fully Automatic
Breakfast	10.90±7.59%	17.58±12.95%
Lunch	10.30±7.03%	12.65±10.74%
Dinner	9.99±6.63%	15.09±9.19%
Overall	10.40±7.03	15.01±11.06

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CHAPTER 6 SEGMENTATION AND CHARACTERIZATION OF CHEWING BOUTS: A WEARABLE APPROACH

Note to the reader: This work has been submitted to the Journal of Biomedical and Health Informatics and is currently under review.

Previous chapter introduced a pattern recognition algorithm for automatic chew counting in a meal using an epoch based approach where sensor signals are divided into fixed time windows called epochs. In practice, chewing bouts are of variable lengths. This work presents a new sensor system and related signal processing algorithms to segment potential chewing bouts and use a chew counting algorithms to automatically count chews.

6.1 INTRODUCTION

Research suggests that changing the eating behavior might be helpful in reducing total energy intake in individuals. For example, the energy intake is proportional to the portion size, thus, reducing the portion size may lead to a decrease in total energy intake [1]–[3]. Reducing the bite rate (the number of bites of food per minute) may reduce the energy intake [4]. Other studies have shown that increasing or decreasing the rate of intake may impact the energy intake [5]–[10]. For example, results in [9] suggest that increasing number of chews per bite by 150% and 200% from the baseline may achieve a reduction of total mass intake by 9.5% and 14.8%, respectively. Authors in [10] claimed that the number of chews per 1 gram of food in obese individuals is lower compared to normal weight individuals while increasing the number of chews per bite in both obese and normal weight individuals reduced their total energy intake.

The counts of chews and chewing rate can also be used for estimation of ingested mass and energy intake. In [11], individually calibrated models were proposed for estimation of the ingested mass and caloric energy intake from the chew counts. Chewing rate estimated from chewing sounds captured through a miniature microphone was proposed for estimating bite weight for three different food types [12].

In many of these studies ([5]–[9]), chew counts were measured by manual counting either by the participants or the investigators. Manual chew counts can be inaccurate, pose participant's burden and limit the applicability of the interventions targeting the modification of the chewing rate. Thus, there is a need for objective and automatic methods for quantification of the chewing behavior of individuals. In [11], chewing sounds were used for estimation of chewing sequences and chewing microstructure. However, acoustic-based approaches are venerable to surrounding acoustic noise or speech. Semi-automatic chew counting methods based on wearable piezoelectric strain sensors have been proposed [12]–[15]. In [13], a piezoelectric strain sensor was used for quantification of sucking behavior of infants. Histogram-based peak detection was used to estimate the chew counts in adults instrumented with a piezoelectric strain sensor and a printed strain sensor, resulting in the mean absolute error of 8% [14]. Currently, there is a need to develop sensor systems which can not only automatically and accurately detect the presence of chewing but also automatically quantify chew counts.

Several wearable sensor systems have been reported for automatic and objective detection of food intake based on recognition of chewing, such as in-ear miniature microphones [16], [17], strain sensors [14], [18], accelerometers [20], and in-ear proximity sensors [19]. In [17], authors presented an earpiece with embedded miniature microphone for capturing chewing sounds of sedentary individuals in quiet laboratory settings. A reference microphone was used for rejecting environmental sounds. Hidden Markov Model (HMM) trained with 16 features from the sensor signals were able to differentiate between chewing and non-chewing sequences with an average accuracy of 83%. One of the few studies conducted in unrestricted conditions of free living [18] used a piezoelectric strain sensor and a subject-independent classification model based on Artificial Neural Networks to achieve the food intake detection accuracy of 89% over the 24 hour period of sensor wear. In [19], authors presented an earpiece with three orthogonally placed infrared proximity sensors for capturing the deformation of the ear canal during chewing. The Hidden Markov Model based subject-independent classifier demonstrated an average accuracy of 82% in the wild experiments.

A significant number of the systems for food intake detection described in the literature are either tested only the in laboratory conditions or only considers food intake in the sedentary postures. People can eat while in sedentary posture or with moderate level of physical activity such as walking (eating “on the go”) [18], [20]. Therefore, it may be of interest to detect and differentiate food consumption while sedentary and while low to moderately active (food intake during high-intensity activities is not common due to the high breathing rate).

Another common limitation is the use of the epoch-based classification to detect chewing ([16], [18], [19], [21]–[23]) and to compute the number of chews. With this approach, the sensor signal is split into short segments (epochs) which then are classified either as chewing or no chewing. The algorithm then counts the number of chews in the epochs marked as chewing. Such approach is prone to accumulation of error as the epochs are not aligned with the boundaries of the chewing bouts, thus, accumulating the error both in classification and chew counting stage.

Main contributions of this paper are as follow: (i) Proposed is a novel wearable sensor system in the form of eyeglasses. Sensor (piezoelectric strain sensor) is placed on the temporalis muscle, compared to below the ear or in-ear sensors presented in the literature. The sensor system is specifically designed to detect eating while participants are performing low to moderate intensity activities so that the system's performance is not hindered by the presence of motion artifacts (speech, walking, head motions, etc.). The sensor system is non-invasive, non-obtrusive and potentially socially acceptable. (ii) Energy based segmentation (similar to voice activity detection [24]) is proposed to identify the boundaries of potential chewing bouts (of variable length) and chew count estimation.

6.2 METHODS AND MATERIAL

6.2.1 DATA COLLECTION PROTOCOL

Ten participants (8 male and 2 female) with an average age of 29.03±12.20 years and range of 19-41 years were recruited for the study. The average body mass index (BMI) was 27.87±5.51 kg/m2 with a range of 20.5-41.7 kg/m2. Recruited participants did not have any medical conditions which would impact their chewing. Each participant read and signed an informed consent form before the start of the experiment. The study was approved by the University of Alabama's Institutional Review Board.

For development and validation of algorithms for identifying chewing sequences and estimation of chew counts, an accurate gold standard is required. Since at present, there is no objective method for obtaining a gold standard in the unrestricted free-living environment, therefore, laboratory experiments were conducted where it was possible to monitor participants and accurately annotate their activities for developing the gold standard. Each participant performed the following activities:

Quiet Rest (5 minutes): Participants used computer or cell-phone while sitting comfortably in a chair. Talking was not allowed.

a) Eating while sitting: A meal where a slice of cheese pizza was consumed. Participants were allowed to talk.

b) Talking (5 minutes): Participants talked to the investigators or read out-loud.

c) Eating while walking: Participants ate a granola bar while walking on the treadmill at 3 mph.

d) Walking (5 minutes): Participants walked on the treadmill at 3 mph.

Activities included in this study were representative of the typical activities performed by people in free living. Eating while walking was included to replicate snacking “on the go”. Normal walking speed for a human is in the range of 2.8 to 3.37 mph, depending on the age [25]. Thus, a speed of 3 mph was chosen. Participant’s body movements were not restricted, and they were allowed to talk during all activities except for the quiet rest activity.

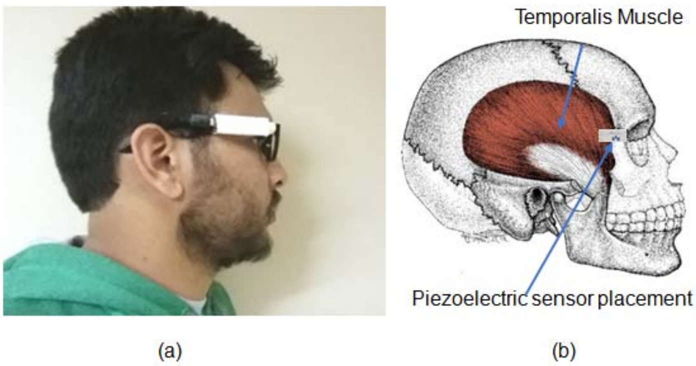

Figure 6-1 (a) A participant wearing smart glasses. The wearable sensor system is connected to the temple of glasses. (b) Temporalis muscle which is involved in controlling jaw movements during chewing and the sensor location on the muscle.

6.2.2 SENSOR SYSTEM AND ANNOTATION

During the experiment, participants were monitored using a portable, wearable sensor system. The presented wearable system consists of a piezoelectric strain sensor and a data collection module which is connected to the temple of the eyeglasses. An off the shelf piezoelectric film sensor (LDT0-028K from Measurement Specialties Inc. VA) was placed on the temporalis muscle (attached via medical tape) for capturing jaw motion. Temporalis muscle (Fig. 1 (b)) is part of the muscles that controls the jaw movements during chewing [26]. The selected sensor consists of Polyvinylidene fluoride (PVDF) polymer film with a thickness of 28 µm. The sensor’s sensitivity (10 mV per micro-strains) has been shown to be good enough to capture vibration due to chewing at the skin surface [43]. The data collection module consisted of circuitry for signal acquisition, signal conditioning, and data transmission. Sensor signals were sampled at 1000 Hz by a microprocessor (MSP430F2418, from Texas Instruments) by a 12-bit ADC. An onboard pushbutton was used by the participants to mark the start and end of chewing bouts. Participants also kept count of the number of chews for each chewing bout using a portable tally counter. Collected sensor signals were sent to an Android Smartphone via Bluetooth from the onboard RN-42 Bluetooth module. Data was logged on the Smartphone for further offline processing in MATLAB (Mathworks Inc.). Fig. 1(a) shows a participant wearing eyeglasses where the piezoelectric strain sensor is placed on the temporalis muscle and the data collection device is connected to the temple of the eyeglasses. Fig. 2 shows signals of the piezoelectric strain sensor and the pushbutton during different activities.

6.2.3 SIGNAL PROCESSING AND PATTERN RECOGNITION STAGES

A novel three-stage algorithm is proposed for automatic detection and characterization of the chewing. The stages of the algorithm are shown in Fig. 3. Each stage uses distinct features computed from sensor signals which are independent of features employed in other stages. First, the segmentation stage identified the boundaries of high energy segments (potential chewing events) based on the short-time energy of the signal. Second, the classification stage used a classifier to differentiate chewing segments from other activities that may result in high-energy signal segments (e.g. talking or walking). The third stage (the estimation stage) used a multivariate regression model to estimate chew counts from the chewing segments recognized in the classification stage.

6.2.4 SEGMENTATION STAGE

Energy envelop of the signal was computed using a sliding window (Hanning), to identify signal segments with high energy (which potentially can be chewing events). Since the sliding window is supposed to capture the energy of the chewing, located in the frequency band of 0.94-2.17 Hz [27], a window size of 1 second with an overlap of 0.5 seconds was used to compute the short-time energy. The short-time energy of each window was combined into a vector, a threshold (*T*) was dynamically estimated with the thresholding criterion presented in [28]. Successive windows for which the computed energies were higher than *T* were combined to form high energy segments that are considered as candidate chewing segments and successive windows with lower energies compared to *T* were combined to form low energy segments considered as non-candidate segments.

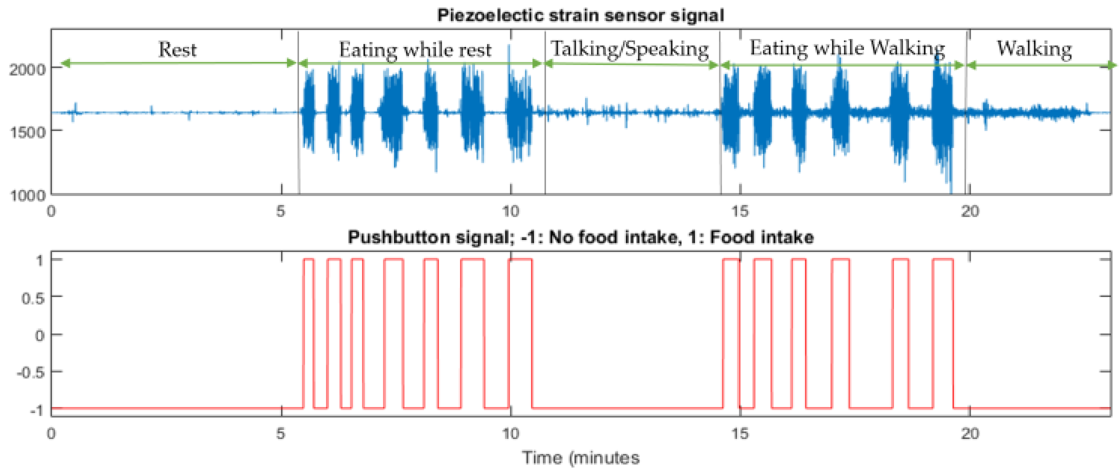

Figure 6-2 Sensor signals captured in an experiment. The first row shows the activities performed by the participants and the corresponding piezoelectric sensor signal; Second row shows the pushbutton signal.

6.2.5 CLASSIFICATION STAGE: FEATURE SELECTION AND CLASSIFICATION

High energy activity segments may or may not belong to chewing events (for example, such segments may be caused by walking or talking). Therefore, a classifier was used to determine whether a given candidate segment belonged to chewing or not. For training and validation of the classification models, each segment (candidate and non-candidate) was assigned a class label i.e. $C_i \epsilon$ {'-1','+1'} based on the pushbutton signals. From the data, it was observed that average overlap between the candidate segments (from the segmentation stage) and the pushbutton (indicating chewing) was 87%. Therefore, a segment was labeled as chewing (C_i

= +1) if the overlap between the segment and pushbutton (indicating eating) was at least 87% or more, otherwise it was labeled as a no chewing (C_i = -1).

Linear Support Vector Machine (SVM) models were selected for classification due to their speed and generalization. SVM models are less prone to overfitting [29]. Training of the models was performed using Classification Learner tool in MATLAB 2015 (from Mathworks Inc.). Linear SVM models were trained using a leave-one-out cross-validation procedure where the SVM model was trained with data from 9 participants, and data from the remaining participant was used for testing the trained SVM model. This procedure was repeated 10 times such that each participant was used for testing once. F1 score was computed for each iteration as:

$$F1 = \frac{2*Precision*Recall}{Precision+Recall}, \tag{1}$$

$$Precision = \frac{TP}{TP+FP}, \tag{2}$$

$$Recall = \frac{TP}{TP+FN}, \tag{3}$$

where TP, FP, and FN denote true positives, false positives, and false negatives, respectively.

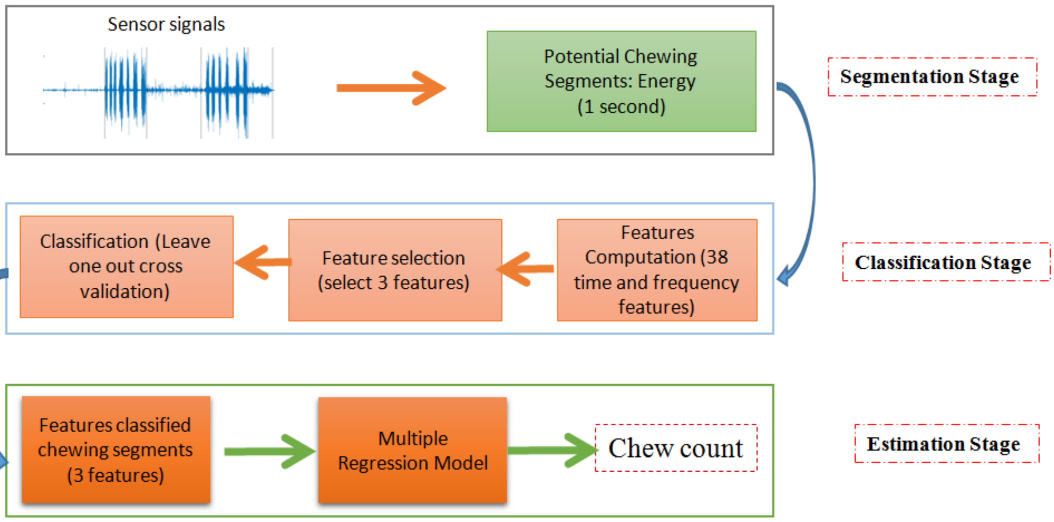

Figure 6-3 Stages of the proposed algorithm. Segmentation stage isolates high and low energy segments. Classification stage uses a classifier to classify these segments as chewing or non-chewing segments. Estimation stage employs a multivariate linear regression m

For each sensor segment, a set of 38 time and frequency domain features (proposed in a previous study for piezoelectric strain sensor [18]) was computed. Using all computed features might be redundant for the given classification task, therefore, a feature selection procedure based on Fisher score [30] was used to obtain a subset of features more suitable for differentiation between chewing and no chewing. Fisher score is a filter-based feature selection algorithm that ranks features according to their discriminatory information, such that in the data space spanned by the selected features, the distance between data points in the different classes is as large as possible while the distance between data points in the same class is as small as possible. The feature selection procedure was performed in two steps. First, all 38 features were ranked using Fisher score algorithm. Second, 38 individual support vector machine (SVM) models were created, where the first SVM model was trained using only the highest ranked feature and the subsequent models were trained by adding one feature at a time to the feature set according to their ranking. Each model was evaluated in terms of its classification accuracy (F1 score) and the feature set achieving the maximum average F1 score was chosen to train the final model.

Participant independent (group) linear SVM models were trained using leave-one-out cross-validation with selected features. Actual labels and predicted labels by the models for test participants were combined to plot the Receiver Operation Characteristic (ROC) curve and compute Area under the Curve (AUC) for each class. Both ROC and AUC were used as metrics for the comparison of classifiers performances.

6.2.6 ESTIMATION STAGE: CHEW COUNTS

In this stage, the segments classified as chewing were further processed for estimation of chew counts. Three features were computed from each chewing segment i.e. number of peaks, duration, and number of zero crossings. Fig. 4 shows a scatter plot of the chew counts (from chewing segments marked by the pushbutton) against these three features. Fig. 4

suggests a linear relationship between the computed features and chew counts. Having more than one explanatory variable might improve the performance of the regression model, therefore, a multivariate linear regression model was used.

6.2.7 LINEAR REGRESSION FOR CHEW COUNT ESTIMATION

Linear regression is a predictive analysis technique used to model the relationship between a dependent variable and one or more explanatory variables [31]. General form of linear regression model is:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ \dots + \beta_k x_k + \varepsilon, \tag{4}$$

where β_0 is the called the intercept coefficient and β_k is the coefficient of the k^{th} explanatory variable and defines the effect of the k^{th} variable on the output of the model. Here ε is called the error term and describes the variance in the data that cannot be explained by the model. The goodness of the fit of the regression model is given by the coefficient of determination, adjusted R^2 (for multivariate regression model).

Leave-one-out cross-validation was used to train the regression models for chew count estimation. For training of the regression models, features were computed from chewing segments marked by the participants with a pushbutton. This was done because the actual chew counts were available for human marked chewing segments only. Total/cumulative human annotated chew counts for n^{th} participant/experiment is represented by $A_{CNT}(n)$. For validation of the regression model, the chewing segments recognized by the classification stage were used. In the leave-one-out cross-validation, 9 participants were used for training of the model and the 10^{th} participant was used for testing. Total estimated chew counts for n^{th} participant is represented by $E_{CNT}(n)$. The mean and mean absolute errors were computed as

$$Error = \frac{1}{M}\sum_{n=1}^{M}\left[\frac{(A_{CNT}(n) - E_{CNT}(n)) * 100}{A_{CNT}(n)}\right] \tag{5}$$

$$|Error| = \frac{1}{M}\sum_{n=1}^{M}\left|\frac{(A_{CNT}(n) - E_{CNT}(n)) * 100}{A_{CNT}(n)}\right| \tag{6}$$

where M=10 is the number of participants, $Error$ mean (signed) error and $|Error|$ is the mean absolute error (unsigned).

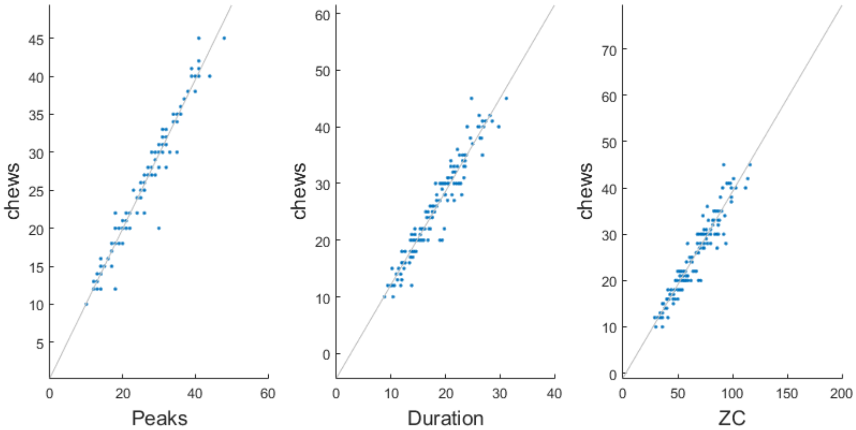

Figure 6-4 Scatter plot of chew counts against features computed from each chewing bout marked by the participants using pushbutton. Scatter plot suggests that there is a linear relationship between the number of chews and the 3 computed features.

6.3 RESULTS

There were 127 chewing segments marked by participants with the pushbutton. The segmentation stage resulted in a total of 286 segments (130 candidate segments and 156 non-candidate segments).

The candidate segments were further classified into chewing and non-chewing segments. The best model achieved the average F-score of 99.17+/-2.63% (average precision and recall of 98.46+/-4.86% and 100+/-0%, respectively). Confusion matrix given in Table I suggests that all no chewing segments were correctly classified by the classifier, whereas only 2 chewing segments were misclassified as no chewing segments. Fig. 6 shows the ROC of the classifier for the whole dataset. AUC of the group model was 0.99.

Table 6-1Confusion matrix for linear SVM classification.

Bouts	Non-Chewing	Chewing
Non-Chewing	156	0
Chewing	2	128

The classification stage relied on the subset of features achieving the highest average F1 score, which was achieved by using 3 features. Selected features were mean absolute value, root mean square (RMS) value and median values of the signal from the piezoelectric sensor. Fig. 5 show a scatter plot of the selected 3 features for two classes (chewing and non-chewing), clearly demonstrating linear separability in the selected feature space.

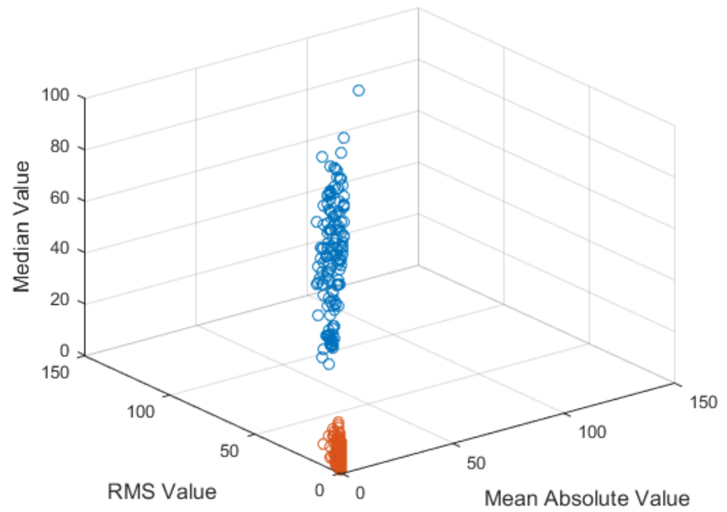

Figure 6-5 Scatter plot of features with respect to two classes. Blue circles indicate chewing, red circles non-chewing.

In the estimation stage, linear regression models estimated chew counts with the mean absolute error of 2.68% and standard deviation of 1.74%. Table II lists the coefficients of the multivariate linear regression model, fitted to the whole dataset. This model was able to achieve an R^2 of 0.98 and adjusted R^2 of 0.98. The corresponding p-values for each feature suggest that all features are signification to the model. Based on human counting, there was a total of 3277 chews across 10 participants whereas the sensor estimated total chew counts were 3350. Table III shows the error estimation for each participant along with the total human chew counts and sensor estimated chew counts.

6.4 DISCUSSION

The focus of the proposed work is automatic detection and characterization of the chewing bouts in the presence of motion artifacts caused by physical activity and speech. Many of the earlier studies have considered food intake detection when participants were sedentary [12], [17], [19], [21], [22], [32]–[35]. The design of this study accounts for the possibility of consuming food while moderately active ("on the go"). The desired functionality is achieved by two innovations. First is a novel sensor system that monitors the activity of the temporalis muscle as opposed to previously reported chewing sounds [16], [17] and jaw motion [18]. Second is a novel algorithm that identifies candidate chewing segments and classifies these variable length segments as opposed to splitting the signal into epochs of fixed length and classifying each epoch individually. The results suggest the viability of the proposed approach.

Table 6-2 Coefficients of the multivariate linear regression fitted to the data. At 0.05 significance level, the results show that all predictors/features are significant.

	Estimate	*SE*	*t-Stat*	*p-value*
Intercept	-1.88	0.57	-3.28	0.001
Number of Peaks	0.46	0.06	7.85	1.09e-11
Duration of chewing	0.72	0.09	8.22	1.89e-12
Number of zero Crossings	0.06	0.03	2.46	0.01

* R^2 = 0.98 and Adjusted R^2 = 0.98, Root Mean Squared Error: 1.22

The sensor signal shown in Fig. 2 suggests that chewing segments have higher energy compared to non-chewing segments. This characteristic allows to segment the signal and identify the candidate chewing bouts using the energy envelope of the signal. The segmentation algorithm results in variable length segments compared to fixed size epoch based approach widely presented in the literature. These high energy segments may or may not be chewing (can be caused by other activities, such as walking). Therefore, it was necessary to use a classification method to verify further whether a given high energy segment was indeed chewing or not.

Feature selection procedure resulted in the selection of three most prominent features, i.e. mean absolute value, RMS value and median values. Selected features suggest that amplitude based metrics of the signal can provide discriminatory information to the classifier. Fig. 5 shows that in the selected feature space, both classes are separable using a hyperplane, therefore, linear SVM models were chosen for classification. In the classification stage, participant independent linear SVM models were used to avoid participant dependent calibration which is necessary for the use of the trained models in the wider population.

Results in Table I show that only two chewing segments were misclassified as non-chewing segments whereas none of the non-chewing segments were misclassified (no false positive). The classifier achieved an average F-score of 99.17% for leave-one-out cross-validation. Several sensor systems have been presented where the accuracy of food intake detection varies from 80% to 96% [18], [19], [22], [23], [33]. For most of these sensor systems, their ability to detect food intake was tested when the participants were sedentary. In comparison to the state of the art for automatic detection of food intake, the proposed device presents a more accurate system tested under challenging conditions that include eating while being physically active.

Table 6-3 Self-reported and algorithm estimated chew counts.

Participant #	Actual Chew Counts	Estimated Chew Counts	$Error$ (%)	$\|Error\|$ (%)
1	283	284	-0.35%	0.35%
2	423	433	-2.36%	2.36%
3	203	215	-5.91%	5.91%
4	307	307	0.00%	0.00%
5	291	284	2.41%	2.41%
6	344	352	-2.33%	2.33%
7	338	349	-3.25%	3.25%
8	299	306	-2.34%	2.34%
9	414	429	-3.62%	3.62%
10	375	391	-4.27%	4.27%
		Mean:	-2.20%	2.68%
		STD:	2.37%	1.74%

For estimation of chew counts, linear regression models were used since linear relationship was observed between the computed features and chew counts for chewing bouts (Fig. 6). Actual chew counts were available only for chewing bouts marked by participants using the pushbutton and not for chewing bouts identified by the classification model. Therefore during the training of the regression models, features computed from chewing bouts marked by participants were used but for the validation phase, the chewing segments identified by the classifier were used. For the same reasons, errors were computed for the cumulative chew counts over the whole experiment rather than for individual chewing bouts. Table II presents an example of the regression model, where slopes of the linear fit are positive which indicates that there is a positive relationship between the dependent variable (chew count estimation) and the explanatory variables. In the case of the multivariate regression model, adjusted R^2 indicates that the model explains about 98% of the variation in the estimation of chew counts which shows a very good fit.

The wearable sensor system presented in this study combines all components into a single module which is connected to the temple of the eyeglasses, reducing the participant burden. The electronics of the device is low power with the battery life of over 24hrs [18]. There is a possibility of further miniaturizing the electronics and integrating of the piezoelectric sensor into the temples which will improve the user comfort. Further research is needed to study the social acceptability and user compliance with using the sensor system.

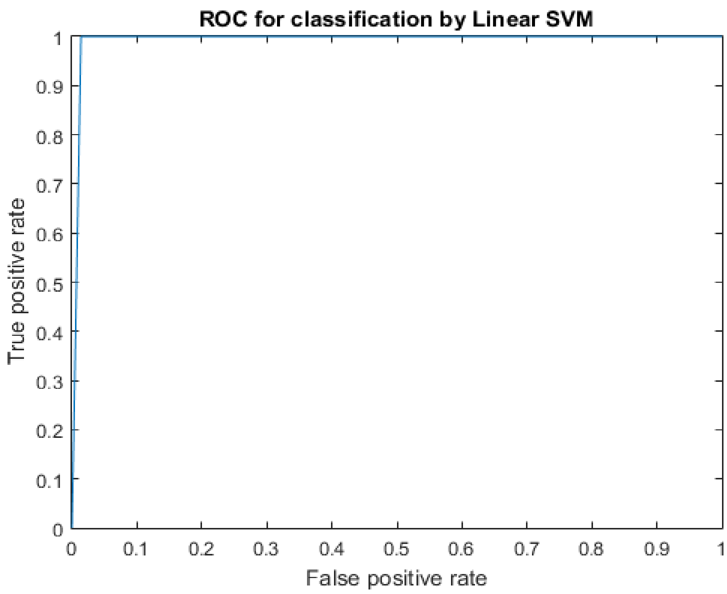

Figure 6-6 Receiver Operation Characteristics (ROC) curve for participant independent SVM models. AUC of 0.9931.

A possible limitation of this study is the exclusion of liquids, which were not included in the study since the main goal was to test the ability of the system for capturing chewing. Previous research suggests that during continuous intake of liquid, characteristic jaw motions similar to the ones produced by chewing are present which can be captured by the proposed device [23]. Further studies are required to test the ability of the proposed sensor system for detection of liquid intake. The study was performed in laboratory conditions because an accurate reference (gold standard) was required to compare the system's performance for identifying chewing bouts and estimation of chew counts. Long-term studies in free-living need to be conducted to establish the performance of the proposed wearable sensor system under unrestricted conditions. The current study presents results for 10 participants as preliminary results, larger studies with a wide variety of food items will be conducted in future to test the system.

6.5 CONCLUSION

This work presents a novel wearable sensor system for detection and characterization of chewing bouts in the presence of motion artifacts originating from physical activity and speech. The proposed sensor relies on monitoring of the activity in the temporalis muscle to detect chewing. A multistage algorithm first identifies candidate chewing segments and then uses linear SVM models to classify chewing bouts with the average F1 score of 99.17%. In the last stage, a multivariate linear regression model estimates the chew counts with the mean absolute error of 2.68%. The results suggest that the system is able to detect the presence of food intake and can accurately estimate chew counts in complex situations involving speech and physical activity.

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CHAPTER 7 A NOVEL WEARABLE DEVICE FOR FOOD INTAKE AND PHYSICAL ACTIVITY RECOGNITION

Note to the reader: This work has been submitted to the Sensors Journal and is currently under review.

So far the presented work in this dissertation focused on the methods for food intake detection i.e. energy intake. But energy expenditure is an equally important part of the energy equation. Apart from BMR, type of physical activities performed by individuals contributes to the energy expenditure. This work explores the sensor system presented in previous chapter for detection of food intake and physical activity recognition. Further it proposes algorithms for detection of “eating on the move” i.e. when participants are on the move.

7.1 INTRODUCTION

Automatic monitoring of food intake is critical to the understanding, and studying of the factors contributing towards the development of obesity and eating disorders [1], [2]. Traditional methods for monitoring of ingestive behavior rely on self-reporting techniques such as food frequency questionnaires [3], 24-hrs recall [4], and use of mobile devices [5]. These methods suffer from limitations posed by participant burden and inaccuracies in self-reporting the data due to reliance on human memory [6]–[8]. In recent years, to alleviate problems associated with self-report, several wearable devices have been proposed for automatic detection and monitoring of food intake. Sensor systems used for this purpose can be divided into two groups, i.e. sensors placed in the environment monitoring the individuals and body worn/wearable sensors. The camera-based system is an example of sensors placed in the environment for monitoring of eating episodes [9], [10]. In [9], a multistage algorithm was proposed to detect chewing from surveillance videos. The proposed algorithm involved detection of mouth region and computation of spatiotemporal frequency spectrum of the small perioral region for recognition of chewing movements. A similar system presented in [10], proposed using Active Appearance Models (AAM) for detection of faces in surveillance videos and used observed variations in AAM parameters for detection of chewing with an average accuracy of 93%, for 37 participants. Sensors placed in the environment around individuals cause least burden to the participants but suffers from limitations such as the need for specially equipped spaces and restriction on participant's movements since they need to be in the field of view of the camera. Additionally, low lighting conditions can also hinder the performance of these systems.

Body-worn sensors have been proposed to capture different stages of eating i.e. bites, chewing and swallowing of food. Several hand/wrist-worn wearable device have been proposed for detection of gestures related to eating including accelerometers, gyroscopes and smart watches [10]–[13]. In [11], Dong et al. proposed the use of a wrist-worn device (in the form of a watch) to track wrist movements associated with food intake and were able to detect and counts bites taken during a meal with an accuracy of 86% in cafeteria settings. In [15], a wearable sensor system with five inertial sensors located on the wrists, upper arms, and upper torso was proposed. Some researchers have suggested wearing audio recording devices on the wrists to record audio and use machine learning and pattern recognition algorithms to detect eating episodes based on the recordings [13], [14]. Wrist worn sensors are the most natural option, but they are relatively inaccurate compared to the other food intake monitoring systems.

The second stage of eating involves chewing which can be monitored via chewing sounds [16]–[18], EMG and force sensors [19]–[21] or capturing jaw vibrations during chewing using strain sensors [22]–[25]. In [18], use of conduction microphone was suggested for capturing chewing sounds. Acoustic based approach for detection of chewing suffers from the presence of environmental acoustic noise and, therefore, requires the use of additional reference microphones to eliminate environmental noise [18], [26]. Another possibility is to measure the deformation in the ear canal walls using proximity sensors due to chewing activities during food intake [27]. In [27], a wearable sensor system in the form of an earpiece was proposed which included three infrared proximity sensors placed orthogonally with respect to each other to allow for a wider coverage of the ear canal. Participant dependent models detected presence of food intake with an accuracy of 93% in a laboratory setting. In [28], the use of a single axis accelerometer placed on the temporalis was proposed to monitor chewing while eating episodes in laboratory experiments. The characteristic jaw movements produced during chewing can also be captured by using a piezoelectric strain sensor [23]. A three module sensor system (hand gesture sensor, accelerometer and piezoelectric strain sensor below the ear) was used by 12 participants to monitoring food intake in free-living conditions for 24-hrs [22], [25], [29]. The system was able to detection presence of chewing with an average accuracy of 89% in unrestricted free living conditions.

Swallowing involves the passage of a bolus of food or liquid from the mouth to the stomach and involves contraction and relaxation of muscles of the tongue (oral preparation), pharynx (the pharyngeal) and esophagus (esophageal phase) [30]. Wearable sensors have been proposed to monitor these muscle contractions and relaxations for detection of food intake such as microphones placed in the ear (to capture swallowing sounds) or on throat or surface electromyography. In [31], researchers used two microphones for capturing swallowing sounds and environmental noise. Other researchers have proposed similar systems [32]–[35] where miniature microphones were placed on the laryngopharynx for automatically differentiating between swallowing sounds related to food intake and other activities.

Acoustic based swallowing detection systems suffer from environmental noise and presence of surrounding speech/talking. Another possibility is to use bio-impedance measurement (such as EMG or EGG) at larynx level for detection of swallowing related to food intake [36], [37]. Piezoelectric strain sensor placed against the throat is subjected to physical strain during muscle contraction and relaxation caused by swallows [38], [39]. These systems are virtually insensitive to the environmental noise. However, these systems are not able to reliably distinguish swallows from the head, and neck movements and, therefore, their use in free-living conditions is limited [34].

Most of the systems presented in literature were tested either in laboratory conditions or assume food intake episodes in sedentary postures. People can eat food while in sedentary posture or while performing low to moderate intensity activities (in the range of 3-6 metabolic equivalents (MET)) such as walking [22], [40]. Several accelerometer-based physical activity monitoring systems have been proposed in the literature to recognize physical activities of different intensities such as sitting, standing, walking, etc. [41], [42]. To the best of our knowledge, no system has been tested for detection of food when participants were physically active. The purpose of this work is to present a new novel wearable sensor system for automatic, accurate and objective monitoring of ingestive behavior that reliably recognizes food intake in physically active users, which makes it potentially suitable for detection of snacking “on the go.” The proposed system also has the ability to differentiate between the states of low physical activity (sedentary state) and moderate physical activity such as walking. The device is integrated into eyeglasses with a piezoelectric strain sensor placed on the temporalis muscle and an accelerometer placed on a temple of the eyeglasses. Food intake detection is performed using features from the piezoelectric strain sensor, and the intensity of physical activity is detected using an onboard accelerometer. Two multiclass classification approaches are proposed to differentiate between different classes of activities.

The wearable device presented in this work is non-invasive, non-obtrusive and potentially socially acceptable. This device has the potential ability to track both energy intake and energy expenditure patterns, which can potentially be used in developing strategies for understanding and tackling obesity.

7.2 MATERIALS AND METHODS

7.2.1 DATA COLLECTION PROTOCOL

A total of 10 volunteers were recruited for this study (8 male and 2 female, average age 29.03 ± 12.20 years, range 19-41 years, average body mass index (BMI) 27.87 ± 5.51 kg/m2, range 20.5 to 41.7). Participants did not suffer from any medical conditions which would impact their chewing. Before the start of the experiment, each participant signed an informed consent form. University of Alabama's Institutional Review Board approved the study. For training and validation of classification models, an accurate reference (gold standard) is required, which at the moment, is not possible to attain in unrestricted free-living conditions. Therefore, the experiments were performed in a laboratory where it was possible to observe participants closely and develop an accurate reference. During a single visit to the lab, participants had to follow the protocol which started with an initial five minute quiet rest, where participants were asked to use their phone or computer without talking while sitting. Next, the participants consumed a slice of cheese pizza while sitting comfortably in the chair. They were allowed to talk during the meal. The food intake was followed by five minutes of talking or reading out loud. Next, participants were asked to eat a granola bar while walking on the treadmill at 3 mph. Last activity was walking on the treadmill for 5 minutes at 3 mph, where they were not asked to eat anything.

Activities performed by the participants were representative of the activities performed in daily free-living conditions. Pizza represented a food item that may be consumed in a meal or a snack. Granola bar represented snacks that may be consumed on the go. A speed of 3 mph was chosen for ambulation because the normal walking speed varies from 2.8 mph to 3.37 mph depending on the age of individuals [43]. Throughout the experiment, there were no restrictions on participant's body movements (including head movements), and they were allowed to talk throughout the experiment, even during eating.

7.2.2 SENSOR SYSTEM AND ANNOTATION

The wearable device proposed in this work combined the data collection, signal conditioning, and wireless data transmission into a single module that was connected to the temple of the eyeglasses. Jaw movements during chewing were captured by placing a commercially available piezoelectric film sensor (LDT0-028K from Measurement Specialties Inc. VA) on the temporalis muscle using medical tape. Temporalis muscle is part of the muscles that controls the jaw movements during chewing [44]. Ultra-low power operational amplifier (TLV-2452, Texas Instruments) with an input impedance of 1GOhm was used to buffer the high impedance of the piezoelectric sensor. Sensor signals were sampled at 1000 Hz by a microprocessor (MSP430F2418, Texas Instruments) by a 12-bit ADC. Body acceleration was recorded with a low-power three axis accelerometer (ADXL335 from Analog Devices) and sampled at 100 Hz. Participants used a pushbutton to mark chewing sequences (sampled at 100 Hz) and to define boundaries of different activities. Collected sensors data was sent via an RN-42 Bluetooth module with serial profile to an Android Smartphone for storage and further offline processing in MATLAB (Mathworks Inc.). Figure 7-1 shows the piezoelectric strain sensor and the data collection acquisition module connected to the temple of the glasses. Figure 7-2 shows example signals of the piezoelectric strain sensor and accelerometer sensor during different activities.

7.2.3 SIGNAL PROCESSING AND FEATURE COMPUTATION

Chewing frequency is in the range of 0.94 to 2.17 Hz [45], therefore, piezoelectric sensor signals were passed through a low-pass filter with a cut-off frequency of 3.0 Hz. For feature computation, both piezoelectric sensor and accelerometer signals (net acceleration) were divided into non-overlapping 3-second epochs. Selected epoch size ensures that even for lower bound of chewing frequency, an epoch will contain multiple chews. Close observation of Figure 7-2 suggests that irrespectively of the activity level of the participants (sitting or walking), for piezoelectric strain sensor, eating episodes have higher energy compared to non-eating episodes. A similar trend can be seen for walking in the accelerometer signal where walking registers higher energy (based on amplitude variations) compared to being physically sedentary. Features listed in Table 1 were computed to represent the sensor signals for classification.

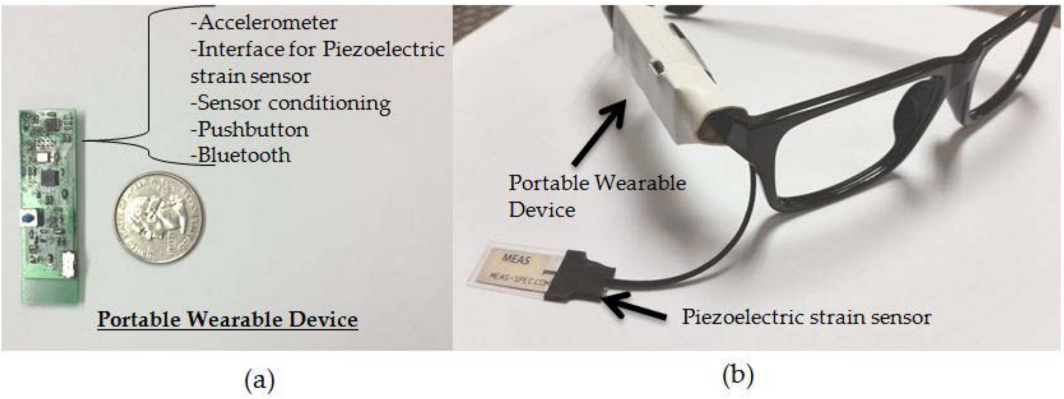

Figure 7-1 (a) Portable wearable device for monitoring of food intake and level of physical activity. Data acquisition module also has Accelerometer and Bluetooth. (b) Eyeglasses with a piezoelectric sensor and data acquisition device connected to the temple of glasses.

For the i^{th} epoch, piezoelectric strain sensor feature vector was represented by $f_{i,chew}$ and feature vector for the accelerometer signal was represented by $f_{i,Acc}$. Pushbutton was used to define the class label for a given epoch. Figure 7-3 shows the distribution of piezoelectric strain sensor features for two classes i.e. eating and no eating, irrespective of the activity level. Similarly, Figure 7-4 shows the distribution of features computed from accelerometer signals, for two classes i.e. epochs with physical activity (walking) and without physical activity (sedentary) irrespective of whether the participant was eating or not eating. From the given feature distributions, it is clear that these classes are easily separable using the respective feature vectors.

Table 7-1. Feature sets computed from both piezoelectric and accelerometer sensor epochs

No	Feature	Description
1	Range of values:	Rng(x(i)) = Max(x(i)) – Min(x(i))
2	Standard Deviation:	STD(x(i)) = $\sqrt{\sum(\mathrm{x(i)} - \overline{\mathrm{x(i)}})/(\mathrm{N}-1)}$
3	Energy:	Eng(x(i)) = $\sum_{\mathrm{n}=1}^{\mathrm{N}} \mathrm{x(n)}^2$
4	Waveform Length:	WL(x(i)) = $\sum_{\mathrm{n}=1}^{\mathrm{N}-1} \lvert \mathrm{x(i)}_{\mathrm{n}+1} - \mathrm{x(i)}_{\mathrm{n}} \rvert$

*where *i* represents epoch number, *n* is the n^{th} sample in the i^{th} epoch; $N = L*f_s$; *N*=number of samples, *L*=3; duration of an epoch in second and f_s=1000; sampling frequency.

7.2.4 MULTICLASS CLASSIFICATION

Each participant performed 5 different activities which were sitting quietly, eating while sitting, speaking while resting, eating while walking and walking. Analysis of the piezoelectric strain sensor features for the rest (sitting quietly) and speaking while resting shows that the distributions of the features for these two classes are similar. Therefore, sitting quiet and sitting while talking were combined into a single class called sedentary. Thus, data was reduced to four classes i.e. sedentary, eating while sitting, eating while walking, and walking. In this work, linear support vector machine (SVM) was used for classification. All classifiers were trained using the Classification Learner App in MATLAB 2015 (Mathworks Inc.). Two different approaches were tested for multiclass classification using features from both sensors i.e. single multiclass classification and multistage classification.

7.2.5 SINGLE MULTICLASS LINEAR SVM WITH SENSOR FUSION

In this approach, for a given epoch; piezoelectric and accelerometer features were combined into a single feature vector, i.e. $f_i = \{f_{i,chew}, f_{i,Acc}\}$. A human expert assigned multiclass labels to different activities based on the activity boundaries marked with the pushbutton by the participants. Epochs were assigned labels for four classes based on the reassigned human expert labels as C_i = *{1: Eating while sitting, 2: Sedentary, 3: Eating while walking, 4: Walking}*. A multiclass linear SVM classifier was trained using one-vs.-all strategy.

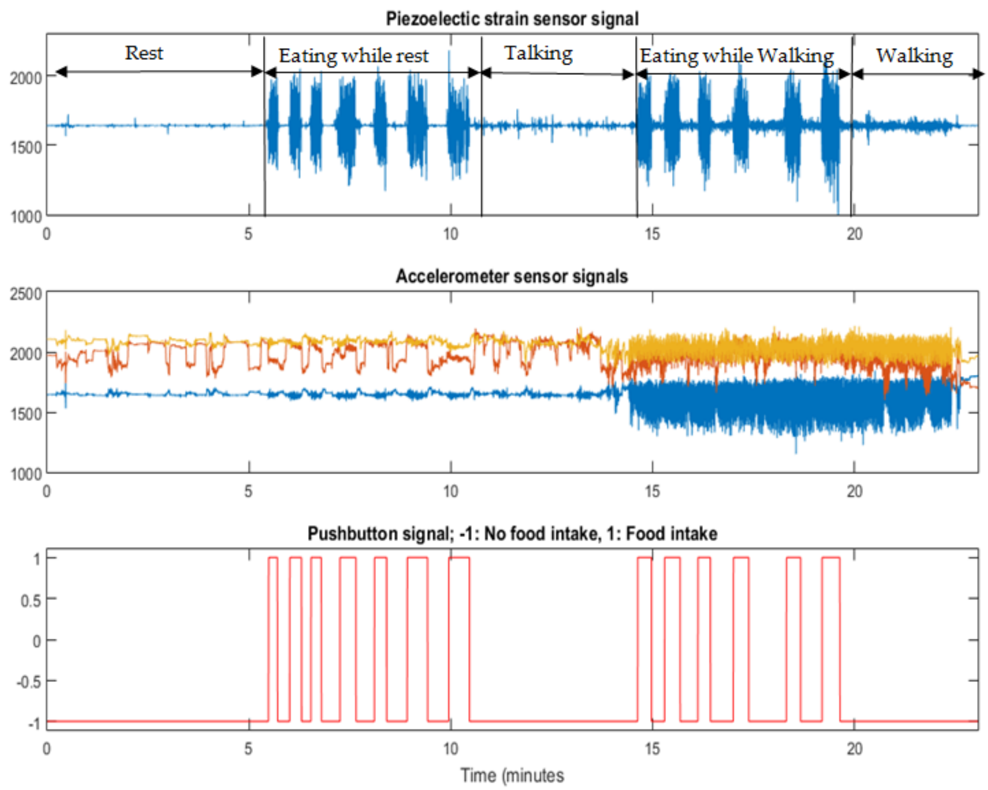

Figure 7-2 The signals collected during the experiment. Piezoelectric sensor signal (first row) and accelerometer signals (second row) are used to differentiate between eating and physical activities. Eating episodes were marked by participants using a pushbutton (third row).

7.2.6 MULTI-STAGE CLASSIFICATION: LINEAR SVM + DECISION TREE

This approach used two stage classification where the first stage used two different classifiers. The first classifier detected food intake solely based on the piezoelectric sensor signals. The second classifier recognized physical activity to differentiate between walking and sedentary classes based on accelerometer signals. Both classifiers were binary linear SVM models. Food intake detection classifier was trained with piezoelectric strain sensor features i.e. $f_{i,chew}$ and predicts the class label $C_{i,chew}$ = {-1: No-Food Intake, 1: Food Intake}. Activity recognition classifier was trained with accelerometer features ($f_{i,Acc}$) and class labels are predicted as $C_{i,Acc}$ = {-1: No-Walking, 1: Walking}. Second stage classification used a simple decision tree to estimate the final class label C_i. A decision tree implements empirical rules given in Table 2.

Each classifier was trained with leave-one-out cross-validation scheme where data from 9 participants were used for training the classifier and the remaining participant was used for evaluating the performance of the classifier. This process was repeated 10 times such that each participant was used for validation once. For each class of activities, F1-score was computed; which is the weighted average of precision and recall. F1-score was computed as follows:

$$\text{F1-score} = 2*\text{Precision}*\text{Recall}/(\text{Precision} + \text{Recall}), \quad (1)$$

$$\text{Precision} = \text{TP}/(\text{TP}+\text{FP}), \quad (2)$$

$$\text{Recall} = \text{TP}/(\text{TP}+\text{FN}), \quad (3)$$

where TP, FP, and FN denote true positives, false positives, and false negatives for each class, respectively. Additionally, data from all validation participants were combined to plot the Receiver Operation Characteristic (ROC) curve and compute Area Under the Curve (AUC) for each class.

7.3 RESULTS

The dataset used in the study included four different classes with 322 epochs of eating while sitting, 1155 epochs of sedentary, 271 epochs of eating while walking and 437 epochs of walking. Table 3 presents the confusion matrix for classification result of the single multiclass classifier. Results show that this classification approach was able to differentiate between four classes with an average F1-score of 95.67% with average precision and recall of 95.42% and 95.93%, respectively. Lowest F1-score of 93.85% was achieved for classification of walking; where 17 walking epochs were misclassified as eating while walking. Table 4 shows the confusion matrix for two-stage classification approach. In this case, the classifier was able to achieve average F1-score of 99.85% for all classes with average precision and recall of 99.89% and 99.82%, respectively.

Table 7-2. Decision Tree rules for determining the final class label from the two-stage classifier

	$C_{i,chew}$		$C_{i,Acc}$		C_i
If	1	and	-1	*Then*	*1: Eating while sitting*
	-1		-1		*2: Sedentary*
	1		1		*3: Eating while walking*
	-1		1		*4: Walking*

Figure 7-5 shows the Receiver Operation Characteristics (ROC) curves for each class for both classifications approaches (Left: single multiclass classifier, Right: Two-stage classification procedure). ROC curves show that the two-stage classification approach produced better results for all classes compared to the single multiclass classifier. Table 5 also lists the Area under the Curve (AUC) for each class for both classification approaches. For single multiclass classifier, the average AUC for all classes was 0.97. For two-stage classification; the classifier was able to achieve average AUC of 0.99.

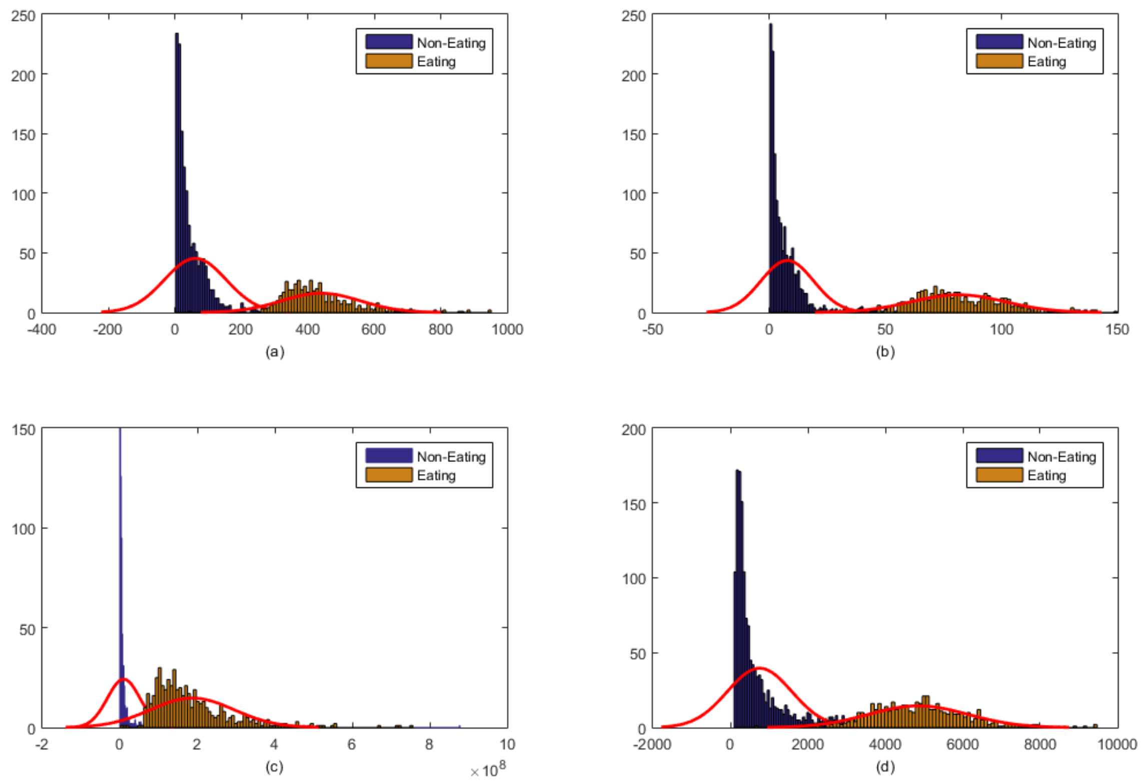

Figure 7-3 Histogram showing the distribution of piezoelectric strain sensor signal features: (a) Range of values (b) Standard Deviation (c) Energy (d) Waveform Length. Feature distribution shows that these features can easily provide information for separation of food intake from non-intake.

7.4 DISCUSSION

It is critical to develop new techniques for automatic, objective, and accurate monitoring of food intake to overcome the limitation posed by current methods which rely on self-reporting of food intake. Most of the systems proposed in the literature either have not been tested in free-living conditions or do not include activities which replicate such conditions. Majority of the studies consider food intake when participants are at rest or sedentary [23], [27], [28], [36], [46], [47]. Although some people may consume food while performing moderate intensity activities (in the range of 3-6 metabolic equivalents (MET) [22], [40]), most of the systems reported do not consider food intake while the participants are moving (e.g. walking). A possible reason is that the presence of motion artifacts may impact the sensor signals and hence impact the performance of the classification algorithm. This work presents a study of a novel wearable sensor system which can detect the presence of food intake both when participants are at rest/sedentary and, or in motion (physically active). This wearable device can also differentiate between being sedentary or physically active. A piezoelectric strain sensor was used for the detection of chewing during food intake, and the accelerometer was used for detection whether the participant is sedentary or in motion.

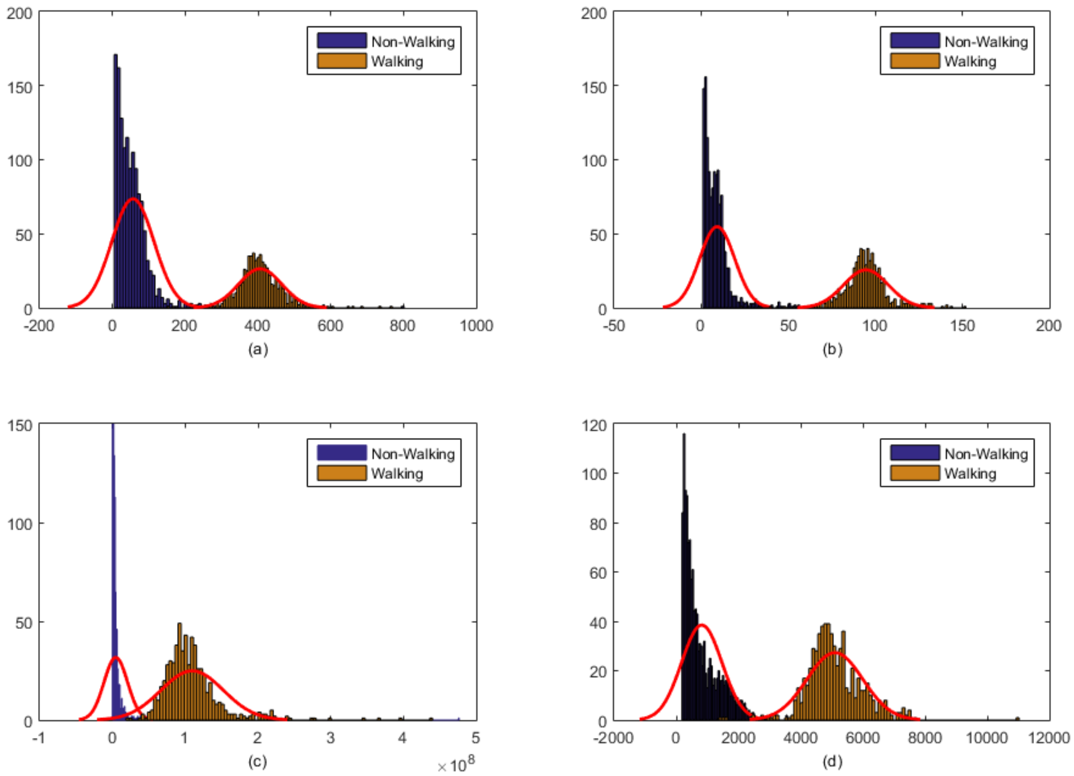

Figure 7-4 Distribution of Accelerometer sensor signal features: (a) Range of values (b) Standard Deviation (c) Energy (d) Waveform Length. Feature distribution shows that these features can easily provide information for separation of walking from the non-walking activity.

This work presents two approaches for multiclass classification. Sensor fusion and single multiclass classifier resulted in average F1-score of 95.67% for four classes. For this approach misclassification occurs among all classes (Table 3). For sedentary class, a total of 27 misclassifications occurred (only 2.35% misclassification for sedentary), where 11 epochs were misclassified as eating while sitting and 16 epochs are misclassified as walking. Highest misclassification rate occurred for eating while walking (5.54%) followed by walking

(5.26%). The highest number of misclassification occurs between eating while walking and walking classes, which was expected since the accelerometer signals have similar amplitude for both of these classes (see Figure 7-2).

Table 7-3. Confusion Matrix for single multiclass linear SVM classifier. Precision, Recall, and F1-score are also listed for each class of activities

	Eating+Sitting	Sedentary	Eating+Walking	Walking	Recall	F-Score
Eating+Sitting	310	9	3	0	96.58%	96.58%
Sedentary	11	1128	0	16	97.66%	98.09%
Eating+Walking	0	0	256	15	95.20%	94.16%
Walking	0	6	17	414	94.28%	93.85%
Precision	96.58%	98.52%	93.14%	93.42%	Mean:	95.67%

The two-stage classification approach reduced the misclassifications. Two separate classifiers were used for food intake detection and walking, and results of both classifiers were combined using a simple decision tree to achieve multiclass classification. The final classifier achieved an average F1-score of 99.85% for all classes with 10-fold cross-validation scheme. Figure 7-5 (Right) depicts the ROC for each class with an average AUC of about 0.99 for all classes. This approach resulted in only 2 misclassifications out of 2185 epochs. Two eating while walking epochs were misclassified as walking.

The results of this work show that both single multiclass and two-stage multiclass classifiers performed with a satisfactory level of robustness. Models developed in the study were based on the whole population (participant-independent) and, therefore, no participant-specific calibration was required. This is critical as it ensures the usage of the device in general population.

Table 7-4. Confusion Matrix for multi-class classification when two stage classification is used. Precision, Recall and F1-score are also listed for each class/categories of activities

	Eating+Sitting	Sedentary	Eating+Walking	Walking	Recall	F1-score
Eating+Sitting	322	0	0	0	100.00%	100.00%
Sedentary	0	1155	0	0	100.00%	100.00%
Eating+Walking	0	0	269	2	99.26%	99.63%
Walking	0	0	0	437	100.00%	99.77%
Precision	100.00%	100.00%	100.00%	99.54%	Mean:	99.85%

Table 7-5. The area under the Curve (AUC) for each class. Mean AUC for each classifier was computed as the average of AUCs for all classes (Mean column)

Classifier	Eating+Sitting	Sedentary	Eating+Walking	Walking	Mean
Single multiclass SVM	0.98	0.98	0.97	0.96	0.97
Two-stage classification	1	1	0.99	0.99	0.99

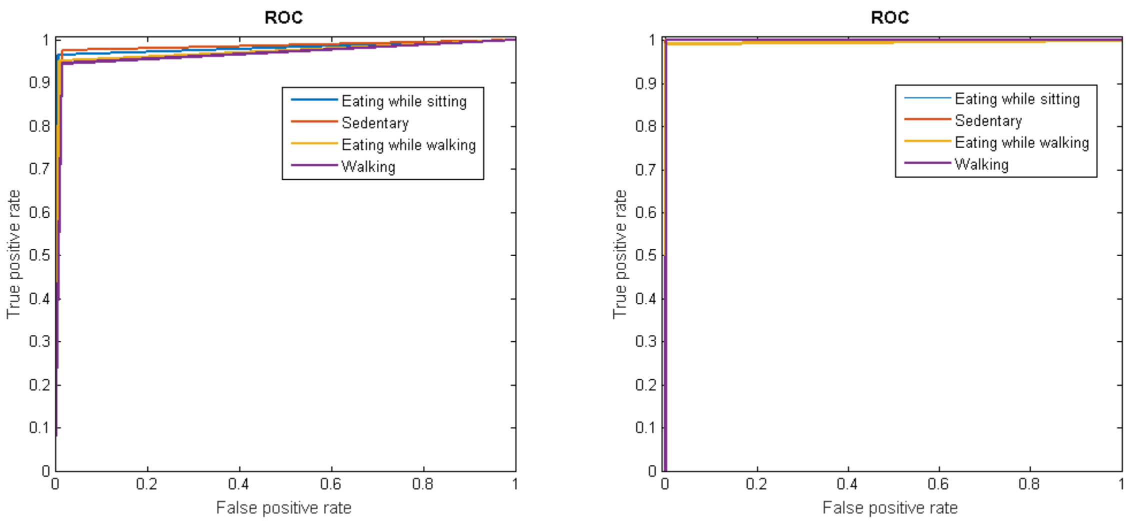

Figure 7-5. Receiver Operation Characteristics (ROC) Curves for two classification approaches. Left: ROC curves for different classes when single linear SVM model is trained. Right: ROC curve for two-stage classification. The first stage uses two linear SVM models for detection of food intake and walking. Next, a simple decision tree is used to predict final output class.

Compared to the current state of the art for automatic detection and monitoring of eating behavior, the device presented in this work performs accurate food intake detection in more challenging testing conditions. Several wearable solutions have been presented for monitoring of food intake where the accuracy of food intake detection ranges from 80% to 96% [22], [27], [36], [38], [39]. Most of these systems have not been tested in the presence of physical activity or other motion artifacts such as head movements. For these solutions to be employed in real life conditions, it is critical for them to be robust in the presence of such conditions. The device and algorithms presented in this work are robust and not impacted by the presence of walking, speech and head movements. The device also has the ability to differentiate whether the participants are sedentary or physically active. Tested in challenging conditions, the proposed device is also more accurate compared to the state of the art.

In the proposed device, the data collection module is connected to the temple of eyeglasses which reduces the number of sensors a participant has to wear compared to a multi-sensor system previously presented [22]. This helps in reducing user burden and user compliance. Eyeglasses make the design non-invasive, non-obtrusive and socially acceptable. This device can be further miniaturized and can be embedded into a headband or hat/cap for people who do not wear eyeglasses. In future, both the feature computation as well as the classification can be implemented either on the device or on the phone to avoid offline processing and provide feedback to the user in real time. Further, a camera can be integrated into the current design of the eyeglasses which may be triggered to take images of the food, whenever the system detects food intake. Computer vision algorithms can be used for recognizing food items from these images [48].

A limitation of the present study is that the device's ability to detect intake of liquids/beverages was not tested as the main focus was on the detection of solid food. Research suggests that even during continuous liquids intake (sips), characteristic jaw movements similar to chewing are present and hence can be used for detection of liquid intake [23]. Detection of liquids will be explored in future research. Another limitation is that the current study was performed in a laboratory setting because of the need for accurate reference/gold standard. During the design of the experiment, activities such as walking, speech, head movements, etc. were included to replicate activities performed by people in their daily living. Further, unrestricted free living studies are required to test the system in real life conditions. A significant decrease of performance is not anticipated in the unrestricted free living conditions as complex activities observed in free living were already included in the protocol. The results are presented for a relatively small cohort of 10 individuals. Further, long-term studies with larger cohorts will be conducted to test the system. Finally, the piezoelectric sensor was placed on the temporalis muscle using medical tape. While no sensor detachment was observed during the experiments, future implementations may include integration of the sensor into the temple of the eyeglasses to improve user comfort.

For a healthy lifestyle, it is critical to maintain a balance between energy intake and energy expenditure patterns [49]. Energy expenditure is associated with the level of physical activity performed by individuals. Accelerometer based physical monitoring systems proposed in the literature are able to differentiate between different activities such as walking, sitting, standing, walking upstairs, walking downstairs, etc. [41], [42]. Each of these physical activities results in a different level of energy expenditure. The proposed system in the current form can differentiate between low (sitting/sedentary) and medium to high level of physical activity (walking). This system can further be developed to recognize a wider range of physical activities. We believe that with these added capabilities, the proposed system will be able to track both energy intake and energy expenditure patterns using a single device and can be used to provide valuable feedback to the users for maintaining a healthy lifestyle.

7.5 CONCLUSIONS

This paper presents a wearable device for automatic detection for food intake in the presence of physical activity and motion artifacts. The device is connected to the temple of glasses and combines a piezoelectric strain sensor, accelerometer, and Bluetooth connectivity. Two approaches for multiclass classification are proposed for detection of food intake in the presence of motion artifacts originating from physical activity, speech, and body movement. The proposed device has the advantage of detecting periods of food intake with a high average F1-score of 99.85%. With further development, this device has the potential ability to track both energy intake and energy expenditure, and monitor energy balance of individuals.

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CHAPTER 8 REDUCTION OF ENERGY INTAKE USING JUST-IN-TIME FEEDBACK FROM A WEARABLE SENSOR SYSTEM

Note to the reader: This work has been submitted to the Obesity Journal and is currently under review.

All previous chapters presented different parts of a wearable sensor system and algorithms for automatic detection and characterization/quantification of chewing during a meal. The ultimate question is that whether such a system can be used for reducing energy intake over a meal. This chapter explores a potential use of the wearable sensor system for reducing the energy intake by providing just-in-time feedback towards a goal based on total chews per meal.

8.1 INTRODUCTION

Excess energy intake is considered to be one of the important contributors to the increase in obesity prevalence [1]. Eating is considered to be an unconscious [2] and automatic [3] behavior in humans, and several studies have shown that certain dietary behaviors contribute to the increased risk of overeating [4], [5]. For example, controlled laboratory experiments [6], [7] have demonstrated that for a given food, individuals consume more when the serving/portion size is increased. Similarly, increasing the number of food items (dietary variety) has shown to increase the energy intake even if controlled for macronutrient composition [8], [9]. Therefore, current treatments for controlling obesity include relying on behavioral modification to changing dietary intake [10]. Additionally, other studies have shown a positive relationship between the body mass index (BMI) and the self-reported eating rate [11], and faster eating rates have been related to weight gain [12]. Reducing the eating rate was shown to reduce the energy intake during a meal [13], [14], [15], [16]. Similar findings were reported in other laboratory studies [17], [18] that demonstrated the positive relationship between the BMI and bite size as well as the eating rate. Eating slow can also impact the satiety and satiation levels of individuals [19], [20]. Other research suggests that reducing the eating rate can help in reducing energy intake. For example, the study in [21] showed that a 50% reduction from the baseline in the number of bites per minute on average resulted in a 70 kcal reduction in energy intake within a meal. Studies of [22], [23] determined that increasing the number of chews or consuming higher viscosity food increased perceived satiety of individuals. For example, [23] showed that increasing the number of chews per bite may help in reducing the total ingested mass. In addition, obese individuals have lower chew counts per 1g of food compared to normal weight individuals [23].

Most of these studies used manual observation for monitoring eating behavior. However, automatic and objective methods for monitoring and feedback are required in a real life unrestricted environment. Several wearable sensor systems have been presented in the literature for automatic and objective detection of eating episodes by monitoring different stages of food intake, i.e. bites [24], swallows [25], [26] and chewing [27]–[29] as well as for characterization of chewing behavior in terms of chew count estimation [30]. Previously, a device called the Automatic Ingestion Monitor (AIM) [29] has been shown to accurately track ad libitum eating in unrestricted free-living conditions via monitoring of chewing using a strain sensor placed below the ear. A modified version of the AIM (glasses where the sensor is placed on the temporalis muscle) was shown to detect chewing with an accuracy of 99.85% even in the presence of walking, with a chew count estimation error of 2.63% [31].

With current advancements in technology, it is now possible to automatically detect human behavior and provide tailored treatments/interventions called just-in-time adaptive interventions (JITAIs) using mobile, computer and sensors. Interventions for eating behavior modifications have been proposed for eating disorders [32] and weight management [33]. Automatic just-in-time (JIT) feedback on bite counts has been shown to help in reducing the mass ingested (grams consumed) with a wearable device called the Bite-counter [34]. Similarly, the data acquired by the AIM can directly support behavioral modeling [35] and inform JITAIs for weight management [36].

Chewing rate and total chew counts per meal have been used for estimation of mass ingested during a meal [37] and mass per bite [38], respectively. This work explores the possibility of using automatically measured chew counts for reducing the mass of intake. The hypothesis was that by reducing the total number of chews per meal, the mass ingested and energy intake can be reduced. This work further explores the use of just-in-time feedback from the sensor system towards a target and the feasibility of the AIM in JITAIs for reducing the energy intake.

8.2 METHODS

8.2.1 SUBJECTS AND STUDY DESIGN

For this study participants (male and female) between the ages of 19 and 60 years and the BMI range of 20-45 kg/m2 were recruited. Participants were recruited by advertisements placed around the campus of the University of Alabama. Upon contact by email, a response email was sent to participants briefly explaining the experiment and asking for personal information in order to start the screening process. Participants were not included in the study if they had any medical conditions which would affect chewing or food intake or if they had allergy to the selected food or allergies to any adhesive. The Institutional Review Board at the University of Alabama, Tuscaloosa approved the study, and each participant signed a consent form prior to participation. Individuals came to the research laboratory for three visits during lunchtime (between 11:30 am - 1:30 pm). The first visit was used to collect baseline measures (total chew counts and total mass ingested), and in visit 2 and 3, where the target was set to either 100% or 75% of the baseline number of chews and JIT feedback was provided to the participants on their progress towards the goal. The order of these two visits was randomly assigned. A washout period of 3 to 7 days was used between the visits, depending on each participant's availability and preference. Participants were instructed to have the same breakfast on all 3 days and not to eat 4-5 hours before the visit. This was done to ensure a similar level of satiety before each meal. Participants were not informed of the purpose of the experiment until the study was completed and recruitment was closed.

8.2.2 SENSOR SYSTEM FOR AUTOMATIC CHEW COUNTING

Before the start of the experiment, participants were instrumented with a wearable system (AIM device) presented in [39]. The wearable device consists of a piezoelectric strain sensor (LDT0-028K from Measurement Specialties Inc. VA), placed on the temporalis muscle and a data acquisition board connected to the temple of the eyeglasses (Figure 8-1). The strain sensor captures the movements of the temporalis muscle caused by chewing and converts these movements into electric signals. Data from strain sensor were sampled at 1000Hz using a 12-bit ADC.

During all three visits, the sensor system was used to monitor participants in real time. Five-second segments of the collected data from the sensor were sent in real time via Bluetooth to a laptop computer for online processing in MATLAB (Mathworks Inc.). A feature computation algorithm and classification models developed in a previous study [39] were used to classify each segment as chewing or non-chewing. The chew count estimation algorithms [31] were used to estimate chew counts for segments classified as chewing. The software recorded the cumulative number chews for every meal. The software also automatically computed the meal duration (from start to the end of the meal, including non-chewing segment) as well as the actual eating duration (only chewing segments) in seconds.

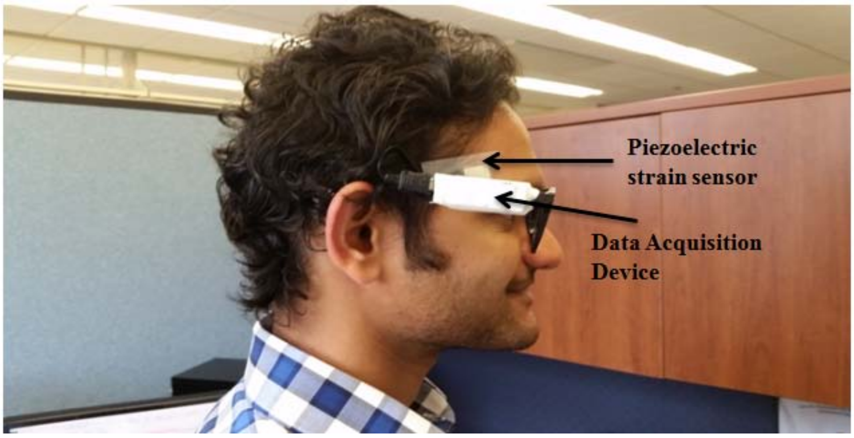

Figure 8-1 Subject wearing eyeglasses which houses the data acquisition system. The piezoelectric strain sensor is placed on the temporalis muscle.

8.2.3 BASELINE CONDITIONS

The first visit was used to obtain baseline measurements of total mass ingested and required total chew counts. Before and after each meal, participant’s ratings of palatability of the food, and perceived hunger, thirst, fullness, prospective consumption, and desire to eat were measured using a standard 9-point scale. Before the start of the meal, participants completed the questionnaire in a room where they could not smell the food to ensure their ratings were not influenced by the smell of the food. While the participants were completing the questionnaire, about 900 g of fried rice from Panda Express (obtained from a cafeteria at the University of Alabama) was prepared for serving in a separate room. The serving size was over three standard portion sizes of fried rice and was chosen so that the participants would be unlikely to run out of food during the experiment. A standard plate size was used during each visit and participants were provided with a plastic spoon. Also, participants were provided with 500 milliliters of water for drinking during the meal in a plastic cup and were instructed to consume as much as they wanted. Once the food was ready for serving, participants were taken to the food serving room and were instructed to eat naturally. After setting up the experiment, the investigators left the room so that the participant's eating was not influenced by their presence. Participants were asked to stop eating when they felt comfortably full. After the completion of the meal, participants again filled out the questionnaire.

The amount of food consumed (in grams) was determined by weighing the plate before and after serving using a digital kitchen scale (Touch II from Ozeri, with 1 gram accuracy). Participants were not aware of this measurement. During baseline visit, the sensor system automatically measured chew counts for each chewing sequence and computed the total chew count at the end of the meal.

8.2.4 JUST-IN-TIME (JIT) FEEDBACK

The JIT feedback experiment explored three important questions. The first one was to investigate the feasibility of using a wearable sensor system to provide feedback on the meal progression towards a desired target based on chew counts. The second question was if such feedback could be used to reduce the mass of intake without affecting the satiety level. The third question was whether the presence of feedback changes the ingestive behavior such as eating rate and meal duration.

To answer these questions, JIT feedback was provided at the second and third visits. In both of these visits, the desired goal was based on the total chew counts from the baseline meal. During 100% target visit, the desired goal was set to the total number of chews of the baseline meal. The objective of this target was to study the impact of sensor-based JIT feedback on the ingested mass and meal duration, even when the feedback was not attempting to modify the ingested mass. Other than the presence of the audio feedback, the rest of the procedure was similar to the baseline conditions. During the visit with the reduced chew count (75% target visit); the target chews were reduced by 25% compared to the baseline visit. This target served two purposes, i.e. to evaluate the ability of the system to reduce the mass intake and to do so without affecting the satiety level.

Progress towards the goal was monitored by the sensor system in real time, and real-time audio feedback from the sensor system was generated at four milestones, i.e. 25%, 50%, 75% and 100% of the goal by the developed software and was delivered via the speakers of the laptop. Audio feedback was pre-recorded in the form, ‘You reached X% of your goal’ and so on. No instructions were provided to the participants on how to act upon the feedback, except the system gave an audio indication to the participants to stop eating when they reached their desired goal. Participants were not aware of exactly how the desired goal for these two visits was generated and that the feedback was based on total number of chews of the baseline visit. Instead, they were told that the investigators were testing a sensor system that can accurately measure the amount consumed (mass ingested) and the feedback was relative to the amount consumed in the baseline visit. The actual purpose was disclosed to the participants at the end of the study after all participants had completed the experiment. The order of the visits with feedback was randomly assigned by computer software and both the participants and investigators were blinded to the assigned order to avoid potential observer-expectancy bias.

8.2.5 STATISTICAL ANALYSES

To study the impact of feedback from the sensor system on the total mass ingested as well as the satiety level, a nonparametric version of repeated-measures analysis of variance (Friedman ANOVA) was used. For Friedman ANOVA, the within-participant factor was the type of visit, i.e. baseline, 100% target and 75% target visit. The Friedman ANOVA was selected because the ingested mass was not normally distributed (Kolmogorov-Smirnov test with 5% significance level) and some of the dependent variables (ratings on the questionnaire) were ordinal. To test the feasibility of using feedback from the sensor system and its ability to reduce total mass ingested and changes in the meal duration due to feedback, the Friedman ANOVA tests were performed to compare total mass ingested (in grams) and duration (seconds) of the meal across all three visits. Absolute changes (between the start and end of the meal) for ratings of hunger, fullness, desire to eat, prospective consumption, thirst and palatability were compared across three visits. The null hypotheses for each dependent variable assumed that they were same across all three visits with the alternate hypotheses that they were different. For significantly different metrics, post hoc Tukey Kramer's test was used for multiple comparisons. A p-value of 0.05 was accepted as significant. Descriptive statistics were expressed as median and inter-quartile range (IQR, q1: lower quartile and q3: upper quartile) i.e. Median (q1, q3).

8.3 RESULTS

Eighteen participants (15 male and 3 female) aged 27.7 $\pm$2.8 years (range 19-41 years) with a BMI of 23.3$\pm$3.3 kg/m2 (range 18.5-31.2 kg/m2) (mean$\pm$SD) volunteered for this study. Median mass ingested for baseline visit, 100% target visit and 75% target visit was 493g (434g, 589g), 491g (419g, 576g), and 431g (314g, 548g), respectively. Figure 2 (left) shows the distribution of mass ingested for each type of visit. There were statistically significant differences across visits (P=0.003) in total mass ingested. The post hoc Tukey-Kramer test showed that total mass ingested during the 75% target visit was lower than the other two visits at p<0.05; the total mass ingested during baseline and 100% target visits were not significantly different. Figure 8-2 (right) shows the distribution of changes in mass ingested for 100% target and 75% target visits relative to baseline visit. Median changes for 100% target and 75% target visits were -2.37% (-5.5%, 1.9%) and -10.1% (-14.7, -6.9%), respectively, where negative values shows decrease. Figure 8-3 (left) shows a Boxplot of the meal duration for three types of visits. There were significant differences across visits in meal duration, (p= 0.0007), where results of multiple comparisons showed that the duration of 75% target visit was significantly shorter compared to other two visits at P <0.05; whereas the durations of baseline visit and 100% target visit were not significantly different. Figure 8-3 (right) shows the distribution of percent changes in meal duration for 100% target and 75% target visits relative to baseline visit. Median changes were -6.5% (-14.7%, 2.2%) and -21.4% (-29.6%, -17.9%) for 100% target visit and 75% target visit, respectively.

The absolute changes in the ratings between the start and end of the meals for hunger, fullness, desire to eat, prospective consumption, thirst and palatability of the food did not differ significantly different across visits. Null hypotheses for hunger, fullness, desire to eat, prospective consumption, thirst, and palatability were accepted at p-values of 0.66, 0.59, 0.17, 0.42, 0.52 and 0.54, respectively. Figure 8-4 and Figure 8-5 shows the distribution of hunger and fullness rating for all visits, respectively. Median (q1, q3) palatability ratings were 6.5 (5, 7), 6.5 (5, 7) and 6.5 (6, 7) for the baseline, 100%, and 75% visits, respectively. This shows that participants in general liked the food served in the experiment.

8.4 DISCUSSION

This is the first study to examine the potential use of a wearable sensor system, the AIM, for providing JIT feedback to the user on their eating and to demonstrate its ability to reduce the total mass intake in a meal. When the AIM was used to provide feedback on the meal progression towards the desired target of 75% of the baseline number of chew counts, the total mass ingested and meal duration were significantly lower compared to the baseline visit and the 100% target visit. While the ingested mass and meal duration were significantly lower in the 75% target visit than the other visits, hunger, appetite and thirst ratings did not differ by the visit type. A possible explanation is that participants were not aware of the reduction of target chew counts in 75% target visit and were under the impression they were eating same amount of food in all visits. These results suggest that the AIM can potentially be used in developing strategies for weight loss interventions where the goal can be tailored to the needs of user and feedback from the system will guide the user towards the goal.

We observed that JIT feedback from the AIM towards a lower goal (75% target visit) was successful in the reduction of the amount ingested, compared to the baseline and 100% target visit. However, there were no differences in the total mass ingested in baseline and 100% visits, which was expected as the total chew counts were similar for these visits. These results show that the AIM accurately estimates chew counts and the provided feedback on meal progress based on chew counts is also accurate. In addition, the duration of the meal at the 75% target visit was also significantly lower compared to other two visits. This was expected as the participants had a lower number of chews for the meal. The differences between the duration of baseline and 100% target visits were not statistically significant, which showed that the presence of feedback alone did not modify the eating rate of the participants. For the 75% target visit, the reduction of total chew counts by 25% compared to the baseline visit resulted in the reduction of the median mass ingested mass by 62 grams (about 10% relative change), compared to baseline and in the reduction of median meal duration by 140 seconds (about 21%). A reduction of 65 seconds (about 10%) was observed in the median meal duration of 100% visit compared to baseline visit, however, the reduction of median ingested mass was not significant (only 2 grams). This shows that reducing total chew counts results in the reduction of ingested mass and meal duration but it is not proportional to the reduction of chew counts. Further research is needed to study the relationship between the chew counts reduction and proportional reduction in meal duration and total mass ingested.

The fact that palatability was also not different across the three visits means that the same food was equally liked across visits and less food was not consumed in the 75% visit because participants were bored with the same meal; rather, less food was consumed because participants followed the JIT feedback that the AIM provided to them. Although this study was performed only over multiple single meals instead of a whole day or more, our results suggest that our technique could potentially help in weight loss, since fewer calories were ingested without impacting hunger and appetite. The selected food (fried rice from Panda Express) has a caloric density of about 2 kcal/gram (520 kcal for serving size of 264 grams or 9.3Oz). Therefore, reduction of the median ingested mass by 62 grams resulted in a reduction of energy intake by 124 kcal. Hypothetically, assuming 3 meals of rice per day, a theoretical reduction of about 372 kcal/day could be achieved using JIT feedback. When combined with additional physical activity, an energy deficit of 500 kcal/day could be achieved. In real life scenarios, the caloric reduction will be dependent on the caloric density of the food selected. Additional studies are needed to investigate the feasibility and effectiveness of longer-term use of the AIM for weight loss and maintenance of weight loss.

Other devices such as Mandometer [40] and Bite-Counter [21] have been proposed for providing JIT feedback to participants for reducing energy intake in a meal. Mandometer uses cumulative intake curves to normalize eating behavior of individuals and has been shown to be effective in weight loss [40]. Mandometer comprises of a portable weighing scale with a display which requires individuals to keep their food on the scale at all time and hence restricts their movements. Another option is to use wearable devices such as Bite-Counter or AIM. By reducing the number of bites per minute by 50% (compared to a baseline) in a waffle meal, the Bite-Counter, reduced energy intake by 70 kcal [21]. However the Bite-Counter has a positive predictive value of about 81% for estimation of bites (about one false positive per five actual bites), in laboratory conditions [24], which is not as accurate as the device used in the present study, which has been shown to be extremely accurate for detection of eating episodes (with F-measure of 99.85%) as well as for estimation of the number of chews (mean absolute error of 2.63%) [31] in laboratory settings. The AIM has been already tested for monitoring of food intake in unrestricted free living conditions for 24hrs and has shown promising results [29]. A more compact version of the system with a detection, characterization and feedback generation algorithms running on Smartphone instead of the laptop computer could be used for JITAIs to the users to potentially reduce their energy intake in unrestricted free living.

This was the first study which used AIM for providing accurate feedback on the cumulative chew count during a meal. Some of the strengths of the study include the randomization of 100% and 75% target visits, concealing the true purpose of the study from the participants, and controlling for food type. One limitation of the study was that the experiments were conducted in controlled laboratory conditions and may not be applicable to unrestricted free-living conditions, however the laboratory setting allowed for an accurate assessment of the eating behavior in this first study. Additionally, although we did not control for variations in eating behavior such as bite size, eating rate, and liquid intake, this suggests that the feedback approach may potentially be used in the wider population. Further studies are required to evaluate this approach for wider food variety and to investigate how the energy density of the different food may affect the effectiveness of the presented feedback system. The sample size used in this study was relatively small and needs to be further extended. Another important limitation is that most of the participants recruited for this study were normal weight individuals. Our future work will include testing of the system in individuals with different levels of adiposity. Further research will also explore the use of feedback in more realistic, unrestricted and social environment to test for social compliance and its ability to reduce total energy consumption.

8.5 CONCLUSION

This work presented the use of a wearable sensor system to reduce the mass intake. The wearable sensor system was able to accurately and objectively track eating episodes in real time and accurately estimate chew counts. The results suggest that the JIT feedback from the sensor system with a goal can be used to reduce the total mass intake in a meal. This system may potentially be developed to provide just-in-time adaptive interventions for reduction of mass and energy intake, and could potentially help with weight loss and prevention of weight regain with long-term use.

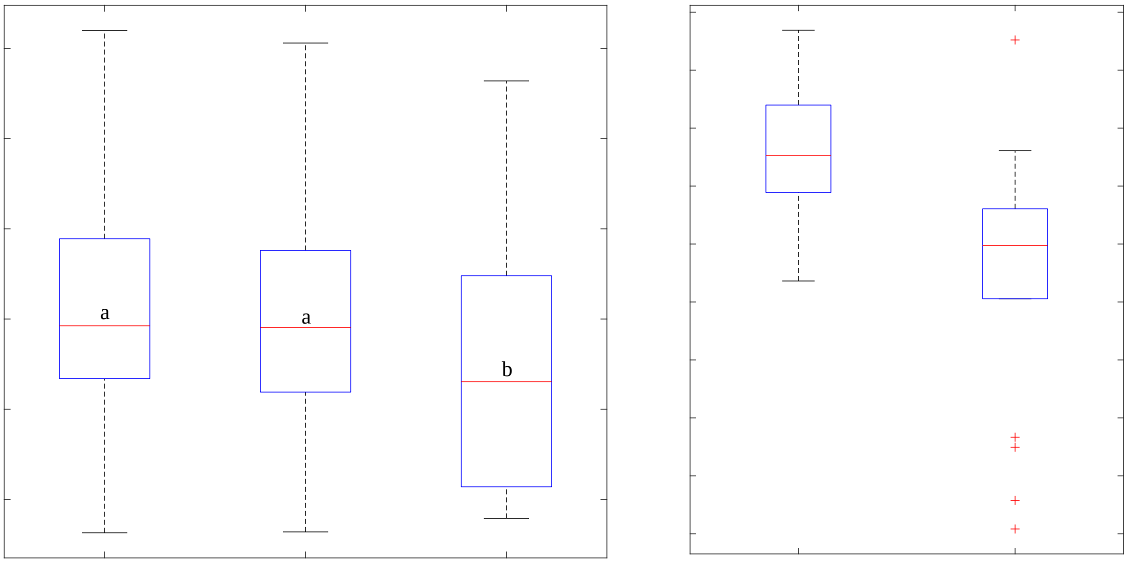

Figure 8-2 (Left) Distribution of mass ingested by the participants across all three visits. Boxes with same letters have medians which are not statistically different whereas boxes with different letter have statistically different median. Mass ingested during the 75% target visit was lower compared to other two visits. (Right) Distribution of percent changes in mass compared to the baseline visit. Negative values indicate decrease in mass ingested compared to baseline. The ‘+’ shows an outlier. Red line on each plot indicate the corresponding median mass ingested (grams) whereas the lower and upper whiskers indicate the minimum and maximum mass ingested within 25th and 75th percentile, respectively. Lower and upper horizontal blue lines (on the box) indicate 1st and 3rd quartile i.e. q1 and q3. 50% of the cases are between 1st and 3rd quartile.

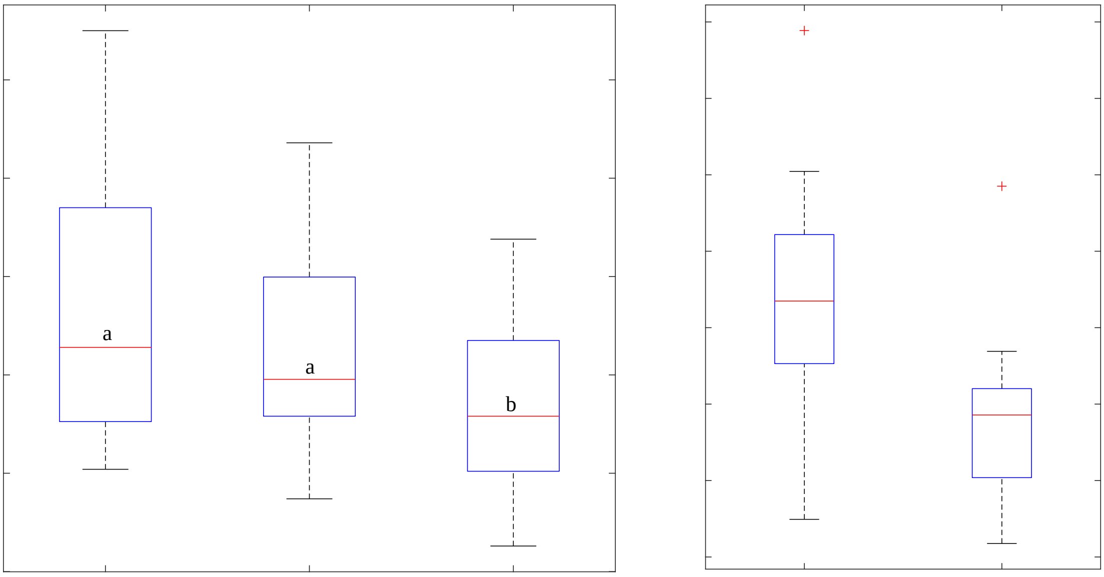

Figure 8-3 (Left) Distribution of the meal duration for all three visits. Boxes with same letters have medians which are not statistically different whereas boxes with different letter have statistically different median. Meal duration for the 75% target visit was lower compared to other two visits. (Right) Distribution of percent changes in meal duration compared to the baseline visit. Negative values indicate decrease in meal duration compared to baseline. The '+' sign shows the outliers. Red lines on each plot indicate the corresponding median duration whereas the lower and upper whiskers indicate the minimum and maximum duration of the meals within 25th and 75th percentile, respectively. Lower and upper horizontal blue lines (on the box) indicate 1st and 3rd quartile i.e. q1 and q3. 50% of the cases are between 1st and 3rd quartile.

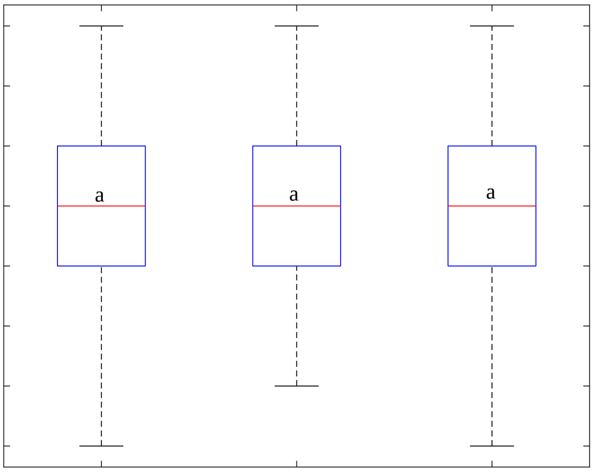

Figure 8-4 Distribution of absolute changes in the hunger ratings between the start and end of the meal. Hunger before and after the meal was measured using standard

1-9 scale. No significant differences were observed for changes in hunger ratings for different visits. For each plot, the red line indicates the corresponding median change in rating. Boxes with same letters have medians which are not statistically different whereas boxes with different letter have statistically different median. Upper and lower whiskers show the minimum and maximum changes within 25th and 75th percentile, respectively. Lower and upper horizontal blue lines (on the box) indicate 1st and 3rd quartile i.e. q1 and q3. 50% of the cases are between 1st and 3rd quartile.

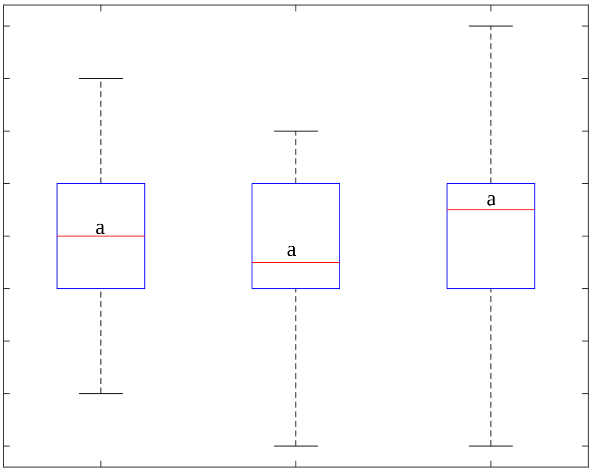

Figure 8-5 Distribution of absolute changes in the fullness rating between the start and end of the meal. Fullness before and after the meal was measured using standard 1-9 scale. No significant differences were observed for changes in fullness ratings for different visits. For each plot, the red line indicates the corresponding median change in rating. Boxes with same letters have medians which are not statistically different whereas boxes with different letter have statistically different median. Upper and lower whiskers show the minimum and maximum changes within 25th and 75th percentile, respectively. Lower and upper horizontal blue lines (on the box) indicate 1st and 3rd quartile i.e. q1 and q3. 50% of the cases are between 1st and 3rd quartile.

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CHAPTER 9 CONCLUSION AND FUTURE WORK

This dissertation contributes to the work on automatic detection and characterization of the food intake using wearable sensors that monitor chewing and swallowing. The main contribution of this work is the development and testing of new signal processing and pattern recognition algorithms for objective, automatic and accurate monitoring of eating episodes. Another important contribution of this work is the development of a just-in-time feedback mechanism to reduce the total mass ingested in a meal. These contributions were achieved through a series of studies that investigated various aspects of sensor-based monitoring of ingestion.

Use of Electroglottograph device was explored for automatic and objective monitoring of ingestive behavior using swallowing. EGG was used to monitor the impedance changes across larynx caused by the motion of cricoid cartilage and the passage of food bolus. The performance of the EGG based approach was compared to the monitoring of ingestive behavior using a microphone placed at the larynx level. The EGG based classification models achieved higher accuracy compared to the acoustic based classification models. The performance of EGG based models was not influenced by the gender or the level of adiposity of the individuals. Further, EGG-based methodology was insensitive to background noise which makes it potentially useful under free-living conditions.

This dissertation also explored the technical feasibility of using a piezoelectric jaw motion sensor for accurate and objective monitoring of feeding behavior in bottle-fed and breast-fed infants. Sensor signals were processed for estimation of the sucking counts of infants. The accuracy was evaluated by comparing the computer-estimated sucking counts to human annotated sucking counts for same feeding episodes (based on video observations). The mean absolute errors and ICC statistics showed a close and acceptable agreement between the estimated sucking counts by the developed methodology and human annotated sucking counts. Results of the statistical analysis suggested that the estimated error (performance of the system) was not dependent on factors such as gender, BMI, length, weight and age of infants but varied with the feeding mode of infants.

This dissertation further presented a method for automatic detection and characterization of chewing in adults using a piezoelectric strain sensor placed on the jaw below the ear. Sensor signals were divided into 5-second epochs for feature computation, classification and chew count estimation. A histogram-based chew counting algorithm was proposed for estimation of chew counts in chewing epochs identified by a preceding classification stage (using subject-independent ANN models). The presented approach was able to accurately differentiate between chewing and non-chewing epochs and was able to accurately estimate chew counts from epochs classified as chewing. This shows that there is a potential of using the sensor for automatic characterization of chewing.

Further, a wearable device in the form of eyeglasses with a piezoelectric strain sensor placed on the temporalis muscle was proposed. The device is able to detect chewing in the presence of motion artifacts caused by physical activity and speech. A multistage algorithm was proposed which first identified candidate chewing bouts using signal’s energy envelope and then used linear SVM models to classify these bouts either as chewing or non-chewing. Next, a multivariate linear regression model was used for estimation of chew counts from the chewing bouts identified in the classification stage. Compared to the sensor placed below the ear, this approach showed improvement both in the classifiers’ performance and in the accuracy of chew count estimation in the presence of complex situations involving physical activity and speech. This device also has the ability to detect physical activity using the embedded accelerometer. With further development, this device has the potential ability to track both energy intake and energy expenditure, and monitor energy balance of individuals.

The last chapter of this dissertation presented a method for providing just-in-time feedback that relies on the reduction of total chews per meal for reduction of the total ingested mass. The results suggest that the proposed method can potentially be used to reduce the total ingested mass in a meal. There is a potential to develop further the method for providing just-in-time adaptive interventions for reduction of total mass and energy intake in free-living individuals.

Further research is needed to increase user compliance, explore new capabilities such as recognition of food items, and new signal processing and pattern recognition algorithms for real time recognition of food intake. Larger free living studies are needed to confirm results reported in this dissertation.

User compliance is a big issue in adopting new technologies such as the ones presented here. Wearable sensor systems used in this dissertation were research prototypes which further need to be developed to improve user comfort and convenience. One of the future research directions is to explore new sensor modalities for monitoring of chewing and swallowing, which are non-invasive and socially acceptable.

Sensors used in this work cannot differentiate between the types of food consumed. Computer vision algorithms can be used for identifying different food items. One possibility is to incorporate a camera into wearable sensors which can be used to automatically take pictures of the food when food intake is detected by the sensors. Such approach can provide information about the type of food consumed, which is not available with the sensors used in this dissertation.

For studies presented in this dissertation, data processing was performed offline. For last study a real time system was implemented however the data processing was performed on a laptop computer. For more realistic use of these approaches in free living conditions, data processing and classification algorithms need to be implemented as part of smart phone applications. Thus there is a need to explore signal processing and pattern recognition which are power efficient to save power and that can be implemented on Smartphone. Learning algorithms such as rule-based such as fuzzy neural networks can be used to describe the eating process.

The studies presented in this dissertation were mostly performed in controlled laboratory conditions with relatively smaller sample size. These studies established the feasibility of using wearable sensor system for automatic detection, characterization and modification of eating behavior of individuals. To generalize these results, further long-term studies with a wider population in free-living conditions are required.

This dissertation presented several signal processing and pattern recognition systems for automatic detection and characterization of eating behavior with improved performance over the current state of the art for automatic monitoring of food intake. Development of robust signal processing and pattern recognition algorithms is an important step towards the realization of sensor systems which can be used in real life scenarios. Further work is needed to develop these systems for practical applications to become a reality.

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APPENDIX A IRB APPROVAL

Office for Research

Institutional Review Board for the Protection of Human Subjects

THE UNIVERSITY OF ALABAMA
RESEARCH

September 22, 2015

Edward Sazonov, Ph.D.
Electrical & Computer Engineering
College of Engineering
The University of Alabama
Box 870286

Re: IRB Protocol # 12-011-ME-R3
"Evaluation of a Wearable Device for Food Intake and Ingestive Behavior Monitoring"

Dr. Sazonov:

The University of Alabama Medical IRB recently met to consider your renewal application. The IRB voted to approve your protocol for a period of one year.

Your application will expire on September 10, 2016. You will receive a notice of the expiration date 90 days in advance. If your research will continue beyond this date, complete the renewal portions of the FORM: IRB Renewal Application. If you need to modify the study, please submit FORM: Modification of An Approved Protocol. Changes in this study cannot be initiated without IRB approval, except when necessary to eliminate apparent immediate hazards to participants. When the study closes, please complete the FORM: Request for Study Closure.

Should you need to submit any further correspondence regarding this application, please include the above application number.

Good luck with your research.

Sincerely,

J. Grier Stewart, MD, FACP
Medical IRB Chair

358 Rose Administration Building
Box 870127
Tuscaloosa, Alabama 35487-0127
(205) 348-8461
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TOLL FREE (877) 820-3066

AAHRPP DOCUMENT

UNIVERSITY OF ALABAMA INSTITUTIONAL REVIEW BOARD

Title of Research: Evaluation of a Wearable Device for Food Intake and Ingestive Behavior Monitoring

Investigator(s): Edward Sazonov, PhD

IRB Approval #: 12-011-ME-R3 OSP #:

Sponsor: None

<u>You are being asked to be in a research study.</u>

The name of this study is “Evaluation of a Wearable Device for Food Intake and Ingestive Behavior Monitoring."

This study is being done by Edward Sazonov, Ph.D. Dr. Sazonov is a professor in the Electrical and Computer Engineering Department at The University of Alabama.

Who is paying for this study?

This study is not financially supported at this moment of time.

What is the purpose of this study—what is it trying to learn?

The first objective of this project is to evaluate a wearable device called AIM (Automatic Ingestion Monitor), for ingestion monitoring. Our goal is to develop a wearable system for detection and characterization of food intake. The monitoring system is developed and built at the University of Alabama and is an investigational device.

The second objective of this project is to study the use of AIM as an interventional device to modify the eating behavior of individuals. The AIM can accurately track and provide feedback on your eating behavior and during meal progression; can provide signals following which can modify your eating behavior. At the end of the study, you will receive a summary of what exactly the applied modification was.

Why is this study important—What good will the results do?

The results will enable researchers to use the device as a clinical diagnostic tool for obesity research and treatment as well as for diagnose and treatment of other eating disorders.

Why have I been asked to be in this study?

You have been asked to be in this study because you do not present any food or adhesive allergy and any disease associated with jaw motion.

What will I be asked to do in this study?

If you agree to participate in this study, you will be asked to come to the laboratory for 3 visits. These visits will be 3-5 days apart, based on your availability. The first day of the study will consists of a laboratory visit (baseline meal) and walking on treadmill whereas the next two days will only have laboratory visits (meals).

The investigators will have you wear two sensor systems for monitoring jaw motion. You will be asked to wear glasses instrumented with a piezoelectric sensor, a modified Bluetooth headset placed around the neck and a piezoelectric strain sensor attached to the skin immediately below the outer ear using medical adhesive and/or medical tape.

On each lab visit, you will spend approximately 1 hour at the human research laboratory. On the first visit (calibration meal experiment), you are expected to eat a bowl of fried rice while instrumented with sensors. You also be given a bottle of water (240ml), and you are expected to finish it with the meal.

During the next two visits, you are expected to wear a headset in addition to the sensors. Audio feedback from the sensor system will be provided on your eating progress (compared to your calibration meal) using the sensors on glasses. Please follow the feedback. Please stop eating when asked by the system to do so.

On the first day, after the calibration meal, you are expected to walk on the treadmill at a self-selected comfortable speed for 5 minutes and eat a chocolate bar while walking on the treadmill (5 minutes). These sensor systems are investigational devices that are not approved by the FDA. There is no known risk associated with wearing this type of measurement device.

You will also be asked to complete questionnaires about the food monitoring devices as well as your hunger level before and after each meal.

How much time will I spend being in this study?

You are expected to come to the human research laboratory for 3 visits. You will spend approximately 1 hour at the human research laboratory on each visit which will involve consumption of a meal and other activities such as walking and eating while walking.

As remuneration for your time, you will receive $20.00 on the successful completion of the study.

Will being in this study cost us anything?

There is no cost associated with this study.

What are the benefits of being in this study?

You will not benefit directly from this study. However, the results may help to better understand eating behavior.

What are the risks (dangers or harms) to me if I am in this study?

There are minimal risks associated with participation in this study. The sensor system does not interfere with a person's ability to eat or perform other activities. The study can also be stopped at any time at your request.

The device that you're going to wear carries no more than a minimal risk. All parts coming into contact with your skin have been disinfected by 70% alcohol solution.

How will my privacy be protected?

We will not tell anyone you are in this study. You do not have to answer any questions or give us any information that you do not want to. All individual information will be erased following this study.

How will my confidentiality be protected?

We will protect your information by giving you an identification number. Your names will not appear on any study document besides this consent form. There is no way to link consent forms and names with data. The data from the study will be kept in locked file drawers in locked offices. No one will have access to it except the investigators. We will publish scientific articles on this study but no names will be identified. No one will be able to tell who you are unless you agree to use of your images.

Do I have to be in this study?

No. If you decide to be in this study it should be because you really want to volunteer. You can refuse to be in the study at all. You can also start the study and decide to stop at any time.

If I don't want to be in the study, are there other choices?

If you do not want to be in this study, the other choice is to refuse.

What if I have questions, suggestions, concerns, or complaints?

If you have questions about the study now, please ask them. If you have questions or concerns later, you can reach Dr. Sazonov at 205-348-1981. If you have questions about your rights as a person taking part in a research study, call Ms. Tanta Myles, The Research Compliance Officer of the University of Alabama at 205-348-8461.

What else do we need to know?

You do not give up any of your legal rights by signing this consent form.

You will be given a copy of this consent form to keep. Save it in case you want to review it later or you decide to contact the investigator or the university about the study.

The University of Alabama Institutional Review Board (IRB) is the committee that protects the rights of people in research studies. The IRB may review study records from time to time to be sure that people in research studies are being treated fairly, and the study is being carried out as planned.

Also, the IRB conducts a survey of research participants about their experiences in a UA study. To complete it, ask the investigator for a copy or call IRB at (205) 348-8461. The survey can also be found on the IRB Outreach website at http://osp.ua.edu/site/PRCO_Welcome.html. The only identification requested is whether you are connected with UA or are from the outside community. Your response helps us improve our research protection program.

You may also ask questions, make suggestions, or file complaints and concerns at this website.

I have read this consent form. I have had a chance to ask questions. My questions have been answered. I understand what I will be asked to do. I freely agree to take part in it.

____ Date__________

Signature of Research Participant

____ Date__________

Signature of Investigator

APPENDIX B PUBLICATIONS

BOOK CHAPTER

1. M. Farooq, E. Sazonov Strain Sensors in Wearable Devices, Springer-Verlag Series of Smart Sensors, Instrumentation and Measurements, ISBN 978-3-319-18191-2.

2. M. Farooq and F. Hu, Language and Programming in SDN/OpenFlow, Network Innovation through OpenFlow and SDN: Principles and Design, ISBN 9781466572096

JOURNAL PUBLICATIONS

3. M. Farooq, PC. Chandler-Laney, M Hernandez-Reif, and E. Sazonov. Objective Monitoring of Infant Feeding Behavior using a Jaw Motion Sensor, Journal of Healthcare Engineering, 6(1): 23-40, 2015

4. J.M. Fontana, M. Farooq, and E. Sazonov, Automatic Ingestion Monitor: A Novel Wearable Device for Monitoring of Ingestive Behavior, IEEE Trans. Eng. 61 (no. 6) (2014) 1772-1779.

5. M. Farooq, J. Fontana, and E. Sazonov, "A novel approach for food intake using Electroglottography" Physiol. Meas., 35 (no. 5) (2014) 739

CONFERENCE PAPERS

6. M.Farooq, E.Sazonov “Automatic Measurement of Chew Count and Chewing Rate during Food Intake”, IEEE EMBC'16, Orlando, USA.

7. M. Farooq, E. Sazonov, “Counting Chews With Sensors”, Obesity Week 2015; The Obesity Society, LA.

8. *Best Poster Award:* M. Farooq, P. Chandler-Laney, M. Hernandez-Reif, and E. Sazonov, “Quantifying Infant Feeding Behavior: A sensor Based Approach”, Obesity Week 2015; The Obesity Society, LA.

9. M. Farooq, E. Sazonov, “A Wearable Sensor System for Monitoring of Food Intake”, IDTechEx 2015, Santa Clara, CA.

10. M. Farooq, P. Chandler-Laney, M. Hernandez-Reif, and E. Sazonov, “A Wireless Sensor System for Quantification of Infant Feeding Behavior”, accepted for Wireless Health 2015, Wireless-Life Sciences Alliance, Bethesda, MD.

11. M. Farooq, E. Sazonov, “Comparative Testing of Piezoelectric and Printed Strain Sensor in Characterization of Chewing”, IEEE EMBC'15, Milano, Italy.

12. M. Farooq, J.M. Fontana, A.F. Boateng, M.A. McCrory, and E. Sazonov, “A Comparative Study of Food Intake Detection Using Artificial Neural Network and Support Vector Machine” ICMLA ’13, Miami, FL.

13. J. Fontana, M. Farooq, and E. Sazonov, “Estimation of Feature Importance for Food Intake Detection Based on Random Forests Classification” IEEE EMBC'13, Osaka, Japan.

14. M. Farooq, J.M. Fontana, and E. Sazonov, “Food intake detection using Electroglottography (EGG)” 2012 Southeastern Workshop on Cognitive Sensing, Computing & Networking and Their Applications in Human-Cyber-Physical Systems, Tuscaloosa, AL.

15. M. Farooq, H. Zheng, A. Nagabhushana, S. Roy, S. Burkett, M. Barkey, S. Kotru and E. Sazonov, “Damage detection and identification in smart structures using SVM and ANN”, Proc. SPIE 8346, 83461O (2012).

16. M. Farooq, J.M. Fontana, and E. Sazonov, “Food intake detection using Electroglottography (EGG)” 2012 Southeastern Workshop on Cognitive Sensing, Computing & Networking and Their Applications in Human-Cyber-Physical Systems, Tuscaloosa, AL

SUBMITTED PAPERS

17. M. Farooq and E. Sazonov “Automatic Measurement of Chew Count and Chewing Rate during Food Intake” under review in Biomedical Signal Processing and Control.

18. M. Farooq and E. Sazonov, “A Novel Wearable Device for Food Intake and Physical Activity Recognition,” under review *Sensors (Basel)*.

19. M. Farooq and E. Sazonov, “Segmentation and Characterization of Chewing Bouts: A Wearable Approach,” Submited to *Journal of Biomedical and Health Informatics*.

20. M. Farooq, M.A. McCrory and E. Sazonov “Reduction of Energy Intake using Just-In-Time Feedback from a Wearable Sensor System", submitted to Obesity Journal.

21. M.Farooq, E.Sazonov “Linear Regression Models for Chew Count Estimation from Piezoelectric Sensor Signals”, under review in International conference on Sensing Technology (ICST) 2016.