
iPhone as a Physical Activity Measurement Platform

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Abstract

iPhone is emerging as a ubiquitous physical activity measurement platform due to its incorporated accelerometer sensor. The iPhone's capacity to accurately measure physical activity has not been put to scrutiny up to now, despite claims from an increasing number of applications. This study examines ways to perform accurate physical activity measurements with the iPhone, at various positions on the user's body. The study focuses on walking and running - the two most prevalent aerobic activities. For walking, a methodology has been developed that translates accelerometer values from peripheral body locations to equivalent readings on the waist and from there to metabolic units. For running, the limitation of iPhone to perform accurate metabolic measurements is documented. The formulas and results in this paper can readily be used by developers to increase the accuracy of fitness applications and improve user experience.

Keywords

Physical activity, accelerometer, iPhone, calibration

ACM Classification Keywords

H5.m. Information interfaces and presentation (e.g., HCI): Miscellaneous.

General Terms

Human Factors, Measurement

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CHI 2010, April 10–15, 2010, Atlanta, Georgia, USA.
ACM 978-1-60558-930-5/10/04.

Introduction

Accelerometers emerge as the preferred sensors to measure physical activity under free-living conditions, due to their non-obtrusive nature. Accelerometer-based mobile phone applications are on the rise. NEAT-o-Games ([5]) is a successful sample that enhances users' daily physical activity level utilizing accelerometer and mobile phone platform.

iPhone stands apart as a practical measurement platform of physical activity. It is a popular mobile phone with an incorporated accelerometer. Users carry iPhones on them throughout the day. Fujiki et al. in [5] demonstrated that when the accelerometer is not embedded in the cell phone, forcing the user to carry an extra device, usability and reliability suffer. Users forget to carry the sensor from time to time and the wireless communication between the phone and the sensor experiences intermittent failures. In these respects, iPhone with its embedded accelerometer has a definitive advantage. In addition, iPhone applications benefit from a very popular and easily accessible distribution network, the App Store. Nowadays, a search in the App Store under the 'Healthcare and Fitness' category reveals dozens of ubiquitous applications that aim to keep track of daily physical activity using the iPhone's embedded accelerometer ([7], [10]).

Despite the growing popularity of physical activity applications on the iPhone platform, there has not been any rigorous study on calibrating the device. Calibration is paramount to accuracy in metabolic sensing and computation. A number of calibration studies have been carried out for stand-alone accelerometer sensors that predate iPhone ([3], [4]). However, most of the

calibration studies assume that users will attach the accelerometer on a specific position (typically on the waist). This expectation has little chance to come true even with a stand-alone accelerometer ([5]), much less with an accelerometer embedded in a mobile phone. This important issue has not been investigated enough. Fujiki et al. [6] developed positional calibration of accelerometer readings using real accelerometer signals obtained from different body locations, i.e., *waist, thigh, ankle, hand, and arm*. However, the study was based on stand-alone accelerometers, in which case body placement preferences are very different with respect to accelerometers embedded in mobile phones.

The present study reveals the potential of the iPhone accelerometer to measure physical activity while walking - the most pervasive physical activity. In fact, based on experimentation and statistical analysis, the study has developed calibration formulas that can be used in walking applications. Furthermore, the study brings to the fore the limitation of iPhone in accurately measuring running activity. In the experiment, iPhones were attached at different locations where iPhone users typically wear them, i.e., *waist, pants pocket, arm, hand, backpack, jacket side pocket, jacket top pocket, and handbag*; then, the relation between these locations was examined. Indirect calorimetry was used to obtain ground-truth metabolic data. Indirect calorimetry is the golden standard for energy expenditure measurements. It gauges volume of O₂ consumed at the lung level (VO₂ (L)), which is proportional to calorie consumption ([2]).

Please note that this is a different study topic from the automatic identification of accelerometer placement

Physical Attribute	Mean	Standard Deviation
Age (years)	25.18	4.75
Body Mass (kg)	72.75	14.46
Body Mass Index (kg/m ²)	23.60	3.21

Table 1 Descriptive statistics of the participating subjects

Session	Positions
Session 1	Waist, pants pocket, arm, hand, backpack
Session 2	Waist, jacket side pocket, jacket top pocket, handbag

Table 2 iPhone body placements in each session.



Figure 1 Experimental set-up for Session 1

and activity classification ([8]). In fact, automatic identification of accelerometer placement and activity classification can be considered as complimentary to this study.

Methodology.

Subjects

We recruited 11 healthy subjects (8 male and 3 female) for the experiments. Their physical attributes are summarized in Table 1.

Experimental Design

A survey of iPhone users revealed 8 preferred locations where they place their phones. The locations are *waist, pants pocket, arm, hand, backpack, jacket side pocket, jacket top pocket, handbag*. Ideally, we would like each subject to carry iPhones on all 8 locations to establish direct correlations. However, because carrying more than 5 iPhones on one’s body is getting cumbersome, we split the experiment into two sessions. The positions measured in each session are listed in Table 2.

The waist is included in both sessions as a master position. It is considered an ideal position to measure physical activity because it is close to the center of body mass ([6], [9]). This is also supported in the results section of this study.

For each subject we recorded his/her weight and height. At the beginning of each session the subject walked on a treadmill for 6 minutes to warm up. After that, the subject was connected to a metabolic cart and sat back on a chair to have his/her basal metabolic rate (BMR) measured. Following the BMR measurement, the subject walked on a treadmill at seven different speeds from 1 mph to 4 mph, while connected to the metabolic

cart and attached with iPhones on different positions (Figure 1). The speed increment was 0.5 mph, which was sufficient resolution for our purposes.

Energy Expenditure

Energy expenditure was measured with the ADInstruments Exercise Physiology Kit [1]. The subject’s expired air was collected in the gas mask and fed to the ADInstruments LabChart Metabolic Module, which calculated VO₂ consumption. Specifically, energy expenditure per body mass purely deriving from physical activity was calculated as follows:

$$E_{PA} = (VO_2 - BMR) * 5 / (Body Mass)$$

The factor 5 was used to convert VO₂ unit (L) to energy units (kcal) [2]. The units for EPA are kcal/kg.

Accelerometer

iPhones (up to 3GS version) use the STMicroelectronics LIS331DL accelerometer. In our study, 5 iPhone 3G devices running iPhone OS 2.2.1 were used as acceleration measurement platforms. A simple application was created to record the accelerometer’s x, y, z-axis readings along with time stamp (Figure 1). The sampling rate was set as 88.5 Hz.

Post-processing of Accelerometer Output

We applied high-pass filtering on the raw accelerometer data. High-pass filtering is essential to acquire the true activity component from a piezo-resistive accelerometer, as its output includes a DC gravitational contribution. In the literature, the ideal cutoff frequency for the filter is under debate; it ranges from 0.1 Hz to 0.5 Hz. Our experiment showed that 0.5 Hz is sufficient

Position	Correlation coefficients
Waist	0.80429
Arm	0.41474
Hand	0.43268
Pants Pocket	0.74243
Backpack	0.66035
Jacket side pocket	0.67102
Jacket top pocket	0.63013
Handbag	0.69293

Table 3 Correlation coefficients (r^2) between physical activity energy EPA and positional accelerometer energy.

to exclude the gravity component while still including all the physical activity contributions to the signal.

To correlate accelerometer with physical activity measurements, the accelerometer's three dimensional vector needs to be summarized as one scalar value that represents physical activity intensity over small time periods. This scalar value is called *accelerometer energy* in this paper.

To calculate accelerometer energy, several different methods have been proposed, but the most popular one is the summation of time integrals of accelerometer output over the three spatial axes [3]. We adopted this method not only because it is popular but also because proved to be the most reliable in our experiments. Hence, the accelerometer energy is calculated according to the following formula:

$$\text{Accelerometer Energy} = \int_{t_0}^{t_0+T} (|a_x| + |a_y| + |a_z|) dt$$

where a_x, a_y, a_z are high-pass filtered accelerometer values corresponding to the x, y, and z axes. The interval of integration (T) is 30 seconds.

Experimental Results

Correlation of EPA and Accelerometer Energy

Table 3 shows the correlation of physical activity energy EPA with accelerometer energy readings from various body placements of iPhone. From all positions, the waist accelerometer energy shows the best correlation with EPA with either filtering method.

Waist Accelerometer Energy versus EPA

Figure 2 shows the scatter plot of waist accelerometer energy versus physical activity energy EPA. Data from

both experimental sessions (Session 1 and Session 2) are combined here. Equation 1 shows the linear regression equation ($r^2 = 0.80429$). The graph and the r^2 value show that the bivariate relationship is very good. The regression line obtained from equation 1 can be used to convert waist accelerometer energy to physical activity expenditure.

$$y = 1.3571 \times 10^{-5} x + 0.0037402 \quad \text{-(Equation 1)}$$

Accelerometer Energy on Waist versus Other Locations

Figure 3 (next page) shows the distribution of accelerometer energy per body positions. The results show distinct order of distribution. The position with the highest energy is the pants pocket, then come waist and jacket side pocket; other upper body positions produce lower energy.

This suggests that accelerometer energy values from various body locations need adjustment.

First, linear regression analysis was attempted to convert accelerometer energy from various positions to the scale of the waist. However, the direct mappings create ever increasing variance and make application of linear regression a poor choice as in the case of stand-alone accelerometer ([6]).

In order to account for the ever increasing variance, accelerometer energy from the waist versus any other position was compared in the natural logarithm scale. The results are shown in Figure 4. All peripheral positions show good correlation with the waist. Most importantly, the variance is constant over the entire range, opening the way for linear regression analysis.

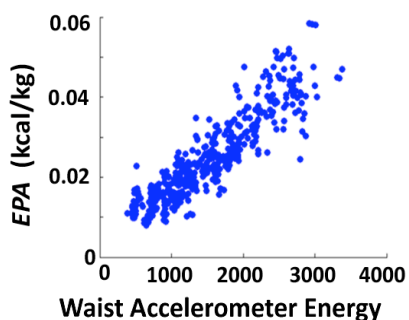


Figure 2 Scatter plot of accelerometer energy on waist versus EPA.

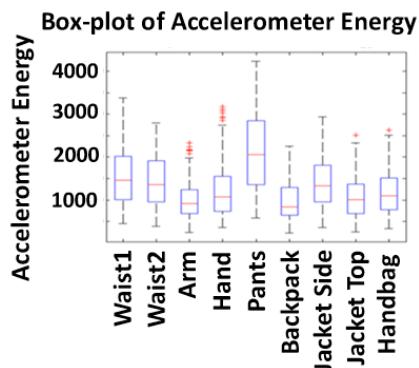


Figure 3 Accelerometer energy distribution per body position. 'Waist1' and 'Waist2' represent waist accelerometer energy from experimental Session 1 and Session 2 respectively.

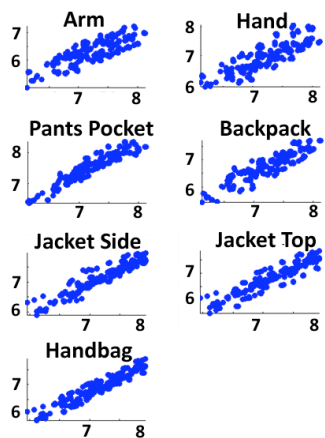


Figure 4 Scatter plots of accelerometer energy on waist versus other body locations in logarithmic scale. In all graphs the x-axis represents the waist accelerometer energy.

To increase accuracy we applied weighted least squares instead of ordinary least squares analysis. The inverse of the speed was taken as the weight to account for the increasing variance along the speed axis. The results are shown in Table 4. The r^2 values show good to very good correlations for all positions.

	y=ax+b		r^2
	a	b	
Arm	0.77091	1.2328	0.65434
Hand	0.89733	0.46088	0.72383
Pants Pocket	0.95847	0.60686	0.87939
Backpack	0.98815	-0.38668	0.82154
Jacket side pocket	0.9671	0.19277	0.8928
Jacket top pocket	0.99051	-0.27129	0.84273
Handbag	0.95993	0.38927	0.90916

Table 4 Linear regression parameters and correlation coefficients (r^2) between accelerometer energy on waist versus other body locations in logarithmic scale.

Running

The running experiment was conducted with a subset (n=6) of the total subjects who were fit enough to perform this more strenuous exercise. At the end of the walking experiment, a preliminary experiment was conducted to test if a subject is fit enough for the running experiment.

As in the walking experiment, the waist accelerometer energy was compared with EPA. The results are shown in Figure 5 (next page). No correlation is observable between accelerometer energy and EPA.

Major reason for this bad correlation turned out to be the limitation of the iPhone accelerometer itself. The iPhone accelerometer (up to iPhone OS 3.1.2) is known to measure only up to $\pm 2.3G$. Figure 6 (next page) shows a sample of running signal from one axis, which clearly demonstrates this statement.

Discussion and Conclusions

This study investigated the potential of iPhone as a ubiquitous physical activity measurement device.

It developed calibration methods for accurate measurement of walking activity and identified limitations in measurement of running activity. Researchers and application developers can use the formulas and results of this study to develop sound 'Healthcare and Fitness' applications that will improve user experience. The ever expanding popularity of these applications and their tremendous outreach through the App Store distribution network, renders science efforts such as this one, not only technically but also socially valuable.

The work builds on preliminary research first presented by Fujiki et al. in [6], where calibration issues were investigated for a custom accelerometer device. The present effort investigates accelerometer calibration issues on the iPhone platform, which has a wide application base. Therefore, the impact of this effort is likely to be far greater.

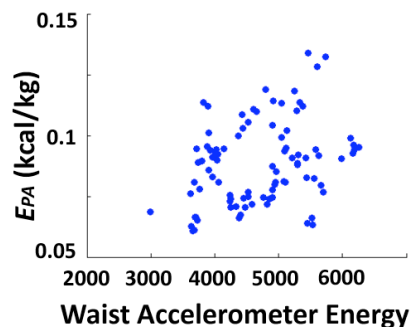


Figure 5 Scatter plot of accelerometer energy on waist versus EPA during running.

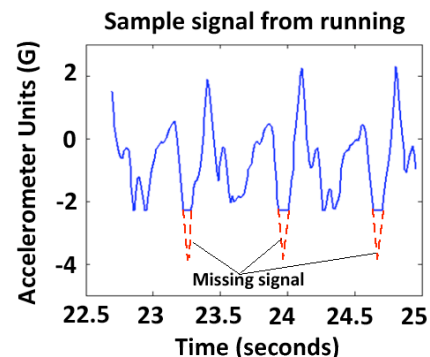


Figure 6 Sample running signal from one axis. Solid line represents measured signal and dashed line represents interpolated missing signal.

The study concluded that the iPhone accelerometer readings have the highest correlation with ground-truth physical activity measurements, when the phone is attached to the waist. This result is aligned with intuition, as waist is a locale very close to the body's center of mass. It is also in agreement with results reported in other studies of stand-alone accelerometers ([6], [9]). In a nutshell, if the user wears the iPhone on the waist, immediate translation of accelerometer values to metabolic values can be obtained through the regression outlined in equation 1.

Although the translation does not work as well for peripheral locations, the study developed a method to transform accelerometer readings from non-waist locations to equivalent waist locations. Once this is achieved, then one can safely correlate these virtual waist readings with physical activity values based on the regression of equation 1.

The experiment was limited on treadmill and free range walking is left as a future work. This very interesting topic was postponed this time since it requires a mobile indirect calorimetry device which we could not afford.

Last but not least, the study demonstrated some limitations in accurate measurement of physical activity during running, which are in part due to iPhone.

Acknowledgements

I appreciate Dr. Ioannis Pavlidis and Dr. Panagiotis Tsiamirtzis for consistent support and advice. I also acknowledge Dr. Tom Krouskop from NCHP for kind support.

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