Activity Recognition and Nutrition Monitoring in Every Day Situations with a Textile Capacitive Neckband

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Abstract

We build on previous work [5] that demonstrated, in simple isolated experiments, how head and neck related events (e.g. swallowing, head motion) can be detected using and unobtrusive, textile capacitive sensor integrated in a collar like neckband. We have now developed a second generation of the band that allows long term recording in real life environments in conjunction with a low power Bluetooth enabled smart phone. It allows the system to move from the detection of individual swallows which is too unreliable for practical applications to an analysis of the statistical distribution of swallow frequency. Such an analysis allows the detection of "nutrition events" such as having lunch or breakfast. It also allows us to see the general level of activity and distinguish between just being absolutely quiet (no motion) and sleeping, as periodic "empty swallows" occur more seldom when a person is sleeping.

Author Keywords

Activity recognition, nutrition monitoring, capacitive sensing, wearable computing

ACM Classification Keywords

I.2.m [Artificial Intelligences]: Miscellaneous.

Introduction

In [5] we have proposed a novel sensing system that uses textile electrodes integrated in an unobtrusive collar to measure the capacitance of the users' neck. In a nutshell it works like a capacitive touchpad except that the electrodes are looking "inwards" into the neck reacting to changes in neck shape and inner composition (e.g. when food is swallowed). In constrained lab experiments we have demonstrated the detection of head and neck related events ranging from head motions, through speaking and coughing to swallowing.

In this demo we build on the above work presenting an improved version of the systems that supports long term monitoring of selected behaviours with a neckband connected to t smart phone using a low power Bluetooh module. A core application idea is that while the detection of individual swallows and head motion works poorly in real life data streams, a statistical distribution of swallow frequency, time between swallows and head motion can be detected reliably enough to be a good indication of certain activities. In an initial expriment with a data set 138 hours from 3 subjects we were able to detect meals, sleeping (including the distinction between just being absolutely quiet (no motion) and actually sleeping), and spot three activity levels: fully quiet (e.g. watchingTV), normal (e.g. working on a computer), and being highly physically active (e.g. walking).

Related Work

A widely used wearable sensing modality are arm/wrist mounted motion sensors which allow the detection of nutrition related gestures [1]. Unfortunately nutrition related gesture can vary widely and resemble to many other gestures (e.g. scratching ones' head). To overcome such problems multi modal approaches are often successful. Thus, for example, Liu et. al., used a microphone and an egocentric camera to detect food-intake [6]. Of course, one cannot wear a camera everywhere (privacy problems) and it might be tricky to tell from the recorded images if the user really eats some food or just looks at it [4]. More reliable is chewing detection using bode conducted sounds from the ear [2], which however involves a more invasive sensor system. Another more obtrusive approach is a sensor worn in the mouth to detect chewing [7]. In lab environments, electrodes mounted on the neck can also reliably detect swallowing and with it eating [3].

System design

As shown in Figure 1 the system consists of a textile neckband with 4 capacitive sensors, operating at a sampling rate of 25Hz. Compared with the system described in [5], it has been modified in several ways.

First, instead of flexible but not stretchable metal textile, we made the sensor pads out from stretchable conductive material (Silver plated 92% Nylon 8% Dorlastan fabric) and embedded them in a stretchable neckband with buttons for length adjustment. Connecting wires are sewed to the pads with conductive thread (Silver Plated Nylon 117/17 2ply.). Thus the band is more comfortable.

Second, the sensor has been equipped with a Bluetooth 4.0 interface for data transmission to a dedictated IPHONE App.

Third, we use one common ground for all the four channels to reduce noise. Because the system is battery powered its ground is floating. The bigger the area of the pads' ground planes, the better the system is coupled to human body. We put two sensor pads in the center, where the larynx moves through when swallowing, and another two across sternomastoids, which also moves with swallowing, and at the same time changes when turning the head aside.

Finally, the 2nd and 3rd stages of the amplification were removed and different settings for the Colpitts oscillator were chosen to reflect that we are now mostly looking for swallowing, which is a mechanical change at the surface level and thus much stronger then the type of signals that we were interested in [5] (e.g. pulse).

Figure 1: The material, the sensor pad design and the ready neckband worn by a test subject

Data Processing

The data stream is evaluated in 3 consecutive steps. First is the spotting of single swallows. Next is the extraction of short windows (1.5min) classified on the basis of swallow frequency and some additional features as (1) eating, (2) sleeping and (3-5) three levels of physical activity (quiet, normal, active). Finally we extend the analysis to longer windows (up to 8min) and the detection of nutrition events. In doing so we distinguish between major meals (breakfast, lunch, dinner) that should be spotted reliably and short snacks which are less distinct.

Single swallows A model of swallowing is built for each subject based on the training set, simply by aligning all labeled swallows then calculate their average (shown as thick black lines in Figure. 2, the other lines are the aligned labelled swallows). Half of the maximum value of the sum of all 4 channels has been determined from the training data as a threshold to select segments possibly containing swallows. To those segments we apply a J48 tree classifier trained with the training set. The features include: the RMS, the mean value, the highest peak's channel index, its peak value and the width, the bandwidth, frequency centroid, the amplitude difference to the model.

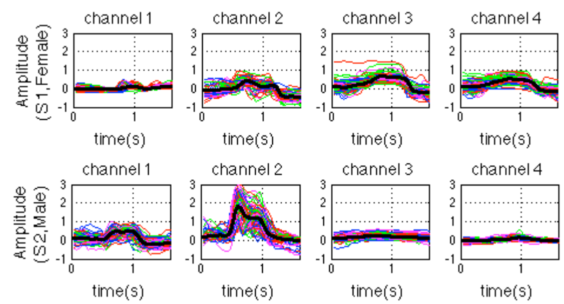

Figure 2: Swallow model of a female (top) and male (bottom) subject.

Short window analysis Running a 1.5 min window moved in 20 sec steps over the detected swallows we compute the swallow rate and the time interval between swallows. The classification of the 1.5 min windows is performed using 10-fold cross-validation method with J48 Tree classifier. The features are: the RMS of each channel, the percentage of signals higher than the overall RMS, the numbers of swallows, the mean and RMS of time interval between swallows, the mean of the shortest and longest swallow intervals (bottom/top 1/3).

Event based meals spotting The event spotting is essentially based on smoothing the 1.5 sec recognition results, merging events that are closer then a certain threshold and throwing away all segments where the resulting eating events are shorter then a certain time threshold. The remaining segments are the meal events. These predicted meals are then compared to the real eating periods noted down by subjects.

A threshold is then set from 0 minute to 8 minutes, at each threshold, only real meals longer than this threshold are taken into consideration for the evaluation. When the threshold is 0, all food/water intakes are considered, and when the threshold is as high as 7 minutes, only the major meals (breakfast, lunch, dinner) are considered.

Initial Results

3 healthy subjects (2 males, 1 female, aged 24-34 years) took part in the experiment. Each has worn the neckband throughout 3 days. The data includes 3 big meals (breakfast, lunch and dinner) as well as light snacks like banana, apple and yoghurt. The subjects have carried out their usual daily activities and note the time and duration of food intakes and "big" drinks (up 5-6 sips, small drinking is neglected) and key activities performed during the day (work in front of computer, shopping, walk to mensa and etc.). Overall the data encompasses 138 hours with 25 big meals (eating longer than 6 minutes), and 39 smaller food or water intakes (the intaking process takes less than 6 minutes). One subject has also worn the neckband at night (2 nights). For training an laboratory data set was recorded for each subject that includes eating bread, apple, banana and drinks a cup of water. The training data are companied with video record and all swallows are labeled.

The overall accuracy for all 3 subject and 5 states in the 1.5min windows is 84.4%, with class 1 and 2 missing for subject 3. Over all 3 test subjects, we are able to recognize 24 out of 25 big meals (recall 0.96), with 3 false predications (precision 0.89); and 46 out of all 64 food/water intakes, with 136 false predictions.

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