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

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UbiComp'13 Adjunct, September 8–12, 2013, Zurich, Switzerland.
ACM 978-1-4503-2215-7/13/09.

10.1145/2494091.2494143

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 an unobtrusive, textile capacitive sensor integrated in a collar like neckband. We have now developed a 2nd generation 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. The neckband can be useful in a variety of applications such as cognitive disease monitoring and elderly care.

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 present an improved version that supports long term monitoring of selected behaviors with a neckband connected to the smart phone using a low power Bluetooth module. The core 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 and head motion can be detected reliably enough to be a good indication of certain activities. In an initial experiment with a data set of 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).

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 Fig. 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, we use a common ground for all channels to reduce noise. We put two sensor pads in the center, where the larynx moves through when swallowing, and the other two across sternomastoids, which move both with swallowing and the head's movement.

Third, 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).

Finally, data transmission is now through a Bluetooth 4.0 module to a dedictated IPHONE App.

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

Data Modellling

3 healthy subjects (2 males, 1 female, aged 24-34 years) have each worn the neckband throughout 3 days. The subjects carried out their usual daily activities and noted the time and duration of food intakes (main meals as well as light snacks like apple or yoghurt), "big" drinks (up 5-6 sips, smaller drinks are neglected) and key activities (work in front of computer, shopping, walk to mensa and etc.). Overall the data encompass 138 hours with 25 big meals (eating longer than 7 minutes), and 39 smaller food or water intakes (the intaking process lasts less than 7 minutes). One subject also worn the neckband at night (2 nights). For training a laboratory data set was recorded for each subject that includes eating bread, apple, banana and drinking a cup of water. The training data are companied with video record and all swallows are labeled.

The all-day 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 swallow model is built for each subject based on the training set, simply by aligning all labelled swallows than calculating their average (as thick black lines in Fig. 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.

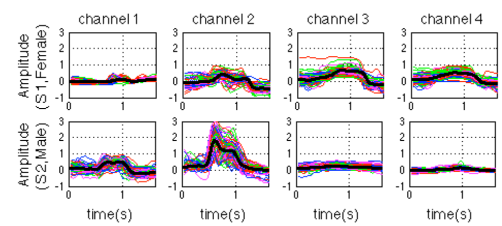

Figure 2: Swallow model of a female (top) and male (bottom) subject.

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 min recognition results, merging events that are closer than 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 to 8 minutes, at each threshold, only real meals longer than this threshold are taken into consideration. When the threshold is 0, all food/water intakes are considered, while when set to 7 minutes, only the major meals (breakfast, lunch, dinner) are considered.

Experiment Results and Conclusion

The overall accuracy for all 3 subjects and 5 states (sleep, quiet, normal, active, eat) in the 1.5min windows is 84.4%, with state 1 and 2 missing for subject 3. Over all 3 subjects, we 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.

We believe that the main significance of this work is the ability to reliably recognize major meals and sleeping periods (as opposed to just being quiet) with a single, unobtrusive sensor. Both are difficult to recognize reliably using other unobtrusive sensors while being valuable for a variety of applications such as cognitive disease monitoring [8] and elderly care.

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