Diet Management by Detecting Chewing Mechanism

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Abstract-In the context of dietary management, attention is given to detect the eating events. An accurate monitoring of chewing and swallowing mechanism is an essential one for controlling food intake. Abnormalities in this dietary management can lead to serious health problems such as obesity and other eating disorders. Obesity is associated with a greater risk of disability or premature death. In this paper, we propose to use wearable sensors like audio, accelerometer sensors with Photoplethysmography (PPG) sensor, which are placed in the mandible region near the external ear. It can be used to robustly extract objective and accurate measurements of human ingestive behaviour with a new high accuracy and real time in chewing detection system. This paper presents a simple sensor system and related signal processing and pattern recognition methodologies to detect periods of food intake based on non-invasive monitoring system. We propose a pipeline that initially processes each sensor signal separately, before going to the fusion process signal is preprocessed to reduce the noise by using the software MATLAB and then fuses the signals to perform the final detection. Features are extracted from each modality, and support vector machine (SVM) classifiers and fuzzy classifiers are used separately to perform snacking detection. Finally, we combine the SVM and fuzzy scores from both signals in a late-fusion scheme, which leads to increased eating detection accuracy. We evaluate the proposed diet management system with a trained dataset of 17 subjects consuming different food items which includes about 48 hrs of monitoring .We propose to use both hardware and software to achieve the maximum accuracy up to 94%.

Keywords- chewing detection, Signal processing, ingestion behaviour, classification, machine learning, acoustic sensors, eating detection.

I. INTRODUCTION

Overweight and obesity, defined as the abnormal or excessive body fat accumulation. The world health organisation estimated that the overweight adult population would increase from 1.5 billion in 2008 to 2.3 billion in 2015 and that obese adult population would rise from 500 to 700 million worldwide during the same period[27]. The main cause of overweight and obesity is a chronic imbalance between the energy consumed in foods and the energy expended due to decrease in the levels of physical activity, which is reflected in body weight gain.[11]Obesity is a medical condition in which excess body fat has accumulated to the adipose tissue. In this paper, we focus on detecting chewing activity in order to detect the eating event with high accuracy. These devices should be non-invasive and unobtrusive extent that it may have an adverse effect on health.[25] In general, obesity is associated with a greater risk due to type II diabetes mellitus and cardiovascular diseases such as hypertension, stroke and coronary heart disease as well as gall bladder disease and certain cancers. Obesity also carries serious implications for psychosocial health, mainly due to societal prejudice against fatness. A central distribution of body fat is associated with a higher risk of morbidity and mortality than a more peripheral distribution[20].In the developing world, women, men, and children from high social classes had greater rates of obesity [5]. In addition to its health impacts, obesity leads to many problems including disadvantages in employment [22][2].The most effective treatment for obesity is bariatric surgery[2] .The types of procedures include laparoscopic adjustable gastric banding, bypass, vertical, and bilio pancreatic diversion[17]. Surgery for severe obesity is associated with long-term weight loss; improvement in obesity related conditions [18] and decreased overall mortality. One study found a weight loss of between 14% and 25% (depending on the type of procedure performed) at 10 years and a 29% reduction in all cause mortality when compared to standard weight loss measures [3]. Complications occur in about 17% of cases and reoperation is needed in 7% of cases [4]. Due to its cost and risks, researchers are searching for other effective yet less invasive treatments including devices that occupy space in the stomach [19] .

The rest of this paper is organized as follows. Section II presents Existing method. Section III presents the proposed method. Section IV presents the hardware of the proposed chewing detection system and Section V the signal processing algorithms. In Section VI, we present the fusion process and trained data sets. In section VII ,we present conclusion. In section VIII, we present references.

II. EXISTING METHOD

In the older days, to reduce the obesity and control the diet of the patient, monitoring of individual eating behaviour through self-reports, such as asking questionnaires were followed. It has proven to be highly unreliable, which is time consuming, burdensome and error prone. This method is not possible to rely on such data analysis, prevention, or treatment purposes. Other approaches for monitoring eating occurrences have been based on audio recordings. It can be detected if chewing and crushing sound of food is present during each eating, a bite is followed by a sequence of chews [23] [7] and swallows, and this process is then repeated throughout an entire meal, where such chewing sounds are naturally amplified due to the ear physiology. Alternatively, microphones have also been placed near throats in order to detect the swallowing sounds based on the frequency changes [21].Other sensors like strain sensors are used to capture the muscular activity (usually masseter and temporalis muscles) [9][14].More recently inertial and proximity sensors are placed on the head and hands of the subject to detect the gesture of the hands that transfers the food from the plate to the mouth[16]. Other approaches which includes both audio and strain sensors are to detect the eating events. But this approach is not reliable and accuracy level is low.

III. PROPOSED METHOD

Wearable sensors and/or portable devices are introduced as a potential solution to replace the manual self-reporting methods. Chewing detection system consists of audio, accelerometer and photoplethysmography sensor. Chewing sounds are captured by means of wearable ear pad sensor. Arduino- Uno (ATMega328) is a single-chip microcontroller. It is used as a interface to process the signals and convert the analog signals into digital signals by means of inbuilt analog to digital converter (ADC).The tri-axial accelerometer is used to capture the lower jaw movement during chewing and crushing of foods. The audio/microphone is used to detect the crushing sounds of food during snacking events. The photoplethysmography sensor is used to detect the blood volume changes during mastication. We evaluate each of the microphone, accelerometer and PPG sensors separately, and also propose a late-fusion pipeline that combines signals from both sensors to increase the system's effectiveness [6]. Contribution: This paper contributes an automated food intake monitoring by introducing a PPG sensor, which combined with the audio and accelerometer sensor. It can lead to accurate snacking event detection and analysis of signal in real-life operating conditions. A complete, non-invasive detection system, proposing a complex signal processing pipeline with late fusion of Support Vector Machine and fuzzy scores. We evaluate through extensive experiments on a challenging dataset consists of over 48hr of semi-free living recordings with 17 subjects which includes various food types like hard food, soft food and liquefied drinks.

IV. WEARABLE SYSTEM HARDWARE

The proposed chewing detection system hardware consists of microphone, accelerometer (ADXL335) and PPG sensors. Wearable sensors are used placed in the ear pad for making it reliable and non obtrusive. The signal is recorded and processed by Arduino. To automatically detect swallow and chew phases/events, Support vector machine and fuzzy classifiers has been trained by means of manually annotated data sets. To accumulate the needed data, several experiments were performed with subjects swallowing and chewing a food bolus. Using a hardware trigger connected to the microcontroller in the arduino, a parallel signal has been recorded.

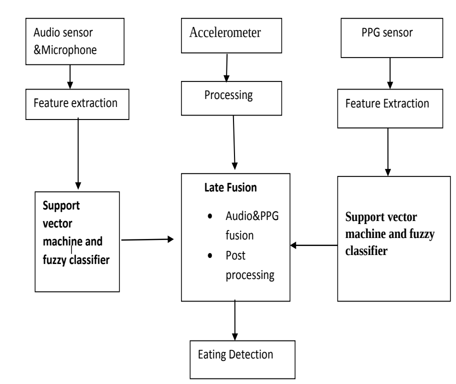


Fig -1. Block diagram of novel chewing detection method.

Relevant features have been extracted using these data sets. To face challenges of interfacing signals, specific constraints have been introduced. The detection of swallowing events is done in a controlled experiment of a subject drinking 50ml of water while sitting. The chew event was detected by the subject to sit still, while still allowing normal movement of jaw and limbs.

A. PPG Sensor

Photophlethysmography or pulse sensor measures the change in volume of blood through any organ of the body which causes a change in the light intensity through that organ (a vascular region) [24]. In case of applications where heart pulse rate is to be monitored, the timing of the pulses is more important. The flow of blood volume is decided by the rate of heart pulses and since light is absorbed by blood, the signal pulses are equivalent to the heart beat pulses. The change in volume caused by the pressure pulse is detected by illuminating the skin with the light from a light-emitting diode (LED) and then measuring the amount of light either transmitted or reflected to a photodiode[8].Chewing mainly involves the use of the masseter, the temporalis, the medial pterygoid, and the lateral pterygoid muscles. These are used to progressively process each bite, transforming it to a wet bolus that can be swallowed. Activation of these muscles affects blood flow in various points around them; one such point is the external ear. These variations have long been detected and reported in [10]. The quality of the PPG signal depends on the location and the properties of the subject's skin at measurement, including the individual skin structure, the blood oxygen saturation, blood flow rate, skin temperatures and the measuring environment. These factors generate several types of additive artefact which may be contained within the PPG signals. This may affect the extraction of features. Thus, the PPG can be used to capture the heart rate, by detecting periodicities in the range of 1-1.5Hz. However, during chewing, variations are created by the masseter and mainly the temporalis. These jaw variations are produced as pressure applied by the jaw to crush the food, and thus occur in synchronization with each individual.

Using PPG sensors for detecting eating event offers many advantages over a microphone and other sensors. The PPG sensor in ear concha region is small and highly non-intrusive, compared to sensors housed in collars placed around the subject's throat. However, the PPG signal is not entirely noise free. Abrupt changes of environmental lighting can create significant artefact. As it does not capture sound, it is not affected by ambient noise, talking and other types of non useful signals. Furthermore, correct placement of the sensor is very important to achieve higher amplification for chewing signals compared to heartbeat. The pulse detection using a comparator on the electronic circuit board to send out a digital signal for time-interval measurements. The analog electronic circuit is implemented as an add-on board for the Arduino microcontroller platform. A microcontroller board used to measure the timing intervals between heartbeats and to send it to a computer using the USB bus. The signal processing on an external computer.

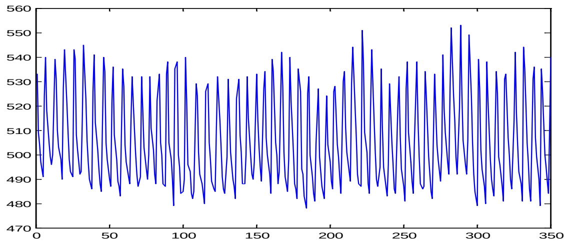


Fig-2 Raw signal from the PPG sensor without applying filter during normal condition while the patient in sitting position.

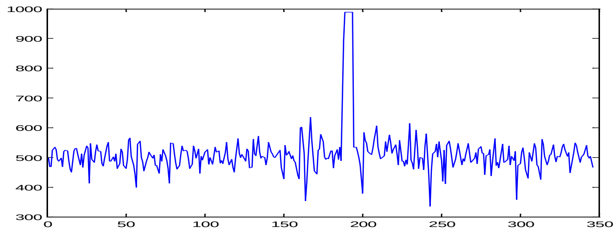


Fig-3 PPG signal during chewing activity without applying filters

B. AUDIO SENSOR

The chewing detection system is also equipped with a microphone. It exhibits a sensitivity of−53dB around the 1 kHz band. It is housed in an ear pad; as a result, the sensor is placed on the outer ear canal. This setup allows the capturing of body-generated sounds, such as the crushing sounds of chews as well as talking, at higher level compared to external sounds, such as ambient noise, other people talking, etc. The entire processing pipeline has been implemented in MATLAB, using the lib SVM and Fuzzy library for training.

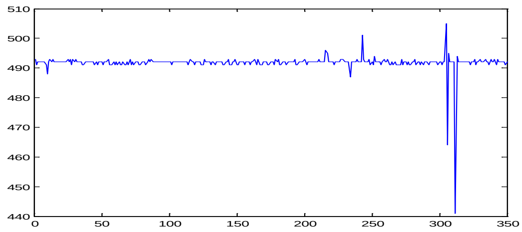


Fig-4 Audio signal during the chewing of food

C. ACCELEROMETER SONSOR

An ADXL335 accelerometer is a sensor that measures the physical acceleration experienced by an object due to inertial forces or due to mechanical excitation. When the accelerometer experiences acceleration, the mass is displaced and the displacement is then measured to give the acceleration. In these devices, piezoelectric, piezo resistive and capacitive techniques are commonly used to convert the mechanical motion into an electrical signal.

They are unmatched in terms of their upper frequency range, low packaged weight and high temperature range. It can measure the dynamic acceleration resulting from motion, shock, or vibration. ADXL335 is a compatible device; it is powered by a 3.3v source and generates 3.3v peak analog outputs.

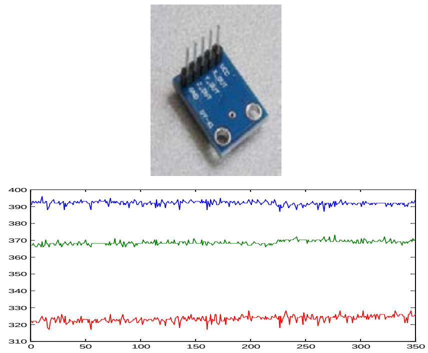


Fig-5 Triaxial Accelerometer sensor(ADXL335) and waveform during chewing of food.

D. ARDUINO(ATMega328):

Arduino boards are able to read analog or digital input signals from different sensors and turn it into an output,by turning LED on/off. Finally, Arduino provides a standard form factor that breaks the functions of the micro-controller into a more accessible package. Arduino board can be powered by using the USB cable from your computer. All you need to do is connect the USB cable to the USB connection . Arduino boards can be powered directly from the AC mains power supply. The function of the voltage regulator is to control the voltage given to the Arduino board and stabilize the DC voltages used by the processor and other elements. The Arduino UNO board has 14 digital I/O pins (15) (of which 6 provide PWM (Pulse Width Modulation) output. These pins can be configured to work as input digital pins to read logic values (0 or 1) or as digital output pins to drive different modules like LEDs, relays, etc. There are two labels: TX (transmit) and RX (receive). They appear in two places on the Arduino UNO board. First, at the digital pins 0 and 1, to indicate the pins responsible for serial communication. Second, the TX and RX led (13). The TX led flashes with different speed while sending the serial data. The speed of flashing depends on the baud rate used by the board. RX flashes during the receiving process.

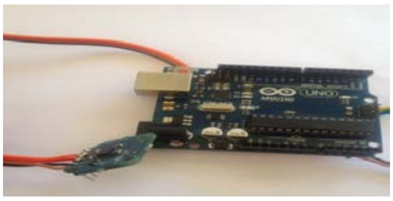


Fig-6 Interfacing Arduino with the sensors.

E. CHEWING DETECTION ALGORITHMS

In this section, we present the proposed algorithm for detecting eating events. We first present an algorithm for detecting eating events based solely on PPG, then another algorithm for audio, and, finally, the fusion of the two cues. Each chew lasts approximately 0.2–0.6 seconds, and subsequent chews are usually close to each other. The signal processing pipeline is shown in Fig. 6.Chews can be grouped into chewing bouts; a bout starts at the moment when food is placed into the subject's mouth and ends at swallowing. Each bout can last for seconds. Finally, bouts can be grouped into eating events. The term eating event to denote any complete session of eating activity. Each eating event lasts for 35-38 seconds. For example, eating a bake cake as a snack is a eating event; a full chewing process is also an eating event. In the following, chews, bouts, as well as eating events are represented by time intervals; they require a start and an end time stamp to be defined.

A.PREPROCESSING:

Data pre-processing is an important step in the data mining process. Analyzing data that has not been carefully screened for such problems can produce misleading results. Thus, the representation and quality of data is first and foremost before running an analysis [26].

Often, data pre-processing is the most important phase of a machine learning project, especially in computational biology [15]. If there is much irrelevant and redundant information present or noisy and unreliable data, then knowledge discovery during the training phase is more difficult. Data preparation and filtering steps can take considerable amount of processing time. Data pre-processing includes cleaning, Instance selection, normalization, transformation, feature extraction and selection. The product of data pre-processing is the final training set [12][13].

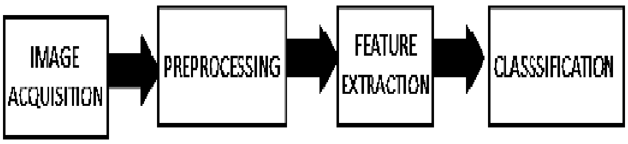


Fig-7 Block diagram for signal acquisition and signal processing.

B.FEATURE EXTRACTION:

In machine learning, pattern recognition and image processing, feature extraction starts from an initial set of measured data and builds derived values (features) intended to be informative and non-redundant, facilitating the subsequent learning and generalization steps, and in some cases leading to better human interpretations. Feature extraction is related to dimensionality reduction. When the input data to an algorithm is too large to be processed and it is suspected to be redundant, then it can be transformed into a reduced set of features (also named a feature vector). Determining a subset of the initial features is called feature selection.[1] The selected features are expected to contain the relevant information from the input data, so that the desired task can be performed by using this reduced representation instead of the complete initial data. In the chewing detection, feature Extraction is based on 1.Time Varying Spectrum, 2. Fractal Dimension, 3. Condition number with respect to inversion. The time varying spectrum includes

Time specification:

Fs = 100,

dt = 1/Fs,

Stop Time = 1,

t = (0:dt:StopTime-dt)'

N = size(t,1).

Fourier transform :

X = fftshift(fft(x))

Frequency specifications:

dF = Fs/N

f = -Fs/2:dF:Fs/2-Df

C.SVM CLASSIFIER:

A support vector machine is an classifier, which is separating the two hyper planes. It is also called as an supervised learning method. This SVM classifier is an machine learning algorithm which is used for classification or regression. This SVM is mostly used in classification process.SVM is an learning algorithm models that analysis the data used in classification and regression analysis. The advantage of using SVM is, it can avoids the difficulties which arises in the usage of an linear functions in an high dimensional feature space.

D.FUZZY CLASSIFIER:

Fuzzy classifier is defined as that, the process of grouping of an element into an fuzzy set. Its membership function is defined by the truth value of a fuzzy propositional function. Fuzzy classification the process of grouping of an individual's having the same characteristics into an fuzzy set. Based on the object description, an algorithm is assigns a class label to an object. The object description which means vector containing values of the features, that is relevant for the classification task. Using the training algorithm and a training dataset the classifier learns to predict the classes. Classification belongs to an general area of pattern recognition and machine learning.

E. PHYSICAL ACTIVITY THRESHOLDING:

One of the biggest challenges of dietary monitoring in real-life conditions is interference from physical activity, such as walking or running. Walking naturally occurs at a frequency of 1–2 Hz which is the same as the chewing band that the PPG chewing sensor captures. To improve the effectiveness of our system, we use a triaxial accelerometer that is interfaced with the arduino. Processing of the accelerometer signal involves first computing the total acceleration a[n] from the axis measurements ax [n], ay[n], and az[n] as a[n]=a2 x[n]+a2 y[n]+a2 z[n]. A high pass FIR filter with cut off frequency at approximately 1 Hz is then applied to remove the DC offset [28].

V. FUSION PROCESS

In order to increase effectiveness, we combine the microphone and the PPG sensor in a late-fusion scheme. We use the smoothed decision scores audio ,PPG and

SVM classifiers. Finally Fuzzy classifiers are used to increase the accuracy of eating detection. Since these signals have different sampling frequencies, we down sample audio (which has the highest rate) to the frequency of PPG using linear interpolation. Audio signals are obtained from the audio sensor during eating process. When the food is crushed ,the sensor that captures the distinct sound.The accelerometer sensor which detects the physical activity at high at high rate. The physical activity includes lower jaw movement. The motion signals vary during walking and talking. So during training process the subjects are asked to do high level physical activity during food intake process. The PPG sensor which is used for detecting the pressure signals the food intake process. All these three signals were obtained as the trained data set. The feature which is extracted from the each modalities, SVM classifier and an fuzzy classifiers are used separately to perform snacking detection. Then both the fuzzy and an SVM scores from both signals are fused. It leads to an detection of eating at high accuracy.

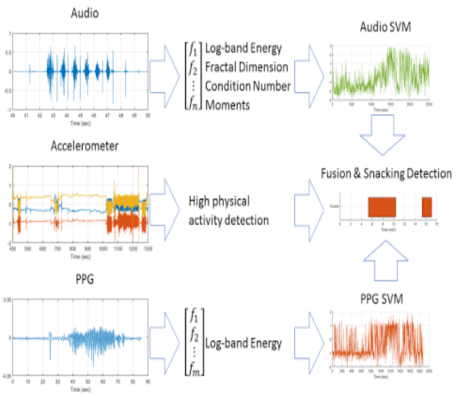
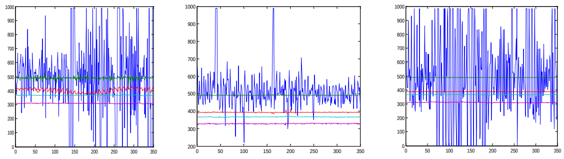


Fig-8. Proposed eating detection pipeline .Features are extracted from windows of the audio and PPG signals and a score is computed for each window of each modality using SVMs. The SVM out puts are combined in a late-fusion approach in order to detect eating events. The effectiveness can be further improved by introducing physical activity information in the last stage of the detection.

A.TRAINED DATASETS:

We collected data from 17 participants (9 females and 8 males; aged 21-24). The training data of an food items for the subjects include (pups, chips, cake, juice, laddu ,sweets and biscuits).Based on the experiments we collected data from each subjects. During first session, a standard size of food was served and no background noise was allowed during the eating period. During second session, a standard size of food is served and background noise is allowed and talking to the subject are used during eating food. Noise was introduced to experiment to simulate realistic environments where people may be eating and that can potentially impact results in future sound recognition. During the third session, a large amount of food was allowed to serve and no background noie was allowed during the meal period. During the fourth session, a large size meal was served and background noise and talking to the subjects were used during the meal period.



(A) (B) (C)

Fig-9 Sensor signals of different subjects A, B and C during eating Chips with a time period of 35-38 seconds

VI. CONCLUSION

Study of ingestive behaviours needs a simple methodology for monitoring of the food intake under free living conditions. The most commonly used method of self-reporting diaries may be insufficiently accurate for this purpose. We propose to utilize counts of bites, chews, and swallows as objective indications of food intake on simple non-intrusive sensors which can be implemented as a wearable device. In this method, chewing and bites are detected by a audio and accelerometer sensor. The hardware and software system described in the paper captures multi-model sensor data. We have presented a chewing detection for the diet management using the sensors audio, PPG and accelerometer for detecting the eating event. The accelerometer sensor and PPG sensors are placed in the mandibles and concha region respectively. The combination of an all three signals using the fuzzy classifier and an SVM classifier yields an accurate results. These trained data sets are used in the two classifiers which is acquired from the 17 subjects. The training data of an food items for the subjects include (pups, chips, cake, juice,laddu,sweets and biscuits). The duration of an food intake for every individuals at about 40 seconds. Here we are obtaining the accuracy up to 0.9486. By using the SVM classifier alone, it provides an accuracy up to 0.8679. The usage of both the SVM and fuzzy yields an accurate output.

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