System and Methodology for Using Mobile Phones in Live Remote Monitoring of Physical Activities
Hamed Ketabdar and Matti Lyra
Quality and Usability Lab, Deutsche Telekom Laboratories, TU Berlin
hamed.ketabdar@telekom.de, matti.lyra@gmail.com

Abstract
In this paper, we propose a system and methodology for using mobile phones for monitoring physical activities of a user, and its applications in assisting elderly or people with need for special care and monitoring. The method is based on processing acceleration data provided by accelerometers integrated in new mobile phones. As the mobile phone is carried regularly by the user, the acceleration pattern can deliver information related to pattern of physical activities the user is engaged in. This information can be sent to a monitoring server, analyzed and presented as different health related factors for assistance, monitoring and healthcare purposes.

1. Introduction
Today, mobile phones are becoming an essential device in our daily life, and carried comfortably and regularly by a huge percentage of population. In this paper, we propose a system and methodology which can turn mobile phones to devices for constantly monitoring physical activities of a user. Such an application can send information related to physical activity pattern of the user and related health factors to a server for monitoring purposes. This can be especially useful for people who are in constant need for assistance and monitoring, such as elderly or people with special movement or psychological disorders. In addition to this group of users, healthy people can also benefit from such an application by constantly receiving reports on details of their activity level and energy consumption over different desired periods of hours, days, etc. We propose to analyse user activity based on data collected by accelerometers which are integrated in new mobile phones. Over the past few years, many mobile phones are equipped with sensors that can capture information related to physical variables such as acceleration. As the mobile phone is carried by the user, these physical variables, e.g. acceleration recorded by phone’s accelerometer can provide some information related to physical activities of user. Accelerometer sensors have been successfully used in several other applications, especially for sensing device orientation. Rekimoto [1,2] discussed the potential of this technique for tasks such as navigating menus and scrolling. Hinckley et al. [3] demonstrate how accelerometers could be useful for an automatic screen orientation device and scrolling application. Oakley and O’Modhrain [4] describe a tilt based system with tactile augmentation for menu navigation. Regarding the issue of heath care and activity analysis, there are a few mobile phone based commercial applications especially for iPhone platform [5,6]. These applications use data provided by GPS position signal to analyse amount of activity during sports. However, these applications are dependent on availability of GPS signal for activity level estimation. In many places (such as home), GPS signal is not available due to coverage problems. In addition, limited and mostly expensive mobile phones are equipped with GPS receivers, while acceleration sensor integration in mobile phones is more widespread and much less expensive. After all, user position information is not strongly correlated with amount or pattern of user activity. In contrast, acceleration information are strongly correlated with amount and pattern of force exerted by user, and thus more directly related to amount and pattern of user activity.

We propose to use data provided by mobile phone’s accelerometer for examining activity pattern of its user. The mobile phone equipped with these sensors should be carried normally by the user in his pocket. The results of examination can be presented to the user or a monitoring agent in different ways as indications of different health related factors. In addition to presenting these data to the user, the mobile phone can then optionally analyse these data, or send it to a server for further analysis. The mobile phone or server can analyse physical activity pattern of the user and compare it against normally accepted pattern for the same user, or normally accepted activity pattern for the users of the same age. In the following, we present our approach for analyzing activity pattern of a user using acceleration data captured by a mobile phone, and its applications in monitoring and assisted life. In this work, we are mostly interested in estimating and monitoring amount (level) of user activity, as well as classifying user activities into certain groups. We also present some initial experiments and results. In
Section 5, we talk about the setup and functionalities of a system we developed based on the idea presented in this paper.

2. Analysis of Acceleration Data

Acceleration sensors integrated in a mobile phone provide linear acceleration information along x, y, and z axis. In this work, we assume that the mobile phone is carried by a user in his pant pocket. Most of usual daily activities involve movement of legs, therefore the best place to position the mobile phone (and acceleration sensors) is pant pocket. Different physical activities results in different patterns (signatures) in data provided by acceleration sensors, and thus can be classified accordingly. Figure 1 is showing an example of acceleration signals (along x, y, and z axis) captured by acceleration sensors over time (samples). The data is captured over a consecutive sequence of walking and resting scenarios. Different activities (walking or resting) has been marked in the figure. As can be seen in the figure, there is a significant difference in pattern of acceleration for different activities.

In this work, acceleration signal samples are sent to a server for further analysis, however the analysis can potentially be done on the mobile device as well.

2.1. Pre-processing

Acceleration pattern captured by a mobile phone (when carried by a user) can be caused by different sources. The acceleration pattern is mainly correlated with physical activity of the user, however other factors such as being in a vehicle can affect acceleration pattern. For instance, if the user is in a vehicle, acceleration of the vehicle in a certain direction can affect sensory data. As we are interested in analyzing user physical activities, other acceleration sources such as those due to vehicle should be filtered out. According to our studies, acceleration pattern caused by physical activities has higher frequency content, while other sources such as vehicle and gravity force result in lower frequency contribution.

For pre-processing step, we have used a high pass filter to remove low frequency components and preserve high frequency components which are more representative of actual user activity. This also removes the constant component which is due to gravity force. The high pass filter is applied on x, y, and z acceleration signals.

2.2. Feature Extraction

In this work, we are interested in estimating actual level (amount) of user physical activity, as well as classifying activities into basic classes of walking, running, resting, and no activity (e.g. mobile phone is left on a table). In order to achieve this goal, we extract certain features from acceleration signals which represent different activities in a discriminative way.

We have used absolute magnitude of acceleration, as well as the rate of change in absolute magnitude acceleration as features. Absolute magnitude of acceleration at a sample is defined as:

$$a = \sqrt{a_x^2 + a_y^2 + a_z^2}$$

where $a_x$, $a_y$, and $a_z$ are acceleration sample values along x, y, and z axis respectively.

Rate of change in acceleration is defined as the difference between absolute magnitude acceleration for current sample and previous one.

2.3. Estimating Activity Level

One of interesting factors for monitoring a user is his level (amount) of physical activity. Acceleration magnitude ($a$) is correlated with activity level, however due to movements of legs, acceleration pattern comes with high frequency oscillations. In order to extract activity level, we measure the absolute difference between a pick in acceleration magnitude and subsequent valley. Activity level estimates can be presented to a monitoring person (agent) at a remote server side. A history of activity level estimates can be also stored for browsing and analysis by a medical doctor.

Monitoring user activities can be further facilitated if the system on the server side is able to assist the monitoring person (agent) by classification of activities. In this way, a semi-automatic monitoring scheme can be applied. This means that monitoring by a person can be applied only in case of risky user activities, or if the activity level extends below or above a threshold (over certain period of time). In the next section, we describe our approach for automatic classification of user activities.

3. Activity Classification

As mentioned earlier, in addition to monitoring user physical activity level, we are also interested in classification of user activities. This facilitates analysis and browsing of user activities by the monitoring agent at the server side, and also helps the agent to detect risky and emergency scenarios related to a certain user. The agent can choose to browse activities belonging to a certain class, search for certain events or activities, or get alarm in case of certain activities. Additionally, the agent can monitor several users when he is assisted by an activity
classification system. Since activity classification can send alerts, monitoring can be limited only to cases which a user is engaged in a risky activity. Therefore, the agent needs less concentration for monitoring and would be able to monitor several users simultaneously.

In this work, we classify user activities in 4 main classes: walking, running, resting, and no activity. We build reference statistical models for these classes during a training phase. The statistical models are built using features extracted from acceleration signals.

As statistical model, we have used Gaussian mixture models (GMMs) [7]. For each class, a GMM is trained to maximize likelihood of instances for that class:

\[ \theta_i = \arg \max_p p(X_i | \theta_i) \]

Where \( \theta_i \) is the set of parameters of GMM for class \( i \), which is adjusted during training to maximize the likelihood and obtain \( \theta_i \). Maximization of likelihood is done using Expectation-Maximization (EM) algorithm [8].

During the test of the system, the trained GMM models are matched against actual instances of acceleration based features. The activity class which maximizes likelihood is selected as ongoing activity class of user:

\[ \hat{i} = \arg \max_p p(X_i | \theta_i) \]

Where \( \hat{i} \) is the selected activity class (result of classification). The activity classification results can be presented to the agent along with the estimation of activity level for a user by marking different activity diagrams with different colors. The activity class label can be also stored along with activity level, in order to allow the agent to browse/search activity data later.

4. Experiments and Results

We set up initial experiments for estimating user physical activity level and activity classification. We have used iPhone 3G [9] as the mobile phone for the experiments. Linear acceleration signals are provided along x, y, and z axis by the iPhone accelerometer at 5 Hz rate. We recorded a database of 320 activity instances with 4 subject users. The database is portioned into 208 activity instances for training and 112 activity instances for testing the system. There are four activity classes: walking, running, resting, and no activity. We have used 2 Gaussian mixtures for each class. The parameters of Gaussians are trained using EM algorithm to maximize likelihood for each class. During testing of the system, extracted features are matched against models for different classes. Each class model provides a likelihood score indicating the match between the actual activity instance and the model. Therefore, we obtain 4 likelihood scores for each activity instance. The class having highest likelihood score is selected as the outcome of activity classification.

We have evaluated the activity classification system in terms of the accuracy in detection of activities. The overall accuracy is 92.9%. Table 1 shows a confusion matrix for the errors. This table indicates which classes are mostly confusable. For instance, we can see that a walk activity instance is detected 26 times as walking, 2 times as running, and never as resting or no activity class. According to the table, confusion between walking and running classes, also between resting and no activity classes is higher.

Table 1. Confusion matrix for different activities.

<table>
<thead>
<tr>
<th>Activity</th>
<th>Walk</th>
<th>Run</th>
<th>Rest</th>
<th>No Act.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Walk</td>
<td>26</td>
<td>2</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Run</td>
<td>2</td>
<td>26</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Rest</td>
<td>0</td>
<td>0</td>
<td>25</td>
<td>3</td>
</tr>
<tr>
<td>No Act.</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>27</td>
</tr>
</tbody>
</table>

5. ActivityMonitor: The Developed System

We have developed a system called as “ActivityMonitor” based on the idea presented in this paper for live remote monitoring of several users physical activities. In this section, we explain the setup and functionalities of this system.
In order to setup and operate the system, two applications are required. The first application is installed and executed on an iPhone. This application sends acceleration data through available data service (Wi-Fi, GPRS, etc.) to a designated server. The user can set certain configuration parameters such as a name for ongoing experiment and sampling frequency. In addition, the application allows capturing data in snapshots in order to reduce traffic of the server.

The second application is a Java application (ActivityMonitor) which can be installed on any ordinary computer. This application connects to the designated server and reads acceleration data. The data is then analyzed and presented (to an agent) in real time as physical activity information, and different statistics and health related factors (Figure 2). The application is able to classify activities in certain categories, and issue warnings in case of irregular activity patterns. It can additionally store the data, browse it, or search for certain activity category. The ActivityMonitor screen has different sections. The main part of the screen is allocated by plots of activity related data. In these plots, activity level and category of the user, warnings, and energy (calorie) consumption can be visualized (Figure 3.a). The ActivityMonitor screen also comes with a log field on the left side, which provides textual information about the ongoing activity and different statistics (Figure 3.b). There is also a settings tab (Figure 3.c) which allows configuring server connection, managing data download, and formatting the data. The monitoring agent can also choose to observe statistical data in a separate window (Figure 4).

The desktop application can be used to monitor several users simultaneously. It can automatically analyze activity data and detect unexpected patterns such as shocks or long periods of high or low activity (Figure 5). Upon detection of an unexpected event for a certain user, the agent is informed by a visual or audio alert, and the monitoring screen related to that user pops up. This allows monitoring multiple users in an automatic or semi-automatic manner.

6. Social Implications of ActivityMonitor

As mentioned in the previous sections, ActivityMonitor system turns regular mobile devices to devices for constantly monitoring physical activities of users. Such a system can be provided to public as a software for different mobile devices, as well as a server and monitoring centre. Users who may wish to be monitored, can register themselves in this service. The registration can be something similar to registration for advanced services such as MMS, Voip, etc. By registering in this service and activating the respective software on the mobile phone, the user allows his activity information to be transferred to the server and be monitored by an agent. As mentioned before, the monitoring process can be done in a semi-automatic manner due to the fact that the desktop monitoring application can automatically check for unexpected patterns. Therefore, monitoring by a human agent can be necessary only if something unexpected happens. This allows possibility of monitoring several users by an agent simultaneously.

As an alternative, the system can be provided in a private manner. This means that the desktop monitoring application can be also sold as a software for personal use. In this way, two people (monitoring agent and the user), or a group of people can establish their own monitoring process based on a local server. For instance, one can personally take care of his/her elderly parents using such a system. In this case, a software can be downloaded and installed on mobile phone, and a second software (desktop monitoring application) plus some space on a server should be purchased. All these steps can be done online very efficiently which means a private monitoring system can be established within a few minutes.

Although such a system can be useful for healthcare purposes, as studied in [10], it can come with some privacy issues. Simply, people may not feel comfortable with having their activities always being monitored. Although this can be an important issue to be studied deeply before commercializing such systems, there are already some potential solutions. For instance, the user may simply switch of the monitoring application on his mobile phone, or leave it unattended when he does not want to be monitored. Another solution could be designing the monitoring software in way that only very general information about ongoing activity of the user such as activity level can be transferred. This allows monitoring the user and helping him in case of unexpected events, and in the same time those not expose detailed information to the agent.

7. Conclusions and Future Work

In this paper, we have presented a system and methodology based on processing data provided by mobile phone accelerometer sensor for monitoring physical activities of users. As a mobile phone can be conveniently and constantly carried by a user, and it does not impose burden of wearing extra sensors, such an application can enable the mobile phone to become a user friendly, precise and constant health and activity monitoring device.

In addition to monitoring activity level and activity classification which is already discussed in this paper, such a system can be used for more detailed analysis of certain activities. For instance, walking pattern of a user
can be analysed to see if there is any deviation from the normal pattern of walking for the same user or users of the same age. Many diseases show their early symptoms in changes of daily activity pattern. Our system can be used for advanced analysis of certain activities and early detection of certain problems, as well as monitoring progress of user after a surgery or medical treatment.

Although such a system can provide a lot of advantages in terms of health care and monitoring, different social implications related to the system such as privacy issues should be considered and studied before the public use.

8. References


---

**Figure 1.** An example of acceleration signals captured by acceleration sensors during walking and resting activities. It can be observed that pattern of acceleration during different activities shows a significant difference.
Figure 2. ActivityMonitor desktop and monitoring agent

Figure 3. Different parts of ActivityMonitor screen: a) main part which visualizes actual activity of user, b) log viewer which can show the ongoing activity class, warnings, etc. as text, and c) control and settings part which can be used for adjusting different parameters in relation with the connection to server, visualization, etc.

Figure 4. Visualizing different statistics on health related factors

Figure 5. Warnings in case on unexpected events