Optimization of accelerometers for measuring walking

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Abstract

Background: The devastating impact of obesity on global health is without question and it is generally agreed that low levels of physical activity, particularly sitting (i.e.; sedentariness) are important in its pathogenesis. Therefore, the measure of physical activity such as walking is vital to its use in the research and clinical milieu.

Methods: This study investigated three accelerometry parameters (sampling rate, range and data depth) on ten healthy subjects (BMI 18-31 kg/m^2) walking on a calibrated treadmill at 8 speeds (0, 0.95, 1.74, 2.48, 3.22, 4.04, 4.83, and 5.70 km/h) while wearing a three-axis accelerometer on the thigh (Crossbow Technology, San Jose, CA) in order to find an optimal system for the determination of walking speed as well as a new data analysis strategy using a differentiation of the acceleration values (jerk). Twenty-four sampling rates (2 to 25 Hz in 1 Hz intervals) and seven acceleration ranges (± 1 *g* to ± 2.5 *g* at 0.25 *g* intervals) were used to create a 24 X 7 factorial design. Data was also truncated from 2 to 7 digits in the mantissa. **Results:** This study found that although there is an improvement in walking speed prediction when sampling rate was set above 4 Hz ($P<0.0002$), there was no further improvement when the sampling rate is set higher. This study found that there is an increase in walking speed prediction accuracy when the range of acceleration is limited to ± 1 *g* ($P<0.0024$ for ± 2 *g* v. ± 1*g*). This study found that increasing or decreasing data depth has no impact on walking speed prediction accuracy. Further, this study found that a model based on jerk was accurate at predicting walking speeds ($r^2 > 0.9$ for all comparisons). **Conclusion:** For measuring walking using a sensor on the thigh, there is no significant improvement gained by large sampling rates, data ranges, or data precision. A model based on the time rate of change of acceleration is a valid analysis tool for measuring walking.

Keywords:

walking, sampling rate, data range, jerk

I. Introduction

Obesity is epidemic worldwide, with developing nations approaching rates of obesity that are comparable to the developed countries (1). The devastating impact of obesity on global health is without question (2-4) and it is generally agreed that low levels of physical activity, particularly sitting (i.e.; sedentariness) are important in its pathogenesis (5-7). A major target for the prevention and treatment of obesity is the promotion of physical activity (8). Thus, devising effective tools to measure physical activity could be useful in combating sedentariness. Many systems have been designed to examine activity but rely on complex analysis systems or proprietary hardware or software. Even the use of commercial pedometers, which are cheap and easy to use, falls off because of their poor accuracy and precision (9). Measuring and changing the level of physical activity (in this case, walking) in a wide range of settings demands a valid, reproducible, and accurate measurement system that is simple enough to implement in settings that lack sophisticated analysis capabilities. We are therefore seeking to optimize the relationship between the accurate determination of walking speed versus the quality and quantity of data used in the determination.

Accelerometers are among the most widely used instruments in the measurement of physical activity. When combined with a unit that captures the data from the accelerometer (onboard, wired, or wire-free), they form a sensor system. The three important parameters of a sensor system are: 1) Sampling rate, which is the rate at which samples are culled from the sensor, measured in samples per second, or hertz (Hz) 2) System range, which is the measurable range of data collection, measured in acceleration units, such as m/s^2, *g*'s ($9.8\ m/s^2$). 3) Data depth, which is the resolution of the acceleration, measured in terms of data size, such as the number of bits required to hold the data or the number of significant digits in the mantissa. In a broad sense, the choice of values for these parameters is driven by the application. In applications involving the forces applied to a body part during normal or abnormal movement, system range and sampling rate may need to be very high in order to capture a large acceleration and the exact duration the acceleration is applied. This study was conceived in order to address the use of accelerometers to accurately detect walking speed, where accelerations and the frequency of periodic movements are much smaller. We wished to resolve the disputes regarding the contribution of different parameter settings to the quality of the data measurement (8).

In order to better define accelerometer settings for measuring human activity, this study examined four hypotheses: 1) Changing sampling rate will change walking speed prediction accuracy. 2) Changing data range will change walking speed prediction accuracy. 3) Changing data depth will change walking speed prediction accuracy. This study also tested a new model for data processing based on the rate of change of acceleration (Jerk, $\mathbf{j}(t)$), with the hypothesis that 4) A model based on jerk can accurately predict walking speeds.

II. Materials and methods

A. Subjects

Upon arrival to the laboratory ten healthy adults of varying weight (54-92 kg, average ± S.D. = 65 ± 13.5 kg), height (1.58-1.83 m, average ± S.D.= 1.69 ± .075 m), *BMI* (18.1-31.4 kg/m^2, average ± S.D. = 22.8 ± 4.2 kg/m^2), and age (average ± S.D.

=33.2 ± 10.8) were oriented to the study and provided informed verbal consent, which was documented, procedures were then demonstrated and tested with the subject. The study was approved by the Mayo Clinic Institutional Review Board.

On the day of the study subjects were weighed and measured for height (Seca Model 644 Digital Hand Rail Scale, Seca Model 242 Electronic Measuring Rod Stadiometer, Seca Corporation, Hanover, MD). The laboratory is temperature controlled and silent. Subjects were maintained in thermal comfort (20-23 °C) throughout the study.

B. Materials:

A triaxial accelerometer (Part # CXL02LF3, Crossbow, San Jose, CA) was attached to tight-fitting Lycra® shorts over the radial aspect of the right thigh 7 cm above the level of the proximal tip of the patella of each subject with duct tape, tested for proper function and attached to a ReadyDAQ data logger (Model # AD2000, Crossbow, San Jose CA) set to monitor at SR=50 Hz. Accelerometer has a nominal range of K=2 *g* and an actual range of K=2.5 *g*. The nominal bandwidth of the sensor is published as SR=50 Hz.

C. Experimental Methods:

Subjects stood still and walked at seven speeds on a calibrated treadmill (treadmill settings of 0, 0.5, 1.0, 1.5, 2.0, 2.5, 3.0 and 3.5 mph, actual calibrated speeds were 0, 0.95, 1.74, 2.48, 3.22, 4.04, 4.83, and 5.70 km/h) for two minutes at each speed plus 5 seconds between each speed to change speeds (Q3000 treadmill, Quinton, Seattle, WA, calibrated before and after the study with no difference in calibrated speed over time). The subjects walked continuously for 20 minutes. The subject was permitted to stop if desired, but none of the subjects stopped during the test.

Accelerometry data were collected and then processed using custom-designed scripts in MATLAB (Mathworks, Natick, MA) as well as custom designed programs in VisualStudio 6.0 and VisualStudio.NET (Microsoft, Seattle, WA). Statistical analysis was performed using the aforementioned programs as well as StatView 5.0 (SAS Institute Inc., Cary, NC) and Excel (Microsoft, Seattle, WA).

D. Analysis and Statistical Methods

In examining accelerometer output the rate of change of acceleration with respect to time, known as "jolt", or "jerk", **j**(t), a widely used engineering concept, was calculated. Examples of jerk include specifications for mass transit systems that specify maximum allowable jerk that may be experienced by a rider (ranging from 0.5 to 2.0 m/s^3) and military electronic systems (such as GPS receivers) that carry a maximum allowed jerk specification (usually 20 m/s^3). Jerk is defined as:

$$\frac{d\mathbf{a}}{dt} \equiv \mathbf{j}(t)$$

Jerk d**a**/dt was approximated by finding the sign-corrected Δa/Δt for each axis and then the area under the curve of **j**(t) was found to find the total acceleration over an arbitrary time interval (5 seconds in our case) through each axis. The vector resultant was calculated.

Accelerometry data was gathered at SR=50 Hz, K=2.5 *g*. Since the logger collected an instantaneous acceleration for each sample, the data were resampled to provide sampling rates of SR = 2, 3, 4 . . . 25 Hz using interpolation to find intermediate points when the sampling rate was not a factor of 50. Since the accelerometer showed a value at its extreme range when sensing an acceleration value greater than +/- 2.50 g, cut-off values less than +/- 2.50 g were simulated by replacing values greater than the simulated K with the appropriately signed value of K. Cut-off points at K=1.00, 1.25, 1.50, 1.75, 2.00, 2.25, and 2.50 *g*'s were simulated, which provided a 24 X 7 factorial design. Finally, data were truncated to reduce precision from the 7 digit mantissa provided by our system to 2, 3, 4, 5, and 6 digit mantissas. To approximate the rate of change of acceleration with respect to time, the difference between each datum and the previous point (the delta) was found, divided by the change in time (delta *t*) and sign-corrected for each of the 168 data sets. Eighty contiguous seconds were selected from each speed, and the data from each axis were summated over 10 seconds and the vector resultant of the summed axes was calculated to provide a comparable value for each sampling rate. The first and last ten-second sections were discarded, leaving a 6-interval (or 60 second) sample for each speed.

Regressions of pooled data were carried out using a random sampling method (with replacement) among the ten subjects. A multiple regression with acceleration and height was calculated using all of the subjects. Single-subject regressions were carried out using the averages of the intervals. Regressions were tested using closeness of fit metrics (r^2) as well as an error prediction scheme where the regression was used to recalculate speeds from the accelerations and the average absolute errors (from the actual speeds). Since a regression of percent error in speed versus speed showed an effect due to speed (data not shown), absolute error (which eliminated the effect) was used. Bland-Altman plots and residual plots of the regressions were generated. ANOVA with Bonferroni correction of P-values were used to compare groups of measures. Measurements of univariate data are recorded as mean ± standard error of the mean (SEM) unless otherwise stated and regression data makes use of the standard error of the estimate (SEE). Statistical significance is defined at $P < 0.05$ unless otherwise stated.

III. Results

To address the first hypothesis that changing the sampling rate changes data quality, the study showed through the factorial regression that increasing the sampling rate from 2-3 Hz did improve the prediction of walking speed, but there is very little improvement past 5 Hz. The low sampling rates were significantly lower than all other comparisons and were significantly different from each other, even using a Bonferroni correction defining significance at $P < 0.0002$ (figure 1).

To address the second hypothesis, the study showed that there was a difference in speed prediction accuracy with respect to dynamic range, but not in the direction expected as a lower dynamic range seemed to give a better fit. Measured at a cut-off of $K=1$ *g*, the fit was qualitatively better than higher ranges, becoming significant (with Bonferroni correction defining significance at $P < 0.0024$) vs. $K= 2$ *g*. $K = 2$ *g* appeared to be the significance cut-off for the other lower cut-off values (figure 1).

In order to further test hypothoses one and two, an error analysis was conducted at all sampling rates and all cut-off values. There were no significant differences in errors from both pooled and subject-specific regression with respect to cut-off values, but there were significant differences between most of the different sampling rates, probably due to increasing signal complexity. The same held true for the variances of the measures. The total average error of the predicted speed of the regressions vs. actual speeds is 0.225 ± 1.77×10^{-3} mph for the pooled regression (with an SEE = 0.248) and 0.145 ± 0.874×10^{-4} mph for the subject-specific regressions (SEE = 0.160). There were no significant differences for the varied cut-off values, but there was an effect due to sampling rate where an increased sampling rate decreased the error (figure 2).

To address hypothesis three the error analysis was conducted across the range of data depth, from 2 to 7 digits in the mantissa. The error analysis showed that there was no significant difference between the errors of speed prediction from the lowest to the highest depth (figure 3).

To address the fourth hypothesis the regression of the acceleration against the walking speed was examined. The model based on jerk appears to be robust. The correlations for all of the data are very high, $r^2 > 0.9$ for all comparisons (Figures 1, 2, and 3). In addition, the Bland-Altman and residual plots demonstrate a lack of bias in the regression (Figure 4). There were differences in the slope and intercept of the linear model with respect to sampling rate (data not shown).

IV. Discussion

Although a major factor in the fight against obesity, physical activity also ameliorates the course of many other diseases, including heart and other cardiovascular disease, diabetes, osteoporosis, mental disorders. Expert committees and government bodies have recently emphasized the importance of increasing physical activity, with or without weight loss (11). The largest hurdle in advancing understanding with respect to physical activity is the lack of adequate measurement tools. In the last 5 years there has been a huge increase in the application of accelerometers, but some questions are unresolved concerning their use and interpretation. Both in the literature and in the context of this laboratory's experiments, there is a lack of consensus regarding parameters of accelerometry, such as the sampling rate and the dynamic range of the sensor (1,12,13,14,15,16,17,18).

Most accelerometer systems are made up of two components: a solid-state device that measures acceleration by detecting the deformation or movement of components (sensing elements) under strain and a unit for recording the output. The output is a continuous analog signal (usually voltage) that is linearly proportional to the acceleration "felt" by the sensor. Accelerometers can measure along one, two, or three orthogonal axes (1,13). Recently another type of accelerometer, known as an omnidirectional accelerometer consisting of a cantilevered silicon chip has been investigated that measures two axes at once. The recording, or logging unit is either physically attached to the accelerometer or linked by wired or wireless connections.

The **sampling rate** of the system is the rate at which data is gathered from the sensor, measured in samples per second or hertz (Hz). In most cases it is set by the data acquisition device, but there is a limit imposed by the bandwidth of the sensor, usually between 50 and 2500 Hz (19,20,21,22). In terms of data accuracy and precision, an increase in sampling rate makes it possible to capture movements of very short duration but also tends to capture sensor placement or mounting artifacts, decreasing the signal-to-noise ratio (Figure 5). Sampling rate also has a powerful effect on the comparability of the data, since the increased complexity of the signal will make data collected from different sampling rates inconsistent. This study's findings demonstrate that for predicting walking speed, sampling rates equal to or greater than 5 Hz produce good accuracy.

The **dynamic range** of the system is the range of accelerations that the sensor will collect, measured in acceleration units. The range can either be designed into the sensor or the sensor can be wired to give different ranges (19,20,21,22). Accelerometers can be chosen to measure any acceleration range, but the literature generally show ranges up to ± 10 *g* (12,13,14,15,16,17,19,20,21,22). An acceleration value that falls outside a sensor's range will saturate the sensor, causing it to report the value at the limit of its range. This study's results show that there is actually an improvement in predicting walking speed with a smaller range over a larger range (23), although this is specific for the system we measured, with a sensor at the thigh.

The **depth of the data** is reflected by the number of significant figures (or bytes of storage) a measurement has and directly impacts the amount of memory required to record the data. Since most accelerometers are analog and can theoretically measure continuous (rather than discrete) values of acceleration, the data depth is generally determined by the analog-to-digital converter in the data acquisition device. The resolution of a system, is directly proportional to the data depth and inversely proportional to its range, and is a measure of the ability to measure small variations in acceleration. Consideration of range and data depth should drive sensor selection and configuration. In predicting walking speed, this study found that data depth was not a significant constraint in our analysis system (23).

While opinions hold that in terms of the sampling rate and the dynamic range, when measuring physical activity, "bigger is better" (from 32 Hz to >250 Hz and > ± 6 *g*) (14,15,16), other studies have shown that sensors also perform well when limited to ± 2 g and 0.25 to 2 Hz (12,13,17). The sensor choice and configuration should rely on a careful optimization of the system to fit the needs of the study. For example, a feasible system for designed to capture all gross movement during walking might be a triaxial accelerometer set to record at 200 Hz and cover a range of ± 10*g*, with a resolution on the order of 0.1 mm/s². Such a system would generate 100 MB per day without recording other streams such as temperature or system voltage. With six sensor systems per subject, 25 subjects monitored 24 hours a day for 20 days (a very common study situation in this lab), a study would require ~290 GB of storage space for raw data and a large amount of computing time to analyze the data. These demands would be significantly lessened by recording at 10 Hz, at ± 2*g*, with a resolution of 156 mm/s². This would require 7 GB of storage per day and also proportionally lower the amount of computer time for analysis (23).

One of the problems with accelerometry is that it is not possible, looking at acceleration, to determine the difference between the acceleration due to gravity and the acceleration due to movement. Another problem is that unless a specific orientation test is conducted at the outset of the experiment and the sensor is considered never to move, initial conditions are impossible to measure. The method in this study used the sign-corrected rate of change of acceleration to provide a value that can be summated over a time interval to give the magnitude of acceleration (1). Since the data were sign-corrected differences, the use of offsets in the calibration and sensor axis orientation could be ignored, and the acceleration values due to position were eliminated.

This analysis system has the advantage of simplicity and can be carried out using a simple spreadsheet without resorting to signal processing algorithms. This enables the user to replicate data from other labs using the same system if accurate accelerometers measuring in g's are used. The disadvantage of this system is that it does not capture the direction of movement and therefore relies more on an empirical model that relates a certain amount of acceleration to a certain amount of speed. This factor means that the acceleration determined by the method is similar in concept to acceleration “counts” used by other systems, but in this case the units are clearly defined and not dependent on the equipment used to measure acceleration.

A limitation of the system was the fact that the slope and intercept of the linear model change with a change in the parameters. This means that data from different groups must be collected using the same parameters in order to be directly compared. Another limitation is that a subject-specific model is the best model, which means for best predictions a calibration treadmill test should be performed for each subject.

There were limitations to this experiment. The complexity of the human gait demands an extremely high performance sensor system to effectively analyze the minutiae of movement in every step, and even at its maximum performance the sensor used did not approach this level of quality (8,10,14). Physical activity monitoring does not require this amount of detail (15,16,17). The ability to detect levels of movement and correlate this movement to a level of activity (and energy expenditure) is the paramount concern in physical activity monitoring. This study was only concerned with measuring walking speed, which is only one facet of physical activity. When measuring non-exercise activity thermogenesis (NEAT), activity that occurs while standing appears to be a critical component (24), and this activity in most circumstances would be either standing still or walking. This study used intervals of homogenous exercise measured at the thigh at discrete speeds on a flat grade under the controlled conditions in this laboratory. This study also relied on an exacting placement of the sensor, and a significant limitation of limiting the dynamic range of the sensor is that it reduces or eliminates the ability to transform the data to correct for small errors in sensor placement. Even with these constraints, these results can be most likely applied to free-living subjects. The use of an 8-bit system (on the order of 2 significant digits in the mantissa) with limited dynamic range will provide valuable clues and will require half the data storage requirement of the laboratory's current 16-bit (on the order of 4 significant digits in the mantissa) system while providing the same quality. Finally, since the leg moves in most activities that are correlated with high-energy expenditure, a sensor on the leg seems to be adequate for the determination and allocation of activity as well as giving posture data.

The aim of this study was to challenge some of the conventional wisdom that addresses accelerometry in measuring physical activity. Through factorial testing the study concluded that for measuring walking speed, sampling rates at 4-5 Hz and above, data ranges at or smaller than 1 *g*, and data depth of 1 byte provide sufficient data quality to ascertain walking speeds in human subjects. Increasing the parameter (higher sampling rate, larger data range, greater depth) past a certain threshold had no effect or was even potentially detrimental in terms of data quality and was not worth the added expense in data storage or processing time.

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Captions for figures:

Figure 1: Goodness of Fit: Effects of Sampling Rate and Cut-Off. Output of regression fit quality (R^2) using a random sampling (with replacement) predicting a walking speed vs. actual walking speed.

Figure 2: Magnitudes of Error and Variance by Sampling Rate and Sensor Cut-Off for General and Subject-Specific Models. Outputs of two models (general and subject-specific) are shown with the average absolute error and variance over all speeds.

Figure 3: Magnitude of Error of Specific Model by Data Depth. Average absolute error of specific model prediction vs. the actual speed ± S.E.M. measured across data depth from 2 to 7 significant digits in the mantissa.

Figure 4: Standardized Residual and Bland-Altman Plots of Model-Predicted vs. Actual Speeds. Z-scores of the residuals are plotted against the acceleration in the residual plots and the differences in predicted vs. actual speeds are plotted against the average of the predicted and the actual speeds in the Bland-Altman plots. The dotted lines show the 95% confidence intervals in all plots. The general model uses a multiple regression of height and acceleration vs. speed for all subjects, and the subject-specific model uses a simple regression of acceleration vs. speed for each subject.

Figure 5: Complexity of Signal with 6 Sampling Rates. Output from the same time interval of a three-axis accelerometer worn at the leg while walking at 2 mph measured at 100 Hz, 50 Hz, 25 Hz, 10 Hz, 5 Hz, and 2Hz.

List of notation:

a = acceleration vector, in m/s^2

ANOVA = analysis of variance

A.U. = arbitrary acceleration unit

BMI = Body Mass Index = mass/height^2, in kg/m^2

g = 9.8 m/s^2

GB = gigabyte

j = jerk vector, in m/s^3

K = data range, in *g*

MB = megabyte

r = correlation coefficient

S.E.E. = standard error of the estimate

S.E.M. = standard error of the mean

SR = sampling rate, in Hz

t = time, in seconds

Δ = change