DETECTION OF TOOTHBRUSHING ACTIVITY USING FREE-LIVING ACCELERATION DATA

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Abstract: The present paper discusses the characterisation of toothbrushing activity, using acceleration data collected for 50 subjects in free-living conditions. The data logging is triggered by super-threshold values of acceleration, which can give rise to false activations by non-brushing activities. Due to large intra and inter individual variations, it is not possible to obtain an exhaustive training-set of all activities that trigger the logging. Thus, a structural analysis of appropriate data features is performed, which reveals a clustering of the data. The comparison with brushing activity traces from laboratory experiments allows the identification of toothbrushing activity, while the remainder corresponds to various false activation events like electronic noise or brush handling. The distribution of the resulting toothbrushing activity shows distinct peaks for morning and night brushing activity.

1 INTRODUCTION

The measurement of human activity plays an important part in medical monitoring, where many applications consider the detection of certain dynamical states which subsequently allows drawing conclusions about the physical state of the subject. Usually, activity is measured in a laboratory environment, where the experiment follows a fixed protocol (e.g., 5min walk, 5min treadmill etc.) (Preece et al., 2009), or the user has to label manually the respective acivity (Bao and Intille, 2004). Due to obvious logistic problems the sample size is usually restricted to 5 - 20 subjects. The labelling of the data allows the training and subsequent validation of different classification techniques. However, little is known about the properties of data collected in free-living conditions for large populations. Typical issues encountered in field experiments are:

- Unpredictable behaviour of the subjects.
- Unexpected noise sources.
- High interindividual variability of activity (see e.g., (Welk et al., 2007)).

In order to obtain a labeling of the activity, experiments can be combined with video observation (Vega-Gonzalez et al., 2007). However, it is plausible that knowledge of being observed changes the individual's behaviour. The last issue also effects the quality of questionnaires, or self-reports, which are often biased towards the 'desired' behaviour. This paper considers an industrial approach to the activity classification based on accelerometer data. The data are taken from a study conducted by Unilever Oral Care (Claessen et al., 2008a), which measured the toothbrushing behaviour of a large population in Xian (China). The subjects were given a Sensor brush, a novel device developed by Unilever, which logged toothbrushing events over a period of 3 weeks. The study was originally designed to evaluate the effect of public health communication, but in the present paper only the technical aspect concerning activity classification shall be addressed.

The paper is organized as follows. First, the Sensor brush technology is introduced. In Section 3 the data format and analysis methods are discussed. This includes results on the classification of logged events together with examples for the different classes.

2 THE SENSOR BRUSH DATA

In order to capture toothbrushing behaviour in free-living conditions, a logging device, called Sensor

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brush (Figure 1), has been developed by Unilever Oral Care (Claessen et al., 2008a). The Sensor brush has the shape of a normal toothbrush with a compartment in the handle that contains the data logger. The latter includes a 3-axial accelerometer, memory, and battery. In order to reduce memory and power usage, the data logging starts when the accelerometer signal exceeds a certain threshold, and then continues for 60 seconds. After 60 seconds the logging either continues if the signal is still above threshold, otherwise it stops. The data thus consists of 60s traces of the x, y, z acceleration, sampled at 10Hz, together with the date and start time of the event.

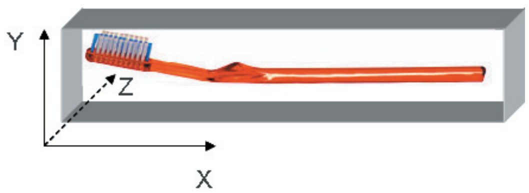

Figure 1: Sensor brush 3-axial measurement.

The validity and reliability of this technology has been established in a number of studies (Claessen et al., 2008b), which confirm that the Sensor brush is able to detect time and date of brushing events, and does not influence the brushing duration when compared to a standard marketed toothbrush.

3 DATA ANALYSIS

As outlined in the previous section, the device starts to log 60s of the acceleration trace after the signal exceeds a threshold. The latter is chosen in a way that no brushing events are lost. As a result, the data is corrupted by false activations, due to handling of the brush, opening and closing of cabinet doors, incidental dropping of the brush, internal electronic noise and many more. Hence, a post-processing of the data is necessary, which should allow for unknown error sources. Since there is no sufficient training set available, the data features are searched for patterns, or structures, which allow extracting the true brushing events via an unsupervised clustering technique.

The data considered in the following consist of logged events (60s of x, y, z acceleration) for 50 male adults over a period of 3 weeks. Each event is labelled by time and date, which allows the extraction of the average intensity of toothbrushing for a given time of the day. The respective analysis steps are described in the following.

3.1 Feature Extraction

The signal of the accelerometers is corrupted by noisy spikes that are removed in a pre-processing step. Each data sample is then divided into adjacent windows of 3s that contain 3x30 data points for the x, y, z acceleration. Because the sampling frequency is 10Hz, which is quite close to typical brushing frequencies (between 3 and 5Hz), a principal component analysis is performed to obtain the linear combination of the three acceleration traces that contains the maximal variance. This is done for each window i, yielding a set of (maximum variance) components $a_i(n)$, $n = 1 \dots 30$. The absolute values of ten Fourier coefficients, corresponding to frequencies $2, 2.33, 2.67, \dots, 5$Hz, are obtained via fast Fourier transformation of the a_i. We denote these values as $s_{i,k}$, $k = 1 \dots 10$.

3.2 Data Analysis and Classification

For the subsequent analysis, the logarithms of the coefficients, $\log s_{i,k}$, for all subjects are merged to form a large data matrix $S_{j,k}$, where j labels the respective 3s window and $k = 1 \dots 10$ indicates the frequency component. In order to reduce the dimensionality a principal component analysis (PCA) is performed on the ten frequency components. The loadings of the first three principal components, which explain 93% of the total variance, can be interpreted as follows: PC1 reflects the total variation of all frequencies; PC2 reflects the variation of the power in the 5Hz frequency component; PC3 contrasts the power in $4, 4.33, 4.67$Hz with the other frequencies. Because 5Hz corresponds to the Nyquist frequency, the second component PC2 is excluded from further analysis. More interesting are the frequencies reflected by PC3, which correspond to the typical range of toothbrushing frequencies (Van Someren et al., 1996).

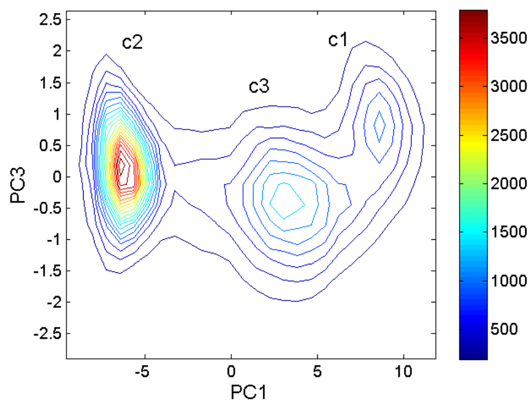

Figure 2: The distribution of the data in the PC1-PC3 plane, indicating a partition into 3 clusters, C1, C2, C3.

A scatter plot of the data in the PC1-PC3 plane reveals a partition into three clusters. This is clearly seen in the contour-plot of the data distribution shown in Figure 2. The upper right cluster, C1, in Figure 2 is characterized by high total power and relatively high power in the frequency components 4, 4.33, 4.67Hz. This is the expected property of toothbrushing events. A visual check of the data and a comparison with test toothbrushing traces (collected in the laboratory) confirms this expectation, such that it can be assumed that the cluster C1 contains toothbrushing events. Accordingly, the false activations (due to non-brushing activity) belong to the clusters C2 and C3. In order to discriminate the data, a Gaussian mixture model is used (Press et al., 2007). The result is presented in Figure 3. The figure indicates a considerable overlap between the clusters, which is a typical feature of real-life data.

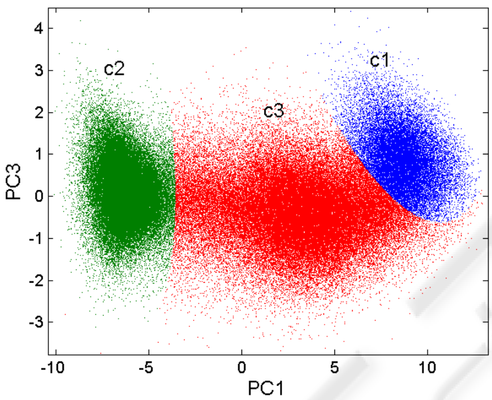

Figure 3: The result of the clustering in the PC1-PC3 plane. The toothbrushing events are contained in C1.

The majority of the data points belong to clusters C2 and C3 with 41 and 46%, resp., while C1 contains 13% of the data. Because the Gaussian mixture model assigns a membership probability to each data point, the probability of misclassification can be estimated. The results shown in the table 1 below suggest that there is a 0.02 probability of misclassifying a toothbrushing event as false activation (false negative) and a 0.13 probability of misclassifying a false activation as toothbrushing (false positive). However, these numbers are obtained under the assumption that the Gaussian mixture model correctly describes the data, while Figure 2 indicates that this is only approximately valid.

In Figure 4 typical examples of logged events belonging to the three clusters are presented. The C1 sample shows strong oscillations combined with baseline changes (due to brush rotations), which is characteristic for toothbrushing activity. The C2 sample

Table 1: The average membership probabilities for the clusters C1, C2, and C3.

classified as	prob. C1	prob. C2	prob. C3
C1	0.87	0	0.13
C2	0	0.98	0.02
C3	0.02	0.01	97

is typical for a logger activation due to exceptional electronic noise (spikes) that is followed by baseline noise. An interesting case is the C3 sample: there are distinct regular oscillations of about 2Hz that might suggest a brushing activity. However, the small amplitude of the oscillations and the absence of baseline shifts indicate a false activation, probably due to static vibrations generated by a washing machine or similar.

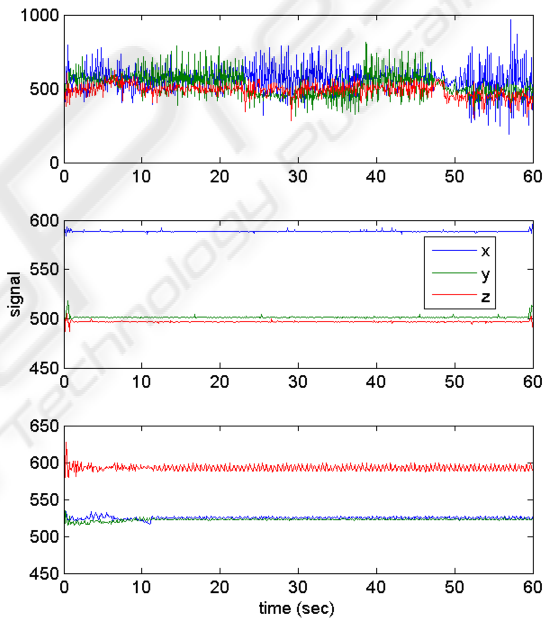

Figure 4: Examples for accelerometer signals for (from top to bottom) cluster C1 (toothbrushing, 1:00am), C2 (false activation due to electronic noise), C3 (false activation due to external perturbation).

An interesting property is the distribution of logged events over the day. The result for the three clusters is shown in Figure 5. The brushing activity has distinct maxima between 7 and 8am and around 10pm, and minima between 3 and 4am and around 5pm. The prevalence of brushing in the morning is typical for the group considered (see (Zhu et al., 2005)). There is a small peak around 12 noon that indicates toothbrushing activity after lunch. The non-brushing events in C2 and C3 have a more ragged distribution, which is in general well correlated with the brushing events. This is not surprising, since toothbrushing is usually accompanied by other activities in the bathroom that are likely to trigger a false logging event. There is a pronounced maximum between 7 and 8pm, which might be caused by a regular routine (e.g. washing after work), but this can only be guessed due to the lack of further information.

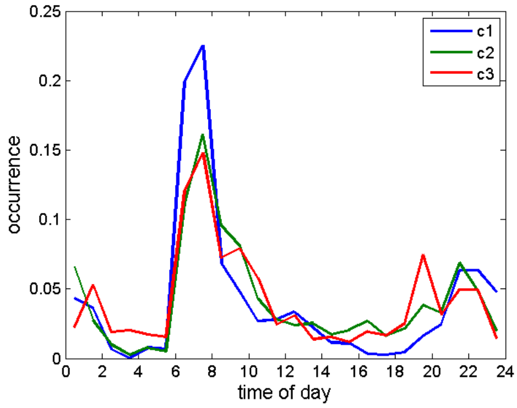

Figure 5: The normalised distribution of logged events over the day for the three groups C1, C2, and C3.

4 CONCLUSIONS

The present paper discusses the characterisation of toothbrushing activity, where the data consists of acceleration traces logged by a sensor that is integrated in the brush. Because the data has been collected under free-living conditions for a large population, it was not possible to obtain an exhaustive training-set of all possible super-threshold activities that trigger the logging. Thus, a structural analysis of appropriate data features is performed, which reveals a partition into three clusters. The comparison with brushing activity traces from laboratory experiments allows assigning one cluster to toothbrushing activity, while the remainder corresponds to various false activation events like electronic noise or handling of the brush in the context of other activities.

An inherent property of real-life activity data is the enormous variability, both within and across subjects. Here, this is reflected by an overlap between the clusters found in the data, that leads to a 13% classification uncertainty for toothbrushing events. A possible remedy for this problem is to collect more variables (e.g., rotation rate) at higher sampling frequencies, which, however, is restricted by memory and energy consumption issues in the logger design. An important point is that the logger should not influence the normal behaviour of the subjects while being in the field for several days.

It would be interesting to gather more information about the possible sources of false activation and their acceleration patterns. This will require elaborate laboratory experiments that take into account learnings from field experiments.

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