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Improving the Energy-Efficiency of GPS based Location Sensing Smartphone Applications

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***Abstract*—Smartphones with an embedded GPS sensor are being increasingly used for location determination to enable Location based services (LBS) deliver location context pervasive computing services such as maps and navigation. Although a Smartphone GPS provides adequate accuracy, it has limitations such as high energy consumption and is unavailable in locations with an obscured view of GPS satellites. Use of alternate location sensors such as Wi-Fi and GSM can be used to augment GPS and to alleviate these GPS limitations, but they can increase the average localization error. The novelty of our contribution is threefold. First we present an accelerometer based architecture that reduces GPS energy-consumption without compromising on either the location accuracy or sampling rate. Evaluation of our system shows energy-savings of up to 27% in typical circumstances. Second, unlike other similar accelerometer assisted GPS systems, our motion determination algorithm is not affected by the phone on-body placement. Third, as a user's mobility state is complex we also propose a method to not only detect that a user is non-stationary but also classify a representative set of mobility states.**

Keywords-component; Energy-Efficiency, Smartphone, GPS, Accelerometer, Location determination

I. INTRODUCTION

Smartphones have embedded sensors that can capture user mobility contextual information such as the location, acceleration, orientation, etc. However these sensors drain the battery power of smartphones faster, requiring more frequent recharging. Excessive energy consumption may become a major obstacle to broader acceptance of location-aware mobile applications or services, no matter how useful the service may be [4]. Smartphone location sensing using GPS provides the necessary location context data for LBS but continuous location sensing using GPS consumes high amounts of energy. For instance GPS provides location accuracy to within 10m [2], but continuous requests for location updates can deplete the battery in approximately 12 hours as compared to 284 hours with all location sensors turned-off. This high energy consumption shows the need to design more energy-efficient GPS based location determination schemes.

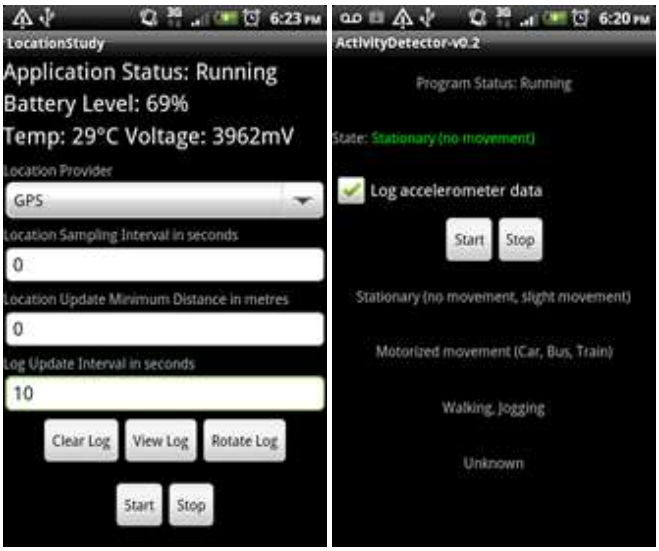

Fig. 1. Screenshots of Android applications LocationStudy used to study the battery decay of GPS; and the ActivityDetector used to detect the user mobility state.

There are alternate location sensing technologies such as Wi-Fi positioning system (WPS) and Global System for Mobile Communications Positioning System (GSMPS) that can be used to augment GPS. In this paper we focus solely on improving the energy-efficiency of GPS due to the increased average localization error introduced from using other location determination technologies such as WPS and GSMPS. The location accuracy for WPS and GSMPS are typically 20-30m [4] and 70-200m in urban areas [2] respectively.

Smartphones can support sophisticated real-time sensing and user activity recognition including location determination and accelerometers are among the most common sensors used for activity monitoring. Research by

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[3], [7]-[10], [17] all use the accelerometer for activity detection.

We have researched and developed an accelerometer based algorithm that detects the user mobility state with a high accuracy. A novel algorithm which we have designed, implemented, and evaluated on Android based mobile devices can be used to manage the process of turning-on and off smartphone embedded location sensing technologies such as GPS.

Research by [3] classified activities by changes in the vertical axis acceleration because it presented the most differences. However using a single axis of the smartphone accelerometer isn't sufficient to successfully differentiate between activities because generally smartphones can have different placements on the body, e.g., [7] requires devices to be worn on the pelvic region. Our user mobility state algorithm can detect the mobility status regardless of the smartphone placement. Target applications for our algorithm include navigation applications such as satnavs and context-based maps.

Location caching can also play a vital role in reducing energy consumption since the device simply has to reference the cache rather than recalculating the present location. Location caching delivers location updates rapidly. It can work in indoor locations where specific location transmission signals, e.g., GPS, are unavailable, and it aids the use of targeted context based information such as finding a coffee shop or medical clinic nearby. The downside of location caching is the associated ethical and perceived privacy issues of being tracked [23]. In addition, the energy cost of location caching could be more expensive if there is no matching historical cache of the user's position. For these reasons, location caching isn't considered as a good single approach to reduce energy consumption.

The rest of the paper is organized as follows: Section II presents an in-depth survey of related work. Section III details our system design. Section IV presents our experimental studies into the battery decay of GPS and user mobility context detection. Section V shows the results of evaluating our method using a typical commuter and worst case scenarios. Also it compares our method to related techniques. Finally section VI concludes the paper and provides details of future work.

II. Related Work

Embedded low energy smartphone sensors such as Wi-Fi detector, Bluetooth, accelerometer, gravity, gyroscope, light, linear acceleration, magnetic field, pressure, proximity, rotation vector, temperature and orientation are being leveraged to aid location determination. Paek et al [12] use the gravity sensor. Azizyan et al [13] use the light sensor. Lloret et al [19] use the magnetic field sensor. Miluzzo et al [14] present a sensing proof of concept model using the microphone. These sensors can provide useful information about the immediate state of the physical environment, which in turn can promote improvements to the use of localization technologies [15].

We ignore the magnetometer which provides orientation readings because of large errors caused in the presence of ferrous metals. Magnetic flux measurements by Thomas et al [15] show strong distortions in means of transportation like trains, buses and cars. We ignore the camera use due to its high energy usage of 1258 mW [16]. Combined use of electronic compasses and accelerometers creates a directional trail of the user [18]. We are not using the compass because there is no need to get the direction.

Accelerometer augmented mobile phone localization (AAMPL) [1] detects the user's movement using the mobile phone accelerometer and in-turn places the mobile phone in the right context. The AAMPL framework accepts the approximate physical location of a mobile phone, and augments it with a context-aware logical localization. Evaluation on Nokia N95 phones shows that AAMPL was able to correctly display physical locations derived from phone GPS on Google Maps. A key benefit is that given the estimated location of a mobile phone can be further improved by augmenting it with an accelerometer. AAMPL scheme can distinguish between subtle location contexts such as a user sitting or stationary in a coffee shop versus standing or moving in a grocery store.

Improving Energy Efficiency of Location Sensing by Smartphones [5] uses a location sensing framework that includes four design principles: Substitution, Suppression, Piggybacking and Adaptation. Substitution incorporates the use of alternative low energy location-sensing mechanisms as compared to GPS. Suppression uses embedded smartphone sensors such as the accelerometer. Piggybacking synchronizes the location update requests from multiple running location based applications. Adaptation adjusts system-wide sensing parameters when the battery level is low. Evaluation results show a reduced usage of the GPS by up to 98% and improved battery life by up to 75%. This is an energy-efficient technique due to the reliance on low-energy location-sensing mechanisms. Also the ability to synchronize location update requests for sensors such as GPS could lead to savings in energy consumption due to reduced number invocations. However there are currently no API's available in the some smartphones, e.g., Android OS to perform the piggybacking design. To be effective it could be better implemented at the operating system level.

Escort [6] is a system that guides a user to the vicinity of a desired person in a public place. An audio beacon, accelerometer and compass are used. These sensors can detect when a user is stationary and disable all location sensors, enabling them again once movement is detected. The Escort technique is quite accurate. On average the location accuracy is 8.2 meters without need for war-driving or signal calibration.

Ravi [7] et al reveal that plurality voting that uses an optimal classifier for activity recognition derived from a

single 3D accelerometer consistently outperforms stacking. Without noise filtering the research was able to distinguish between walking and running.

Wang et al [8] prove that acceleration synthesization method outperforms acceleration decomposition method.

Cornelius et al [9] show how sensors can wirelessly communicate their data to smartphones using an accelerometer. They claim if sensors are worn on the same part of body, then at a coarse level all of the accelerometer sensors experience similar accelerations.

Reddy et al [10] use a mobile phone with a built-in GPS receiver and an accelerometer to detect transportation modes such as stationary, walking, running, biking, or using motorized transport. In the absence of GPS signals then it could fail, because it requires a second GPS speed data. The accuracy level is 93.6%.

The Energy efficient mobile sensing system (EEMSS) [4] uses embedded mobile phone sensors to recognize user states and detect state transitions. It uses a combination of sensor readings from the accelerometer, Wi-Fi detector, GPS, and microphone to automatically recognize user state as described by three real-time conditions; namely motion (such as running and walking), location (such as staying at home or on a freeway) and background environment (such as loud or quiet). An evaluation of EEMSS with 10 users over one week, used to identify transitions between end-user activities, reveals that a mobile device battery life can be increased by over 75% while maintaining both a high accuracy and low latency.

GPS-Accelerometer-Compass GSM localization (GAC) [11] is a hybrid GPS/accelerometer/compass scheme that depends mainly on using the low-energy accelerometer and compass sensors and uses the GPS infrequently for synchronization. Evaluation results from both highways and intra-city driving show that the proposed hybrid scheme has an exponential saving in energy, with a linear loss in accuracy as compared to GPS accuracy.

Rate-adaptive positioning system (RAPS) [12] uses the location-time history of the user to estimate user velocity and adaptively turn on GPS only if the estimated uncertainty in position exceeds the accuracy threshold. It also efficiently estimates user movement using a duty-cycled accelerometer, and utilizes Bluetooth communication to reduce position uncertainty among neighbouring devices. Finally, it employs cell tower-RSS blacklisting to detect GPS unavailability and avoid turning on GPS in these cases. Test results reveal it has over 3.8x longer battery lifetime as compared to continuous GPS sampling.

EnTracked [20] tracks mobile devices and can reduce power consumption. It guarantees robustness by calculating the optimal plan, using an accelerometer to decide when to turn on and off sensors such as the GPS in mobile devices. It requires the use of both an accelerometer and GPS to detect a user's mobility state change.

Azimuth Based Localization for Mobile Phones [15] is a GPS-free localization and traveling route estimation concept based on measured acceleration and compass data of smartphones. The built-in mobile phone compass is used to measure the relative direction changes of the traveling user. The resulting azimuth trajectories are then matched to a vectored street map. Tests reveal the concept can deliver route estimates, if knowledge of the starting point, region of the measurement and if proper azimuth measurements are given. This isn't a localization technique, but can be used to augment other technologies such as GPS. This technique could provide route estimates once the starting location is known. Also it relies on the use of a compass and accelerometer which are low energy sensors to determine the user location context.

These techniques are energy-efficient, but can be improved once the user mobility context can be estimated. Knowledge of the user mobility context provides the ability to manage high energy consuming sensors such as GPS.

III. METHODOLOGY

Achieving reduced energy consumption requires the ability to detect the user mobility context which will aid in the management of location sensors such as GPS. The architecture we propose implements the accelerometer sensor. This is because of the accelerometer's ability to detect movement and low energy consumption of 96 mW [16].

Our scheme is only concerned about whether the user mobility state is "in-motion" or "stationary". For instance sitting in a moving train or bus is classified as an "in-motion" state. Asleep at home or sitting at your office desk is classified as a "stationary" state.

A user's mobility transition from being stationary to in-motion can be detected by checking changes to the cell ID details. In urban areas this will suffice, but in remote locations where the cell size range could be up to 35km [21] this method could be highly.

Our earlier research using the Sun SPOT[1] 3D-accelerometer sensor platform revealed that accelerometer noise values within the range -0.01g to 0.02g can be classified as being static. In the Android OS there are four modes for sampling accelerometer readings. Schemes that sample the accelerometer in normal mode aren't consuming any additional energy as long as the screen is lit or CPU running. This is because this mode is already being used continuously to detect tilting of the mobile device for use in different applications [11].

Using probability statics we can differentiate between stationary and in-motion mobility states using the signals from the smartphone accelerometer. Fig. 2 shows the flowchart for our GPS location sensing model (AAGPS). Several mobility detection systems require the sensor to be placed on specific parts of the body. Our architecture doesn't

[1] Sun SPOT http://www.sunspotworld.com/

require this as it works regardless of the smartphone placement. To combine (x, y, z) readings regardless of the smartphone placement we use the magnitude of the vector.

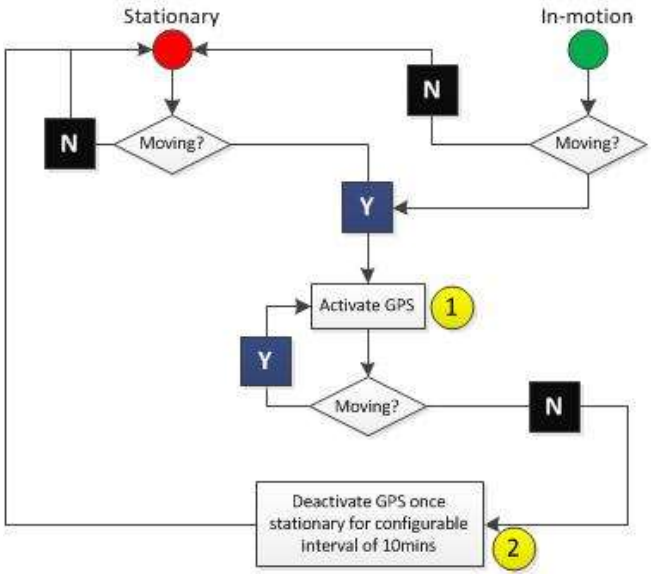

Fig. 2. Flowchart for the accelerometer assisted GPS location sensing model (AAGPS).

Given the accelerometer readings (x, y, z), calculate the magnitude of the vector using the formula $\|v\| = \sqrt{x^2 + y^2 + z^2}$. Fig. 4 shows a graph of plotting the magnitude of the vector for selected activities. In the rest of this section we detail the steps to detect the mobility state of a user within 2 seconds using the smartphone 3D accelerometer signal readings. Fig. 1 shows a screenshot of the ActivityDetector Android application used for mobility state detection.

A. Peak Calculation

$$P = \sum_{i=0}^{n-2} \left[(X_{i+1} > X_i) \Lambda (X_{i+2} < X_{i+1}) \right] \Rightarrow \Delta P \qquad (1)$$

X_i is the $\|v\|$ of each accelerometer data reading.
n is the total number of datasets (X_i).
P is the total numbers of peaks.
The peak formula calculation translates as follows, for $i = 0$ to $n-2$ if the condition $(X_{i+1} > X_i)$ is true and $(X_{i+2} < X_{i+1})$ is true then increment the counter P by 1.

B. Trough Calculation

$$T = \sum_{i=0}^{n-2} \left[(X_{i+1} < X_i) \Lambda (X_{i+2} > X_{i+1}) \right] \Rightarrow \Delta T \qquad (2)$$

X_i is the $\|v\|$ of each accelerometer data set.
n is the total number of datasets (X_i).
T is the total numbers of troughs.

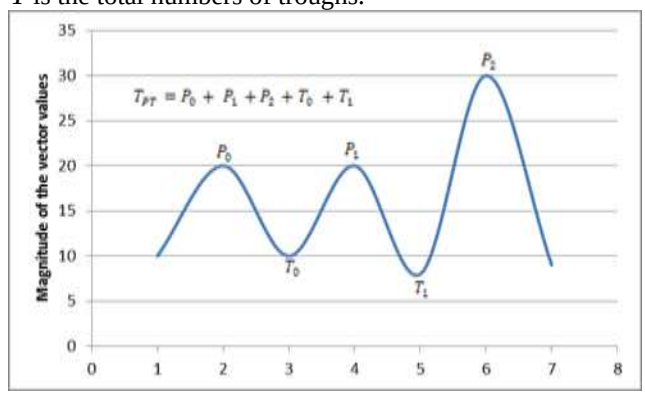

Fig. 3. Shows how peaks and troughs are determined and how $\boldsymbol{T_{PT}}$ is calculated.

The trough formula calculation translates as follows, for $i = 0$ to $n-2$ if the condition $(X_{i+1} < X_i)$ is true and $(X_{i+2} > X_{i+1})$ is true then increment the counter T by 1.

C. Results

Let T_{PT} be the sum of the total peaks and troughs. Our experiments results show the range of values of T_{PT} are integer values between S_{min} and S_{max} where $S_{min} = 0$ and $S_{max} = 6$. We group the results based on the number of occurrences of T_{PT} at every 8 events (2 seconds). 2 seconds was selected because it represented the most differences of T_{PT} for the various activities within the shortest time. Table II shows the generated probability statics for the grouped results. Fig. 3 shows how T_{PT} is derived. Our analysis of the results revealed the following results:

1. Over 57% of the distribution tends to be either 4 or 5 for motorized movements.
2. Over 98% of the distribution tends to be either 5 or 6 for walking.
3. Over 69% of the distribution is 1, 2 or 3 for activities with slight movements like sitting on the sofa.
4. Over 98% of the distribution is 0 or 1 for stationary activities with no movements in the (x, y, z) direction.
5. Over 88% of the distribution is 0, 1, 2 or 3 for activities with very slight movements like lying in bed.

From the 8 events let mm denote the difference of the max and min values. We can deduce when $T_{PT} > 3$ and $mm >$ 1.4 enable location sensors else turn-off power hungry location sensors. We derived the value of 1.4 based on our study of the accelerometer features. The features studied are: range, mean, standard deviation, and correlation of $\|v\|$ of accelerometer data. We found for stationary activities the difference between the max and min values were always less than 1.4 as compared to non-stationary activities which have a greater value.

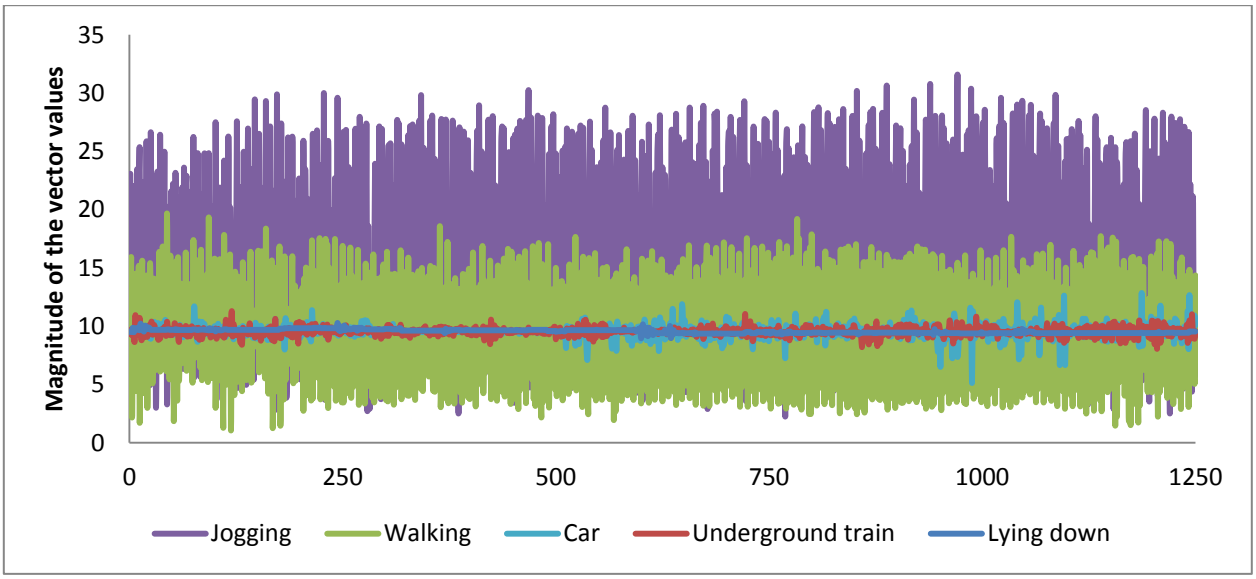

Fig. 4. Graph of magnitude of the vector values for various activities

Table I. Shows participants and activities for which accelerometer data was gathered.

Participant	Activity
Ax2	Sitting, standing, walking, jogging, climbing up stairs and climbing down stairs.
Bx2	Travel by underground train, car, bus, cycling, taxi, and walking.
Cx2	Stationary, in-motion, and lying down
Dx1	Top-jacket pocket, trousers pocket, and back-pack while walking

IV. Evaluation

We conducted two phases of experiments using a Samsung Galaxy S Android smartphone. The first phase involved the study of accelerometer data gathered from various activities. The second phase involved the battery decay study of GPS. The details of the experiments are as follows:

A. *Accelerometer data study*

The data collection process was conducted by 7 participants for 18 different activities. We extended our experiments to several activities in order to potentially detect the variability that could distort the results of our algorithm. Table I shows the activities recorded by each participant. Participants A, B, and C were permitted to carry the smartphone regardless of the body placement. Participant D had to place the smartphone in the identified body positions. This allowed us to study the differences based on body placements. For each activity we used a training set of 62.5 seconds. This is equivalent to 1250 samples per activity. Android based smartphones were used for the data gathering. For this paper no noise filtering was done.

B. *GPS battery decay study*

We developed a battery exhaustion method to determine the battery decay of GPS over a configurable set time interval $T_{interval}$. Fig. 1 displays a screenshot of the LocationStudy Android application used for the experiments. Samsung Galaxy S smartphones were used. The device runs Android version 2.2 and has a 1500 mAh standard battery capacity. The battery statistics were recorded from full battery charge until exhausted using the BatteryManager API provided by the Android Software Development Kit (SDK).

1) *Experimental Setup*

The experiments were started by launching the LocationStudy application. LocationStudy is the Android application we developed to study the battery decay of GPS. Below is a brief description of the data captured by the Android application:

- *System timestamp* is the current date in the time format "*dd/MM/yyyy HH:mm:ss*".
- *Battery level* specifies an integer value of the remaining battery from 0 to the battery scale.
- *Battery scale* specifies an integer value of the maximum battery level. For all our experiments this value was 100.
- *Temperature* is the current battery temperature in Celsius.
- *Voltage* is the current battery voltage level in millivolts.
- *Longitude* is the longitude of the location fix.
- *Latitude* is the latitude of the location fix.

The experiment conditions are as follows:

Table II. Shows the distribution percentage of total peaks and troughs $\boldsymbol{T_{PT}}$ from $\boldsymbol{S_{min}}$ to $\boldsymbol{S_{max}}$.

	Distribution percentage of T_{PT} from S_{min} to S_{max}						
Activity	S_0	S_1	S_2	S_3	S_4	S_5	S_6
Bus		1.92	4.49	14.74	**44.23**	**28.85**	5.77
Overground train		0.64	5.13	25	**35.26**	**28.21**	5.77
Underground train		0.64	8.97	19.87	**42.95**	**22.44**	5.13
Car	6.41	1.28	10.26	16.67	**35.9**	**23.08**	6.41
Walking					0.64	**69.23**	**30.13**
Jogging				3.21	**50.64**	**46.15**	
Sitting	6.41	**21.15**	**25**	**23.08**	19.23	4.49	0.64
Stationary (no movement)	**85.9**	**12.82**	1.28				
Lying down	**46.79**	**16.67**	**14.1**	**10.9**	7.69	1.92	1.92

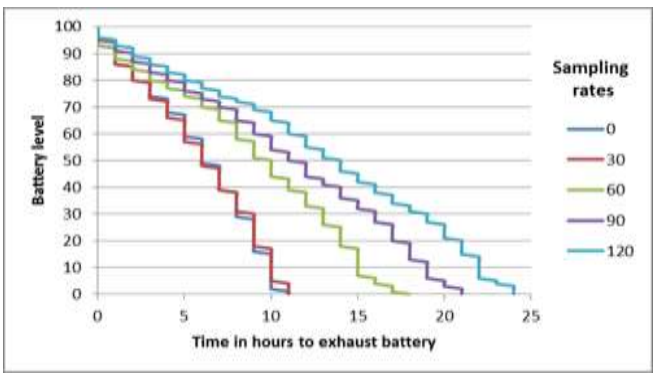

Fig. 5: The time taken to exhaust a Samsung smartphone battery given various GPS sampling rates.

1. Before commencing each experiment, the mobile device was charged to 100%, then restarted, and charged to 100% again. This last recharge is done to ensure no additional power drain from restarting the phone affects the battery level.
2. Experiment data was stored on the phone local disk storage and retrieved at the end of each test.
3. The mobile devices were used solely for these controlled experiments, that is, no phone calls, web browsing, or messaging during the experiments.
4. The experiments were executed in indoor and outdoor environments. For indoor experiments the mobile device was placed on a flat surface with limited GPS signals. For outdoor experiments the mobile device was carried through an actual commuter day in either the front jacket pocket, bag pack, or trouser pocket.
5. The mobile device had only the default manufacturer processes running. There were no third party software or email accounts configured or activated.

The goals of the experiments are as follows:

1. Gather battery energy level and location measurements at set intervals $T_{interval}$ as GPS is being used.
2. Determine the power consumed by GPS in an active and idle state.
3. Determine the power consumed by GPS with respect to location sampling rate. This provides a basis in deducing an optimal GPS sampling rate that offers the least average localization error.

V. Results & Discussion

Based on our experiments using the Samsung Galaxy S smartphone, continuous location sampling using GPS can exhaust the battery within 12 hours as compared to 284 hours with all location sensors turned-off.

Energy savings is the presumption for reduced location sensor sampling rates which in-turn leads to increased average localization error. For instance EEMSS [4] sample GPS every 20 seconds and EnLoc [2] sample GPS every 30 seconds. Our experimental study reveals that sampling GPS for location updates at intervals less than 60 seconds had very subtle differences in the battery decay over time as compared to continuous location sampling. Fig. 5 show the battery consumption based on various GPS sampling rates. The energy-efficiency can be improved by activating GPS based on the user mobility state.

A. *Linear cost formulation for GPS*

$$TC_{gps} = \alpha\left(C_{gps} * T_t\right) \qquad (3)$$

C_{gps} is the evaluation cost for gps location sensor and T_t is the total time. The weight factor for GPS is denoted by α, where $\alpha \leq 1$ and $C_{gps} = \frac{1}{12}$

B. *Linear cost formulation for the AAGPS model*

$$TC_{aagps} = \left(C_{gps} * T_{tgps}\right) \qquad (4)$$

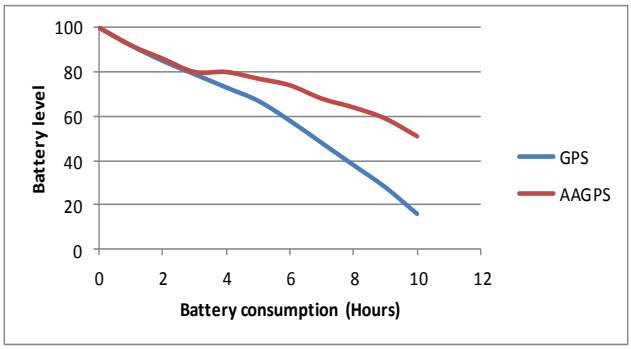

Fig. 6. Shows the energy-savings of the GPS vs. AAGPS location sensing based on scenario A.

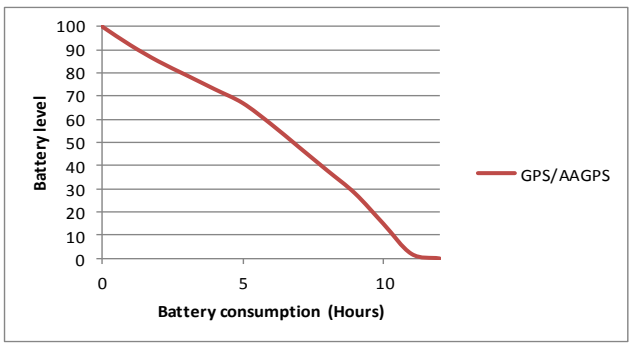

Fig. 7. Worst case scenario for GPS vs. AAGPS location sensing

where $C_{gps} = \frac{1}{12}$ and T_{tgps} is the running time for GPS

We evaluate our algorithm based on two scenarios. Scenario A, based on the daily commuter trail of a delivery driver we show the energy-savings from implementing our algorithm. The daily work schedule is from 8:00 until 18:00. It should be noted that most days delivery destinations alter and as a result location caching will not be useful. The total stationary periods is approximately 4 hours per day. Such periods include having lunch, parking the van to make a delivery by foot, or if the smartphone is carried on the body then time waiting at doors before completing each delivery. Finally we present the worst case scenario.

Rather than enabling GPS for 10 hours, our location sensor selection algorithm ensures GPS is sampling for location updates only when required, leading to significant savings in battery life. If in a stationary state for more than 10 minutes then the GPS sampling is halted. We determine the user mobility state is stationary if 90% of detected activities within any 10 min window are classified as stationary. As long as the screen lights are on or CPU running the energy-consumption during the switching stages is negligible due to low energy utilization of the accelerometer.

C. *Typical case scenario*

Applying the AAGPS model to scenario A utilizes approximately 55.6% of the smartphone battery as compared to 83.3% with continuous GPS location sampling. As shown TC_{aagps} outperforms TC_{gps}. Fig. 6 displays the energy-savings in using our AAGPS model as compared to GPS.

D. *Worst case scenario*

The worst case will occur when the user is continuously in an "in-motion" state. In such a case there will be no need to turn-off GPS since the user mobility state is constantly in an in-motion state. Fig. 7 shows the worst case scenario of using our AAGPS model. The following is the cost of algorithm.

$$TC_{aagps} \leq TC_{gps} \qquad (5)$$

E. *Comparison of our Method to the Surveyed techniques*

There is readily available research on energy-efficient location determination techniques for smartphones and in this paper we have presented a technique that improves the energy-efficiency of GPS based systems by pervasively managing GPS activation and deactivation using an accelerometer based user mobility context detection algorithm. We discuss how our location sensing algorithm differs from selected related architectures.

Similar to [1], [5], [10] we also use a 3D accelerometer to determine the mobility context of users and are able to distinguish between different motorized movements such as travel by car, bus, or underground train. From our previous research using the Sun SPOT sensor device [22], we were able to use just the Y-axis to distinguish between travel modes with 77.27% accuracy in 5.4 seconds. Our current work is focused on user mobility state detection regardless of the placement of the smartphone. As a result it is challenging to distinguish between activities using just a single axis.

Our experiments also show the magnitude of the force vector method outperforms acceleration decomposition methods [8]. Whereas [9] can classify activities, it requires smartphone placement on the body not to vary, in contrast our accelerometer based method can handle different on-body placements.

Reddy et al [10] use a mobile phone with a built-in GPS receiver and an accelerometer to detect transportation modes, we rely solely on accelerometer signals to detect the user mobility state.

In comparison to RAPS [12] our architecture uses real-time and not historical user activity to determine when to activate or deactivate GPS.

EnTracked [20] architecture requires both the accelerometer and GPS to detect a user's mobility state change. However our system requires only the accelerometer to determine the user mobility state.

With EEMSS [4] there is the issue of increased average localization error due to GPS sampling every 20 seconds as compared to continuous sampling. For improved accuracy, we sample GPS continuously.

VI. Conclusion And Future Work

In this paper, we have presented an algorithm to improve the energy-efficiency of GPS based location sensing applications used by smartphones. In an effort to improve the battery life we have been able using the embedded smartphone accelerometer to differentiate between subtle activities with high accuracy. We designed, implemented and validated our mobility state detector algorithm on Android based smartphones.

The energy-efficiency of LBS where continuous location updates is of high importance can be further improved by implementing location sensor selection algorithms. Due to battery limitations in smartphones it is essential to conserve battery power by ensuring power hungry sensors like GPS are only active when needed.

The user mobility context detection algorithm design is based on a limited number of activities such as being stationary (lying down or sitting) and in-motion (walking or jogging). It's not feasible to cover all activities and as such the next phase of our research will involve activities being performed by the user for a set time so that it can be personalized. This will allow our algorithm to cover a wider range of activities. We plan to apply machine learning techniques to the activity data supplied by the user to further improve the accuracy of the user mobility state detection process.

Although, we focused mainly on Android phones, we envisage that our smartphone battery decay and user mobility context detection models can be applied to any type of smartphone.

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