Providing Services on Demand By User Action Modeling on Smart Phones

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Abstract
In this paper, we show a novel approach to schedule services like Wi-Fi, 3G etc. according to user demand level. We have chosen Wi-Fi as our example and showed intelligent scheduling of Wi-Fi according to a user's activity level may lead to less power consumption without affecting the user experience a lot. Sensor's data is used to learn and model the user activity on smartphone.

Author Keywords
Energy Efficiency; User Activity Modeling; Smartphone

ACM Classification Keywords
[Pattern Recognition]: Applications

Introduction
Services like Wi-Fi and 3G continue to consume significant amount of battery on smartphones. Hence, reducing the power consumption by these processes could help in huge power savings.
In this work, we model and monitor the user activity level to decide when the wireless data module should be turned off for maximal energy saving without compromising the user experience. The problem is formulated as a classification problem, where Wi-Fi is scheduled based on the predicted smartphone usage level by the user in the next time window. The major contributions can be

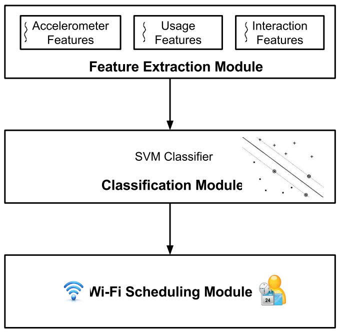

Figure 1: Primary steps in the algorithm with data flow. Feature extraction module extracts the Accelerometer based, usage based and interaction based features. Classification module predicts the user activity level using SVM Classifier and Wi-Fi Scheduling Module schedules the Wi-Fi state based on the predicted output.

summarized as follows.

- *Activity Modeling on Smartphone:* We propose a power-efficient approach to modeling the user's activity level on the smartphone device using accelerometer sensors and other parameters that are easily available on most smartphones.
- *Wi-Fi Scheduling with Activity Level:* An approach to schedule Wi-Fi service for better energy management.

Although the approach is tested with the Wi-Fi, but it can be easily extended to other services like 3G.

Related Work

A lot of work has also been done on activity and gesture recognition with the help of accelerometer sensor data. Sun *et al.* [1] proposed a mechanism to classify physical activities of the bearer of the device using accelerometer data with varying positions and orientations. In this work, along with accelerometer data, we also took other important indicators that suggest the type of user activity such as user interaction, and CPU and RAM usage on the device. Zhuang *et al.* [2] looked at the problem of energy-efficient location sensing on a smartphone. They tried to find the location using substitution, suppression, piggybacking and adaptation methods. Unlike the above works that tries to do a specific task in an efficient manner, we use combination of activity recognition and usage features for intelligent scheduling the Wi-Fi service which in turn leads to low power consumption by device.

Design Approach

The approach consists of three main modules, the feature extraction module, the classification module and the scheduling module. Figure 1 shows a flow diagram of our approach.

Feature Extraction Module

The features are divided into three categories- accelerometer based, system usage based and interaction based features. These features are explained in details below.

Accelerometer Based Features

Accelerometer based features are indication of the physical activity of the user. The assumption behind is if the user is running or sleeping the probability of using his phone is much less as compare to sitting state. Accelerometer continuously samples the acceleration at the specified sampling interval and produces 3-D acceleration readings $S = (S_X, S_Y, S_Z)$ along X, Y and Z direction the overall acceleration $S_\phi = ||S_X, S_Y, S_Z||$ is also considered as feature. The accelerometer data is tracked for 30 seconds in half an hour regular interval with the sampling frequency of $5Hz$ and the following 26 features are extracted.

- *Average mean* along S_X, S_Y, S_Z and the S_ϕ vector.
- *Standard deviation* along S_X, S_Y, S_Z and the S_ϕ vector. Standard deviation indicates the dispersion in the acceleration along different axis.
- *Correlation* among each pair of S_X, S_Y, S_Z and the S_ϕ vector. Correlation implies the strength between two corresponding axis signals.
- *Fourier energy* for S_X, S_Y, S_Z and the S_ϕ vector. The energy feature is the sum of all the squared DFT component magnitudes except the DC component of the signal as the DC component (mean) has been used as an individual feature. The magnitudes are divided by the number of components for normalization.
- *Fourier entropy* for S_X, S_Y, S_Z and the S_ϕ vector. Fourier entropy is the normalized information

	Messages Received	Number of Calls	E-Mails Received and Replied	Drop in Battery (Dev.1)	Drop in Battery (Dev.2)
Without Scheduler	25	15	25	38%	52%
With Scheduler	25	15	25	28%	15%

Table 1: Energy Efficiency Testing: Percentage battery dropped in Samsung Galaxy S (Dev.1) and HTC Explorer (Dev.2) during controlled tests.

present in the DFT of the signal, excluding the DC component.

System Usage Based Features
System Usage Based features tells how extensively the phone is being utilized. System usage based features are computed based on the following values.

- The average CPU utilization of the smartphone.
- The average memory used by the applications in the smartphone.

Interaction Based Features
Interaction based features tells how frequently user is using his phone. Interaction based features are computed based on the following values.

- *Screen On Time*: In half an hour duration, total time in milliseconds for which screen was on.
- *Frequency Of Interactions*: In half an hour duration, number of time the screen has been turned off and on.

All the features are extracted in parallel to get consistent data and reduce the battery consumption due to wake-lock acquisition by the application. Finally we concatenate all the features to form a final feature vector of length 30 for the classification.

Classification and Scheduling Module
Feature vector from the feature extraction module is used by SVM classifier to predict the activity label and schedule Wi-Fi for next half an hour as follows:

- *Very Low* (l_0): Corresponds to no or very low activity by the user in the next half an hour. We turn of the Wi-Fi for next half an hour.
- *Low* (l_1): Corresponds to low activity by the user in next half an hour. We turn off the Wi-Fi for next 25 minutes then turn it on for the next 5 minutes.
- *Medium* (l_2): Corresponds to moderate activity usage by the user in next half an hour. We turn off the Wi-Fi for next 20 minutes then turn it on for the next 10 minutes.
- *High* (l_3): Corresponds to intense activity by the user. We turns on the Wi-Fi for the next 30 minutes.

To train our classifier and find appropriate weights for each class we create an application that logs accelerometer, screen on duration, internet, CPU and RAM usage of the device at every half an hour interval. Class label of a feature vector of current time window is decided based on the internet usage by the user in previous time window. We ran the application for 6 working days which resulted into 310 feature vector. For preserving the usability of the application, the classes are given different penalty weight such that W_i*N_i is equal for each class (where W_i is the penalty weight and N_i is the number of training samples of i$^{\text{th}}$ class). Table 2 shows the penalty weights assigned to different classes while training.

Class Label	Weight
Very Low (l_0)	1
Low (l_1)	2.71
Medium (l_2)	8.92
High (l_3)	4.92

Table 2: Penalty weight assigned to different activity level while training.

Implementation and Results

We implemented the software on Android OS. The trained SVM model along with the feature extraction, classification and scheduling module is deployed on the smartphone. After each half an hour, the application starts a service to collect the data. The service runs for the duration of 30 seconds and executes the following processes.

1. Partial wake-lock is acquired to prevent smartphone from going to sleep during the process execution.

	Wi-Fi turn-on count (Usr 1)		% Battery Drop (Usr 1)		Wi-Fi turn-on count (Usr 2)		% Battery Drop (Usr 2)	
	Working Hrs.	Non-Working Hrs.	Working Hrs.	Non-Working Hrs.	Working Hrs.	Non-Working Hrs.	Working Hrs.	Non-Working Hrs.
Without Scheduler	NA	NA	38	26	NA	NA	33	8
With Scheduler	5	2	29	19	3	0	13	7

Table 3: User Happiness: Count of Number of times Wi-Fi was manually turned on.

2. The required data is collected for the duration of 30 seconds. Activity label is predicted by the classification module from the collected data.
3. The Wi-Fi is scheduled for next half an hour based on the predicted label.
4. Wake-lock is released and phone is allowed to go to sleep.

We evaluated our approach based on two metrics: (i) power saved metric to measures the overall power saved by our method and (ii) user happiness metric to measures user's satisfaction with the services scheduled.

Power saved by the software
To evaluate the power saving by our software we took two device of each category[1] having same set of applications, battery state and memory. One device from each category have our software installed and other does not have our software. A predefined set of activities are performed on all the devices and drop in battery is recorded. Table 1 lists the activities carried out on the smartphone. All the activities are performed at almost same time and for same duration. For example, the calls on all the devices are performed simultaneously for 2 minutes duration. Similarly, all the messages and emails are also send simultaneously so that the loss incurred by other processes remains same. The controlled experiment was performed for 4 hours in similar settings and the battery dissipated on each device is recorded. Our application took only 5MB of RAM and 101KB external memory, with power consumption equal to 1% of battery in 24 hours[2].

[1] Samsung_S_plus http://www.gsmarena.com/samsung_i9001_galaxy_s_plus-3908.php and HTC_Explorer http://www.gsmarena.com/htc_explorer-4102.php

[2] The power consumed by the application is recorded through battery info manager on Android OS.

Measuring User Happiness
We conducted an experiment in which we have given our software to users and logged there battery usage in two categories, when the user is very active (Working hours) and when the user is less active (Non-Working hours). Along with battery usage, the number of times the Wi-Fi state is changed manually is also recorded. Each Wi-Fi switch by the user is considered as misclassification by the algorithm. The higher the number of switches by the user, the more unhappy the user is with the application. Table 3 shows 6 hrs. analysis of the application. We observed that application is able to conserve battery without effecting the user experience much.

Conclusions and Future Work

We have proposed a way by modeling user activity we can make smartphones more intelligent and personalized. Future work involves scheduling the time interval of the application dynamically, making it more adaptive to user's activity level.

References

[1] Sun, L., Zhang, D., Li, B., Guo, B., and Li, S. Activity recognition on an accelerometer embedded mobile phone with varying positions and orientations. In *Proceedings of the 7th International Conference on Ubiquitous Intelligence and Computing*, Springer-Verlag (Berlin, Heidelberg, 2010), 548–562.

[2] Zhuang, Z., Kim, K.-H., and Singh, J. P. Improving energy efficiency of location sensing on smartphones. In *Proceedings of the 8th International Conference on Mobile Systems, Applications, and Services* (2010), 315–330.