Wi-Fi Mobility Classification on a Mobile Phone for Energy Efficient Activity Tracking

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Abstract
Tracking user location and physical activity is quite common especially among fitness and utility applications on modern smartphones. However, use of GPS and accelerometer sensors to obtain such data is energy consuming and in general cannot be used for extended periods of time. In this paper we describe an approach to detect mobility states and thus turn on and off these energy consuming sensors using Wi-Fi analysis, which compared to GPS and accelerometer is much less power consuming. This allows us not only to save battery life but also to perform activity measurements throughout the whole day.

Categories and Subject Descriptors
C.3 [**Special-Purpose and Application-Based Systems**]: Real-time and embedded systems

Keywords
Mobility Classification, Location Sensing, Energy Efficiency, Smartphone

1. Introduction
Fast growth of smartphone market over the last few years has made the mobile phone an appealing platform for context sensitive and location based applications. However, common issue for all these applications is high power consumption and subsequent lack of battery life, not allowing such application to run for extended periods of time.

In our work we focus on classification of human mobility states, concretely stationary and active (e.g., walking or driving, while not differentiating between them). We use this information to turn on and off GPS sensor to allow continuous location monitoring throughout the whole day along with additional power saving methods. We have successfully integrated proposed classifier in Move2Play [2], a system which provides physical activity management and supports its users in achieving the required amount of physical activity per day.

We were fairly constrained by platform limitations (most common Android platform versions at the time of development were 2.1 and 2.2) which generally did not allow GSM scans and accelerometer to be run on background with screen turned off. Therefore we have chosen to explore possibilities of using Wi-Fi sensor for energy efficient human mobility states classification.

Several approaches has been developed to classify mobility states using various available sensors. Classification of mobility can be performed by analysing data from GSM sensor [7, 1], using combination of GSM and Wi-Fi [6], analysing accelerometer data [9], using microphone[5] or by creating framework in which all can be integrated together [8]. Experimental results of some of them are shown in Table 1. Couple of projects also work on predicting user mobility [3, 4]. This approach however introduces trade-off between battery efficiency and recall, and is therefore used mostly for meaningful place recognition and not for actual activity tracking.

2. Preliminaries
We used mobile phones featuring IEEE 802.11n Wi-Fi sensor module. Currently 5 GHz band is not supported. However, that is not a problem as the 2.4 GHz band is generally much more populated. Wi-Fi sensor module allows us to initiate scan for available access points. Wi-Fi scan contains information about zero or more detected access points containing BSSID, SSID, signal strength, frequency and access point capabilities. Throughout the paper we use the following terms:

Access Point (AP) a_i: contains information about given AP obtained at time i.

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Table 1: Overview of mobility classification results using Wi-Fi and GSM

	Precision			Recall		
	Mun [6]	Sohn [7]	Anderson [1]	Mun [6]	Sohn [7]	Anderson [1]
Stationary	90,26%	95,4%	92%	88,41%	92,5%	96%
Walking	65,45%	70,2%	82%	55,40%	80,0%	91%
Driving	75,73%	84,3%	93%	90,73%	81,7%	80%

Current APs $C = \{a_n, b_n, ..., x_n\}$: contains APs detected in last scan, e.g. at current time n.

Recent APs $R = \{A_n, B_n, ..., X_n\}, A_n = (a_n, age, timeout)$: contains APs detected in last 3 minutes. Age represents timespan during which the AP was available, i.e., since its discovery till the last AP scan in which it was still present. Timeout decreases each time we do not find an AP in current scan and resets to value of 3 minutes if we do find it again. If $timeout \leq 0$ we remove AP.

Similarity $S = \frac{v_1.v_2}{||v_1|| \times ||v_2||}, t(C_1, C_2) = v_1, v_2$: cosine similarity is used to compute similarity between current APs C_1, C_2. Transformation into vector is based on BSSID (i.e. MAC address) not including APs signal strength.

3. Mobility Classification Approaches

We have proposed five heuristic based approaches to classify user mobility state. These approaches generally perform well only for specific data inputs. Our goal was therefore to identify under which conditions they perform well and use this knowledge when designing actual mobility classificator.

Place-based Mobility Classification. Place-based method is built on an idea, that we spend most of our time on relatively small number of places, e.g., at home, work or school. We capture footprint of these places and compute their similarity. If their similarity is above threshold, we assume that the user is stationary and that he is moving otherwise.

This method is suitable if we have small number of places (footprints), which do not change very often and at which we spend lot of time. Disadvantages are that the learning process is quite long, what makes capturing places with short and medium stay time difficult. Also if we learn many places that are close to each other or on our path between two other places, performance decreases.

Short-term Mobility Classification. Based on a similar concept than place-based method with two main differences. Firstly, all footprints are stored in-memory and their weight decreases periodically until it reaches zero and are removed afterwards. Secondly, learning rate is much faster compared to place-based method. This allows us to capture especially short and medium time stationary intervals.

Mobility Classification based on Context. Instead of searching for similar footprints in the whole log history as in place-based method, we only compare the current footprint with the one which represents the place where user stays at the moment. We call this special footprint a *Context*.

This method has proven to be very effective especially if we set very loose similarity threshold. This method is also capable of recognizing short stationary time spans. One disadvantage is longer time it takes to recognize movement, which can be partially reduced by periodically changing context even when footprints are evaluated as similar.

Method based on Wi-Fi Features. This method uses various features of current and recent APs such as age, timeout, number of new, current and recent APs. Output $o \in \{-10, -9, \ldots, 9, 10\}$ represents *stationary* (-10) and *active* (10) states. Giving much finer output compared to other methods, this method is suitable when detecting possible mobility state change.

Method based on Wi-Fi Fluctuation. Inspired by classification method using GSM fluctuation, we made mapping to Wi-Fi domain by substituting GSM tower cells by Wi-Fi access points. Fluctuation is calculated as difference of access points signal levels between consecutive Wi-Fi scan readings.

Unfortunately we found this method performing poorly because of two main reasons. First, unlike GSM signal fluctuation, AP fluctuation is very high even in a case of stationary state and is very hard to distinguish from fluctuation when user is actually moving. Second, user tends to get out of available APs very quickly, mostly allowing us to obtain 1 or 2 Wi-Fi scans before running out of range what is insufficient for accurately recognizing user mobility.

4. Advanced Mobility Classification

The Advanced mobility classifier processes continous input stream $\{v_1, v_2, \ldots, v_i, \ldots\}$, where $v_i = (F_i, R_i, t_i)$, into three output classes – *stationary*, *active* and *unknown*. We use *unknown* state when $R_i = \{\}$, i.e., we could not find any Wi-Fi access points in last 3 minutes. This method is based on context mobility classification method and consists of following base parts:

Initialization. Current context is set to input F_1 and reset each time we classify state as *unknown*.

Time span selection. To achieve low response time when recognizing mobility state change in real usage, we need to control time span between Wi-Fi scan readings. For this purpose we use classification method based on Wi-Fi features, which is very sensitive and is therefore very suitable for this task. We use 8, 16 and 40 seconds time span intervals.

Context change. For every v_i in input stream, we compute similarity with current context using cosine similarity. We set threshold as $\tau = 0.4$, to reflect Wi-Fi access point instability over time. If the similarity is below threshold, we set a new context as F_i and classify this and subsequent instances for 2 minutes as *active*. During this period, context change is not allowed.

Context adjustment. Because we use low similarity threshold, current context often describes a place visited just before we became stationary, but similar enough to the current one so that we do not detect change. This can prolong duration to recognize that we are leaving current place, because we often leave using the same path we came by. To solve this problem we periodically adjust context using R_i, which removes APs not longer active and adds new ones.

In real usage false *active* state classification occurs mainly due to unstable nature of Wi-Fi signal resulting into receiving incomplete or empty Wi-Fi scans. False classifications spikes (Figure 1.) leads to high battery consumption as GPS is turned on. To reduce this kind of error we integrated empty Wi-Fi scans confirmations, change state confirmations and no-change interval reduction.

Empty Wi-Fi scans confirmations. Upon receiving empty scan, we repeat scan up to three additional times, to make sure that there really are not any available APs.

Change state confirmations. After mobility state change, we immediately issue an additional scan to confirm this change. This can be very effective at places where there are only a few APs.

Reducing no-change interval between successive context change. 2 minutes of no-change interval after each context change, even if crucial for proper classification of active state, poses serious problem when a misclassification occurs. Therefore we introduced a mechanism to reduce this interval in case of a misclassification by remembering two successive contexts instead of only one and computing similarity of current footprint with both of them.

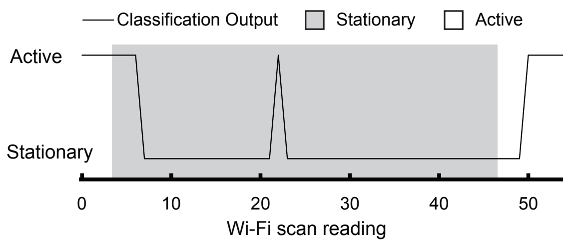

Figure 1: Stationary classification output showing typical errors: delay after transition and occasional spikes.

As the main purpose of mobility states classification is to conserve battery life by turning off GPS sensor when a user is stationary, we developed two additional battery saving techniques - passive Wi-Fi state and night idle state. *Passive Wi-Fi state* disables mobility classification and activity tracking in case of active Wi-Fi connection. *Night idle state* at which we perform scans at larger intervals, or turn off scans completely, and therefore we are able to conserve additional battery life.

5. Evaluation

For data acquisition we have developed an application for Android platform. Application performs periodical Wi-Fi scans and allows users to easily annotate what type of activity they are performing. Available activity types are unknown, stationary indoors, stationary outdoors, walking indoors, walking outdoor and driving. Users were able to edit previous scans and change activity type if necessary. Users then uploaded valid time span of annotated scans to our server.

Data was collected during 3 months, with 8 unique android devices and 7 users. Over this period of time we were able to collect 112 reports containing 8000 unique Wi-Fi access points and over 18 000 Wi-Fi scans with 126 hours of logged time. Most of the reports were collected in Bratislava, but we have also several reports from other places including PieÅąÅĕany, Brno, Wien and Miami.

The data inherently contains some unrepairable discrepancy between reality and annotated states as it was collected over extended period of time and by multiple users. Users differ on how they annotated activity, especially when they switched between stationary and walking. Also because annotation duration was between 30 to 60 minutes, users occasionally forget to switch states. There was also certain inconsistency within data such as that similar sequences often led to both walking and stationary states.

Our main goal in Wi-Fi mobility classification was to accurately classify *stationary* state and its transitions to active state, i.e., the states where a GPS sensor is turned off. The classification of other states can benefit from GPS data. Table 2. shows results of our advanced mobility classification method. Typical errors observed when classifying stationary state are short delays after transitions from active state and occasional spikes.

Spikes are very important for battery efficiency because they trigger actual activity tracking. We observed 57 spikes in 4295 minutes of stationary logs, what represents in average a spike every 75 minutes. However, 19 spikes of these 57 were observed within 60 seconds from previous spike, possibly due to errors in data annotation or very unstable environment.

Time in which we can capture state transitions is essential for an activity tracking application accuracy. Transition times from stationary to active were $\mu = 45s, \sigma = 91s$ and from active to stationary were $\mu = 25s, \sigma = 82s$. The phenomenon of "foreseeking" where it seems that we captured a state transition shortly before it actually happened can be explained by delayed annotation of state transition by users. Time between Wi-Fi scan reading was 8s (60%), 16s (11%) and 40s (27%).

We benchmarked power consumption of three possible states of our method – *night idle*, *passive state* and *active state* (state in which we classify user mobility) – against four states of android smartphone – *Wi-Fi and Wake lock*[1] *acquired*, *only Wi-Fi lock acquired*, *only Wake lock acquired*, *no lock acquired* – as shown in Figure 2. Power consumption of *night idle* and *passive state* is identical to *no wake lock acquired* and *only Wi-Fi lock acquired* re-

[1] Wi-Fi lock ensures that Wi-Fi will be kept active while Wake lock ensures that the CPU is running.

Table 2: Evaluation of advanced mobility classification.

	Ground Truth				
	Stationary	Walking	Driving	Precision	Recall
Stationary	93.39%	26.48%	15.66%	91.8%	97.3%
Walking	2.59%	66.91%	73.22%	91%	75.9%
Driving	4.02%	6.61%	11.12%	-	-
#	13136	2904	2050		

spectively. We performed measurement on four devices. Samsung Mini and HTC Desire were phones used only for development with no SIM and SD cards and with around 10 application installed. Xperia Arc and second HTC Desire were normally used phones with SIM and SD cards inserted with 30 to 50 different application installed.

When achieving better power efficiency, main issue was that we could not control Android OS sleeping policy, and thus to perform a Wi-Fi scan with duration of 1 second with subsequent classification, we need to keep device awake also for remaining 59 seconds. Releasing wake lock between Wi-Fi scans does not help as a device go to sleep mode only after few additional minutes.

6. Conclusions

Main contribution of our paper is the proposal of mobility classification method capable of classifying user mobility states based on Wi-Fi scans with high precision and recall, especially for stationary state important for activity tracking purposes. We believe that our method has a big potential as the results were obtained on relatively big dataset (123 hours of annotated activity compared to 9 [1], 12.5 [6] and 90 [7] hours) obtained from multiple users and devices. Development and testing on real devices was important part of our solution. We were often constrained by both available hardware (e. g., available sensors and their performance) and software (e. g., available APIs and Android platform behaviour such as service killing policy or sleep mode policy). These constraints forced us to make several changes of our design choices, but in the final we have higher confidence.

We further believe that misclassification rate along with spikes ratio achieved in *stationary* state classification is very close to actual natural error contained in data. Therefore we think that further improvements in this area would yield little contribution compared to the complexity required to detect and properly classify such instances. On the other hand, there certainly is space to improve classification of *active* state, especially in terms of integration with GPS sensor.

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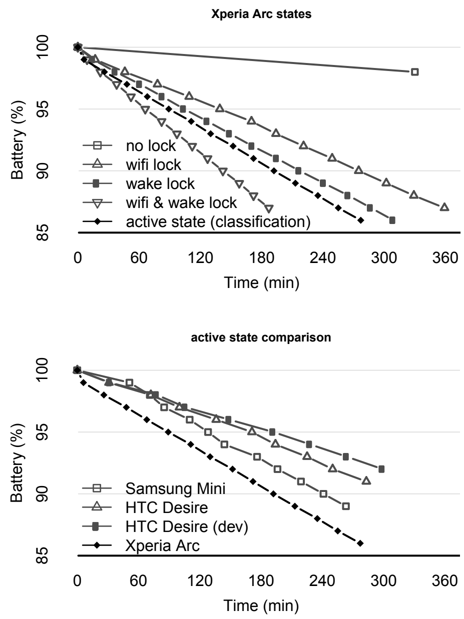

Figure 2: Battery consumption on Xperia Arc (Top) and active state comparison (Bottom).

References

[1] I. Anderson and H. Muller. Context awareness via gsm signal strength fluctuation. In *In: Pervasive 2006, Late Breaking Results*, pages 27–31, 2006.

[2] P. Bielik, M. Tomlein, P. Krátky, v. Mitrík, M. Barla, and M. Bieliková. Move2play: an innovative approach to encouraging people to be more physically active. In *Proceedings of the 2nd ACM SIGHIT International Health Informatics Symposium*, IHI '12, pages 61–70, New York, NY, USA, 2012. ACM.

[3] Y. Chon, E. Talipov, H. Shin, and H. Cha. Mobility prediction-based smartphone energy optimization for everyday location monitoring. In *Proceedings of the 9th ACM Conference on Embedded Networked Sensor Systems*, SenSys '11, pages 82–95, New York, NY, USA, 2011. ACM.

[4] I. Const, S. Gaonkar, M. Sayler, R. R. Choudhury, and O. Cox. Energy-efficient localization via personal mobility profiling, 2009.

[5] H. Lu, W. Pan, N. D. Lane, T. Choudhury, and A. T. Campbell. Soundsense: scalable sound sensing for people-centric applications on mobile phones. In *Proceedings of the 7th international conference on Mobile systems, applications, and services*, MobiSys '09, pages 165–178, New York, NY, USA, 2009. ACM.

[6] M. Y. Mun, D. Estrin, J. Burke, and M. Hansen. Parsimonious mobility classification using gsm and wifi traces. hot-emnets, 2008.

[7] T. Sohn, A. Varshavsky, A. Lamarca, M. Y. Chen, T. Choudhury, I. Smith, S. Consolvo, J. Hightower, W. G. Griswold, and E. D. Lara. Mobility detection using everyday gsm traces. In *in Proceedings of the Eighth International Conference on Ubiquitous Computing (Ubicomp 2006*, pages 212–224. Springer, 2006.

[8] Y. Wang, J. Lin, M. Annavaram, Q. A. Jacobson, J. Hong, B. Krishnamachari, and N. Sadeh. A framework of energy efficient mobile sensing for automatic user state recognition. In *Proceedings of the 7th international conference on Mobile systems, applications, and services*, MobiSys '09, pages 179–192, New York, NY, USA, 2009. ACM.

[9] Z. Zhuang, K.-H. Kim, and J. P. Singh. Improving energy efficiency of location sensing on smartphones. In *Proceedings of the 8th international conference on Mobile systems, applications, and services*, MobiSys '10, pages 315–330, New York, NY, USA, 2010. ACM.