Micro-context Recognition of Sedentary Behaviour using Smartphone

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Abstract— **embedded sensors of smartphone provides a unique opportunity to recognize the micro-context of sedentary behaviour. In this paper, we present our research findings on how to recognize micro-contexts by utilizing on board sensors of smartphone. Our proposed approach consists of two stages process. First, we recognize the situation of a person to be either stationery or moving. If stationary, then high probability to be sedentary, in which we can then find micro details about the current context. Second, we process environmental sound and recognize the person's micro-context such as watching television, working on computers or relaxing. Furthermore, we also provide the lifestyle analytics over cloud computing infrastructure to make it available anywhere and anytime for self-management purpose. We developed an initial working prototype to evaluate the applicability of our approach in a real-world scenario.**

Keywords— **Micro-context Recognizer, Sedentary behaviour, Smartphone, k-NN**

I. Introduction

Sedentary behaviour is increasing due to societal changes and related to prolonged periods of sitting. Sitting while watching television, using the computer while working or playing games for long hours, to name but a few, are examples of sedentary behaviours that are currently common worldwide [1]. These kinds of activities increase sedentary behaviour across all age groups. A person is considered sedentary if they spend large amount of their day with such activities and do not spent sufficient time for physical activity or exercise. Similarly, many jobs require people to sit in front of computer all the day, which also promotes sedentary behaviour. Sedentary behaviour is associated with poor health outcomes, including the high risk of overweight and obesity [2], physiological and psychological problems [3], heart disease and diabetes [4]. A self-management approach is required to support self-awareness and healthy behaviour to reduce the health risks caused by sedentary behaviour.

To promote healthy behaviour, there should be some efficient mechanisms to track and estimate the time spent in sedentary activities. The most common methods to capture the total time spent in sedentary activities are self-reporting diaries, direct observations, external devices mounted with tri-axial accelerometer and inclinometer [5]. Such methods are intrusive and unable to process the sensor data inside the devices. Furthermore, they provide limited information about the sedentary behaviour in daily routines.

There is a need to develop a ubiquitous system to track the sedentary elapsed time accurately with all its micro-context ranging from office work or home to watching television in leisure time. The advancement of smartphone in built-in sensors, high storage and computation power along wireless communication technologies have introduced new ways to develop tremendous applications ranging from the interactive games to healthcare domain [6]. Especially the medical domain applications, which enable the users to interact with the system to provide real time user assistance and help to improve the people life's style [7][8].

In order to track sedentary behaviour in daily routines, we propose a tracking application based on the accelerometer and audio sensor of smartphone. We compute the acceleration and acoustic features over the collected sensory data and recognize the contexts by applying non-parametric nearest neighbour classification algorithm [9]. The main contribution of this paper is a model for processing the collected sensory data in real-time and inside the smartphone environment, which proves the ubiquity of our solution and demonstrates how it does not require any server side processing nor external data storing, which can obviously underpin the privacy. Furthermore, it relaxes the assumption of strong reliable communication channel to transfer the bulk amount of collected sensory data. We believe that our application can help the people to monitor their sedentary behaviour in a proactive way. Based on the tracked behaviour, users will be able to monitor and manage their daily routines that may help to adopt healthy lifestyle.

The rest of the paper is organized as follows. We briefly describe related works and their limitations in Section 2. In Section 3, we introduce our proposed approach and its implementation inside the smartphone environment to recognize the sedentary behaviour. In Section 4, we analyze

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and evaluate our experimental results to validate our approach. Finally, we conclude our paper in Section 5.

II. Related Work

Several research studies and a large number of lifestyle tracking devices are available [2], [7], [10], [11], [12], [13]. Barwais *et al.* [2] assess the effectiveness of a four-week intervention. An external device mounted with tri-axial accelerometer was used to reduce sedentary behaviour among sedentary adults. In this device users needed to connect the device with USB port and send the data to computer where it was visualized using developed software.

ActiHeart [10] is another commercial product available in the market and offers accelerometer and heart rate monitoring over several days. This device is able to detect the sedentary behaviour but still unable to distinguish between types of sedentary behaviour (i.e., watching TV verses PC). Moghimi *et al.* [7] analyze the sedentary behaviour in life-logging image using SenseCam. This device is capable of storing up to 30,000 images. It consists of light sensors, an accelerometer, a thermometer, and a passive infrared sensor to detect the presence of people. User needs to wear this camera all the time and this solution is obtrusive.

Dunton *et al.* [14] investigate children's physical activity and sedentary behaviour and developed a protocol using electronic surveys administered on the display screen of mobile phones. It involves cumbersome process for participants. While other applications related to sports and physical activity recognition are available but do not make the user aware of detected unhealthy behaviour [8].

Smartphone have been used to monitor the physical activities as well as mHealth applications [15]. We believe that smartphone can play a significant role to capture sedentary behaviour continuously in daily routines and help the user's to be healthy and active. It can be seen one of the most ubiquitous, easy to use device and capacity to adopt the solution for a large number of people.

III. The Proposed Approach

The proposed approach consists of smartphone environment, cloud computing infrastructure, and behaviour analytics of daily routines to make it an acceptable and usable solution. The micro-context recognition of sedentary behaviour is illustrated in Figure 1 and details of sub-components are as follow:

A. *Smartphone Environment*

Google Android is one of the most competitive markets due to its open source platform. We implemented our model in Android-based smartphone to recognize the micro-context of sedentary behaviour. The details are as follow:

***Sensory Data Acquisition*:** Accelerometer and audio sensor data is collected to sense the body motion and environmental sound of the user. We read accelerometer sensor's reading at normal delay and no overlapping window with a size of 3 seconds. While audio sensor data is collected at 8000 sampling rate and window size is 8 seconds, we collected the sensory data in hierarchical fashion.

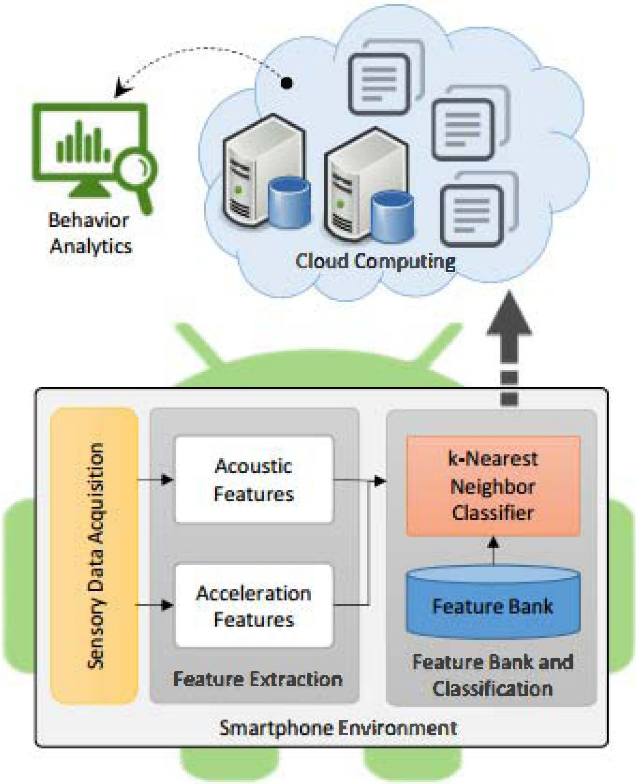

Figure 1. The Proposed Architecture

We first collect the accelerometer data and if we found user is stationery then environmental sound is sensed for further processing. In order to keep the user privacy, we did not store the audio signal, but rather we processed it immediately in real-time. Figure 2 shows example scenes of micro-contexts recognition.

Figure 2 Example photos for 'short break', 'active', 'working on PC', 'watching TV', and 'Unknown'.

Feature Extraction: After collection of the sensory data we apply feature extraction technique and classification algorithm to know the micro-context of users (i.e., sedentary, short break, active, watching TV, or working on computer). Firstly, we solve the orientation issue of accelerometer data suggested by Mizell [16] and then extract *mean* to measure the central tendency, *standard deviation* to measure the data spread for different activities and *energy* feature to find the quantitative characteristics of the data over a defined time period. In order to capture the characteristics of environmental sound, we extract the Mel-Frequency Cepstral Coefficients (MFCC) feature vector. It is calculated on the basis of fast Fourier transform, which is closest to the human auditory system due

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to the utilized Mel scale and represented as the short-term power spectrum of a sound [17].

Feature Bank and Classifier: Feature bank contains both accelerometer and audio sensory data extracted features. These features (i.e., explained in feature extraction section) will feed to the classifier for classification of sedentary behaviour. Our model is two-step process. First we classify the accelerometer feature by non-parametric nearest neighbor algorithm. It is one the most used algorithm in many applications and proved itself lightweight and easy to implement [9]. In the proposed method, Euclidean distance metrics is applied to find the neighbors and four neighbors (i.e., k = 4) are considered to classify activities. It identifies us about the user current state either stationary or moving. If state is stationery then we activate the audio sensor to sense the environment sound and recognize the micro-contexts by providing MFCC features to non-parametric nearest neighbor algorithm.

B. Cloud Computing

Cloud computing provides scalable and flexible computing model, where resources, such as computing power, storage, network and software are abstracted and provided as services over the Internet [18]. We have deployment of open source OpenStack cloud environment in our Machine Learning laboratory [19] to provide the storage, computing and access services anywhere and anytime. Our smartphone application recognize user micro-context in real-time inside the smartphone environment and send sedentary behaviour to our deployed cloud through the Internet. Furthermore, recognized behaviour is analysed to infer the useful information.

C. Behaviour Analytics

Our behaviour analytics provide information about the user daily patterns in terms of sedentary time, active time, short breaks, watching television during leisure time, and working in the office while using computer. This micro-context of sedentary behaviour provide better understanding of user's daily routines and may help users to minimize the amount of prolonged sitting and adopt active lifestyle. We are using Google charting [20] for presenting behaviour analytics. We create the limited number of credentials that is equal to number of participants to interact with the system and visualize the sedentary behaviour patterns.

IV. Evaluation and Discussion

The result of proposed micro-context recognition of sedentary behaviour is evaluated in this section. In our pilot study, four healthy subjects with different gender, height and weight participated for one week. Each participant installed our developed lifestyle application on their smartphones to analyze and visualize their sedentary patterns. Our application is capable to run in the background while user's can use their smartphone for other tasks. We construct the feature bank by short duration trails of all recognized contexts (i.e., Active, sedentary, working on pc, watching television, and unknown context). We applied non-parametric nearest neighbor algorithm for classification and it does not required training. During the classification phase, stored features from the feature bank found the Euclidian distance from each stored class and classify the current situation. In order to preserve the privacy we did not store the environmental sound. We extract the features in real-time from the sensory data and fed to the classifier for recognizing the micro-contexts. Time scale for inferencing is set to one-minute epoch that is sufficient to distinguish among the micro-contexts. If a user is found sedentary then we activated the audio sensor for 8 seconds to analyze the environmental sound and recognize the micro-context. Furthermore, if we found the micro-context and user is still in sedentary state then we checked the environment after fifteen minutes to distinguish between the micro-contexts while staying sedentary. In this way, we save the battery consumption of the smartphone by only checking the environment when user is in sedentary state. Flow chart of the process is shown in Figure 3.

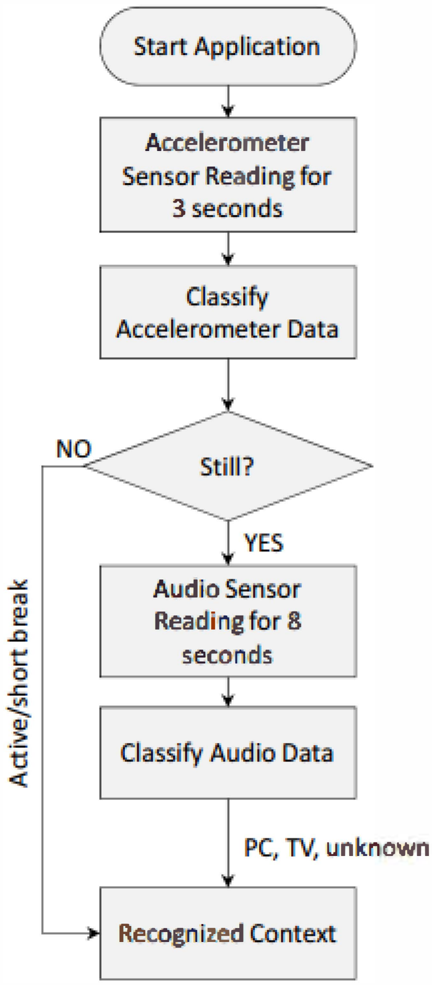

Figure 3 Flow chart of application information flow

For discussion, we are presenting one subject's 24 hours data of a working day. Table I shows one day activities for the

ISBN: 978-1-4673-9609-7

subject with total hours spent in sedentary state along micro-contexts, short breaks and active time.

Table I Twenty Four Hour Routine with Time Spent Duration

Activity	Duration (Hours)
Active	4.85
Short Breaks	0.25
Working on PC	3.58
Watching TV	1.58
Sedentary– context unknown	13.74

In Table I, we showed the quantification of the amount of time spent in sedentary behavior by subject that was around 18 hours including working on computer, watching television and unknown context. In the contexts class label "Sedentary—context unknown", we consider the subject sleeping time and all other micro-contexts such as subject went to library for studying or any other that is not included in the recognized micro-context. Even though short break time is 25 minutes but important to indicate the state of being active. In order to get insight of the sedentary patterns of daily routines, we showed observed pattern from 12:00 to 23:59 by presenting each minute of 24 hours in Figure 4. Where x-axis shows the time in minute while y-axis shows the micro-context with class labels sedentary (1), working on PC (2), watching TV (3), active (4) and short breaks (5).

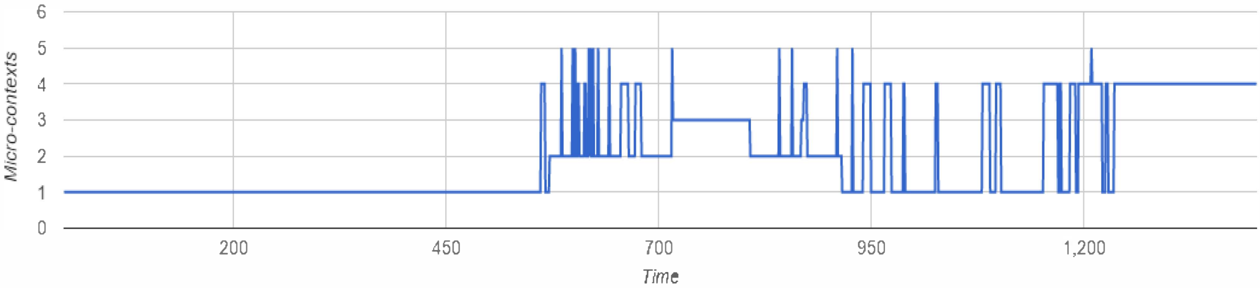

Figure 4 Daly routine with time spent of activity pattern

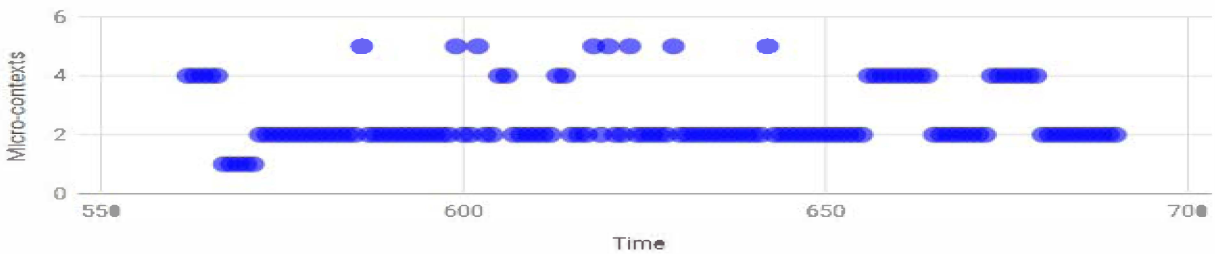

Figure 5 Activity patterns with micro-context

In Figure 4, the subject activity is sedentary because of night and subject was sleeping. After that we can see active patterns, using computer, watching television and on off state of active and sedentary. In order to get closer look of the daily routines of the subject, Figure 5 presents the two hours and nine minutes routines of the first half of the day. It shows the subject's activities pattern of working on computer consists of 8 short breaks and 4 active times. We classify "short breaks" if subject's activity time is less than or equal to one minute and "active" if time is more than one minute.

In Figure 6 and 7, daily routine pattern is visualized and provide us information on percentage of time in 24 hours spent in different micro-contexts activities. We also extract the information about the number of short breaks (i.e., 15 short breaks) that help subject to avoid longer sedentary activity.

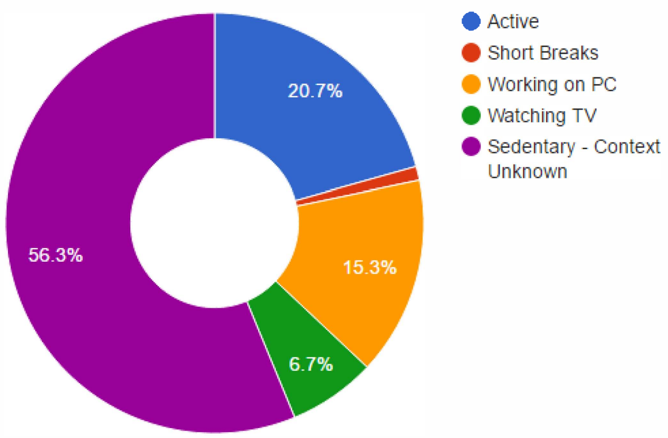

Figure 6: Sedentary behaviour along percentage of time spent in different activities

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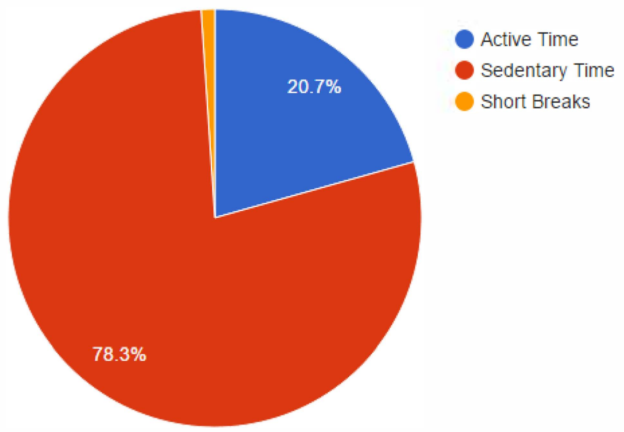

Figure 7 Sedentary behaviour with three broad categories of 24 hour routine

Our behaviour recognition analysis may help the users to minimise the amount of time spent in prolonged sitting and encourage them to break up long periods of sitting as often as possible. We can quantify the time spent in electronic media during leisure time (e.g. television, video games and computer use) and set the limit hour of their usage. It will consequently help to adopt the active lifestyle and reduced the health risks.

V. Conclusion

In this study, we presented our research findings of how to recognize micro-contexts of sedentary behaviour by utilizing on-board sensors of smartphone. We recognized active state, short breaks during the sedentary time including watching television during leisure time or working on computer. In order to keep the privacy of the user's we are processing sensory data in real-time inside the smartphone without storing the environmental sound and acceleration signals. We presented behaviour analytics by utilizing cloud infrastructure and google charting to get insight of daily routines. It can facilitate the individuals to monitor their sedentary behaviour and provide a proactive platform for self-management. Currently, our application is limited to the micro-contexts recognition. We have plan to increase the number of micro-contexts and provide recommendations in terms of alerts and messages.

Acknowledgment

This research work was supported by Zayed University Research Initiative Fund # R15132.

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