## Making Sense of Accelerometer Measurements in Pervasive Physical Activity Applications

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#### Abstract

In the last few years, accelerometer-based entertainment and health applications have been receiving increased attention in the research and commercial worlds. The effect of accelerometer placement on different parts of the body, despite its apparent significance, received little consideration. This paper documents through experimentation the different characteristics of accelerometer output on the waist, arm, wrist, thigh, and ankle in the context of translational body motion (walk). Furthermore, it offers experimental formulas that transform peripheral body measurements to more reliable, center body (i.e., waist) measurements, and these in turn to caloric measurements, which are the standard physical activity units. The importance of these results on the design of ubiquitous health applications and the ensuing user experiences cannot be underestimated. The paper's methodology can be used in further studies in other physical activity contexts, where more elaborate body motion patterns are involved.

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## **Author Keywords**

Ubiquitous health applications, Physical activity interfaces, Accelerometer placement

## ACM Classification Keywords

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

#### **Introduction and Previous Work**

Accelerometer-based pervasive applications including health games and physical activity trackers are gaining popularity. Fujiki et al. [4][5] developed NEAT-o-Games, where the players' physical activity "fuels" running avatars in a virtual race that is taking place over the cellular network throughout the day. Consolvo et al. [3] developed an entertainment application in which the cell phone's wall paper design changes based on the user's accelerometer values. Vito [9] tried to increase the user's activity levels by disabling the TV remote until enough activity points have been recorded through the accelerometers. Nowadays, a search in the App Store under the `Healthcare and Fitness' category can reveal dozens of ubiquitous applications that aim to keep track of daily physical activity.

The problem with almost all these applications is that they do not take into account the dramatic effect the accelerometer placement has on the measurement. Fujiki et al. [5] have shown that different users prefer to attach the accelerometers in different parts of their bodies in physical activity games that involve walking. The question is how different positions affect the accelerometer output and bias these games or other ubiquitous physical activity applications. Such bias should be taken into account in application design to enhance the user's experience.

Furthermore, accelerometers give indirect and sometimes misleading indications of physical activity intensity. Unfortunately, many applications report only raw accelerometer values or simple derivatives, like steps, for what is in essence a metabolic activity measurement. But, a step taken from a 150 lb individual is vey different from the step taken by a 250 lb individual, as different mass is carried around. For this and other reasons, the gold standard for reporting physical activity is metabolic units (i.e., Kcal) measured through a gas analyzer.

Therefore, variability from different body placements is compounded with inherent inaccuracy of the accelerometric measurement space to ruin user experiences in pervasive physical activity interfaces. Thus, a way has to be found not only to reconcile accelerometer measurements from different parts of the body, but also to transform these measurements to metabolic units.

Please note that this is a different problem from the automatic identification of accelerometer placement and activity classification [7][8]. In fact, automatic identification of accelerometer placement and activity classification could be considered as complimentary to the work reported here.

## Methodology

#### Accelerometer

A custom accelerometer system, built in the University of Houston's Computational Physiology Lab, was used for the experiments. The system's sensing device is the Hitachi H48C Tri-Axial Accelerometer Module; its output is processed by Parallax P8X32A-M44 MCU and sent to the data logger (cell phone and/or computer) via Blue Radio C40AH Bluetooth module. The H48C accelerometer is a mainstream piezo-resistive type with a small scale factor. The sampling rate of the (a)



(b)



Figure 1. (a) Conceptual figure of experimental setup. (b) A snapshot of the actual experimental set-up.

Physical Attribute	Statistics (n=10)	
Age(years)	$\mu = 27, \sigma = 4.80$	
BMI (kg/m <sup>2</sup> )	$\mu = 25.22, \sigma = 3.45$	

Table 1. Descriptive statistics of the participating subjects

accelerometer is 55 Hz, which is more than adequate for recording human physical activity. The minimum frequency bound reported in the literature is 25 Hz [1]. In the last few months, with the spread of 3G cell phones that feature embedded tri-axial accelerometers (e.g., iPhone), such custom accelerometers are not necessary anymore. But, the result for the purpose of this paper is all the same.

#### Experimental Setup

The experimental setup included 5 custom accelerometers (see description above) and a Proform 400T treadmill, as well as an ADInstruments ML206 Gas Analyzer. The accelerometers were attached to each subject on the following body positions: wrist, upper arm, waist, thigh, and ankle. The accelerometer data were logged to a computer via Bluetooth for postprocessing. Each subject also wore a gas mask, which was connected to the gas analyzer. The ADInstruments Gas Analyzer calculates the volume of  $O_2$  burnt inside the body  $(VO_2)$ , which is widely known to be proportional to caloric expenditure [6]. First, the subject sat on a chair and relaxed for 5 min while his/her baseline metabolic rate  $(VO_2)$  was measured. Then, the subject was asked to walk on a treadmill at 8 different speeds from 1 - 4.5 mph. The speed was incremented by 0.5 mph, and each speed level was maintained for 4 min. No inclination was employed (Figure 1).

Ten healthy adults (8 males, 2 females) were recruited for the experiments. All subjects, except for one, repeated the experiment on a different day (a week to two weeks later). The exception was a subject who moved out of town, and thus, could not participate in the repeat session. Some descriptive statistics of the participating subjects can be found in Table 1.

#### Post Processing

The collected data were high-pass filtered. High-pass filtering is essential to acquire the true activity component from the piezo-resistive accelerometer, as its output includes a DC component (due to gravity) by default. Next, the time integral of the accelerometer output from the three measurement axes was calculated using the following formula [2]:

$$IA_{tot} = \frac{1}{T} \int_{t_0}^{t_0 + T} \left( \left| a_x \right| + \left| a_y \right| + \left| a_z \right| \right) dt, \quad (1.1)$$

where *ax*, *ay*, and *az* are high-pass filtered accelerometer values corresponding to the *x*, *y*, and *z* axes. The interval of integration (*T*) is 30 sec. The unit of *IAtot* is *milli-g*, which corresponds to one thousandth of the gravitational acceleration of the earth.

## **Experimental Results**

#### Relation between IAtot and VO2

Figure 2 shows the scatter plots of waist accelerometer output calculated via (1.1) and the corresponding normalized metabolic ( $||VO_2||$ ) measurements. The

latter are computed by subtracting the resting from the exercise  $VO_2$  measurements and dividing the difference by the subject's weight. Please note that Kcal can be computed by multiplying the normalized metabolic values by the factor 5 [6]. There is high linear correlation ( $r^2=0.7515$ ) between the two variables. Linear regression analysis yields formula (1.2), in which *IAtot (waist)* is calculated via formula (1.1).

 $||VO_2|| = (3.7408 \times IA_{tot}(waist) - 2.4918) \times 10^{-5}$  (1.2)



Figure 2. Relation between *IAtot* on the waist and normalized metabolic activity. The pink line is produced by ordinary least squares regression analysis.

## Thus, for an accelerometer worn on the waist, it is possible to calculate accurate metabolic expenditure by using linear equation (1.2). However, numbers on other body locations are not as promising as the waist's. Figure 3 shows scatter plots on different body locations (i.e., wrist, arm, waist and thigh). Thigh and ankle plots show degrading linear relationship, with correlations worse than waist's ( $r^2$ =0.6649 and $r^2$ =0.7002 respectively). Wrist and arm show nonlinear relationships ( $r^2$ =0.3434 and $r^2$ =0.4968 respectively). These results indicate that the waist is the best location to measure metabolic consumption.



Accelerometer output

# Figure 3. Relation between *IAtot* and normalized metabolic activity on various body locations ((a):wrist (b):arm (c):thigh (d):ankle).

#### IAtot on different body locations

Figure 4 shows a box-plot graph of *IAtot* for different body positions. The figure illustrates that there is a distinct trend in the distribution of accelerometer responses on different body locations while people are walking. The ordering (from lower to higher) is: wrist, arm, waist, thigh, and ankle. To illustrate the importance of the point, consider the following specific example from the experimental data: The average response from the wrist, when fast walking at 4.0 miles/hour is 609.49, whereas the average response from the ankle, when slow walking at 2.0 miles/hour is 727.30. In other words, when a subject wears the sensor at the ankle and walks at 2.0 miles/hour, the system erroneously shows that he/she is more active than a person who wears the sensor on the wrist and runs at 4.0 miles/hour. This can be interpreted from the kinematics point of view as follows: Both thigh and ankle are affected by complex rotational components along with shock from the ground, which result into big accelerometer responses. By contrast, arm and wrist have small rotational components while walking, and the shock from the ground does not reach these upper parts of the body, thus resulting into small accelerometer responses.

Figure 5 shows the bi-variate response relationship between the waist (x-axis) and the remaining four locations. The waist was chosen to be the basis, because as demonstrated earlier, the waist is the best position for metabolic consumption measurements. All scatter plots show moderate linear relationships. Furthermore, one can observe that the response variability is increasing from lower to higher speeds, indicating heteroscedasticity. This prevents the application of ordinary least squares (OLS) regression.



Figure 4. Box-plot of *IAtot* for different locations. Red points are outliers. The ordering of the distributions is clearly from wrist to ankle (lower to higher).

Body Position	Parameters of fitted line (y = ax +b)	$r^{2}$
Wrist	a = 0.71, b = 1.32	0.64
Arm	a = 0.75, b = 1.17	0.84
Thigh	a = 0.99, b = 0.61	0.94
Ankle	a = 0.90, b = 1.36	0.90

Table 2. Linear regression parameters and their corresponding  $r^2$ 



Figure 5. Scatter plots of *IAtot* between peripheral body locations and waist. Moderate linear relationship is present in all graphs and variability is increasing along with speed.

To deal with this issue, the authors transformed the data by taking the natural logarithm of *IAtot* and applying weighted least-squares regression. The inverse of the speed was taken as the weight to account for the non-constant variance, which is analogous to speed. Figure 6 shows the resulting scatter plots and regression lines. All four graphs now reveal strong linear relations. Note also that the residuals are small and almost constant over the entire data range. These linear relations can be used to "correct" responses from different body positions to produce a unified range of output. Parameters of the regression lines are shown in Table 2.  $r^2$  values indicate we got reliable regression lines for all positions. Using

Log scatter plots of accelerometer output (milli-g) on different locations



Figure 6. Scatter plots of *ln(IAtot)* between peripheral body locations and waist. Green lines are regression lines produced by weighted least-square regression analysis.

Table 2, accelerometer responses from peripheral body positions can be transformed to equivalent waist responses. Then, using formula (1.2), they can be transformed to metabolic rate values.

## Conclusions

The paper demonstrates the dramatic difference that accelerometer placement can have on the measurements used in ubiquitous entertainment and health applications. Ignoring these factors will result in faulty interfaces, responsible for unfair physical activity gaming or erroneous physical activity recording. Most importantly, the paper offers transformation formulas that can reduce accelerometer measurements from various peripheral body positions to equivalent waist positions. The waist position is the one that best correlates to metabolic rate consumption, as it is in the center of the body, shielded from shock from the ground, and featuring only a translational component. Finally, the paper offers a formula that can transform the equivalent waist measurements to normalized metabolic measurements, which are the proper units for physical activity reporting.

The paper comes to fill an important gap in the current literature and practice at the moment that ubiquitous physical activity applications proliferate. The current state of affairs ranges from oblivion to half-baked solutions in a multi-step problem. An example of the latter is transformation of the accelerometer values to metabolic values based on heuristic tables and without consideration of the accelerometer's position.

The paper reports results for walking, which is the most common daily physical activity. The same methodology can be used to produce formulas for other physical activities, like stair climbing. The methodology uses accelerometers attached at various parts of the body, where cell phones are usually tacked, to generate measurements for a range of intensities precisely produced by a relevant exercise machine. To ensure statistical significance, these measurements are produced for various subjects and in repeat sessions. The data are statistically analyzed and modeled and experimental formulas are extracted that can be incorporated in ubiquitous interfaces. These formulas, when supported by automatic activity classification and sensor placement algorithms reported elsewhere, can form a complete and reliable physical activity interface.

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