31st Annual International Conference of the IEEE EMBS
Minneapolis, Minnesota, USA, September 2-6, 2009

Fast matching of sensor data with manual observations

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Abstract – **In systems and trials concerning wearable sensors and devices used for medical data collection, the validation of sensor data with respect to manual observations is very important. However, this is often problematic because of feigned behavior, errors in manual recording (misclassification), gaps in recording (missing readings), missed observations and timing mismatch between manual observations and sensor data due to a difference in time granularity. Using sleep activity pattern monitoring as an example we present a fast algorithm for matching sensor data with manual observations. Major components include a) signal analysis to classify states of sleep activity pattern, b) matching of states with Sleep Diary (SD) and c) automated detection of anomalies and reconciliation of mismatches between the SD and the sensor data.**

Keywords: sleep activity pattern monitoring, wearable sensors, device trials

1 INTRODUCTION

In our work we are trialing the use of wearable sensors (accelerometers) to chart activity patterns and circadian rhythm in elderly for extended periods. Our specific objectives are to conduct a two-phase trial at a nursing home and in selected patients' homes. Two groups of patients are identified, those with dementia and hence altered circadian rhythm, and other elderly with subjective complaints of insomnia. This paper discusses the non-clinical aspects of our trial aiming to provide efficient and sensible ways of relating and reporting sensed and manually recorded information.

In dealing with wearable sensors it is often necessary to classify activities from raw data collected by the wearable sensors, extract features from the raw data and annotate these features with high level semantics. Given a sequence of wearable sensor data and a much more coarse grained sequence of manual observations concerning the activity of the wearer, we present an algorithm to perform fast annotation of the data sequence by focusing on key points of interest, rather than going through each and every data point in the sequence. We evaluate the effectiveness of this algorithm by means of analysis on real data collected in a trial. The remainder of this paper is structured as follows. Section 2 presents the architecture for data collection, and section 3 the algorithm for processing and classification of the collected data. Section 4 presents the matching algorithm in greater detail. Section 5 and 6 presents results and related work. Section 7 concludes the paper.

I. ARCHITECTURE FOR DATA COLLECTION

The infrastructure includes off-the-shelf wearable sensors, a mobile platform acting as a gateway and the necessary interfaces to a database server via internet and GSM network (see Figure 1). The wearable sensor we use is the commercially available sensor, the AliveHeart ™ sensor from Alive Technologies. The patient's activity signals are transmitted from the wearable device through the internet infrastructure to the hub. The medical team can have instant access to the information on the server, and make the appropriate medical decisions and prescriptions. The data recorded in this manner provides health care providers with a clear picture of each patient's history without having to physically see the patient.

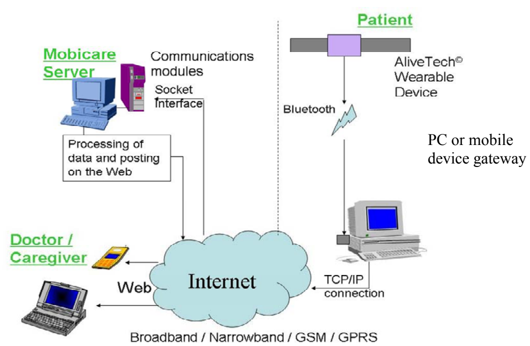

Fig 1. Architecture

The trial proceeds as follows. A wearable accelerometer is placed in a pouch and worn on the wrist. Since we study circadian sleep patterns, we collect data for 12 hour periods daily, starting at 6pm in the evening, and ending at 6am on the following morning. Subjects are asked to wear the accelerometer for a 2-week period, and may take off the sensor during the day if there is discomfort. However they are asked to wear the sensor in the evening, and throughout the night. The data is transmitted wirelessly to a nearby mobile phone, which transmits it to the server. Staff at the nursing home record i) start time of the sleep period, and ii) an hourly record of sleep of each subject.

II. Data Collection Procedure and Classification Algorithm

The sleep/activity data is stored on a database hosted in the Institute for Infocomm Research. To ensure privacy, all data is properly anonimized and subjects' identifiable information (e.g. names, addresses) is removed. Fig 2 depicts the data collection procedure. Since data is continuously recorded it is important that there are no errors or inconsistencies in recording timing information about the data items. For this purpose, data received after long periods of break are stored in separate files and timestamps noted for each of these recordings. Thus by processing consecutive filenames the timing information about the recorded data can be recovered to within an acceptable level of accuracy.

Given a sequence of values $\{a_1 \ldots a_n\}$ that represents raw sensor data, one oft-repeated task is to analyze a *window* or a sub-sequence of the data (signals). When consecutive windows are classified into the same class, the entire duration for which the class is exhibited is a *segment*.

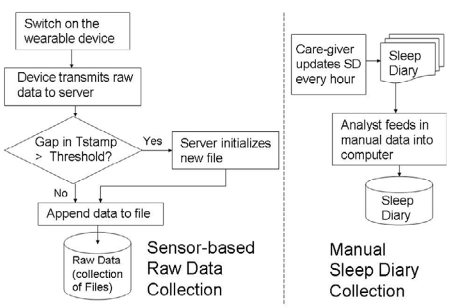

Fig 2. Data Collection Procedure

The algorithm for classification of the segments is shown in Fig 3.The raw data is processed offline to remove outliers and to deal with gaps that might arise due to various reasons such as the device not being worn, or battery failure. The output of this algorithm is another file containing filtered raw data. This file is next processed to extract features. In our case two features in question are "asleep" and "awake" classification, although "no-data" is third. Our algorithm may be generalized to multiple classes, characterizing multiple activities (gauged by the intensity of movements measured by the accelerometer). The algorithm has two parameters, namely *window size* and *sleep threshold*. Both parameters can potentially affect the classification of the data. An important step in the classification process is the computation of signal energy level (a feature that is used to determine the possible classification state of a signal).

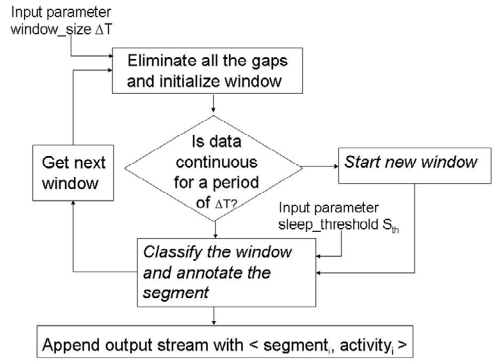

Fig 3. Classification Algorithm

III. Matching Sensor Data with Manual Observations

We present an iterative procedure to reconcile the extracted classifications in the processed data (PD) with the manual observations in the sleep diary (SD) that is currently maintained at a granularity of one hour. Since the window size is far less than this, we need a way to summarize the data to the same level of granularity as that of the SD. We do this is through the use of simple rules based on observed heuristics. These high level rules are typically expressed in statement form. It is worth noting that these rules are merely guidelines and do not capture the fullness of the real life phenomenon being recorded in all its complexity. In this sense, even the SD is only a snapshot of the phenomenon, albeit a more reliable one. Our algorithm uses a bottom-up strategy and assigns classes to each high level time period (usually one-hour). Since the algorithm is linear in time it is a fast algorithm.

A. Details of the matching algorithm

We first classify sensor data, aggregating the data into windows of constant size. These windows are then classified by applying rules to them based on experience, heuristics and observations. Below we present a sketch of the algorithm and low level and high level rules used to perform the classification using the bottom up approach. Preliminary results using this approach are in [8]. In summary these results demonstrate that the algorithm classifies sleep patterns of dementia patients (and the control group, normal elderly) quite accurately.

Algorithm:

1. Set W (window size) and T (sleep threshold) and periods P1 and P2
2. Classify each window by aggregation
3. Classify at higher level to match SD (sleep diary), using rules with rule thresholds P1 and P2
4. If FOM is met, match with SD giving each time period a label Sleep or Active.
5. If FOM (Figure of Merit) is not met, select new rule thresholds. Repeat steps 2 thru 4

Low Level Rules:

1. Server detects loss of communication for more than five minutes - close the data file and create a new file when the data stream is detected.
2. Sanity check - to check that data is not lost within the five minute interval

High Level Rules:

1. If (>P1 windows) of sleep is followed by (<P2 windows) of activity followed by (>P1 windows) of sleep, merge the activity period with the neighboring sleep periods.
2. Similarly, if (>P1 windows) of activity is followed by (<P2 windows) of sleep followed by
(>P1 windows) of activity, merge into an overall active period.

IV. RESULTS

Figure 4 depicts the results of the matching algorithm presented against the corresponding output of the activity visualization (derived from sensor data) and manual observations. Three consecutive days are presented in a stacked manner (which is useful for spotting shifts in circadian patterns). In the figure, for each day, the activity data is aligned below each of the algorithm graphical outputs. The colored line in between the graph and the activity data represents the manual observation (SD) with a simple color scheme to reflect “outdoors – purple”, “active – green” and “sleep – orange”. Blue indicates non availability of SD data.

In the graphs, for each day, there are three plots; the manual observation, processed result for 15 minutes window size and result for 1 minute window size. For each day the graphs are plotted for the period of data collection, 6pm to 6am. Setting a small window size (one minute) gives us a result that matches the SD in all the cases. However small window sizes are unable to capture information about movements made in between sleep, which are reflected in the sensor data (shown below the respective graphs). Setting the window size to be quite large (15 mts) enables us to capture this information. However, it is clear that these graphs do not match very well with the sleep diary.

Certain outcomes were unexpected. First, we found that the sleep thresholds do not vary significantly from person to person or from day to day. Therefore the learning phase, that we thought may be necessary to personalize the algorithm settings was found to be unnecessary.

Another observation was that for sleep classification only (i.e. to detect sleep versus activity alone), a far smaller sampling rate than the 75Hz rate that we used would have been sufficient. Performing a correlation of the sequence of observations obtained by concatenating the first sample of each second with the second sample of each second, we found that the correlation was amazingly consistent and extremely high. These told us that we could down-sample the measurement down to a far less sampling rate and still not lose significant information.

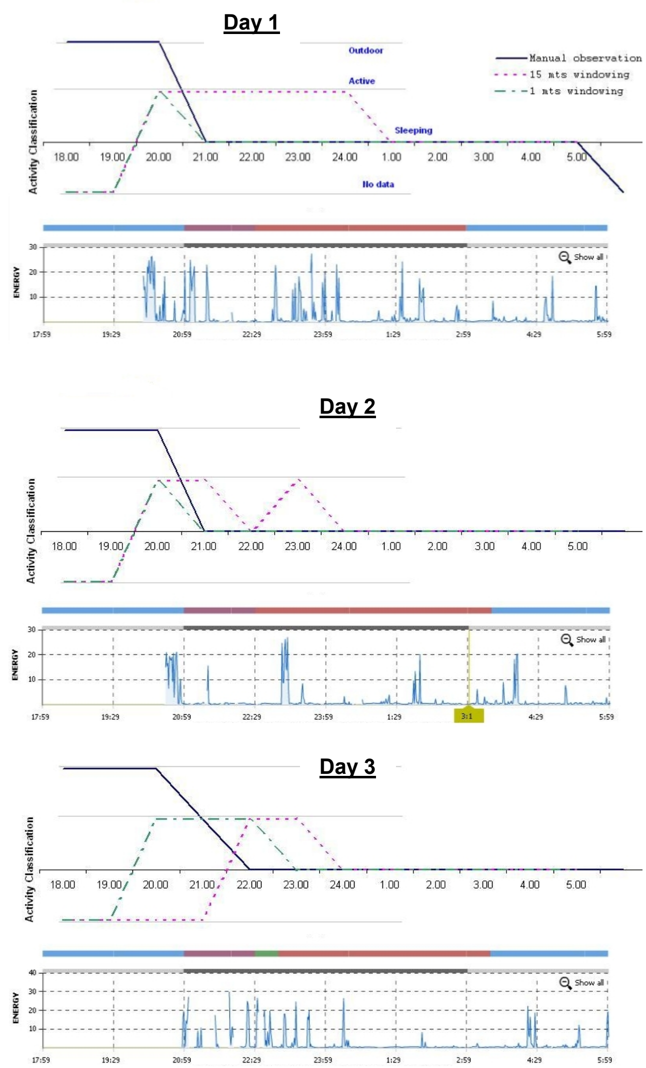

Fig 4: This figure depicts a consolidated presentation of the output of the matching algorithm and the visualization of the sleep diary and sensor data for three days (12 hour periods, 6pm – 6am) for the same subject. The different levels in the graphs are “Outdoor”, “Active”, “Sleeping” and “No data”.

The reduction in sampling rate has important ramifications on the usability of our system and algorithms in settings where wireless bandwidth may become congested. We anticipate this is going to be an important issue in future, especially in environments where there are multiple patients being monitored in the same place, for example in Nursing Homes where several patients are being monitored together using the same system and infrastructure. For further discussions on this topic and related issues the reader is referred to [6, 7].

T results presented in [8] indicate that the use of accelerometers in daily living environments afford a simple and effective way of accurately charting sleep and

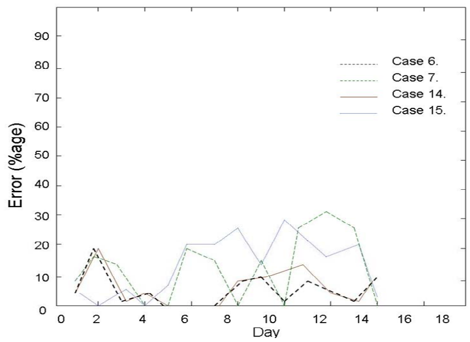

Fig 5. Daily error for two weeks for four subjects

activity patterns. Fig 5 shows plots of the errors recorded via the sensor-reported classification vis-à-vis the manually recorded ground truth, for four randomly selected subjects (referred to as cases 6, 7, 14 & 15 in the figure), for the two week trial period. It may be noted that on certain occasions no data was available due to loss of network connectivity or battery outage at the device. The overall error rate of 20% to 30% is due to the various factors reported in this paper, which account for mismatches between the sleep diary and the processed data.

V. Related work

A comprehensive account of actigraphy (using wearable accelerometers to classify activity patterns) in the study of sleep is presented in [1]. Paavilainen et al [2] conducted a survey among 16 residents of a long term care facility for elders. Using a proprietary activity detection system, they established an association between changes in actual health status and circadian activity rhythm. Thus they concluded that telemetric activity monitoring helps detect long term changes in health status among older adults in their normal environments. Sarela et al [3] provide further details on their implementation and study. In our work we initially experimented with the same proprietary sensor used in [2, 3], however due to its closed architecture we decided to switch to another sensor.

Lotjonen et al [4] provide details of the long term on-line monitoring of the activity of elderly, commenting on the ability of the device to discriminate sleep/wake patterns during night time and during napping. The effectiveness of wearable sensors for sleep / awake activity classification is further discussed and supported in [8, 9, 10]

VI. Future work and conclusions

In ongoing work, multi-modal sensors are being used to collect sleep data. In general it can be said that when data at different granularities have different levels of accuracy or dependability it is possible, using techniques represented herein, to reclassify the weaker data sets using the stronger ones. Manual observations may also be erroneous, though this is not considered in this paper. In this case, the iterative procedure presented herein may be modified to detect and fix the errors in manual observation. Rules presented herein are a very basic set and useful for the application that we have considered herein, namely sleep activity pattern monitoring. It is conceivable that other applications (eg. ECG monitoring) will have vastly different rules and operating conditions. In this sense, it will be a mistake to attempt to generalize to other applications, the rules that are used in a particular application.

Acknowledgements. The authors would like to thank the staff at the St Josephs Home for their help with administering the Sleep Activity Pattern Monitoring trial at the home. The research was supported in part by a grant from A*STAR, SERC.

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