Using Accelerometer Data to Estimate Surface Incline and Its Walking App Potential

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Abstract
Walking is a fundamental human activity and its diminution a potential morbidity factor. Recent developments in mobile computing have enabled ubiquitous monitoring of walking activity via the smartphone accelerometers. Typically, walking apps map accelerometer values to caloric values through calibration algorithms. However, these calibration algorithms assume a flat surface, which is not always true and can introduce significant errors. In this paper, we outline a novel calibration method that estimates surface inclination for uphill walking, thus, improving the caloric estimation in walking apps.

Author Keywords
Inclination measurement; energy expenditure; walking activity; walking activity monitoring; smartphone accelerometer; iPhone

ACM Classification Keywords
H.5.m [Information interfaces and presentation (e.g., HCI)]: Miscellaneous.

Introduction
Sedentary lifestyle is linked to the onset of chronic diseases such as diabetes and cardiovascular ailments [10]. One of the factors contributing to sedentary lifestyle is diminution

of walking. Walking is becoming less pervasive in our daily routine. Many walking monitoring apps are available to make the users aware about their walking behavior. Typically, these apps estimate energy expenditure by mapping the smartphone accelerometers' readings to caloric values [4][5][6][8]. The mapping assumes that the walking surface is leveled. This assumption is valid for walking scenarios in cities established in plain fields. However, for cities situated on hilly (e.g., San Francisco, CA) or mountainous grounds the mapping algorithm significantly underestimates the energy expenditure.

Table 1 demonstrates this limitation. It summarizes energy expenditure results of a pilot experiment that we conducted to study the mapping error in a walking monitoring app (iBurnCalorie). A participant was asked to walk on a treadmill at two different speeds (2 mph and 3 mph) and at four different surface inclines (0%, 10%, 20%, and 30%) for each speed. Each walking session was 3 min. Energy expenditure was measured through a respiration gas analyzer [1], a high-grade treadmill [3], and the iBurnCalorie app [4]. The respiration gas analyzer measures energy expenditure in Respiratory Exchange Ratio (RER) and is the gold standard for metabolic measurements. The results show strong agreement (correlation coefficient, $R = 0.95$) between the treadmill estimations and the RER values. This validates the treadmill's energy estimation.

The app's energy estimations for the 2 mph walking and 3 mph walking on the leveled surface (0% incline) are on par with the treadmill's estimations. However, estimation differences increase with the rise in surface incline. The culprit is the app's insensitivity to inclination changes.

Speed [mph]	Incline [%]	RGA [RER]	Treadmill [calories]	iBurnCalorie [calories]
2	0	12.427	11	9
	10	14.434	24	10
	20	14.528	39	9
	30	18.582	51	9
3	0	12.425	14	12
	10	12.988	30	12
	20	18.623	51	13
	30	21.663	67	13

Table 1: Energy expenditure of treadmill walking measured through a respiration gas analyzer (RGA), a treadmill, and a walking monitoring app (iBurnCalorie).

Kane *et. al.* investigated this issue for the Nike+ device [8]. They measured energy expenditure at 3 mph treadmill walking having surface incline of 0%, 5% and 10%. They reported that the Nike+ device was unable to detect increased energy expenditure for increased inclination.

An alternate approach is to extract elevation information from the web in real-time (e.g., Google Elevation). The major limitation of this approach is the gross spatial resolution. Google elevation offers an accuracy range of ± 30 m. Also, it allows only 2500 free URL calls per 24 hour period. Additionally, the URL calls consume the user's data plan. Therefore, the web-based approach does not appear to be a practical solution.

In this study, we propose a linear model to estimate surface incline from accelerometer readings. The computed surface incline is factored into the energy expenditure estimation as described in [9]. We simulated various uphill walking scenarios in a lab experiment to construct the model.

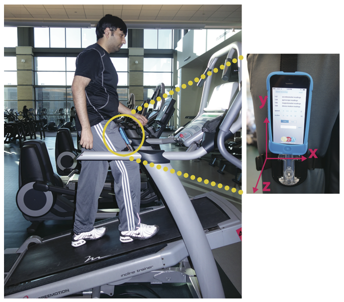

Figure 1: The experimental setup. The inset image shows the iPhone attachment.

Experimental Design

A total of $n = 9$ participants (4 normal weight, 4 overweight, and 1 obese) volunteered for the experiment. Their ages ranged between 23 and 34 years ($\mu \pm \sigma = 26.77 \pm 3.59$) and their Body Mass Index (BMI) ranged between 22 and 32 kg.m^{-2} ($\mu \pm \sigma = 25.95 \pm 3.30$). The experiment has been approved by the University of Houston Institutional Review Board.

Figure 1 shows the experimental setup. A treadmill's surface incline is measured as the percentage rise in height for every 100 m distance. Standard treadmills incline only by 15%. We used a high-end treadmill (*Incline Trainer* from FreeMotion) that inclines up to 30%. Each participant's body movement was recorded via the accelerometer embedded in the iPhone 5. The iPhone was attached to the participant's thigh location in a portrait orientation to minimize oscillation. The attachment was randomized between right thigh and left thigh to ensure unbiased data recording.

The experiment featured a warm-up session of 3 min followed by eight exercise sessions of 1.5 min each. Each walking session was followed by a 4 min relaxation period where participants rested in a comfortable chair. In the warm-up session, the participants walked on the treadmill at 3 mph with 0% surface incline. The exercise sessions included two different speeds (2 mph and 3 mph). For each speed, the participants walked at four different surface inclines: 0%, 10%, 20%, and 30% corresponding to 0^o, 5.74^o, 11.53^o, and 17.45^o elevation angles, respectively. We randomized the order of the exercise sessions for each participant to minimize confounding factors.

We recorded the accelerometer data during all the exercise sessions. Thus, we collected a total of 72 (9 participants x 8 recordings/participant) accelerometer signals in this study.

Data Analysis

From each accelerometer signal, we discarded the first and last 10 sec of the data. We took this precautionary step to exclude data collected during the transient period when the treadmill was gradually reaching its predefined speed and the participants were adjusting to their walking rhythm. The portrait orientation of the iPhone's attachment in the thigh position situated the accelerometer's Y-axis in the direction of the legs' motion and the other two axes (X-axis and Z-axis) orthogonal to the motion (see Figure 1). This arrangement mapped the vertical component of gravity acceleration to Y-axis, and its horizontal components to X-axis and Z-axis. Hence, the vertical component (Gravity Y) captured the maximum amount of motion. We, therefore, included in the statistical analysis the gravity readings from the Y-axis only. If the phone was placed in the landscape orientation, we would have used the X-axis gravity component. The phone orientation can be easily calculated via the smartphone's operating system (iOS in this case).

Figure 2 shows raw Gravity Y (GY) signals at different surface inclines. The signals were acquired from participant P2's walking sessions at 3 mph. The figure clearly illustrates that the GY signal's mean value (μ_{GY}) as well as its spread (σ_{GY}) are gradually increasing with the rise in the surface incline.

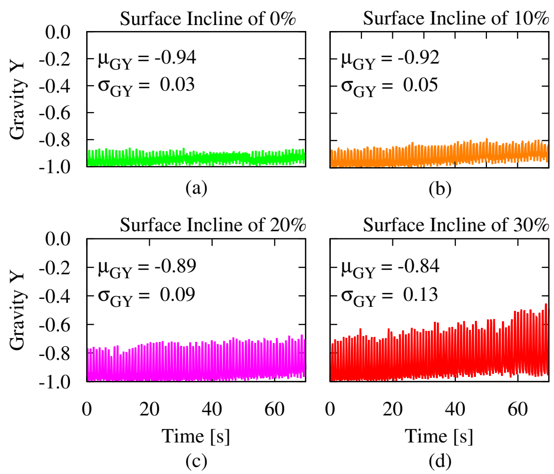

Figure 2: Y-axis Gravity values from participant P2's walking sessions at 3 mph for various surface inclines.

Linearity Tests

Figure 3 shows box-plots of the Gravity Y readings for all nine participants. Qualitatively speaking, the results confirm the gradual increasing trend of Gravity Y in both walking speeds for all nine participants. To validate the findings, we computed the correlation coefficient (R^2) between the mean Gravity Y (μ_{GY}) and surface incline. Specifically, we first computed the R^2 value per participant per speed. Then, we computed the mean (μ_R) of the R^2 values for each walking speed. The results are reported in Figure 4. Figure 4(a) illustrates strong linearity ($\mu_R = 0.96$) between the mean values (μ_{GY}) and the surface inclines for 2 mph walking. Figure 4(b) also indicates strong linearity ($\mu_R = 0.96$) between the mean values (μ_{GY}) and the surface inclines for 3 mph walking.

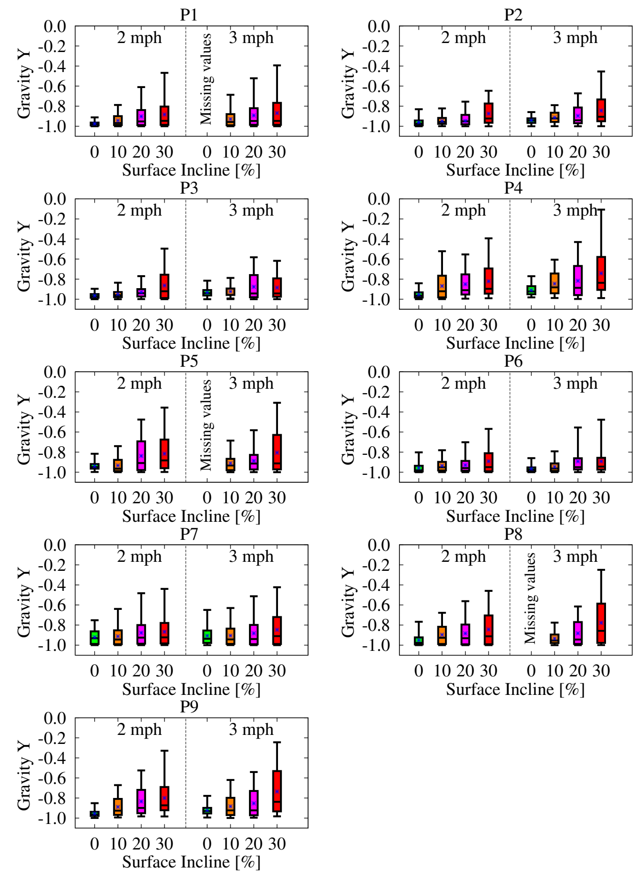

Figure 3: Box-plots of the Gravity Y readings for the entire dataset.

Significance Tests

Having established the linear relationship between Gravity Y and surface incline, we explored the specificity property of Gravity Y. In particular, we investigated if Gravity Y yields significant differences between two surface inclines

(10% resolution level). For each walking speed and pair of surface inclines, we performed a paired t-test on the corresponding μ_{GY} values. The test was run exhaustively on all surface incline pairs. Table 2 summarizes the test results (p values) for the 2 mph walking sessions. Table 3 summarizes the test results for the 3 mph walking sessions. The results show that all pairs have statistically significant differences ($p < 0.05$).

Surface Incline	0%	10%	20%
0%	-	-	-
10%	0.0080	-	-
20%	0.0023	0.004	-
30%	0.0001	0.0000	0.0006

Table 2: Paired t-test results (p values) for the 2 mph walking sessions. $n = 9$ for all the tests.

Surface Incline	0%	10%	20%
0%	-	-	-
10%	0.0311	-	-
20%	0.0003	0.0000	-
30%	0.0008	0.0001	0.0130

Table 3: Paired t-test results (p values) for the 3 mph walking sessions. $n = 9$ for all the tests except for the 0%-10% pair for which $n = 6$.

Linear Modelling

We modelled the bivariate relationship via least-squares linear regression. Figure 4(a) illustrates strong linear fit ($R^2 = 0.99$) for the 2 mph walking scenarios.

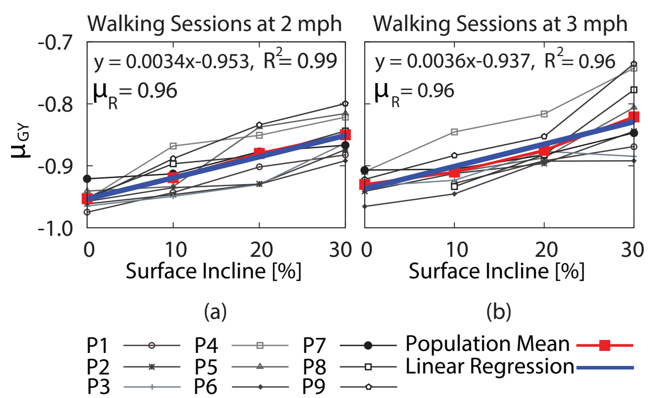

Figure 4: Means of Gravity Y per surface incline for all nine participants walking at (a) 2 mph and (b) 3 mph.

Figure 4(b) illustrates strong linear fit ($R^2 = 0.96$) for the 3 mph walking scenarios. The regression equations shown in the figure map Gravity Y to surface incline.

Once the surface incline is estimated from the statistical model, its value is factored in the following equation to estimate the metabolic consumption of walking [9]:

$$VO_2 = 3.5 + 0.1(speed) + 1.8(speed)(incline). \qquad (1)$$

The speed parameter of this equation can be estimated from the accelerometer [7]. Finally, the metabolic estimation (VO_2) is mapped to caloric consumption via the following equation [2]:

$$E = (VO_2 - BMR) * 5/(Body\_Mass). \qquad (2)$$

BMR in Equation (2) is the basal metabolic rate.

Conclusion and Discussion

In this paper we present an innovative approach for estimating surface inclination via a smartphone's accelerometer. Specifically, we show that the accelerometer's gravity component linearly correlates with the surface incline. Furthermore, we outline a calibration method that incorporates incline estimation to caloric mapping algorithms, thus, improving caloric estimation in walking apps. Although we used the iPhone platform in this study, the proposed method is generic and can apply to any smartphone platform.

Admittedly, the thigh location is not the most convenient site for smartphone attachment. The reason for selecting the thigh location is because it gives the best results due to walking kinematics. Currently, we are collecting data for other body positions. In particular, the arm location has favorable kinematics and may produce comparable results, while it is more user-friendly.

This feasibility investigation is limited to uphill walking only. In the near future we plan to expand the investigation to a full-scale study that will include a larger participant pool, and a full range of walking speeds (2 mph, 2.5 mph, 3 mph, 3.5 mph) for both uphill and downhill walking.

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