Balancing Power Consumption and Data Analysis Accuracy through Adjusting Sampling Rates: Seeking for the Optimal Configuration of Inertial Sensors for Power Wheelchair Users

Tao Liu, Chuanwei Chen, Melicent King, Gang Qian, Jicheng Fu

Department of Computer Science
University of Central Oklahoma, Edmond, United States

Abstract. Smartphones have already been used to capture wheelchair maneuvering data to analyze a wheelchair user's activity level, which is directly related to his/her quality of life. Typically, the inertial sensors (e.g., accelerometer and gyroscope) in a smartphone are used for data collection. However, the limited battery life of the smartphone has become a major barrier to effective data collection. The sampling rate, as a primary configurable parameter of an inertial sensor, may have important impact on power consumption. Presumably, a lower sampling rate would consume less battery power. However, it may compromise the accuracy of data analysis. In this study, we investigate how the sampling rate of inertial sensors impacts the battery power consumption as well as the accuracy of data analysis. The four pre-defined sampling rate settings of the Android OS were evaluated for their impact on the smartphone's power consumption. Additionally, we also measured the accuracy differences of the four sampling settings by comparing the sensor data-derived wheelchair maneuvering distances with the actual distances. The experimental results showed that it is possible and practical to balance the power consumption and data analysis accuracy by switching between appropriate sampling rate settings.

Keywords: smartphone, inertial sensors, power wheelchair, power consumption, sampling rate

1 Introduction

Physical activity is associated with a decrease of depression and anxiety effects while enhancing the psychological well-being of individuals [1]. Unfortunately, only 15 percent of Americans achieved the recommended level of physical activity [2]. For wheelchair users, the situation is even worse since they face a higher risk of certain serious diseases due to their limitation of physical activities. For instance, a wheelchair user with spinal cord injury (SCI) suffers a significant higher rate (225%) of mortality due to the coronary heart disease than normal people [3].

Nowadays smartphones have found the way into our daily lives. Smartphones are usually equipped with a rich set of sensors, e.g., accelerometers, gyroscope, compass, GPS, etc. [4]. Due to its prevalence and functionality, smartphones can be an ideal choice for wheelchair users to monitor their daily activities and collect wheelchair maneuvering data for the subsequent analysis [5, 6]. It is then possible to quantify the wheelchair users' physical activities and motivate them to be more active and healthier to improve their quality of life [7].

A problem of using smartphones for activity monitoring is that they have only limited battery life, which will be a serious barricade between high accuracy and the service time. When a smartphone's inertial sensor is working at a high sampling rate, it will generate a large volume of data and consequently cause heavy workload on networks and/or system storage, which can drain the battery rapidly. On the other hand, if a low rate setting is applied, it may yield unsatisfying accuracy in data analysis. In this study, we aim to investigate the effect of sensor sampling rates on the power consumption as well as how to configure the inertial sensors to collect acceptable accurate data while consuming relatively low energy.

This paper is organized as follows. Section 2 introduces the related research works, and limitations on smartphone inertial sensors and the power consumption. Section 3 presents our evaluation method on power consumption of the 4 pre-defined sampling rate settings. Section 4 shows the experimental results and discussion of the evaluation. Section 5 concludes the paper with our consideration on balancing power consumption and analysis accuracy. We also identified our contributions to researches in similar areas.

2 Related works

In order to address the balancing issue between energy and accuracy, a lot of works need to be done on smartphone network connection, operating system (e.g. Android, iOS), programming and configuration [8-11].

A recent research in [12] evaluated some major inertial sensors on a Google Nexus 4 smartphone for accuracy, sampling frequency, sampling period jitter and power consumption of two pre-defined sampling rate settings. The authors demonstrated that the inertial accelerometers and gyroscope could offer reliable readings and the "Normal" setting consumed 25%-28.6% less power than the "Fastest" setting during one hour. The authors did not present further data analysis for other sampling settings or practical applications. In order to see the impact of power efficiency of each subsystem and/or app running on a smartphone, Gordon et al. developed a power monitoring app [13] to directly demonstrate and record the battery usage status. This app can collect consumed power data for the major system components on a smartphone. However, currently this app mainly works for HTC G1, G2 and Nexus One phones and may only obtain rough results on other phones [13]. Another app related to smartphone energy consumption is a benchmark suite [14], which provided energy evaluation for smartphone platforms by executing a series of representative applications. This benchmark suite can evaluate mobile systems from architectural aspects and mainly focused on the application cores, memory and storage subsystem.

For power saving approaches, Qiu et al. proposed an algorithm [9] based on dynamic voltage scaling (DVS) to reduce the total energy consumption for smartphones for up to 34.2%. The algorithm focused on CPU voltage and OS concerns, but did not consider the inertial sensors. For the GPS sensor in [15], a power efficient touring scheme (PETS) is presented for smartphone power saving. This scheme adjusts the sampling rate of GPS dynamically to keep yielding accurate positioning for pedestrians with 45% less power consumption. Another way for energy management is to switch between working and sleeping mode. A mode, namely, O-Sleep was given in [16], which could make a smartphone UI to sleep when no meaningful output was detected. The authors reported that it could save 37% of the power consumption in the experiments for some key applications, e.g., Internet browsing, email sending, Facebook accessing of different scenarios. Network connection type is a crucial concern for cloud and mobile computing. Hence, a measurement was taken in [17] included Wi-Fi, 2G and 3G networks on Samsung Galaxy SII and SIII phones. The Wi-Fi connection is found to consume by far the least energy for the same uploading task. Additionally, the author also proposed an energy consumption model, which can help decide whether to migrate computational tasks to the cloud or take a local processing.

In this paper we tried to find out a solution to balance the power consumption and data analysis accuracy. To the best of our knowledge, this is the first study that aims to investigate the impact of sensor sampling rates on battery power consumption and data analysis accuracy.

3 Method

We have developed an Android app to capture and transmit wheelchair maneuvering data to a cloud computing environment for storage and analysis [5] as shown in Fig. 1.

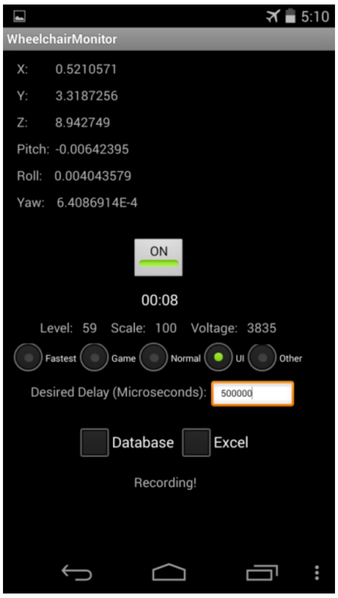

Fig. 1. The Android app for this study

This app controls the accelerometer and gyroscope in a smartphone for data collection. Specifically, it captures accelerations in 3 axes (x, y and z) with the accelerometer and collects angular velocities (yaw, pitch and roll) with the gyroscope, as shown in Fig. 2. In addition, this app can monitor power consumption by periodically recording battery voltage and percentage. The Android system predefines four sampling settings, namely, Fastest, Game, Normal and UI. We tested two LG Nexus 5 smartphones and found that the actual sampling rates ranged from 4-134 Hz for these predefined settings. As shown in Fig. 1, our app allows users to either select sampling setting or define the sampling rate by themselves. The recorded power consumption data is saved in a local file on the smartphone. The purpose is to save battery power by alleviating the network load, i.e., only wheelchair maneuvering data is transmitted to the cloud.

The Android app was designed to be easy-to-use. The user can simply click the button in the center of the interface, and then the app will start to collect and transmit data to the cloud. The app also offers the option of storing wheelchair maneuvering data locally on the phone (i.e., by selecting the “Excel” option).

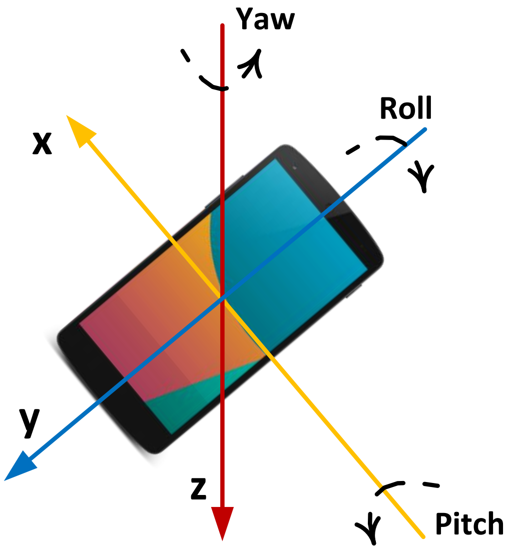

Fig. 2. Three axes of a smartphone

3.1 Experiments for Evaluating How the Sampling Rate Impacts Power Consumption

In the Android OS context, the sensor reading is event-driven, i.e., a data item is read whenever the sensor detects a change. We have conducted an experiment to investigate how the sampling rates impacts battery power consumption. Table 1 illustrates and explains the four predefined settings of sampling rates for an inertial sensor supported by the Android SDK [18]. Since the sampling rate for each setting is not fixed, but falls within a range, the smartphone app also keeps the time when a data item is read, i.e., the timestamp for each data item.

Considering the fact that the Android OS is a multi-tasking system, it allows different applications to run simultaneously. To avoid the disturbance from other applications, we performed a factory-reset and only kept necessary system apps. Then, we installed our app for data collection and power consumption monitoring. The same experiment was performed for each sampling setting for five times in order to guarantee a sturdy result. To ensure the fairness of comparisons, the smartphone (LG Nexus 5) was fully charged before any experiment. During each experiment, the app kept collecting accelerometer and gyroscope data for 120 minutes. The battery power consumption, in terms of battery percentage and voltage, was recorded every 10 minutes.

Table 1. Sampling settings of inertial sensors (unit: *Hz*)

Option	Sampling rate		Description
	Accelerometer	Gyroscope	
SENSOR_DELAY_FASTEST	127-134	46 - 49	get sensor data as fast as possible
SENSOR_DELAY_GAME	46 - 49	46 - 49	suitable for games
SENSOR_DELAY_UI	14 - 16	14 - 16	suitable for the user interface
SENSOR_DELAY_NORMAL	14 - 16	4 - 6	suitable for screen orientation changes

3.2 Experiments for Evaluating How the Sampling Rate Impacts Data Analysis Accuracy

In this experiment, we conducted experiments to evaluate how the sampling rate impacts data analysis accuracy. Particularly, we use wheelchair maneuvering distance as the evaluation metrics for analysis accuracy. During the experiments, we still used the LG Nexus 5 smartphone, which was installed on the left armrest of a wheelchair and was oriented with its Y-axis aligned to the driving direction as shown in Fig. 3.

Fig. 3. The smartphone and the wheelchair

Additionally, we attached an ActiGraph sensor on each side of the wheels to obtain referential distances [19, 20]. The maneuvering data was collected inside an academic building for 20 trials for each of the 4 predefined sampling rate settings. During a trial, the wheelchair would be driven for a distance of 60.855±1.847 meters and would make four 90-degree and one 180-degree turns. Hence, the trials included major wheelchair maneuvers for the user's daily activities.

After data is collected, we performed noise reduction and distance calculation using the approach we proposed in [21]. We developed a *k*-nearest neighbors (KNN) algorithm that could classify fine-grained wheelchair maneuvers. First, the wheelchair maneuvers were classified into 8 classes, namely, idle, acceleration, deceleration, constant speed, left turn, right turn, spot turn to left, and spot turn to right. The training samples for KNN were setup by pre-collected data. Since the Y axis of the smartphone was oriented to the driving direction, acceleration data in the Y axis was used for classification. The data sequence was divided into data segments, with each segment containing 10 consecutive data elements. We used 40 training samples for each class of the wheelchair maneuvers (totally 320 samples for 8 classes). The maneuvering class was determined by the majority of the nearest neighbors. To determine the nearest neighbors, the Euclidian distance was used for measuring the distance between the testing data and each of the training samples. Once the maneuvering class was obtained, we used the trapezoidal rules [22] to calculate distances for the moving maneuvers individually. The overall distance was obtained by summing up the individual distances. As a result, the accumulated errors were significantly reduced.

4 Results

Fig. 4 illustrates the experimental results for battery power consumption which was introduced in Section 3.1. The smartphone indeed consumed the most battery power with the "Fastest" setting: after 120 minutes, the smartphone consumed 50% of the total battery power. When it worked with the "Normal" setting, it only consumed 28%. Moreover, the "UI" and "Normal" settings had very close power consumption due to their similar sampling rates for accelerometers.

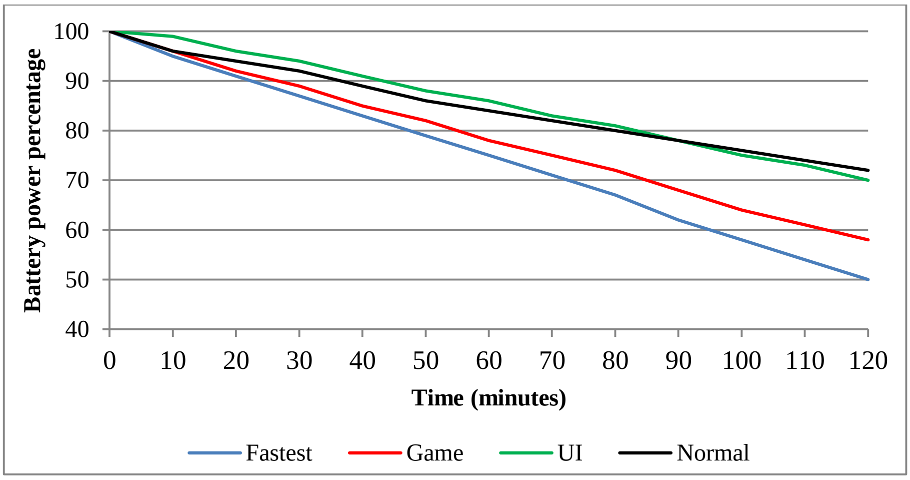

Fig. 4. The battery power drop percentage for different sampling settings

Table 2 displays the distance calculation accuracy. The “Fastest” setting had the smallest average error, while the “Normal” setting had the largest. Furthermore, statistical significance existed only between the “Fastest” and “Normal” settings ($p=0.024$). Thus, we will not experience significant accuracy loss if we configure the app to collect data with a lower sampling rate, such as the “UI” or “Game” setting.

Table 2. Relative error of distance calculation on different rates (unit: %)

	Fastest	Game	UI	Normal
Min. error	0.73	0.08	5.49	6.23
Max. error	28.6	34.05	27.39	31.71
Avg. error	**9.86**	13.00	13.09	**14.82**

5 Discussion and Conclusions

In this study, we aimed to investigate how to balance the battery power consumption of smartphones and data analysis accuracy through adjusting inertial sensors’ sampling rates. Correspondingly, we conducted two types of experiments to evaluate how the sampling rate of inertial sensors impacts battery power consumption as well as data analysis accuracy. Experimental results confirmed that higher sampling rates indeed consumed more battery power. As shown in Fig. 4, the battery power was consumed almost linearly as time elapsed. The higher sampling rate corresponded to a steeper slope. Hence, to save battery power, a lower sampling rate is preferable. In addition, the experiment for evaluating data analysis accuracy demonstrated that higher sampling rates achieved relatively better analysis accuracy (as shown in Table 2). It appears that a higher sampling rate is preferred if we desire to achieve good analysis accuracy. The good news is that the accuracy differences are not statistically significant between “Fastest” and “Game”, and between “Fastest” and “UI”. Hence, the sampling rates of “Game” or “UI” may be a good tradeoff, which balances battery power consumption without significantly decreasing data analysis accuracy.

Based on information obtained from this study, we will develop a context-aware algorithm in our future work, which can adjust the sampling rate of an inertial sensor based on the actual context, e.g., stationary, moving, etc., to achieve efficient power consumption while maintaining satisfactory data analysis accuracy.

Study limitations exist in this study. First, we only tested the LG Nexus 5 smartphone. Different smartphones may demonstrate different power consumption patterns. Second, we only used the wheelchair maneuvering distance as the metric to evaluate the impact of inertial sensor’s sampling rates. In the next step, we will test other brands of Android smartphones to evaluate more metrics that are related to wheelchair users’ activities, such as maneuvering time, number of bouts [23], etc.

In summary, the approach proposed in this study and the experimental results may generate immediate benefits to researchers, who use Android smartphone sensors in research.

Acknowledgement

This study was supported by the National Institute of General Medical Sciences of the National Institutes of Health through Grant Number 8P20GM103447.

Reference

1. G. C. W. Wendel-Vos, A. J. Schuit, M. A. R. Tijhuis, and D. Kromhout, "Leisure time physical activity and health-related quality of life: Cross-sectional and longitudinal associations," *Quality of Life Research*, vol. 13, pp. 667-677, 2004.
2. "Healthy people 2010: Understanding and improving health," Washington, DCNovember 2000.
3. P. L. Jacobs and M. S. Nash, "Modes, benefits, and risks of voluntary an delectrically induced exercise in persons with spinal cord injury," *The journal of spinal cord medicine*, vol. 24, pp. 10-18, 2001.
4. E. M. Nicholas D. Lane, Hong Lu, et al., "A Survey of Mobile Phone Sensing," *IEEE Communications Magazine*, vol. 48, p. 11, 2010.
5. J. Fu, W. Hao, T. White, Y. Yan, M. Jones, and Y. K. Jan, "Capturing and analyzing wheelchair maneuvering patterns with mobile cloud computing," *Conf Proc IEEE Eng Med Biol Soc*, vol. 2013, pp. 2419-22, 2013, PMID: 24110214.
6. S. V. Hiremath, D. Ding, and R. A. Cooper, "Development and evaluation of a gyroscope-based wheel rotation monitor for manual wheelchair users," *J Spinal Cord Med*, vol. 36, pp. 347-56, Jul 2013.
7. M. L. Tolerico, D. Ding, R. A. Cooper, D. M. Spaeth, S. G. Fitzgerald, R. Cooper, *et al.*, "Assessing mobility characteristics and activity levels of manual wheelchair users," *J Rehabil Res Dev*, vol. 44, pp. 561-71, 2007.
8. G. Anastasi, A. Bacioccola, C. Cicconetti, L. Lenzini, E. Mingozzi, and C. Vallati, "Performance evaluation of power management for best effort applications in IEEE 802.16 networks," in *Wireless Conference, 2008. EW 2008. 14th European*, 2008, pp. 1-6.
9. Q. Meikang, C. Zhi, L. T. Yang, Q. Xiao, and W. Bin, "Towards Power-Efficient Smartphones by Energy-Aware Dynamic Task Scheduling," in *High Performance Computing and Communication & 2012 IEEE 9th International Conference on Embedded Software and Systems (HPCC-ICESS), 2012 IEEE 14th International Conference on*, 2012, pp. 1466-1472.
10. R. Mizouni, M. A. Serhani, A. Benharref, and O. Al-Abassi, "Towards Battery-Aware Self-Adaptive Mobile Applications," in *Services Computing (SCC), 2012 IEEE Ninth International Conference on*, 2012, pp. 439-445.
11. S. Alawnah and A. Sagahyroon, "Modeling Smartphones Power," *EUROCON, IEEE*, p. 6, 2013.
12. Z. Ma, Y. Qiao, B. Lee, and E. Fallon, "Experimental Evaluation of Mobile Phone Sensors," *Signals and Systems Conference (ISSC 2013), 24th IET Irish*, p. 8, June 20-21 2013.

13. M. Gordon, L. Zhang, and B. Tiwana, "A Power Monitor for Android-Based Mobile Platforms," October 9 2011. Available: http://ziyang.eecs.umich.edu/projects/powertutor/instructions.html
14. D. Pandiyan, S.-Y. Lee, and C.-J. Wu, "Performance, energy characterizations and architectural implications of an emerging mobile platform benchmark suite - MobileBench," 2013, pp. 133-142.
15. H. Chung-Ming, L. Chao-Hsien, and C. Wei-Shuang, "A power efficient pedestrian touring scheme based on sensor-assisted positioning and prioritized caching for smart mobile devices," in *Software, Telecommunications and Computer Networks (SoftCOM), 2013 21st International Conference on*, 2013, pp. 1-5.
16. K. Jungseok, J. Hyunwoo, and K. Hyungshin, "O-Sleep: Smartphones' Output-Oriented Power Saving Mode," in *Computational Science and Engineering (CSE), 2012 IEEE 15th International Conference on*, 2012, pp. 334-340.
17. M. Segata, B. Bloessl, C. Sommer, and F. Dressler, "Towards energy efficient smart phone applications: Energy models for offloading tasks into the cloud," in *Communications (ICC), 2014 IEEE International Conference on*, 2014, pp. 2394-2399.
18. *Android developers reference (Android 4.4 r1 ed.)*. Available: http://developer.android.com/reference/android/hardware/SensorManager.html#registerListener(android.hardware.SensorEventListener
19. Actigraph. (2013). *GT3X+ and wGT3X+ Device Manual (v2.0.0 ed.)*. Available: http://dl.theactigraph.com/GT3Xp_wGT3Xp_Device_Manual.pdf
20. S. E. Sonenblum, S. Sprigle, J. Caspall, and R. Lopez, "Validation of an accelerometer-based method to measure the use of manual wheelchairs," *Med Eng Phys*, vol. 34, pp. 781-6, Jul 2012.
21. F. Jicheng, L. Tao, M. Jones, Q. Gang, and J. Yih-Kuen, "Characterization of wheelchair maneuvers based on noisy inertial sensor data: A preliminary study," in *Engineering in Medicine and Biology Society (EMBC), 2014 36th Annual International Conference of the IEEE*, 2014, pp. 1731-1734.
22. R. Tallarida and R. Murray, "Area under a Curve: Trapezoidal and Simpson's Rules," in *Manual of Pharmacologic Calculations*, ed: Springer New York, 1987, pp. 77-81.
23. S. E. Sonenblum, S. Sprigle, F. H. Harris, and C. L. Maurer, "Characterization of power wheelchair use in the home and community," *Arch Phys Med Rehabil*, vol. 89, pp. 486-91, Mar 2008.