A Smartphone System for Unobstructive Personal Living Routine Monitoring

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ABSTRACT
Living routine is a very important element that reflects both physical and mental wellbeing of humans. The detection and analysis of the living routine could accelerate the recovery or even prevent many diseases and disorders. This is especially true for diseases such as diabetes and obesity, which in most cases are the result of inappropriate living routines. However, conventional clinic-centered healthcare technologies are not able to monitor the living routine on a daily basis. We propose a smartphone-based system that provides unobtrusive and continuous monitoring of several key daily activities in an individual's living routine including eating, exercise, TV viewing and sleeping. Based on the detection results, regular feedback could be provided to the users to help them understand the consequences of their actions and make positive changes in their living routine.

1. INTRODUCTION
Living routine is often considered as one of the most reflective aspects of physical and mental health. A healthy living routine is able to facilitate early discovery, prevention and the treatment of many diseases and disorders such as diabetes [16] and autism [14]. For example, the frequent TV viewing has been associated with the risk of overweight among younger children [4]. Detecting one's living routine requires continuously monitoring important daily activities, such as eating, watching TV, exercise and sleep quality. As the current healthcare practice, patients are typically asked to self-report their living routine. However, this approach is often inaccurate and time-consuming. In addition, it is not able to capture detailed information about activities and often prone to bias.

By taking advantages of the growing popularity of smartphones, we aim to develop an unobtrusive system that continuously monitors living routine using smartphones. Such a system needs to meet several requirements. First, based on data collected from various built-in sensors of smartphone, it should be able to yield relatively accurate and reliable detection results for further analysis. Second, as it requires long-term and continuous sensing, the sensing schedule and power consumption need to be optimized. Last, users' privacy needs to be preserved, especially when camera and/or microphone are used to collect information.

Recently, various sensor-based systems have been proposed for automatic monitoring of a broad range of human activities. Jigsaw, a sensing engine for mobile sensing applications is proposed in [13]. It continuously monitors and classifies human activities such as walking, running and cycling. A smartphone-based system that is able to reliably estimate the energy expenditure during cycling is proposed in [17]. [15] demonstrates a novel approach to estimate walking distance by using gyroscopes and accelerometers placed at both legs. Besides physical activities, efforts have been made towards detecting the mental state of users. StressSense [11] enables unobtrusive recognition of stress from human speech using smartphones. Empath [5] is a real-time depression monitoring system designed to detect and track signs of depressive illness. MoodScope [10] utilizes communication history and application usage patterns to infer users' daily mood.

Several systems have also been developed to detect or measure health-related activities. Lullaby [7] aims to provide a comprehensive capture of the sleep environment by combining various sensors such as temperature, light and motion sensors. [9] presents a privacy-preserving cough detection method using audio stream of the smartphone. [8] and [6] demonstrate smartphone-based solutions that enable the measurement of lung function and heart beat rate, respectively.

Our goal is to develop a smartphone-based system that provides automatic and continuous monitoring of the uses' living routine. In contrast to existing health monitoring systems that typically require users to wear extra sensors, our solution leverages off-the-shelf smartphones. As a result, it is unobtrusive to users and enables the users to monitor and track their living routines on a daily basis, which is often difficult to realize in the conventional healthcare system.

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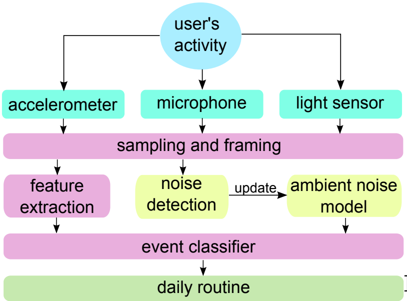

Figure 1: System overview

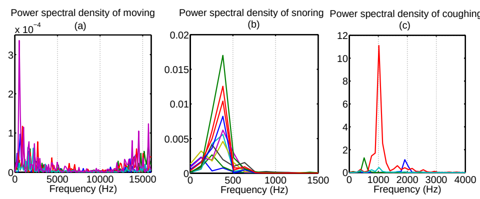

Figure 2: (a), (b) and (c) show the power spectral density of typical acoustic signals associated with moving, snoring and coughing events, respectively.

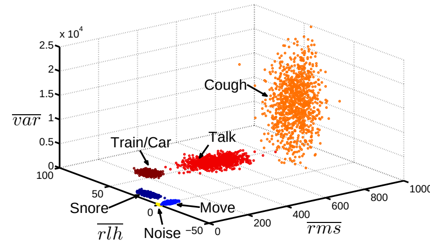

Figure 3: The acoustic feature vectors of different events in the feature space.

2. SENSING FRAMEWORK

Our living routine monitoring system employs the following sensing framework. The data stream captured by several sensors including microphone, accelerometer and light sensor of the smartphone are able to provide rich information about the user's current activity and the surrounding environment [12] [3]. Our sensing pipeline typically involves several components (as shown in Fig.1). First, signals are continuously sampled from microphone, accelerometer and light sensor, and segmented into *frames*. Second, the frames are fed into *noise detection*, e.g., the system determines whether a frame only contains the sound of ambient noise. The *model of ambient noise* is then updated based on detected noise frames. As a result, the system is able to adapt to the changes of ambient noise. Third, signal *features* will be extracted from the frames that potentially contain events of interest. Typical features used in acoustic sensing include root mean square, energies in different frequency band and etc. The extracted features, along with the updated ambient noise model, are fed to the *event classifier* where events will be detected. Commonly used classifiers include decision tree, Support Vector Machine (SVM) and Gaussian Mixture Models (GMM).

As a common challenge for event detection, noise identification is critical to the detection accuracy. Since they could be generated by various sources and subject to change over time, it is necessary to keep track of the current ambient noise by maintaining a continuously updated noise model. Therefore, by taking the current ambient noise model into account, the classifier is able to adapt to the environment with dynamic ambient noise, thereby making the system more accurate and stable.

3. EVENT DETECTION

Several existing smartphone systems [13] [17] can monitor the physical exercise of users. In this section, we focus on discussing the detection of three significant events in one's living routine, which are sleeping, eating and watching TV.

Since most people sleep in a relatively quiet environment, the sleep event along with some human activities (e.g. body movement) during sleep can be captured by processing the acoustic signal. Besides the duration of sleep, we are also able to assess the sleep and wakefulness using actigraphy [2], which models the relationship between overnight movement and sleep state. Therefore, we can calculate sleep efficiency as a metric of sleep quality. Specifically, it can be computed as the ratio of the actual sleep time (i.e., the total duration of sleep state) to the total in-bed time. Figure 4 shows the detected actual and in-bed times. Besides body movement, we are also able to detect several other activities that can be used to infer sleep quality based on Pittsburgh Sleep Quality Index (PSQI), such as snoring and coughing (as shown in Fig. 5). In order to detect the sleep-related events, we adopt a lightweight algorithm to classify various events based on carefully selected statistical acoustic features. By keep tracking of the current ambient noise, the system also adapts to dynamic ambient noise characteristics to improve the robustness of classification.

For example, Fig. 2 shows the energy distribution of typical acoustic signals associated with moving, snoring and coughing. We can see that their distributions are distinct from each other. Based on this observation, we select the ratio of high-band to low-band energies as a feature, whose change over time reflects the transition of dominant frequency (rlh). The other two selected features are root mean square (rms), which captures the loudness of sound, and variance (var), which reflects how far the amplitudes of acoustic signals within the frame are spread out. Fig. 3 shows the distribution of three normalized features based on the real data collected from 7 subjects over multiple nights. We can observe that in the feature space, same events are grouped together and different groups are clearly separable.

The detection of eating activity has not been well studied. We assume that at least one phone is placed on the table while eating. Eating activity can be recognized by detecting and combining several common indicators. One example of such indicators could be the clatter of knives and forks, which can be detected through sound recognition. Similarly, chewing food and drinking also have distinctive acoustic signatures. Moreover, the vibration of table can be sensed through accelerometers. We will develop learning-based algorithms that can take into account the information gathered by multiple sensor modalities. Note that there are existing smartphone apps that allow users to scan their receipt using camera [1]. Therefore, it enables the possibility that we can access the users' grocery shopping list. However, this approach is subject to several limitations. For example, it can not measure the user's calorie intake on a daily basis when the user shops groceries for multiple days.

Watching TV can be potentially detected by fusing the information collected from multiple sensors including microphone

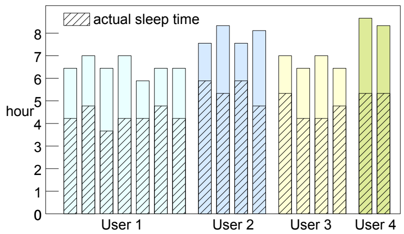

Figure 4: The actual sleep times and in-bed times of 4 users over multiple days.

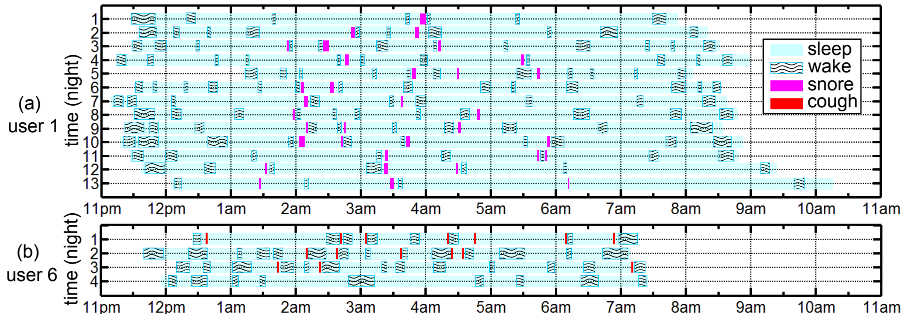

Figure 5: The detection result of sleep states and events of two users over multiple nights. The sleep states are calculated using the body movements based on actigraphy.

and light sensor. Moreover, since people tend to watch TV together, when multiple phones are available, we may fuse their samples together to improve detection accuracy. To our best knowledge, there are no existing methods for detecting TV watching. Our approach is based on the observation that a working TV may lead to a more frequent light intensity change and often yield sounds distinct from regular human conversation. Such differences may be detected through light sensor and microphone, and used in combination to recognize TV watching activity.

4. CONCLUSION

We have described the design of a smartphone-based system that monitors several key activities related to individual's daily routine. Compared with other approaches, it is unobtrusive and more suitable for continuous monitoring on a daily basis. In order to improve the reliability of the classification, our approach leverages the fusion of measurements from various sensors such as microphone and accelerometer. The measured daily routine is able to help users track their everyday activities, understand the consequences of their actions, and make positive changes toward healthy living styles.

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