DISSERTATION

PHYSICAL ACTIVITY: IMPROVING ASSESSMENT TOOLS AND BEHAVIOR IN CHILDREN

Submitted by

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ABSTRACT

PHYSICAL ACTIVITY: IMPROVING ASSESSMENT TOOLS AND BEHAVIOR IN CHILDREN

Adequate physical activity (PA) is a critical component of chronic disease prevention and a healthy lifestyle. Unfortunately, studies suggest that US children do not meet the recommended 60 minutes of PA per day (11, 68). However, recent advances in measurement techniques are enabling researchers to gather more detailed objective PA data, allowing for an improved understanding of children's PA accumulation and patterns. This information will enable researchers and policy makers to better design and evaluate interventions aimed at increasing PA, ultimately reducing the prevalence of chronic disease. These ongoing advances in objective PA monitoring devices call for studies to test and refine the methods by which PA data are processed and interpreted. Specifically, although these novel PA devices and methods (e.g., accelerometers and activity intensity classification methodologies) are being calibrated and validated using laboratory protocols, their accuracy in estimating children's free-living PA has not been well-established. Additionally, given the well-established sporadic nature of children's activity, it is critical to measure activity during very short time intervals (i.e., 1-2 second bouts), requiring devices that can record and store acceleration data at a relatively high-resolution (e.g. 30-100 Hz). Importantly, though many intervention studies have been conducted with the goal of increasing daily PA, none have used high frequency acceleration data to examine the accumulation of PA in a free-living setting, nor to evaluate the effectiveness of these PA interventions. However, the need to do so is widely recognized among the PA monitoring

community (7, 21, 34). Therefore, the following dissertation describes a series of experiments with the overall aim of improving PA measurement tools and behaviors in children.

In the first study (Chapter 2), we attempt to establish cutpoints to distinguish between sedentary, light, moderate and vigorous activity using a novel wrist-mounted accelerometry device. We also examine the effects of various bout lengths (periods of consecutive seconds of activity above the moderate threshold) on the estimated MVPA accumulation. Moderately accurate cutpoints resulted (~70-75% accuracy). We also found very high estimates of daily MVPA (>300 minutes). Because of the high estimates of daily MVPA as well as the relative difficulty in distinguishing between light and moderate activity by the confusion matrix, we began to further investigate the effects of the specific processing methodologies we used.

This led us to the second study (Chapter 3), whereby we attempted to investigate the ability of three different processing methodologies to accurately detect MVPA. In this study, we applied three different processing methodologies (band pass filtered: BPEN, unfiltered: ENMO, and low pass filtered: LPENMO) to three separate independent samples of children: a calibration sample, a direct observation (classroom/recess) sample, and a multi-day, free-living sample. Results from this study suggested that BPEN is likely overestimating MVPA. ENMO and LPENMO both appeared to accurately detect MVPA compared to direct observation data (~85%). Because of these relatively good accuracies, and because low pass filtering is considered a best practice in signal processing, we elected to move forward with the low pass filtering methodology.

Once we had established a methodology that we felt accurately detected MVPA, we were able to process and analyze data from the IPLAY (Intervention of PhysicaL Activity in Youth) study. IPLAY is a large-scale, school-based intervention aimed at increasing activity through either curriculum intervention (SPARK), environmental intervention (renovated playgrounds), or the combination of the two (see Chapter 4 for a more detailed description of the intervention). Results revealed no differences in lunch recess, school day or full day MVPA between the groups. In addition, relatively high estimates of daily MVPA resulted (~140 minutes), as well as a lack of effect of BMI z-score on MVPA accumulation.

The combination of these studies adds a significant contribution to the literature around PA in children. Specifically, the investigation into processing methodologies demonstrates how critical this step is in being able to interpret acceleration data. It also provides a framework for other investigators to process acceleration data, with the goal of producing comparable results. The evaluation of the IPLAY study suggests the need for additional opportunities for children to be active during the day. The high estimates of daily MVPA suggest the need to further investigate how/when activity is being accumulated. Finally, an investigation into whether the PA guidelines ought to be re-established given novel methodologies for quantifying PA is warranted.

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CHAPTER 1: INTRODUCTION AND EXPERIMENTAL AIMS

The current US population is said to be the most overweight, sedentary, diseased cohort in our history. It is well-established that physical activity (PA) is associated with protection against nearly every preventable chronic disease (74). Specifically in children, PA has been shown to protect against type 2 diabetes, bone mineral density losses, decrements in academic performance, low self-esteem and depression(18, 30). Recent advances in measurement techniques are enabling researchers to gather more detailed objective PA data. These detailed PA data will allow an improved understanding of individuals' PA habits and enable researchers to better design and evaluate interventions aimed at increasing PA, thereby reducing the risk for, and prevalence of, chronic disease. While advances in developing accurate, objective PA assessment are promising, several challenges remain (12). Namely, although these PA devices/methods (e.g. accelerometers and activity/intensity classification methodologies) have been calibrated and validated using laboratory protocols, their accuracy in estimating free-living PA, particularly in children, has not been established (10). Given the sporadic nature of children's PA, there is a need to measure PA across short sampling intervals (e.g. 1-2 second bouts), which requires devices that can sample and store data at frequencies of ~30-100 Hz (66). To date, there are no studies reporting estimated levels of free-living PA using these newer, high-resolution devices that would permit comparisons to studies using older, lower resolution devices. Thus, there is a critical need for devices and methods that provide accurate PA data that can be used to assess interventions aimed at increasing PA. No studies have used high frequency acceleration data to examine the accumulation of PA in a free-living setting, nor to evaluate the effectiveness of PA interventions. However, there is a widely recognized consensus for the need to do so (10, 21).

Our long-term goal is to develop, validate and employ devices that can objectively and accurately measure motion in order to quantify PA as well as facilitate the design and assessment of sound interventions that promote sustained PA habits. The overall objectives of this project are to improve methods for quantifying PA in children via accelerometry, and to test the efficacy of a curricular and environmental intervention to increase PA in elementary school-aged children. Our central hypothesis is that high-resolution accelerometry data can be used to accurately estimate the accumulation of moderate-vigorous intensity PA in children, as well as to evaluate the effectiveness of interventions aimed at increasing the accumulation of PA in this population. The rationale for this research is that by improving our measurement techniques, researchers and public health professionals will be able to gain a more comprehensive understanding of PA behaviors, and will be better equipped to design strategies that lead to adequate amounts of daily activity, ultimately providing protection against multiple major chronic diseases. With that in mind, I propose the following three specific aims:

SPECIFIC AIM 1

To establish wrist-based cutpoints for the GENEActiv accelerometer in children ages 6-11 years. A secondary aim is to apply these cutpoints to a free-living sample and to examine how the estimated accumulation of minutes of moderate-vigorous (MVPA) is affected by various bout length criteria.

Approach

A laboratory calibration study will be conducted in 6-11 year old children wearing the GENEActiv accelerometer device and portable metabolic system while doing child-specific tasks. Receiver Operator Characteristics (ROC) curves will be created to establish wrist-based cutpoints. Confusion matrices will be developed to examine the accuracy of the cutpoints.

Hypotheses

1) The GENEActiv will discriminate between sedentary, light, moderate and vigorous activity with at least 80% accuracy and 2) children's estimated PA accumulation will decrease significantly as bout length increases.

SPECIFIC AIM 2

To examine the accuracy (compared to direct observation, DO) of three data processing methodologies applied to free-living accelerometry data in children, including 1) Band pass filtering (0.2-15Hz) the Euclidian Norm (vector sum of accelerations along each axis, BPEN) 2) calculating the Euclidian Norm minus one (ENMO) and Low pass filtering (15 Hz) followed by calculating the ENMO (LPENMO). A secondary aim is to apply cutpoints established using each of the three methods to an independent sample of free-living, multi-day data to explore differences in MVPA accumulation.

Approach

Data recorded by wrist-mounted GENEActiv accelerometers from three independent samples of children including: 1) a laboratory calibration protocol 2) an elementary school-day direct observation sample and 3) a multi-day free-living period will be compared using three data processing techniques. Cutpoints established using each technique will be applied to distinguish between sedentary, light, moderate and vigorous activity. Each set of cutpoints will then be applied to a single school day of DO data to determine the accuracy of each processing methodology as well as to the multi-day dataset to examine the effect of processing on estimates of MVPA in free-living children.

Hypotheses

1) The accuracy of ENMO and LPENMO will be significantly greater than BPEN; LPENMO will be significantly more accurate than ENMO, and 2) when applied to free-living estimates, significantly different estimates of daily MVPA will result.

SPECIFIC AIM 3

To quantify the effects of an elementary school-based environmental and curricular intervention on levels of PA during lunch recess, the school day and full day activity using wrist-mounted accelerometers.

Approach

A subset of accelerometry data from a large, multi-year study will be collected in elementary school students as part of a multi-site intervention study (Intervention of PhysicaL Activity in Youth, IPLAY study) which aims to examine the effects of curriculum and environment on PA levels. Published, laboratory-established cutpoints will be applied to the IPLAY dataset to examine minutes of MVPA as well as to evaluate the effectiveness of the intervention.

Hypothesis

Those schools receiving a combination of the curricular (SPARK) and environmental (Learning Landscapes playground) interventions will participate in significantly more MVPA compared to either curriculum-only or environment-only schools, which will participate in significantly more MVPA than control schools. Because the intervention took place only during lunch recess, our secondary hypothesis is that these differences would only be observed during the lunch recess period.

By completing the aforementioned aims, we expect the following outcomes: 1) establishment of wrist-based cutpoints for children using the GENEActiv accelerometer, 2) improvement in the accuracy of high-frequency acceleration data collected in children to detect MVPA and 3) evaluation of a novel environmental and curricular intervention aimed to increase PA in elementary school children. By achieving these outcomes, we will successfully attain our overall goal of evaluating and improving methods for quantifying and increasing physical activity in children. By accomplishing this, not only will we move the field of PA monitoring forward in a significant way, but we will also gain a better understanding of individuals' PA habits which will enable the design of more effective interventions aimed at increasing PA and providing protection against multiple chronic diseases.

CHAPTER 2: ESTABLISHING AND EVALUATING WRIST CUTPOINTS FOR THE GENEACTIV ACCELEROMETER IN YOUTH[1]

SUMMARY

The purpose of this study was to establish physical activity (PA) intensity cutpoints for a wrist-mounted GeneActiv accelerometer (ACC) in elementary school-aged children. A second purpose was to apply cutpoints to a free-living sample and examine duration of PA based on continuous 1s epochs. **METHODS**: Metabolic and ACC data were collected during nine typical activities in 24 children ages 6-11. Measured VO_2 values were divided by Schofield-estimated resting values to determine METs. ACC data were collected at 75 Hz, band pass filtered and averaged over each one-second interval. Receiver Operator Characteristic (ROC) curves were used to establish cutpoints at <1.5, 1.5-3, 3-6 and ≥6 METs for sedentary, light, moderate and vigorous activity, respectively. These cutpoints were applied to a free-living independent data set to quantify the amount of moderate-vigorous PA (MVPA) and to examine how bout length (1, 2, 3, 5, 10, 15 and 60 seconds) affected the accumulation of MVPA. **RESULTS**: ROC yielded areas

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[1] This chapter was accepted for publication in the Journal of *Medicine and Science in Sports and Exercise* and published in the March 2013 issue. Details of the publication are listed below:
Establishing and evaluating wrist cutpoints for the GENEActiv accelerometer in youth
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under the curve of 0.956, 0.946 and 0.940 for sedentary, moderate and vigorous intensities, respectively. Cutpoints for sedentary, moderate and vigorous intensities were 0.190, 0.314 and 0.998 g, respectively. Intensity classification accuracies ranged from 27.6% (light) to 88.7% (vigorous) when cutpoints were applied to the calibration data. When applied to free-living data (n=47 children ages 6-11), estimated daily MVPA was 308 minutes and decreased to 14.3 minutes when only including 1 min periods of continuous MVPA. **CONCLUSION**: Cutpoints that quantify movements associated with moderate-vigorous intensity, when applied to a laboratory protocol, result in large amounts of accumulated MVPA using the 1s epoch compared to prior studies, highlighting the need for representative calibration activities and free-living validation of cutpoints and epoch length selection.

INTRODUCTION

Accurate, objective physical activity (PA) monitoring is crucial to our understanding of current activity levels, as well as to evaluate the effectiveness of interventions aiming to increase PA. Accelerometers (ACC) are the most widely used objective measure of PA in both children and adults (54). Multiple ACC devices are now commercially available. Historically, the device software has applied proprietary processing algorithms to the unfiltered acceleration signal. This method results in count values generated by the devices that are difficult, or in many cases, impossible to compare across devices. This significant limitation has prompted the PA research community to support and encourage the development of devices that collect and store raw (i.e, high-frequency, pre-processed, unfiltered) ACC data (28). Fortunately, advances in data storage and battery life have made these devices readily available to the researcher (21). This new generation of ACC devices should facilitate comparisons across studies and devices (e.g. GENEActiv and Actigraph GT3X+), permit robust PA quantification (including activity classification) and improve estimates of activity intensity (10, 28). However, particularly in the short-term, activity classification approaches are unlikely to take the place of intensity cutpoints. While recent research has investigated the accuracy of activity classifiers in children (70), other studies suggest that although these classifiers are accurate when applied to data collected in a laboratory, classification accuracy is relatively poor when applied to free-living data (14). Given that PA guidelines continue to be recommended in minutes of moderate-vigorous PA (MVPA), and no robust activity classification system has been validated for use in children, researchers still require a way to quantify minutes of MVPA. Therefore, cutpoints must be established and evaluated for ACC devices that collect and store raw data, particularly to understand how interventions impact children's accumulation of daily MVPA.

Although multiple investigators have cited the need to collect raw ACC data to assess PA, few have done so (10, 28). Given the relatively recent capability to collect raw ACC data in multi-day, free-living studies, we do not yet have clear data processing guidelines, and there are unanswered questions regarding interpretation of the data. For example, over what period of time (epoch) should researchers process data collected at frequencies of up to 100 Hz? While a shorter epoch allows improved temporal resolution of PA, it could be argued that at very short epochs (<1 s), the device is quantifying movement that may not equate to purposeful (e.g., hand movement from reading, computer gaming, etc.) PA. However, direct observation of children indicates that they engage in short, intermittent periods of movement, with higher intensity activities lasting an average of 3s (5). This suggests that epochs of 1-2 seconds may be necessary to provide the resolution needed to detect all PA in children.

Another important consideration in quantifying PA accumulation is the duration of the activity bouts taking place. Here, we define the bout as a continuous period of PA above a given intensity threshold. Current guidelines for adults state that MVPA be accumulated in a minimum of ten consecutive minutes (52). To date, no such recommendation has been established for children, but children are recommended to participate in at least 60 minutes of MVPA most days of the week. However, as noted above, it is well known that children typically do not choose to participate in long periods of sustained PA, but rather engage in sporadic movements (5, 8, 43). In one of the only studies to examine the effects of minimum bout duration on reported PA accumulation in children, the number of moderate bouts of activity decreased from an average of ~193 bouts per day using a two-second minimum bout duration (the epoch length of the study) to 5.3 bouts using a 20-second bout minimum (6). This highlights the significance of bout duration in the interpretation of daily PA accumulation in children. Importantly, no studies have yet reported PA accumulation using a one second epoch or bout in children.

The move toward collecting raw ACC data is logical and necessary. While this raw ACC data will eventually allow a much more detailed understanding of PA, estimating minutes of MVPA remains an important objective. One of the devices currently capable of raw ACC data collection is the GENEActiv ACC (Activinsights Limited, Cambridge, UK). It is waterproof and has been validated for wrist placement (20). The wrist is an attractive location, particularly in children, given improvements in compliance typically observed. For example, in our large Intervention of PhysicaL Activity in Youth (IPLAY) study of approximately 1400 children over 3 years, we have achieved compliance rate of ~92-97% (75) (see Methods for additional IPLAY details). However, to date only one study has attempted to create cutpoints specific to the GENEActiv device when placed on the wrist in children. Therefore, the primary purpose of this study was to establish wrist-based cutpoints for the GENEActiv ACC in children ages 6-11 years. We hypothesized that the GENEActiv would accurately discriminate between sedentary, light, moderate and vigorous activity. Our secondary aim was to apply these cutpoints to a free-living sample and to examine how the estimated accumulation of minutes of MVPA is affected bout length criteria.   We hypothesized that children's PA accumulation would decrease significantly as bout length increased.

METHODS

We conducted a calibration experiment on 24 children ages 6-11 years (Table 2.1).

Table 2.1 Subject characteristics for calibration sample and Independent IPLAY subsample Mean (SD)

	Subjects (n)	**Height (cm)**	**Weight (kg)**	**Age (yrs)**
Calibration/Validation Study				
Girls	13	140.0 (7.3)	34.0 (5.8)	9.5 (1.1)
Boys	11	141.4 (12.5)	35.2 (10.1)	9.3 (1.3)
Total	24	140.6 (9.8)	34.6 (7.9)	9.4 (1.2)
IPLAY Subsample				
Girls	20	139.65 (11.1)	36.9 (11.1)	9.6 (1.5)
Boys	27	136.7 (14.1)	37.9 (14.9)	8.9 (1.9)
Total	47	138.0 (12.9)	37.5 (13.3)	9.2 (1.8)

We placed the GENEActiv ACC on children's non-dominant wrist while they participated in 10 activities in a laboratory. Approval for this study was provided by the Institutional Review Board for Human Subjects Research at Colorado State University. All children and parents signed informed assent and consent forms, respectively, prior to children's participation in the study.

Study Design and Activities

Prior to participation, we conducted a phone screening with the parent to assess any contraindications to exercise. We asked that children arrive at the Physical Activity Laboratory having fasted for a minimum of two hours. Participants typically came in pairs, which allowed them to feel more comfortable in the laboratory setting. Upon arrival, staff explained the study details to the child, and obtained informed assent from the child and consent from the parent. Next, we measured each child's weight (Health o meter professional, Model 349KLX) and height (Detecto, Webb City, MO). We then fitted one of the children with the portable indirect calorimetry system as well as the GENEActiv ACC device. Upon completion of the activities by the first child, study staff recalibrated the indirect calorimeter for the second child, who then completed the nine activities sequentially. The protocol began with an initial six-minute resting trial, during which children were asked to lie quietly in a clinical bed while watching a parent-approved DVD. Additional activities included (in order): coloring (seated), Lego® building (seated on the floor), Wii Sports ® Tennis, Wii Sports ® Boxing, treadmill walking at two speeds (0.75 and 1.25 m/s), jogging (1.75 m/s), and running (2.25 m/s). Each activity trial lasted six minutes. In order to synchronize the metabolic system with the ACC data, we simultaneously placed markers in the metabolic data file and on the ACC device, marking the end of each trial. We then analyzed the last two minutes of metabolic and accelerometry data preceding the event markers. On average the study visit lasted 1.5 hours per child (~3 hours per pair of children).

Instrumentation

Accelerometry

The GENEActiv ACC is lightweight (16 grams), triaxial and waterproof. It collects raw acceleration data (range- +/-8 g). It has storage capabilities of 0.5 Gb at recording frequencies ranging from 10-100 Hz and can collect data for up to 7 days at 100Hz. Data is downloaded using a USB 2.0 Charging Cradle. Devices were calibrated by the manufacturer prior to use. We collected data at 75 Hz and downloaded the data using the GENEActiv software (Version 2.1). We used a customized Matlab program (Matlab v 12.0, Mathworks, Natick, MA) to filter the data (band pass with cutoff frequencies of 0.2 and 15 Hz). We filtered the data to remove gravitational acceleration and reduce the inclusion of accelerations associated with the device moving relative to the wrist. Although we did not perform a frequency analysis of the accelerometer in a "noise-free" protocol, studies have reported that the frequency content of ground reaction forces (most relevant to acceleration) during human locomotion are <9-17 Hz (2, 31). We then calculated an average gravity-subtracted signal vector magnitude (SVM_g) for each second (see Equation 1, f= sampling frequency, x, y and z are accelerations in each axis). The average one-second value of the last two minutes of SVM_g values of each trial was used to establish cutpoints.

$$\mathrm{SVM} = \sum_{i=1}^{f} \left| \sqrt{x^2+y^2+z^2} \right| / (f) \qquad (1)$$

Metabolic Measures

We measured the rates of oxygen consumption (VO_2) and carbon dioxide production (VCO_2) to determine metabolic rate using a portable open circuit respirometry system (Oxycon Mobile, Yorba Linda, CA). Pediatric-specific masks were used on our subjects when necessary. The

Oxycon Mobile provides valid measures of oxygen consumption across a range of exercise intensities (53) and has been used in calibration experiments with children (3, 4, 69). Before the experimental trials, we calibrated the system using gases with known concentrations. During each activity trial, expired gas data were averaged every 30 seconds. We allotted six minutes to ensure subjects reached steady state, which was defined as no significant increase in VO_2 during the final 2 minutes and a respiratory exchange ratio <1.0. We then calculated the average VO_2 and VCO_2 (ml/sec) for the final two minutes of each trial.

Data/Statistical Analysis

To establish subject-specific resting metabolic rates, we used the Schofield equation for estimating resting energy expenditure (61). We then divided the measured VO_2 value for each activity by the Schofield predicted resting value to determine MET values for each activity. Receiver Operator Characteristics (ROC) curves were generated using a leave-one-out cross validation (LOO) to determine appropriate SVM_g values for cutpoints associated with sedentary (≤1.5 METs), light (>1.5-2.99 METs), moderate (3-5.99 METs) and vigorous (≥6 METs) activity. To generate these ROC curves, the last two minutes of SVM_g values (N=120 values) for each activity for all subjects (less the left-out subject) were associated with the average MET value over the same time period of each trial. For each ROC curve, MET values were coded as a zero or one according to the cutpoint being established (per SPSS methodology). For example, when the vigorous cutpoint was being established, a one was assigned to all vigorous activities, while a zero was assigned to all activities not of vigorous intensity. Area under the ROC curve was calculated for sedentary, moderate and vigorous activity, and cutpoint values were selected where the sum of the sensitivity and specificity was greatest. The sedentary and moderate cutpoints established the boundaries for light activity. The final set of cutpoints was established by averaging the values generated from each iteration. To examine the accuracy of the average cutpoints in estimating activity intensity, each left out child then served as the test subject. This LOO process was repeated for all children. An average confusion matrix was constructed to examine how well the final set of cutpoints accurately classified activity on the left-out subject (i.e., the test subject). A confusion matrix is a tool used primarily in machine learning that allows for the visualization of the performance of a classifier. The columns typically represent predicted cases, while the rows represent actual cases. SPSS was used (Version 20, IBM, Somers, NY) for all statistical analysis.

Application to a Free-Living, Independent Sample

To determine estimates of daily PA using the cutpoints as well as to examine the effects of various bout duration minimums, we applied the cutpoints to an independent sample of free-living data from the Intervention of PhysicaL Activity in Youth (IPLAY) Study. IPLAY is a multi-school intervention that aims, in part, to examine the effects of playground renovations on levels of PA in elementary school students. The subsample to which the cutpoints were applied comprised 47 elementary school children (one 1st, 3rd and 5th grade class). Table 2.1 includes the descriptive statistics for the IPLAY data sample. GeneaActiv ACCs were attached to each child's non-dominant wrist and secured using a plastic, non-elastic, hospital-type band (Wristbands MedTech USA, Orlando, FL). The devices were worn for six days (including two weekend days) and data was recorded at a sampling frequency of 75 Hz. As in our calibration experiment, a custom Matlab program was used to process the data into 1 second average SVM_g (see Methods, Equation 1), to analyze the ACC data and to define custom intervals for the time periods of interest (e.g., weekday, school day, recess). We examined a single weekday (midweek, to avoid atypical activities including field day and field trips), with an outcome measure of minutes of MVPA, based on bout lengths of 1, 2, 3, 5, 10, 15 and 60 seconds using cutpoints established in the laboratory-based protocol. In an attempt to better understand how much of children's activity is vigorous in nature, we then examined vigorous PA (VPA) based on bout lengths of 1, 2, 3 and 5 seconds. The bout analysis was done using a custom Matlab program whereby consecutive seconds of data above the moderate (or vigorous) threshold were summed. Independent samples t-tests were conducted to determine differences in age, height and weight between the calibration sample and the IPLAY sample population. Analysis of Variance with Tukey's post hoc was used to examine differences in the minutes of MVPA when applying the different bout durations to the IPLAY sample. Sigmaplot (Version 11.0, San Jose, CA) was used for the statistics involving the IPLAY subsample.

RESULTS

ACC Data and Oxygen Consumption

Descriptive statistics for the ACC SVM_g output, VO_2 value and MET value for each activity trial are listed in Table 2.2.

The average cutpoints resulting from the LOO validation, as well as the average values for area under the curve (AUC), sensitivity and specificity are listed in Table 2.3. Sedentary, moderate and vigorous cutpoint values were 0.190, 0.314 and 0.998, respectively. We encountered an error with one subject's ACC data, and one subject was unable to complete two trials, therefore the subject sample size ranges from 22-23.

When examining the ability of the cutpoints to accurately classify intensity, we found that sedentary and vigorous activities were classified with relatively good accuracy (83.3 and 88.7%, respectively) while light and moderate activities were less accurately classified (27.6 and 41%, respectively, see Table 2.4).

Table 2.2. Descriptive statistics for each laboratory calibration activity. Values are reported as mean (SD). Pref=average preferred walking speed

Activity	**N**	**Mean SVMg**	**Mean VO2 ml/kg/min**	**Mean METs**
Resting	23	0.050 (0.05)	4.89 (0.6)	1.00 (0.0)
Coloring	23	0.112 (0.04)	7.68 (1.6)	1.57 (0.2)
Legos	23	0.234 (0.06)	8.06 (2.4)	1.65 (0.5)
Wii ® Tennis	23	0.353 (0.13)	13.55 (4.2)	2.78 (0.8)
Wii ® Boxing	22	1.290 (0.46)	18.72 (5.4)	3.90 (1.2)
Slow walking, 0.75 m/s	23	0.296 (0.16)	14.16 (2.1)	2.91 (0.4)
Pref walking, 1.25 m/s	22	0.381 (0.07)	18.39 (2.6)	3.76 (0.5)
Jogging, 1.75 m/s	23	1.277 (0.24)	30.33 (5.7)	6.24 (1.2)
Running, 2.25 m/s	22	1.594 (0.20)	37.74 (2.8)	7.83 (0.9)

When grouping sedentary and light activity together (SL), as well as moderate and vigorous activity (MV), classification accuracies improved (SL-75.2%, MV- 69.7%). The values for area under the curve (AUC), sensitivity and specificity are listed in Table 2.3.

Table 2.3. ROC-established Cutpoints (SVM_g) and corresponding sensitivity and 1-specificity values per 1 second epoch. (N=23)

	1 sec epoch cutpoint, Mean (SD)	**Sensitivity**	**Specificity**	**Area under ROC curve**	**Std Error**	**Significance**
Sedentary	0.190 (.0016)	.970	.876	.956	.015	P<.001
Light	NA	NA	NA	NA	NA	NA
Moderate	0.314 (.0004)	.910	.873	.946	.015	P<.001
Vigorous	0.998 (.0024)	.949	.853	.940	.016	P<.001

Table 2.4. Average Confusion Matrix (N=23) indicating ability of cutpoints to accurately classify activities (% accurately classified). Columns indicate actual activity while rows indicate predicted activity

	Sedentary	Light	Moderate	Vigorous
Sedentary	83.3	5.8	4.7	0
Light	47.6	27.6	21.1	3.6
Moderate	5.5	24.9	41	28.7
Vigorous	0.7	1.2	9.3	88.7

Application to IPLAY Subsample

Using a one-second bout, mean daily MVPA in the free-living sample was estimated to be 308.2 minutes. Results of the bout duration analysis when applied to the free-living sample are displayed in figure 2.1 (MVPA) and 2.2 (vigorous PA, VPA).

As hypothesized, total accumulated minutes of MVPA and VPA decreased as the length of the bout increased. When a 60-second minimum bout duration was used, the average MVPA was 14.3 minutes. One-second MVPA values were significantly greater than 5, 10, 15 and 60 second bouts, but not significantly different from 2 and 3 second bouts. VPA decreased from 32.7 minutes when assessing activity using a one-second bout minimum to 12.4 minutes when using a five second minimum bout duration. One-second VPA values were significantly different than three and five second bouts. When bout length was increased from one to five-seconds, MVPA decreased by ~32% while VPA decreased by ~60%.

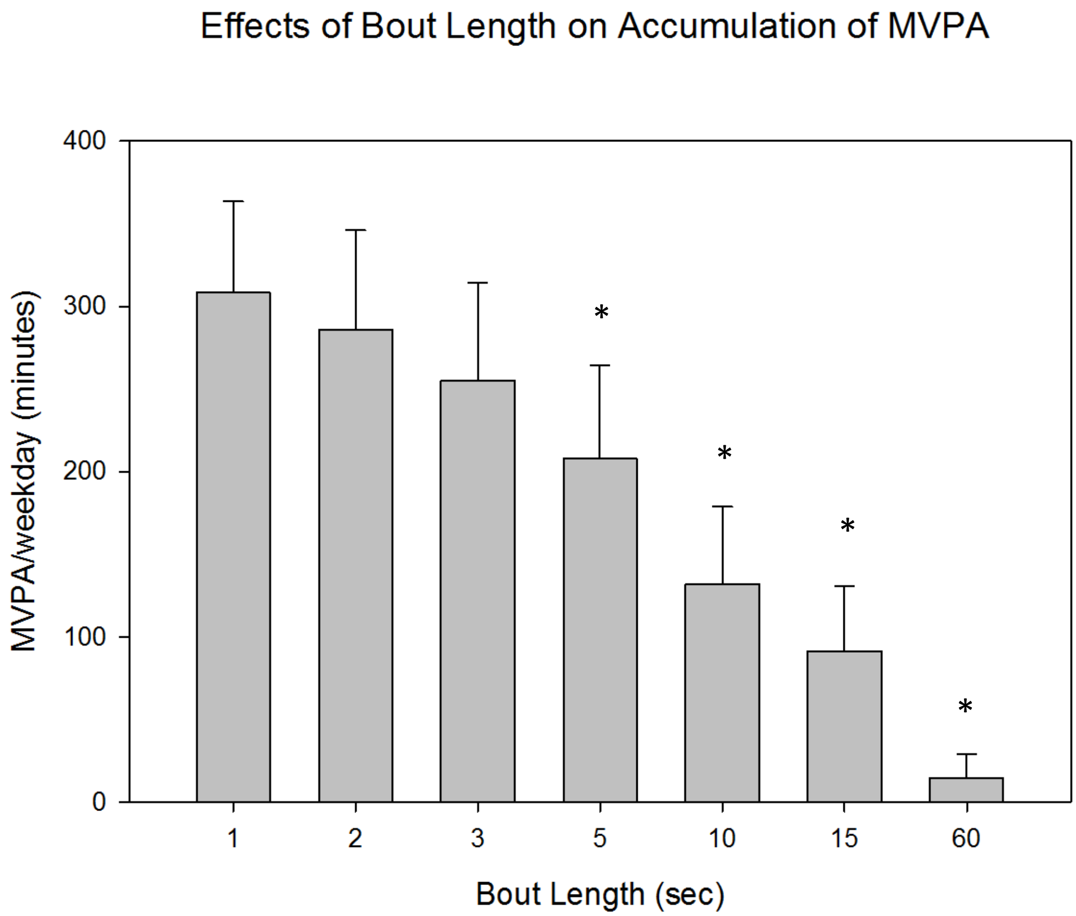

Figure 2.1. Effects of bout length duration on the accumulation of minutes of MVPA during a single weekday (mean, SE). significantly different* compared to one-second bout (p<.05)

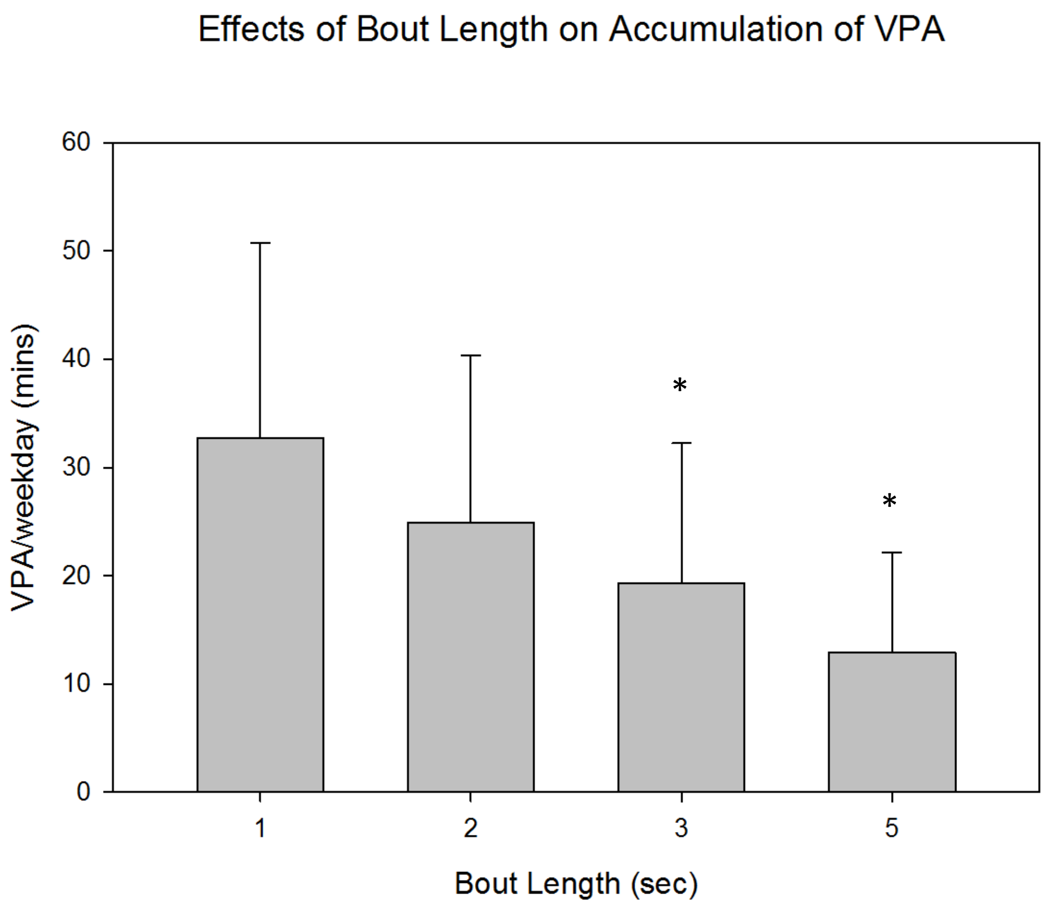

Figure 2.2. Effects of bout length duration on the accumulation of minutes of VPA during a single weekday (mean, SE). significantly different* compared to one-second bout (p<.05)

DISCUSSION

The primary aim of this study was to establish cutpoints for sedentary, light, moderate and vigorous activity in 6-11 year old children using a wrist-mounted GENEActiv ACC sampling at 75 Hz. SVM_g cutpoints were 0.190, 0.314 and 0.998 g for sedentary, moderate and vigorous activity, respectively. The cutpoints distinguished MVPA with reasonable accuracy (~70%), supporting our hypothesis. Using these cutpoints, accumulated minutes of daily MVPA were estimated to be ~300 minutes in an independent free-living sample and, as hypothesized, decreased with increasing bout duration.

Few published studies have attempted to establish wrist-mounted cutpoints using the GeneActiv ACC (20, 46). A recent study by Phillips et al. established activity intensity cutpoints for the wrist mounted GENEActiv in children using a similar methodology to our study (46). Age group, activity choice and much of the post-processing methodology was similar. By multiplying our cutpoint values by the sampling frequency we were able to compare our values to those established by Phillips, et al. Values established in this study (sed-14.25, mod-23.4, vig-74.85 gs) are greater than those reported by Phillips, et al (sed-7, mod-20, vig-60 gs). However, the AUC values from the ROC curves were similar, suggesting similar classification performance (46). The most notable difference between our values and those established by the Phillips group is in the sedentary cutpoint (14.25 vs. 7). This likely reflects our selection of sedentary tasks involving the use of the hands/wrist (i.e., coloring and legos ®), while the sedentary activities performed by Phillips et al. included lying, sitting and DVD watching (minimal wrist movement). The similarity of the moderate cutpoints is encouraging and not surprising given the similarity of the moderate intensity activities (e.g. walking). If the Phillips et al. cutpoints were applied to our free-living, independent sample, fewer minutes of sedentary activity would be classified, but a similar or slightly greater number of minutes of MVPA would be observed compared to what we report here. As no study has yet applied the Phillips et al. cutpoints to an independent free-living sample, we are not able to compare the ability of these cutpoints to quantify accumulated minutes of MVPA.

We examined the ability of the cutpoints to accurately classify activity in our participants by creating a confusion matrix based on the calibration data. To our knowledge, no groups have used a similar methodology to quantify how well cutpoints are able to distinguish activity intensity levels. Our results demonstrate that sedentary and vigorous activities are classified with good accuracy (83.3 and 88.7%, respectively). Though the classification accuracies of light and moderate activity are not as precise, by grouping SL and MV activities, accuracies improve substantially (SL- 75.2%, MV- 69.7%). While these values indicate that up to 30% of activity may be misclassified, a similar percentage of activities are likely classified too low as those classified too high. Importantly, these classification accuracies likely represent a best case given we used the same subjects for cutpoint determination and classification testing. The challenge associated with accurately classifying activity intensity using accelerometers is similar to that of using these devices to classify free-living activities and predict metabolic rate. Laboratory based validations of activity classification report good accuracies (>90% for general classes of activities) (77), a significant improvement compared to those reported here. The better activity vs. intensity classification accuracies are likely due to the more sophisticated classification methodology (e.g. machine learning with multiple features) used in activity classification and suggests intensity classification could improve with such approaches. Calibration studies that have used linear regression to estimate metabolic rate or energy expenditure report R^2 values ranging from 0.35 to 0.84 (22, 45, 48), indicating that a substantial portion of the variance in the relationship (16-65%) is not explained by ACC output. Although the ability of accelerometers to accurately estimate activity intensity may improve as additional calibration studies are conducted, using acceleration data to classify activities and estimate activity specific energy expenditure potentially offers a promising alternative use of this data. However, even robust classifiers are only as good as the data used to develop them and our results suggest the possibility that the way children move in a calibration experiment is not the way they move in a free-living study. If true, classifiers intended to quantify intensity and activity in children may improve when free-living data is used to develop them.

When we applied the cutpoints to an age, height and weight matched, free-living sample of children wearing GENEActiv ACCs collecting data at 75 Hz and processed identically to the calibration study, estimates of minutes of MVPA (mean MVPA=308 minutes) were much larger than those typically reported for children of this age. However, the vast majority of published studies reporting objectively measured average daily minutes of MVPA in children have been conducted using one-minute epochs (68). No studies have quantified MVPA in children using a one-second epoch, though many have acknowledged the need to do so (6, 19, 35, 54). Studies that have used hip-mounted devices recording 2 s epochs report MVPA ranging from 80 (6)-160 min/day (56). Possible explanations for the wide range of accumulated MVPA include significant variation in children's activity levels, seasonal variations, differences in wear time, device location and on-board processing of the data (e.g., data filtering). Interestingly, in a series of studies conducted by Sleap and Warburton that involved direct observation of 5-11 year old children using the Children's Physical Activity Form (CPAF, which measures children's PA every 3 seconds,) (44), an average of 122 minutes of MVPA was accumulated per observation period (~ 418 minutes), more than double the suggested daily guideline (63). Approximately half the observed time during school playtimes and one quarter of the time outside of school was observed to be MVPA. If we extrapolate these percentages to a full day, assuming an estimated eight hours of out of school time (6-8AM and 3-9PM) and two hours of school playtime, including break time, lunch, recess, PE, before and after school, estimates of nearly 200 minutes of MVPA may be observed (25% x 8 hrs. out of school time each day + 50% x 2 hours of school playtime = 3 hours of MVPA). These direct observation studies support our finding that children engage in substantial amounts of daily MVPA. However, the modest intensity classification accuracy reported here, combined with the MVPA estimates that exceed other published estimates, suggests that wrist-mounted ACC cutpoint derived estimates of MVPA may, at present, be better suited for measuring changes in MVPA, rather than as an accurate measure of MVPA.

There has been little attempt to explore how much continuous MVPA children perform. Studies examining the average bout duration of activity in various intensity levels suggests that children perform MVPA for short periods of time. Using a two-second epoch, a study conducted by Baquet, et al., found the average duration of moderate (3-6 METs), vigorous (6-9 METs) and very high (> 9 METs) bouts of PA to be 9, 4.7 and 3.9 seconds, respectively (6). Additional studies exploring children's activity patterns at two-second epochs suggest similar trends (55, 65). Our results are consistent with these findings. When increasing minimum bout duration from one to five-seconds, estimates of vigorous activity decreased by over 60% (32.7 vs. 12.9 minutes of VPA). This information is useful in the design of interventions aiming to increase children's MVPA. A novel strategy may be to focus on increasing the duration of short bouts (e.g., extending PA from one to five consecutive seconds) rather than encouraging prolonged PA (i.e., anything longer than ~10-15 consecutive seconds). An alternative strategy may be to increase the number of (rather than the duration of) short bouts. These may be more effective strategies for accumulating PA, given that it may mimic children's natural PA patterns. Future studies that investigate the dose/response of MVPA bout duration on health outcomes are also needed to establish effective PA guidelines for children (68).

We acknowledge that our findings indicating that children accumulate > 300 minutes of MVPA per day are much greater than estimates in many published studies. One potential explanation was our use of 3 and 6 METs as the cutoffs for moderate and vigorous activity, respectively. Some groups have suggested that 4 and 7 METs are more appropriate cutoffs for children (68).

However, this recommendation appears to have been based upon using a standard resting metabolic rate value of 3.5 mL/kg/min, rather than using age-specific resting metabolic rate estimates. To examine the difference in MVPA accumulation using 4 vs. 3 METs, we created a 4 MET cutpoint and applied it to our data. The moderate cutpoint changed by approximately 22% (from 0.314 to 0.400), and estimates of MVPA changed by 27% (from 308 to 225 minutes). Another contributing factor to the amount of MVPA reported here could be that light PA is being misclassified as MVPA. While we acknowledge this possibility, it is also likely that some MVPA is also being misclassified at light. An additional explanation for our free-living estimates may be that the activities in the calibration study were not performed the same way in a free-living setting, making it difficult for the correct intensity to be estimated. Of course, it is also possible that our calibration activities are not representative of typical children's activities. This points to the critical need for a taxonomy of child-specific activities from which to select in order to more appropriately calibrate devices. Clearly, future studies are needed that validate the amount of MVPA children accumulate during a day using direct observation or other technique with an equivalent short sampling interval.

The move toward the collection of raw acceleration data highlights the need to standardize methodologies for data processing, establishing cutpoints, classifying PA and quantifying duration and intensity of PA (76). Potential ways by which to do so include standardizing 1) the activities/speeds selected for validation studies, 2) the method selected for processing the data, including the frequency with which data is collected and the filtering applied to the raw signal 3) the analysis method for deriving and validating the cutpoints or classifier (e.g., ROC vs. machine learning) and 4) the ACC and device location selected (e.g., wrist versus hip) (28). To facilitate comparisons across studies, in the appendix we have included sample .docx versions of the

Matlab code used to process the raw .bin file (binread.docx- reads the bin file, convertbin.docx- converts the file from a .bin to a .csv file, filterbin.docx- applies the band pass filter). We have also included a sample output file from the calibration study (Sample1_Filtered_Timestamp.xlsx) along with the time codes used in the calibration trial (Sample1_ActivityTimes.xlsx). Samples of the raw .bin data files may be obtained by contacting the corresponding author.

Limitations

Our study is not without limitations. First, our sample size for the calibration trial was relatively small (n=24) and not widely ethnically diverse, which may limit the generalizability of our findings. Additionally, we elected to use a prediction equation that is validated for children (61), rather than using our measured values for resting EE. Because we did not measure resting EE under the stringent conditions required for a true resting measurement, we believe using the well-established Schofield equation would minimize any potential error associated with the baseline resting value. The degree to which the established cutpoints can be applied to a population is dependent upon the similarity in age, size, behavioral patterns and activities undertaken between the two populations (76). The subsample of children to which our cutpoints were applied was not significantly different in terms of age, sex, height or weight from the calibration sample. However, there may be behavioral differences between the two populations that we are unable to detect. Understanding the degree to which behavioral differences affect the estimated levels of PA is important to accurately quantify PA in children. Additionally, the differences between the activities selected for the calibration study and the actual activities undertaken during free-living activity is an important consideration and should be addressed in future calibration studies. Finally, though we conducted a LOO cross-validation to create the confusion matrix (Table 2.4), we did not apply the cutpoints to an independent sample. As a whole the field of PA monitoring acknowledges that this is an important future step in assessing the accuracy of both intensity and activity classifiers (14).

Conclusion

Using ROC curves, the calibration of the wrist-mounted GENEActiv in elementary school-aged children resulted in intensity cutpoints of .019, .314 and .998 SVM_g for sedentary, moderate and vigorous activity, respectively. MVPA intensity classification accuracy was moderately good (~70%). When applied to a free-living data set, we estimated 308 minutes of MVPA/day, suggesting that children move frequently and intermittently throughout the day. As we move toward raw data collection, researchers will need to explore how to interpret the physiological meaningfulness of these very short bouts of activity.

CHAPTER 3: ACCELEROMETRY DATA PROCESSING AFFECTS ESTIMATED ACTIVITY ACCUMULATION IN CHILDREN[2]

SUMMARY

Accelerometry devices that record high frequency, unfiltered acceleration data are now widely available to quantify physical activity (PA). **PURPOSE**: The purpose of this study was to compare the ability of accelerometry data processing methodologies to accurately estimate free-living moderate-vigorous PA (MVPA) in children. **METHODS**: We processed data recorded by wrist-mounted GENEActiv accelerometers from three independent samples of children including: 1) a laboratory calibration protocol (N=24), 2) an elementary school-day direct observation sample (N=21) and 3) a multi-day free-living period (N=59). Data were unfiltered, low-pass filtered (15Hz) or band-pass filtered (0.2-15Hz). We then computed the acceleration magnitude (Euclidian Normalization) and subtracted one to remove gravitational acceleration from the unfiltered and low-pass filtered data. We used average one-second accelerations from the laboratory sample to establish process-specific cutpoints to distinguish between sedentary,

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Title: Accelerometry Data Processing Affects Estimated Activity Accumulation in Children

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light, moderate and vigorous activity. Each set of cutpoints was then applied to the school day direct observation dataset to determine the accuracy of each processing methodology as well as to the multi-day dataset to examine the effect of processing on estimates of MVPA in free-living children. **RESULTS**: Compared to direct observation, unfiltered and low-pass filtered cutpoints achieved ~85% accuracy in estimating MVPA in the school day sample, however the accuracy was 79.3% when the data was band-pass filtered. Accumulated daily MVPA in the multi-day sample was 282, 143 and 137 minutes using band-pass filtered, unfiltered and low-pass filtered data, respectively. **CONCLUSION**: Data processing methodologies, specifically the selection of filter frequency and method for accounting for gravitational acceleration, significantly affect the estimate of daily MVPA accumulation in children. Our results suggest that low-pass or unfiltered methodologies may result in more accurate estimates of MVPA in elementary-aged children.

INTRODUCTION

Accelerometry is one of the most commonly employed methodologies for quantifying free-living physical activity (PA). Recent advances in processing capabilities, battery life and storage capacity have made these devices widely available to researchers interested in objectively quantifying PA in a variety of populations. Until recently, the vast majority of research accelerometers applied processing procedures (e.g. filtering, summing) to the acceleration signal before storing the output. In response to the needs of the research community to gain more control over the acceleration data, more recent devices have the capability to record and store the unfiltered acceleration signal at a user-defined frequency. Although these devices allow researchers the ability to apply a variety of processing methods to the acceleration data, little is known about how these methods affect the accuracy and validity of the PA estimates.

As described in a recent study conducted by Van Hees, et al., an acceleration signal comprises three components, namely the movement component, the gravitational component and noise (73). To extract relevant movement data from the acceleration signal, both noise and the gravitational component are typically removed (71). To remove the high-frequency noise, it is commonly recommended to apply a low pass filter to the signal (33). With regard to removing the gravitational component, two methods are most commonly suggested. The first of these is to apply a high-pass filter to the data such that only portions of the signal above a given threshold (e.g., 0.2 Hz) pass through. Importantly, when the device is motionless, the summed acceleration signal will be equal to the gravitational component (recorded as a value of 1 g). Therefore, the other commonly used technique to account for gravity is to subtract one from the vector sum of the acceleration channels (71).

Devices that record and store high-frequency acceleration data have allowed researchers much more flexibility in data processing decision-making, yet little is known about the sensitivity and relative accuracies of various methodologies. In a recent study, we established wrist-based intensity cutpoints for children by applying a band pass filter (0.2-15Hz) to high frequency acceleration data (75Hz) recorded by a wrist-mounted GENEActiv accelerometer (60). Band pass filtering is a common signal processing technique, with the justification that the high pass cutoff frequency (0.2Hz) removes the effects of gravitational acceleration, while the low pass cutoff frequency (15Hz) removes noise in the signal not representative of human movement (71). However, when applying these cutpoints to free-living data, estimates of daily moderate-vigorous PA (MVPA; ~308 min/day) were substantially greater than reported by other studies, ranging from 54-122 minutes/day (13, 63, 68). Although we validated our methodology using the calibration sample, no independent validation has been performed. A logical next step, then, is to examine the accuracy of these various methods and apply them to independent free-living data to determine the most appropriate method for estimating MVPA in children.

The primary purpose of this study was to examine the accuracy (compared to direct observation, DO) of three data processing methodologies applied to free-living accelerometry data in children. These methodologies include 1) Band pass filtering (0.2-15Hz) then calculating the Euclidian Norm (BPEN) 2) calculating the Euclidian Norm (vector sum of accelerations along each axis) minus one (ENMO) and Low pass filtering (15 Hz) followed by calculating the ENMO (LPENMO). A secondary purpose was to apply cutpoints established using each of the three methods to an independent sample of free-living, multi-day data to explore differences in MVPA accumulation. Based on our previous estimates of daily MVPA using BPEN, as well as results from others (71), we hypothesized that the accuracy of ENMO and LPENMO would be significantly better than BPEN. Additionally, because ENMO does not apply any filter to the signal to remove high frequency noise, we hypothesized that LPENMO would be significantly more accurate than ENMO.

METHODS

Overall Study Design

Unfiltered, high-frequency (75 Hz) acceleration data recorded from a wrist-mounted GENEActiv accelerometer during a laboratory-based calibration experiment were processed using three separate procedures, including 1) BPEN, 2) ENMO and 3) LPENMO. Cutpoints to distinguish between sedentary, light, moderate and vigorous activity were created with each of the three methodologies using receiver operator characteristics (ROC) curves. To investigate the relative accuracy of each method, we simultaneously collected school day video and accelerometry data from an independent sample of 22 fourth grade students ages 10-11. We applied each set of cutpoints to the accelerometry data and compared the accelerometry results to those obtained from direct observation (DO) of the video recording. Finally, to examine how each data processing method affected the estimation of daily accumulation of MVPA, we applied each set of cutpoints to a separate independent sample of multi-day, free-living data. In each of the three samples of children, height to the nearest 0.001 meters (standard tape measurer) and weight to the nearest 0.2 kilogram (Health o meter professional scale, Model 349KLX) were measured by a trained research team member. From these measurements, BMI was calculated as kg/m^2, children's BMI percentiles-for-age were determined from a Centers for Disease Control and Prevention (CDC) macro, and children were dichotomized as normal weight (NW, $<85^{th}$ percentile) vs. overweight/obese (OW/OB, $\geq 85^{th}$ percentile). One way ANOVAs with Tukey's HSD post hoc test were run to examine differences in the subject characteristics between the calibration, DO and free-living samples (see Table 3.1). Study approval was provided by the Institutional Review Board for Human Subjects Research at Colorado State University. All children and parents signed informed assent and consent forms, respectively, prior to children's participation in the studies.

Instrumentation

We used the GENEActiv accelerometer (Activinsights, Cambridgeshire, UK), a lightweight (16 grams), triaxial and waterproof device that collects raw acceleration data between +/-8 g. It has the capacity to store 0.5 GB of data, records at user-specified frequencies ranging from 10-100 Hz and can collect data for up to seven days at 100Hz. Data were downloaded from the devices using a USB 2.0 Charging Cradle. All devices were calibrated by the manufacturer prior to use.

In all studies, devices were attached to the non-dominant wrist of the children using a non-elastic, hospital-type band (Wristbands MedTech USA, Orlando, FL).

Acceleration Data Processing

Acceleration data from the calibration, DO and free-living samples were sampled at 75 Hz and downloaded using the GENEActiv software (Versions 2.1 and 2.2). We used a customized Matlab program (Matlab v 12.0, Mathworks, Natick, MA) to process the data and calculate the Euclidian Norm (EN) per second (see Equation 1) in the following three ways: 1) BPEN (4th order Butterworth recursive, band pass filter, cutoff frequencies of 0.2 to 15 Hz), 2) ENMO (absolute value of the unfiltered EN minus one) and 3) LPENMO (absolute value of the low pass filter at 15 Hz minus one). See Equation 2 for details regarding calculation of the absolute value and subtraction of one.

$$\text{EN} = \left(\sum_{i=1}^{f} \sqrt{x^2+y^2+z^2}\right) / (\text{f}) \qquad (1)$$

$$\text{ENMO} = \left(\sum_{i=1}^{f} \left| \left(\sqrt{x^2+y^2+z^2}\ / -1\right) \right| \right) / (\text{f}) \qquad (2)$$

Equations 1,2: EN=Euclidian Norm, x, y and z = accelerations in each axis, f= sampling frequency

Calibration Study

Data Collection

For details of the calibration data collection procedures, see Schaefer, et al (60). Briefly, we conducted a laboratory calibration experiment with 24 children ages 6-11 years. We collected metabolic data using a portable, open circuit respirometry system (Oxycon Mobile, Yorba Linda, CA) while children wore the GENEActiv on their non-dominant wrist. Acceleration data were collected at 75 Hz while children participated in 10 activities for six minutes each. Measured VO_2 values per activity were divided by each subject's estimated resting metabolic rate (using Schofield equations, (61)) in order to obtain the MET value for each activity.

Intensity Cutpoint Determination

ROC curves were generated to determine appropriate BPEN, ENMO and LPENMO values for cutpoints associated with sedentary (≤1.5 METs), light (>1.5-2.99 METs), moderate (3-5.99 METs) and vigorous (≥6 METs) activity, selecting the value where sensitivity and specificity were maximized (See Chapter 2 for specific procedures for generating ROC curves (60)). A confusion matrix comparing measured versus predicted intensities was constructed for each data processing methodology (i.e., BPEN, ENMO and LPENMO) to examine how well the cutpoints accurately classified activity intensity in the calibration sample (See results, Table 3.2). Because our primary variable of interest is time spent in MVPA, confusion matrices are collapsed to show the accuracy of the distinction between sedentary/light (SL) and moderate/vigorous (MV) intensities, though full matrices can be found in the supplemental material. SPSS was used (Versions 21 and 22, IBM, Somers, NY) for all cutpoint data analysis.

Direct observation sample

Data Collection

We collected a single day of video data in one fourth grade classroom during the Fall of 2013. Video data were recorded mid-week during a typical school day when no special events were taking place. This classroom was participating in the USDA-funded Fuel For Fun study, which is a school- and family-based obesity prevention effort that utilizes experiential cooking and tasting curricula as well as active recess lessons within the school environment (15). Video data were collected during the baseline assessment of the Fuel for Fun study, and thus, no intervention components had been delivered prior to video data collection. Concurrent with video data collection, children wore GENEActiv devices, and accelerometry data were recorded at a sampling frequency of 75 Hz. A video camera (GoPro, San Mateo, CA) was mounted on the ceiling in the corner of the classroom prior to students' arrival for the day. To ensure synchronization of the camera with the accelerometer, we videotaped a research staffer dropping an accelerometer onto a table and matched this frame of video (collected at 30 frames per second) to the spike in the acceleration data file associated with contact with the table. This was done at the beginning of the school day, and the camera continued recording throughout the length of the school day. All accelerometer units were synchronized by initializing them using the same computer clock. At the start of the school day, the teacher explained the presence of and reasoning for the camera in the classroom, and asked that children carry-on with normal classroom activities. Continuous video recording of the classroom space took place from 8:15am-2:05pm. During this time, children spent approximately 3 hours and 40 minutes in the classroom space. We then moved the video camera to the playground area to collect data during an afternoon recess period (2:31-3:05pm).

Data Processing/Analysis

The DO video data were separated into periods of classroom time (8:30-9:30am, 10:18-11:30am, 11:58am-12:23pm and 1:05-2:05pm) and recess time (2:31-3:05pm) and directly observed frame-by-frame. However, to enhance accuracy of the DO sample for comparison purposes, only consecutive periods of sustained activity (e.g. sitting, standing or walking) were coded and used in the analysis (typically $\geq$ 2 seconds). The observation team included a lead observer, who developed a standard protocol for activity classification and coding for both classroom and recess, and three additional trained observers, who coded only classroom footage. For the classroom time periods, the lead observer developed a seven-code activity classification system based on an initial, in-depth observation of the overall range and types of prolonged activities displayed among the children throughout the school day. Classroom activities were then coded on a random sub-sample of children (n=9, 56% boys) (child-by-child, frame-by-frame, over a span of 180 minutes) using the seven defined classifications, including 1) sitting floor, 2) sitting quiet, 3) sitting active, 4) standing quiet, 5) standing active, 6) walking and 7) running/skipping/jumping. To enhance accuracy in classification and to increase inter-coder reliability, any transitional activities (i.e. movements between any of the seven defined activities, or miscellaneous movements that did not fall clearly into one of the seven defined classifications) were not coded. Subsequently, using the compendium of physical activities in children, a 1-4 coding system for activity intensity was used to assign an intensity level to each classroom activity as follows: 1=sedentary (sitting floor, sitting quiet), 2=light (sitting active, standing quiet, standing active), 3=moderate (walking), 4=vigorous (running/skipping/jumping) (51). Intraclass Correlation (ICC) was calculated between the coders in order to evaluate inter-rater reliability.

For the recess time period, the lead observer developed an eight-code activity classification system based on the same initial, in-depth observation of the overall range and types of prolonged activities displayed among the children throughout recess. Due to more frequent ambiguous movement patterns, the recess footage was coded by the lead observer to ensure consistency in recess activity coding. Recess activities were coded on a sub-sample of 19 children (child-by-child, frame-by-frame, over a span of 27 minutes) using the eight defined classifications, including 1) sitting play, 2) standing quiet, 3) standing active, 4) playing catch, 5) walking, 6) playing tag, 7) playing ball, and 8) running/skipping/jumping. To increase classification accuracy, any recess activities that were difficult to identify, either due to ambiguity of movement or lack of child identification from the observer's perspective were not coded. For instance, two children were unable to be accurately coded due to occlusion by the play structures. Subsequently, a similar 1-4 coding system for movement intensity was developed based on the childhood compendium and applied to each recess activity: 1=sedentary (none identified), 2=light (sitting play, standing quiet, standing active, playing catch), 3=moderate (walking, playing tag, playing ball), 4=vigorous (running/skipping/jumping). Because only one individual coded all recess data, no inter-rater reliability was calculated.

A custom Matlab program was created to process these data and create confusion matrices to examine the accuracy of each set of cutpoints relative to DO. For intervals of the school day that were coded by DO, the Matlab program matched corresponding DO intensity classification and ACC intensity classification values to the nearest second. Using DO activity intensity as the measured value and ACC activity intensity as the predicted value, confusion matrices were generated in Matlab. Similar to the calibration sample, we combined confusion matrix values to examine only the distinction between SL and MV for each set of cutpoints. To further examine the ability of each method to estimate MVPA, we calculated the percent of time spent in MVPA coded via DO versus each data processing procedure (see Table 3.4).

Free-Living Sample

Data Collection/Processing/Analysis

To determine how each data processing procedure affected the accumulation of daily MVPA, we separately applied each set of cutpoints to an independent sample of free-living data from the Intervention of PhysicaL Activity in Youth (IPLAY) Study. IPLAY is a multi-school intervention that aims, in part, to examine the effects of playground renovations on levels of PA in elementary school students. The subsample to which the cutpoints were applied comprised 59 elementary school children (one first, third and fifth grade class, see Table 3.1). GENEActiv devices were attached to each child's non-dominant wrist and were worn for six days while data were collected at 75 Hz. Full day (6am-11pm) custom intervals (i.e., periods of time of interest) were created for one school from the IPLAY dataset to quantify minutes of daily MVPA using the cutpoints developed from each data processing methodology. A univariate ANOVA with Tukey's HSD post hoc test was run to examine whether significant differences existed between processing method (BPEN, ENMO, LPENMO) in the free-living estimates of daily MVPA.

RESULTS

Subject Characteristics

See Table 3.1 for subject demographics for the calibration, DO and free-living samples. No significant differences between any of the groups' sex (F=.611, df=1, p=.436), age in months (F=1.350, df=47, p=0.143), height (F=1.129, df=72, p=0.364), or weight (F=1.635, df=85, p=0.126) were observed. The calibration sample had a significantly smaller percentage of children who were overweight/obese compared to the free-living multi-day sample (F=5.057, *df*=2, *p*=.013) but not compared to the DO sample (*p*=.103). The DO sample was not significantly different from the IPLAY sample with regard to weight status: (*p*=.847)

Table 3.1. Subject Characteristics for the calibration, direct observation and free-living samples. Values are reported as mean (standard deviation).

	Subjects (n)	Height (cm)	Weight (kg)	Percent Overweight/ Obese	Age (yrs)
Calibration/Validation Study					
Girls	13	140.0 (7.3)	34.0 (5.8)	15.4%	9.5 (1.1)
Boys	11	141.4 (12.5)	35.2 (10.1)	9.1%	9.3 (1.3)
Total	24	140.6 (9.8)	34.6 (7.9)	12.5%	9.4 (1.2)
Direct Observation					
Girls	9	139.3 (6.2)	34.4 (7.2)	22.2%	9.4 (0.49)
Boys	13	141.0 (3.6)	35.0 (8.6)	15.4%	9.7 (0.29)
Total	22	140.3 (4.7)	34.8 (7.9)	20.0%	9.6 (0.41)
IPLAY Subsample					
Girls	25	135.6 (10.7)	39.5 (24.9)	40.0%	8.9 (1.6)
Boys	34	136.9 (11.9)	40.2 (22.6)	47.1%	9.2 (1.8)
Total	59	136.3 (11.3)	39.9 (23.4)	44.1%	9.1 (1.7)

Calibration Cutpoint Comparisons

Cutpoints, area under the curve (AUC) values and confusion matrices distinguishing between SL and MV for each set of cutpoints are reported in Table 3.2. ENMO (overall accuracy, 84.6%) and LPENMO (85.7%) appeared to outperform BPEN (79.3%) in distinguishing between SL and MV activity during the calibration study.

Direct Observation Comparisons

A total of 14 hours and 22 minutes of DO data were collected (classroom- 657 min, recess- 205 min.) DO accuracy (SL vs. MV) per set of cutpoints in classroom and recess are found in Table 3.3.

In the classroom, ENMO (88.7%) and LPENMO (89.2%) cutpoints resulted in similar classification accuracies and were significantly more accurate than estimates using BPEN (75.9%) cutpoints. During the recess period, however, the opposite was true, whereby BPEN cutpoints (78.6%) proved slightly more accurate in classifying intensity than ENMO (72.8%) and LPENMO (72.6%) cutpoints. Overall, cutpoints established using ENMO (84.9%) and LPENMO (85.3%) outperformed BPEN cutpoints (76.6%) in correctly classifying intensity. When examining the ability of each method to accurately identify accumulation of MVPA compared to the DO estimates, BPEN cutpoints resulted in a significant overestimate of the percent of time identified as MVPA (61% overestimation) compared to ENMO (1.6% underestimation) and LPENMO (4.4% underestimation), see Table 3.4.

Table 3.2. Calibration Cutpoints, AUC (area under the curve) values, and Confusion Matrix Accuracies (predicted percent versus measured percent, SL=sedentary/light, MV=moderate/vigorous) for the calibration subsample for BPEN (Band Pass Euclidian Norm), ENMO (Euclidian Norm Minus One) and LPENMO (Low Pass Euclidian Norm Minus One).

	Cutpoint			**Area Under the Curve**			**Confusion Matrix Accuracy**				
									Predicted (%)		Overall Accuracy (%)
	Sed	Mod	Vig	Sed	Mod	Vig			SL	MV	
BPEN	0.1620	0.2849	0.8180	0.857	0.877	0.887	Measured (%)	SL	**74.8**	25.2	79.3
								MV	17.1	**82.9**	
ENMO	0.0886	0.1862	0.4451	0.896	0.908	0.909		SL	**87.8**	12.2	84.6
								MV	18.0	**82.0**	
LPENMO	0.0935	0.1847	0.4532	0.905	0.922	0.903		SL	***88.1***	11.9	85.7
								MV	16.3	***83.7***	

Table 3.3. Direct Observation Confusion Matrices (predicted percent versus measured percent) for classroom and recess data (SL=sedentary/light, MV=moderate/vigorous) for BPEN (Band Pass Euclidian Norm), ENMO (Euclidian Norm Minus One) and LPENMO (Low Pass Euclidian Norm Minus One).

			Predicted (%)				Overall Accuracy Classroom (%)	Overall Accuracy Recess (%)	Combined Accuracy (%)
			Classroom		Recess				
			SL	MV	SL	MV			
BPEN	Measured (%)	SL	**76.6**	23.4	**50.6**	49.4	75.9	78.6	76.6
		MV	33.3	**66.7**	14.5	**85.5**			
ENMO		SL	**91.7**	8.3	**69.5**	30.5	88.7	72.8	84.9
		MV	54.7	**45.3**	26.3	**73.7**			
LPENMO		SL	**92.4**	7.6	**70.2**	29.8	89.2	72.6	85.3
		MV	55.9	**44.1**	26.8	**73.2**			

Table 3.4. Percent of time spent in MVPA during classroom, recess and overall as measured by Direct Observation (DO), BPEN (Band Pass Euclidian Norm), ENMO (Euclidian Norm Minus One) and LPENMO (Low Pass Euclidian Norm Minus One).

	DO	BPEN	ENMO	LPENMO	
Classroom	6.5%	26.2%	10.7%	10.0%	
Recess	80.0%	78.3%	65.0%	64.5%	
Overall	24.0%	38.6%	23.6%	23.0%	

Free-Living MVPA Comparisons

When we applied each set of cutpoints to a free living, multi-day independent sample of children, average estimates of daily MVPA across first, third, and fifth graders were 282, 143 and 137 minutes for BPEN, ENMO and LPENMO, respectively (see Figure 3.1).

The univariate ANOVA resulted in a significant F test (F=183.1, df=2, p<.001). Post hoc tests revealed that BPEN resulted in significantly greater estimates of daily MVPA compared to ENMO (p<0.001) and LPENMO (p<0.001), however no significant differences were observed between ENMO and LPENMO (p=0.270).

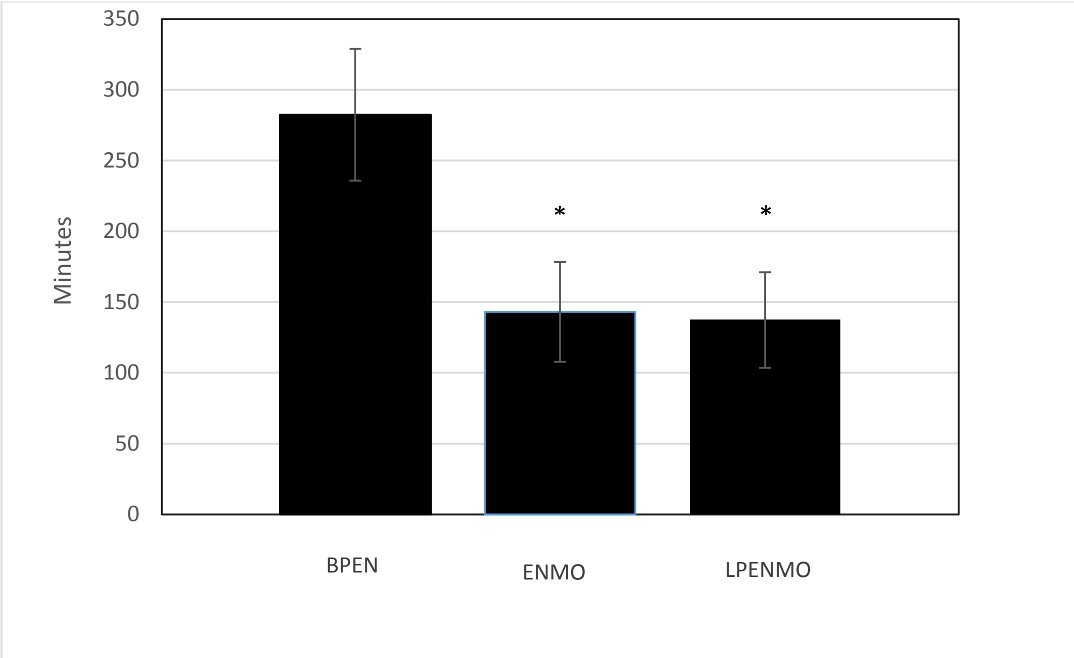

Figure 3.1. Mean minutes of daily moderate-vigorous physical activity (MVPA) in an independent sample of elementary-aged children *significantly different from BPEN, *p*<.001.

DISCUSSION

In this study, we demonstrate that the data processing methodology, including the selection of filter as well as the method for accounting for gravitational acceleration, impacts the accuracy of MVPA estimation. We found support for our hypothesis that ENMO and LPENMO would outperform BPEN in MVPA accuracy. However, we reject our second hypothesis that LPENMO would be more accurate than ENMO, as accuracies were not different. These differences in accuracy of BPEN vs. ENMO and LPENMO were observed in calibration data as well as when validated using an independent sample of data that was classified using DO. Though the differences in classification accuracy appear modest, when applying the methods to a separate independent, free-living sample, large differences in accumulation of daily MVPA resulted. These differences highlight the critical need to adopt standardized processes for collecting, processing and analyzing high-frequency acceleration data in children in order to meaningfully interpret these data.

Very few studies have examined the accuracy of accelerometer classifications of intensity of physical activity by directly comparing to estimates of physical activity intensity using DO in children. Those that have done so have used relatively longer epochs (5-60 seconds) and nearly all recommend adopting a shorter epoch length (16, 36). In a study by McClain, et al., the effect of the epoch length was assessed in children participating in a PE class by comparing various cutpoints and epoch lengths to DO. Three sets of cutpoints were each re-integrated into 5, 10, 15, 20, 30 and 60 second epochs. Results revealed that nearly all the metrics employed underestimated MVPA compared to DO. McClain et al, recommended that a shorter epoch be adopted to minimize error during intermittent PA periods, including free play (36). In an additional study, school day and after school periods of time were directly observed in elementary school-aged children in three-second bouts, and an average of 19.7% of the observed time was coded as MVPA (5). Sleap and Warburton also conducted DO studies in children to examine time spent in MVPA and recorded an average of 29% of the observed time as MVPA (mean MVPA minutes: 117) which is quite consistent with the estimates we report here (63). This provides evidence of the relatively large amount of accumulated MVPA when collected in shorter bouts and via direct observation.

Importantly, given our methods employed for DO classification, our results likely represent a best case scenario in detecting accuracy. Specifically, only consecutive periods of known activity were coded (typically ≥ 2 continuous seconds). Though this enabled us to be confident in the accuracy of the DO data that was coded, we consequently eliminated much of the transitional activity from our sample. Given the short, sporadic nature of children's movement patterns, we likely excluded a great deal of the higher intensity activity, which is critical to consider in a child population. For example, obtaining classroom MVPA was difficult, given that much of the higher intensity activity such as jumping and running, was typically observed in 1-2 second chunks and thus, although observed, was rarely coded. Though this may have led to an underrepresentation of overall MVPA estimates in the classroom setting, given that it was not included in the accuracy evaluation, it would not have negatively impacted results reported here. Importantly, when we investigated the amount of transitional movement during a subset of classroom activity, up to 10% of time was reported to be transitional in nature (i.e., movements between any of the defined activities, or miscellaneous movements that did not fall clearly into one of the defined classifications). Extrapolated to a full day, this may represent a large amount of unclassified time (10% of ~1000 minutes=100 minutes). Therefore, future studies should investigate these transitional periods of activity to better understand how much of the full day is spent in this way, as well as the metabolic contribution that transitions make to accumulated energy expenditure and daily MVPA. Finally, though we only collected a single day of classroom video data, the purpose was not to extrapolate to estimates of daily MVPA, but rather to examine the ability of these three methods to accurately detect MVPA. Therefore, we believe a single day of DO data was sufficient for this purpose.

Though we observed relatively good confusion matrix accuracies in predicting MVPA compared to DO using all three methods, large differences in free-living estimates resulted. Therefore, it is important to further investigate the inaccuracies. For example, overall accuracy of the BPEN cutpoints was 76.6%, yet the overall amount of time estimated as MVPA was 333 min (compared to DO: 207 minutes, 24%). This difference is likely due to the much greater amount of time spent in SL activity during the classroom and MV activity during the recess, both of which were more accurately classified. This would then lead to what appears as an underestimation of the misclassification. ENMO and LPENMO performed better relative to BPEN, and in fact, slightly less time was classified as MVPA (ENMO- 203 min, LPENMO- 198 min) compared to DO (207 min). Thus, it is important to examine not only the overall classification accuracy, but also the amount of time correctly classified. An additional possibility to improve accuracy may be to develop intensity classification based on additional features within the dataset (e.g., standard deviations, coefficient of variation, minimum and maximum values).

In a recent paper, we published cutpoints using a band pass filter to remove noise and the effects of gravitational acceleration (60). When applying these cutpoints to our free-living data, we observed very large estimates of daily MVPA (~308 min/day). Our results reported here for estimates of daily MVPA accumulation using BPEN are similar (282 min/day). We attribute this overestimation of MVPA to the use of the high pass filter to remove gravitational accelerations. This filtering step distorted the acceleration signal by increasing the magnitude relative to the unfiltered acceleration during periods of relatively small accelerations. This effect may be due to rotational movements and warrants further investigation.

To the best of our knowledge, no other studies have evaluated the effects of various data processing methodologies on estimates of MVPA in children. In a recent paper by Van Hees et al., several data processing methodologies were applied to acceleration data recorded while mounted on a robotic arm and in an adult sample in an attempt to separate the gravitational component from the translational acceleration component. Authors concluded that across a wide range of standardized kinematic conditions none of the processing methods outperformed the others (71). However, when they applied these methodologies to a free-living sample of women to predict PA energy expenditure (PAEE) compared to doubly labeled water (DLW), they demonstrated that at best, 36% of the variance in daily PAEE was explained by one of the metrics (HFEN+). Although authors did examine various signal processing methods, they did so in adults with an outcome of EE. Therefore it is difficult and inappropriate to attempt to compare their results to ours. However, their work and ours provide a framework for evaluating various data processing methods and suggests that this is an important step in better understanding high-frequency acceleration data.

Cutpoints remain the most common strategy for quantifying MVPA in children (47, 59, 60). In the only other study to establish wrist-based cutpoints using the GENEActiv device in children, Philips et al. employed very similar methodologies to ours (e.g., child population, a variety of treadmill speeds and active gaming activities, ROC curves for analysis, and estimated resting oxygen consumption (VO_2) to establish MET values for each activity) (47). Yet, their moderate and vigorous cutpoints are significantly higher than those reported here (Phillips (ENMO): 0.263 and 0.700 vs. our ENMO: 0.186 and 0.445). These differences in cutpoints can be attributed to the different methods for estimating children's resting VO_2. We estimated resting metabolic rate using the Schofield equations (61) (average resting VO_2=5.00 ml/kg/min), while Phillips et al. used values reported in a study by Harrell, et al (resting VO_2=5.92 ml/kg/min) (24). This difference in resting metabolic rate has a significant impact on the MET equivalents associated with each activity and thus the cutpoints. These differences highlight not only the importance of using an accurate resting VO_2 value, but also the importance of being clear about each step in the process, as small differences along the way can propagate into large free-living differences. This provides additional support for the critical need to standardize calibration methods.

Conclusion

This is the first study to independently validate methodologies for processing high-frequency acceleration data to quantify MVPA in children. Our results suggest that the methodologies by which researchers elect to process high-frequency acceleration data impacts the ability of the signal to correctly classify activity intensity. Compared to direct observation, unfiltered (ENMO) and low-pass filtered (LPENMO) cutpoints achieved higher accuracy (~85%) in estimating MVPA in the school day sample compared to band pass filtered data (BPEN, 77%). The resulting accumulated daily MVPA in the multi-day sample was 282, 143 and 137 minutes using BPEN, ENMO and LPENMO, respectively. With the increased availability of devices collecting and storing unfiltered, high-frequency acceleration data, this information is critical to inform researchers how to appropriately process these data. Standardizing processing methodologies is a necessary next step to accurately interpret high-frequency acceleration data in children, and this study establishes a framework to do so.

CHAPTER 4: EFFECTS OF AN ENVIRONMENTAL AND CURRICULAR INTERVENTION ON PHYSICAL ACTIVITY ACCUMULATION IN ELEMENTARY SCHOOL CHILDREN

INTRODUCTION

The benefits of physical activity (PA) in children are numerous (30), including not only improved physical health (23, 64), but also mental and emotional health (1) as well as cognitive improvements (18). According to current public opinion, and based on NHANES data, there is a consensus that children do not accumulate sufficient PA (68). Because of this, multiple interventions have been implemented in an attempt to increase the amount of PA that children accumulate throughout the day (17, 72). Given the large percentage of waking time that children spend in school, schools provide an excellent opportunity to increase daily PA (17, 32). However, various intervention studies have been conducted to increase levels of school day activity in children (40, 72). Though findings overall have been inconclusive, the effectiveness of, and need for multi-component interventions has emerged as a common theme (17, 32, 40, 72).

One potential facet of multi-component interventions involves modifications to the physical environment. There have been multiple attempts to modify aspects of the physical school environment with mixed results (25, 50). In a study by Stratton, et al., painting school playgrounds resulted in a significant increase in moderate-vigorous PA (MVPA) during school lunch recess periods assessed by heart rate monitoring, while no change was observed in the control group (67). Provision of facilities has also been associated with higher levels of physical activity (49). In a study by Ridgers et al., equipment provision and playground space were positively correlated with greater MVPA and less sedentary time, while no effect of playground markings was observed (49). One environmental intervention that has been implemented in Denver Public Schools is the Learning Landscape Initiative (LL), which provides renovated playgrounds to elementary schools. In an initial evaluation, these playgrounds resulted in an increased number of children on the playground, as well as an increased amount of energy expended compared to control schools (9). Though various studies have examined the effects of environmental modifications, few have done so in combination with the provision of recess curriculum (29).

Various curricular interventions have been created with a goal of increasing school-day MVPA in children. One such program is Sports, Play, and Active Recreation for Kids (SPARK), which provides evidence-based PA programs for children. SPARK has developed curriculum designed to provide opportunities for all children to engage in PA, irrespective of ability or experience. It is led by instructors who are able to alter lessons by modifying level of difficulty/skill, intensity and duration of the given exercises (38). The SPARK Active Recreation (SPARK AR) curriculum was recently designed for active recreation environments including recess. However, no studies have been conducted to test the effectiveness of this application of the program.

A critical component in assessing the effectiveness of PA interventions is examining the effects on whole-day PA (40). In a recent review by Kriemler et al., authors noted that the critical parallel from intervention-related increases in activity to overall daily PA accumulation is generally not clear (32). This is critical given that a large percent increase in a short recess period would translate into very small increases in total daily PA. For example in a 20 minute recess where MVPA initially comprised 25% (5 minutes), even a 50% increase in MVPA translates to only two and a half additional minutes of daily MVPA. Therefore, it is critical to evaluate the effects of interventions on whole day MVPA (40).

Various interventions have attempted to increase levels of daily PA within elementary school-aged children, yet few have done so by combining recess curriculum and environmental changes. Therefore, the purpose of this study was to quantify the effects of a curricular and environmental intervention on levels of recess and school day MVPA in elementary school-aged children using accelerometry. We hypothesized that the combination of the recess curriculum (SPARK AR) and the environmental intervention (Learning Landscapes playground) would result in significantly greater amounts of MVPA during the recess period. A secondary purpose was to examine the effects of the intervention on whole day PA. Given that the intervention only took place during the lunch recess period, and no consensus exists for the role of activity compensation in children, we hypothesized that the intervention would not result in significant differences in MVPA accumulation over the course of the full day.

METHODS

The Intervention of PhysicaL Activity in Youth (IPLAY) study was implemented in 24 elementary schools in the Metro Denver area between Spring 2010 (baseline only) – Spring 2013. A subset of eight schools was evaluated using wrist-mounted accelerometry (ACC). All study procedures were approved by the Institutional Review Board at Colorado State University as well as the University of Colorado. Prior to participation in the study, parents and children signed informed consent and assent forms, respectively.

Intervention:

This five-year study employed a 2 (environmental intervention vs. no environmental intervention) x 2 (curriculum intervention vs. no curriculum intervention) factorial design with repeated measures (baseline, year one intervention, year two intervention, one year follow up). Importantly, data reported here represent the baseline and two years of intervention only. The environmental intervention comprised the Learning Landscapes Initiative (LL). LL is a partnership between Denver Public Schools (DPS) and the University of Colorado Denver that provides elementary schools with new playgrounds designed to facilitate community interaction and physical activity (9). The curriculum intervention is composed of SPARK Active Recreation (SPARK AR) delivered during recess for eight weeks in the fall and 8 weeks in the spring over the two intervention years. SPARK has been shown to be effective for increasing PA during physical education (57). To facilitate study implementation, a staggered start design was employed whereby one half of the selected schools began the intervention in the first year (Spring 2011, Wave 1) and the other half began one year later (Spring 2012, Wave 2).

School Selection/Recruitment:

Recruitment of DPS schools was based on 1) their willingness to implement the curricular intervention during recess, 2) their cooperation with the random assignment to curriculum or non-curriculum conditions and 3) their agreement to participate in data collection over the five-year project period. Random assignment to the environmental condition was not possible as Learning Landscape playgrounds (LL) had been installed within the previous 3-5 years. After the 12 Denver Public Schools (with LL) were selected, each was assigned a matched control (non-LL) from the Adams School district. Matching was done on school size (number of children in K-5), percent of students receiving free or reduced lunch (%F&R), and ethnicity (% of Hispanic and African-American students). Matched pairs were assigned a random number and subsequently sorted by this number. Assignment to curriculum intervention or no curriculum intervention was made based on position on the sorted list (every second pair received the curriculum).

Objective PA Assessment

During the spring of each year (baseline through one year follow up), we collected six consecutive days of ACC data on a cross-sectional subset of first, third and fifth grade students in eight of the 24 schools (two schools per condition). These data were collected immediately post-intervention. A single class in each of these grades was selected to participate in the ACC measurement. Each subsequent year, the same teacher's class was selected for ACC data collection. In cases where teachers were no longer employed at the school, study staff worked with principals to select a replacement teacher in the same grade. During the first year (baseline Wave 1 schools only), we used the Actical accelerometer (Philips Respironics, Bend, OR), a lightweight (17g), omni-directional, waterproof device that detects low frequency accelerations (0.5-2.0 Hz). It generates an analog voltage signal that is then filtered, amplified and digitized by an A-to-D converter at 32 Hz. These digitized values are summed over the epoch and stored in the device. These stored values are proportional to the duration and magnitude of the movement (26). Devices were calibrated by the manufacturer prior to use. During the baseline year in wave 1 schools (4 schools), we collected data in 15-second epochs, which is the shortest available epoch for the Actical device. After this baseline data collection, the benefits of a device that would collect and output unprocessed acceleration data so that we could select an appropriate epoch length (i.e. 1 sec) became evident. Additionally, devices that collected these high-frequency acceleration data were becoming more widely available to researchers. Because of this, we elected to begin using the GENEActiv ACC device (Activinsights Limited, Cambridgeshire, UK), a light-weight (16g), wrist-worn, triaxial, waterproof device that collects high frequency acceleration data up to 100Hz. It has been validated for use among both children and adults (20). Devices were calibrated by the manufacturer prior to use and data were collected at 30Hz (a subset of data collected in three schools during the Spring of 2011) and 75Hz (all remaining data).

Data Collection Procedures:

ACC data were collected for six consecutive days in one 1st, 3rd and 5th grade class in each of the eight measurement schools. Data were collected during April and May of 2010- 2013, after the conclusion of the Spring intervention period. On the day of accelerometer drop off, study staff explained the study and assented all children who had returned parental consent. Children then filed out into the hall where study staff assigned a device serial number to each child and attached the ACC device to the child's non-dominant wrist using a semi-non-removable hospital-type band (MedTech Wristbands, Orlando, FL). Children were instructed to go about their normal daily activities while wearing the device consecutively for the next six days. Study staff measured each child's height to the nearest 0.5 cm (standard tape measure) and weight to the nearest 0.2 kg (Health O Meter professional scale, Model 349KLX) while shod. BMI was calculated and BMI percentiles were assigned based on the Center for Disease Control and Prevention (CDC) growth charts. Children were assigned as normal weight (NW, <85th percentile BMI-for-age score) or overweight/obese (OW/OB, ≥85th percentile BMI-for-age score).

Parents and teachers were given instructions about the devices and were asked to report any abnormalities in activity during the data collection. Teachers provided school day schedules indicating when school started and ended and when children were at lunch, recess, and physical education (PE) classes. On the sixth day of data collection, researchers returned to the school to collect the devices and children were provided a gift card as remuneration for their participation in the study.

Data Processing:

Actical data were downloaded using the Actical software (Version 2.12). A custom Matlab (Mathworks, etc.) program was created to process the ACC data and clean for nonwear (see below). Any periods of 60 minutes or greater of zero count values were summed over the day to assess completeness of the data file.

All GENEA devices were downloaded using a USB 2.0 Charging Cradle and the GENEActiv software (Version 2.1). We created an additional custom Matlab program to read and subsequently filter the .bin file. We applied a low pass filter to the data (15Hz cutoff frequency) to remove any noise in the signal not representative of true human movement. Once the data were filtered, we calculated a signal vector, the Euclidian Norm minus one (ENMO, see equation 2 where f=sampling frequency). This low pass ENMO value (LPENMO) was calculated on a per-second basis.

$$\text{LPENMO} = (\sum_{i=1}^{f} | (\sqrt{x^2+y^2+z^2} \ / -1) |) / (f) \qquad (2)$$

After filtering the data, we cleaned the files to remove any periods of non-wear. Using a custom Matlab program, we identified periods of sixty consecutive minutes of LPENMO values below .06 g seconds (laboratory established non-wear threshold). These periods of time were summed over each day to assess completeness of the data file.

For all ACC data files, any day found to have less than 10 hours of wear time was considered invalid and removed. Any data file that did not contain at least four valid days was also considered invalid and removed (n=31). Custom time intervals were created to identify standard time periods of interest throughout the day. These intervals include the full day (FD, 6am-11pm), school day (SD, school-specific start and end time) and lunch recess (LR, class-specific start and end time). The times used for SD and LR were determined from the class schedule completed by teachers. After identifying custom intervals, the Matlab program applied published Actical cutpoints established using ROC curves (59) to the baseline Actical data, and GENEActiv wrist cutpoints derived using the same methodology as the Actical cutpoints to the GENEActiv data. Cutpoints were applied to determine the number of minutes and percent of time spent in sedentary (SED), light (LPA), moderate (MPA), vigorous (VPA), and moderate-vigorous PA (MVPA; sum of MPA and VPA) during each of the custom intervals.

Statistical Analysis

In order to confirm that output from the Actical device was comparable to that of the GENEActiv, data collected during a calibration study while wearing both monitors were analyzed (see Chapter 2 for a description of this study). Briefly, 24 children participated in a variety of activities while simultaneously wearing both monitors as well as a portable metabolic system (Oxycon Mobile, Yorba Linda, CA). Pearson product-moment correlation coefficient was calculated to examine the strength of the linear relationship between the two device outputs. Descriptive statistics, reported as mean (SD) calculated for age, height, weight, and BMI percentile and frequencies for sex and grade are reported in Table 4.1. The dependent variables, (i.e., full day minutes of MVPA and percent of time during the school day and lunch recess spent engaged in MVPA) were analyzed with a general linear mixed model. Fixed effects included year and condition, and their two-way interaction. Sex and BMI z-score were included as covariates. Random effects included school within condition and the year by grade by school within condition. Kenward-Roger's approximation was used to estimate denominator degrees of freedom. For significant fixed effects ($p<0.05$), pairwise mean comparisons were made using t-tests. All statistical analysis was conducted in SAS Version 9.4 (SAS Institute, Inc., Cary, NC).

RESULTS

Results from the Pearson correlation revealed a strong correlation between the two device outputs ($R=.86$). A total of 1726 students (50.4% boys) participating in the IPLAY study are reported here. Overall, 34.7% of this sample was overweight or obese, defined by the Centers for Disease Control and Prevention (CDC) as greater than or equal to the 85th percentile BMI for age score (see Table 4.1). No significant effects of BMI z-score on MVPA were observed either during lunch recess ($p=0.44$), school day ($p=0.06$) or full day ($p=0.42$). A significant effect of sex was observed in all time periods, whereby boys accumulated significantly more MVPA than girls ($p<.001$ for all time periods). Significant differences were observed in the percent of children who were overweight/obese between conditions

Table 4.2. Subject Characteristics by Condition, OW/OB- overweight/ obese

	Boys (N)	**% OW/OB**	**Girls (N)**	**% OW/OB**
Control	214	44%	188	34%
Curriculum	232	33%	247	33%
LL	254	26%	210	23%
Both	170	47%	211	43%
TOTAL	**870**	**36%**	**856**	**33%**

During the lunch recess period, boys and girls spent a mean (SE) of 40.8 (1.8) and 33.9 (1.8) percent engaged in MVPA, respectively. No significant interaction between condition and year was observed during lunch recess (*p*=0.27, see Figure 4.1). During the school day, boys spent an average of 15.6 (.37) % of time in MVPA, while girls spent an average of 13.8 (0.37) % of time engaged in MVPA (Figure 4.2). Though a significant interaction between condition and year was observed (*p*=0.008) pairwise comparisons revealed no differences between conditions within each year (baseline: *p*=0.77, year 1: *p*=0.44, year 2: *p*=0.68).

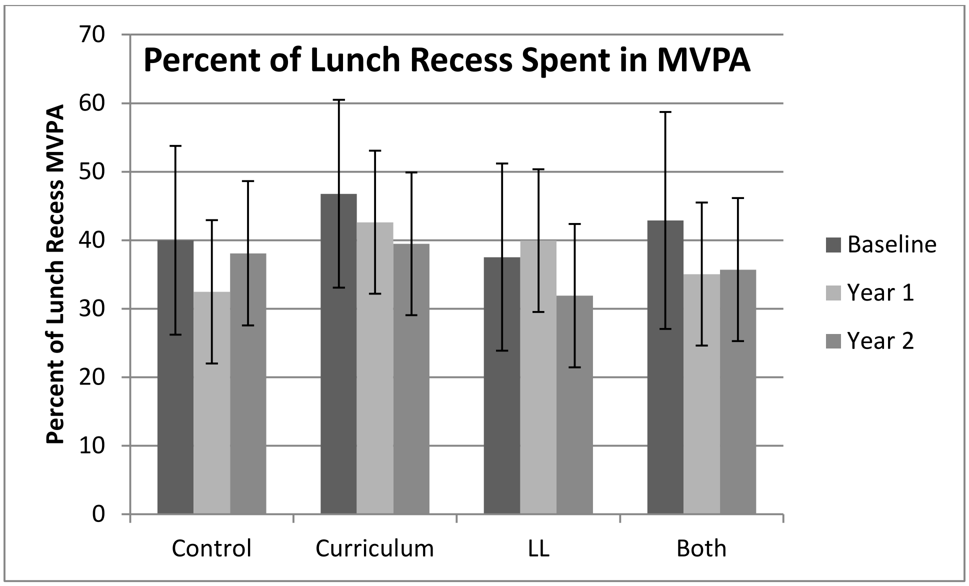

Figure 4.1. Mean percent of Lunch Recess Spent in MVPA by condition and year. Error bars indicate ±2 SE.

Full day minutes of accumulated MVPA for boys and girls were 151 (1.7) and 136 (1.7), respectively (Figure 4.3). A trend toward significance was observed in the interaction between year and condition (*p*=.051, see Figure 4.3). Pairwise comparisons of full day activity revealed significant differences in the baseline (no intervention) year (*p*=0.02) between the combination condition and all other conditions, whereby the combination schools had significantly greater accumulation of MVPA than control (mean difference=29.3 min, *p*=.05), curriculum (mean difference=35.6 min, *p*=.01), or LL schools (mean difference=28.1 min, *p*=.05) at baseline. In year 1, no significant between-group differences were observed (*p*=0.07). In year 2, pairwise comparisons revealed significantly greater daily MVPA accumulation in the LL-only schools compared to curriculum-only (mean difference=17.3 min, *p*=.02) and combination schools (mean difference=16.6 min, *p*=.04).

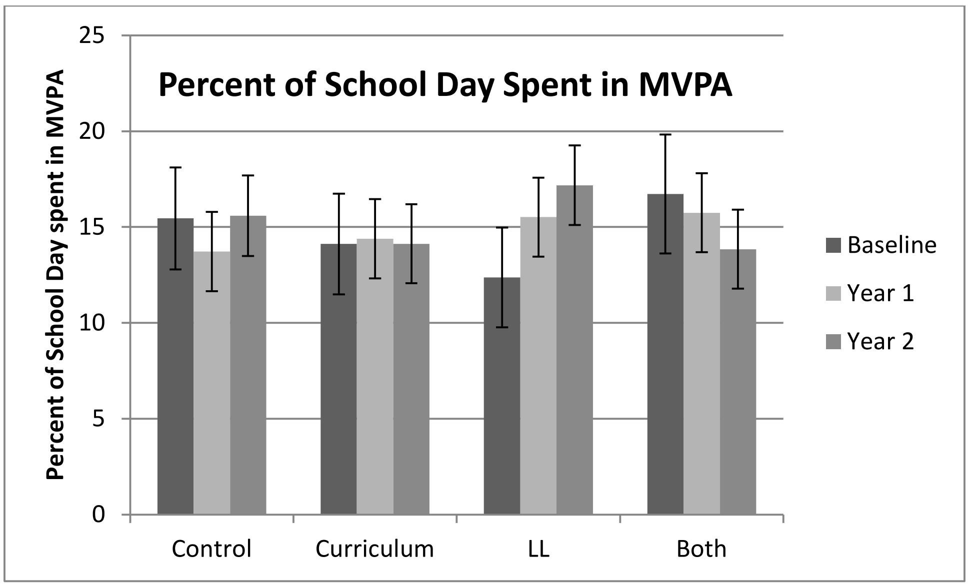

Figure 4.2. Mean percent of School Day spent in MVPA by condition and year. Error bars indicate ±2 SE.

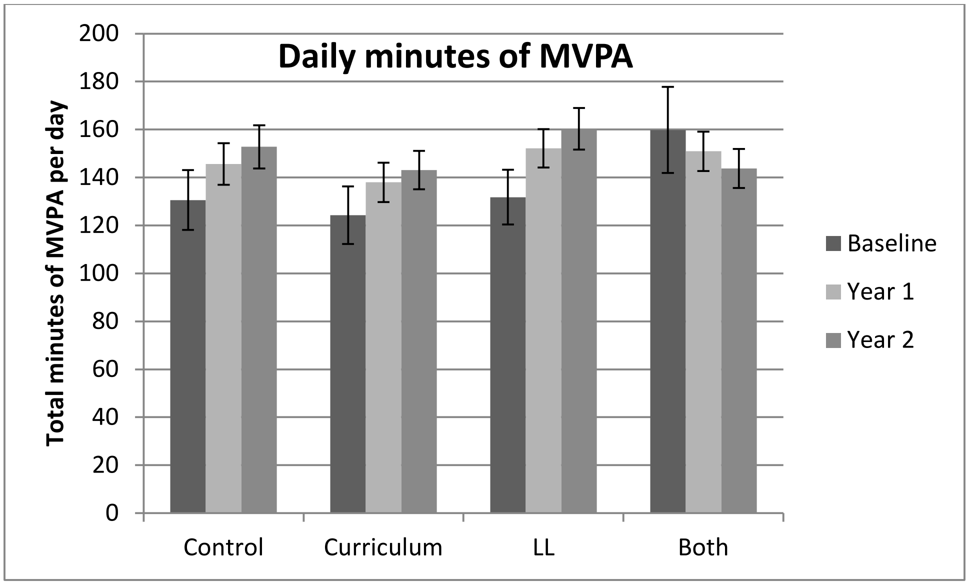

Figure 4.3. Mean Full Day Minutes of MVPA by condition and year. Error bars indicate ±2 SE.

DISCUSSION

In this study we aimed to quantify the effects of a curricular and environmental intervention (IPLAY) on estimates of objectively measured MVPA. Results revealed no significant effect of the curriculum or playground alone, or of their combination on the percent of time spent engaged in MVPA during recess or the school day during the intervention years. Though slight differences were observed in full day activity, because the intervention took place only during recess, whether these differences are a direct result of the intervention is inconclusive. Finally, we observed relatively high estimates of daily MVPA across our sample and no effect of BMI percentile on estimated MVPA.

Results in our sample of full day MVPA revealed significant differences between conditions during the baseline and year 2 data, while no differences were observed during year 1. Because there was no clear pattern or trend in these full day data, and because the intervention took place only during the lunch recess period, we don't believe these differences are due to the intervention.

Perhaps the lack of significant increases in MVPA as a result the IPLAY study should not have been surprising given a recent meta-analysis showing little to no effect of physical activity interventions (40) on MVPA accumulation. In this systematic review by Metcalf, et al., the magnitude of effect across 14,326 participants was approximately four minutes of additional MVPA per day. Evidence from this review and others suggests that interventions must not only attempt to increase PA during already established free-time, but also provide additional opportunities for PA to take place (27). Potential alternative explanations behind this lack of significant intervention effect warrant further discussion.

SPARK has been implemented in various school settings (27, 37, 57). However, to our knowledge, no studies have evaluated SPARK AR implemented during recess, either alone or in combination with environmental modifications. Our results suggested that SPARK AR did not result in greater amounts of accumulated MVPA during the lunch recess period. It is possible that individuals participating in the SPARK AR curriculum during recess simply replace one type of activity with another activity of equally high intensity. Our sample overall spent approximately 38% of recess time engaged in MVPA, which aligns with guidelines suggested by Nettlefold and colleagues of 40% (42), providing additional evidence of possible activity substitution. Furthermore, the structured SPARK AR delivery period in the spring had concluded prior to ACC data collection. The purpose of this study design was to examine any residual effects of the curricular intervention. However, it may have been that once the structured SPARK AR curriculum was completed, teachers/staff and children did not continue to engage in these activities. Though this design enabled us to examine whether SPARK AR was adopted by the schools after the structured delivery of the program, thus allowing us to examine the sustainability of the study design, this is a significant limitation in assessing the true immediate effectiveness of SPARK AR.

Given the lack of change in MVPA during the intervention, an examination of potential ways by which to improve the efficacy of SPARK is warranted. Because girls accumulated significantly less MVPA than boys during lunch recess across all conditions, a future strategy worth investigating may be to tailor SPARK AR such that girls are targeted with recess curriculum and activities that are of particular interest to them. Studies also suggest that SPARK results in better PA outcomes when delivered by a trained SPARK staff person (58), and that ongoing training and support is required for continued success. In a study conducted by McKenzie et al., although delivery via trained classroom teachers initially resulted in increased MVPA, over a 1.5 year time frame, a significant decrease in lesson quality and student activity resulted (37). These findings suggest effective training strategies to preserve the fidelity of the program in schools are needed.

The presence of Learning Landscapes playgrounds did not result in greater estimates of MVPA during lunch recess or the school day. It is possible that the age of the playgrounds played a role in this finding. All playgrounds had been installed in the LL schools at least three years prior to the start of the IPLAY study. While this likely helped eliminate any novelty effect associated with a new playground environment, it may benefit the community to consider ways to capitalize on this novelty effect. As landscape architects and designers plan new play structures, one strategy to prolong the novelty effect would be to create modifiable and/or mobile structures as well as coming up with novel uses for existing structures.

An alternative explanation of the lack of differences between conditions is that children are accumulating more activity than we previously thought. Our results reveal significant accumulation of daily MVPA across the entire sample (151 and 136 minutes of MVPA per day for boys and girls, respectively), which are in contrast to our current paradigm regarding children's relative inactivity (e.g., ~42% meet the 60 min MVPA/day guideline) (68). Thus, perhaps this sample did not respond to the intervention because they were already sufficiently active. However, upon further investigation, this is not the first study to demonstrate daily MVPA estimates of > 60 min/day in a large, objectively measured sample of children. In a study conducted by Nader et al., a longitudinal analysis of 1,032 participants of the National Institutes of Child Health and Human Development Study of Early Child Care and Youth Development, hip-mounted accelerometry using a one minute epoch measured an average of 134 minutes per day among 9-12 year old children (41), a number very similar to our estimates. An additional study using accelerometers recording data at 2 second epochs revealed approximately 86.1 minutes of daily MVPA in a sample of 8-10 year old children (6). Direct observation studies also demonstrate large estimates of daily MVPA. In one study conducted by Sleap and Warburton, a sample of 56 preadolescent children accumulated an average of 117 minutes of MVPA per day when directly observed (62). These estimates are in stark contrast to the NHANES estimates of daily MVPA suggesting that only 42% of children ages 6-11 are meeting the guideline of 60 minutes of MVPA per day (68). These discrepant findings ought to question our current thinking around how we quantify and interpret MVPA data collected via accelerometry. Additional direct observation data needs to be collected in order to gain a better understanding of how and how much children move. A more in-depth examination of the metabolic consequences of these short-sporadic bouts of movement also needs to be undertaken. Finally, these results suggest the need for high fidelity direct observation data, as well as standardization of accelerometry data processing techniques.

Importantly, we observed no difference in activity accumulation across the range of BMI z-scores. This is also in contrast to our current paradigm around PA and obesity (i.e., that overweight/obese children are less active than their normal weight counterparts). However, in reviewing the literature, this is not the first study demonstrate a lack of effect of BMI. In a systematic review of recess activity that examined 16 individual variables, no association between PA and BMI/central adiposity was observed (50). In addition, in a large scale longitudinal analysis, little to no effect of BMI was observed on PA (41). In fact, lower BMI percentiles had a faster linear decline in activity over time. A 10% decrease from the mean BMI (65^{th} percentile) was associated with a less than one minute per day per year decrease in MVPA. Future studies that examine how children accumulate activity (e.g., consecutive bout length) will enable us to better understand whether differences exist across BMI. Additionally, if we continue to observe a lack of difference in PA, nutrition may need to become a greater focus of interventions aimed at reducing weight in children.

Limitations

Given the community-based nature of this study, various limitations warrant further discussion. A critical component to community-based interventions is high fidelity of the program and adoption by the participants. To examine this, we conducted program implementation surveys in all participating schools. An Intervention Coordinator (IC) conducted weekly sites visits at each school to ensure that the intervention was being delivered as scheduled. A fifteen-question form session checklist, adapted from the SPARK–AR Curriculum Session Quality Assessment was used as the process evaluation checklist. Results from year one revealed that 70.8% of all intervention sessions were implemented as planned, with a mean intervention score of 11.4/15 points (76%). Additionally, during the baseline and two years of intervention, teacher turnover was significant. Across three years and eight measurement schools, there were 11 instances of teacher turnover and three instances of principal turnover. Though this may have an effect on program delivery, because the turnover was not more or less common in any of the conditions, we don't believe this impacted the overall findings. In addition, given the study design, we were not able to examine the effects of SPARK AR while being implemented, but rather allowed for the assessment of the curriculum uptake by staff and students. Finally, the use of two different accelerometers may be viewed as a significant limitation. However, our analysis of the calibration data revealed a strong correlation in device output (R=.86).

Conclusion

ACC results from the IPLAY Study suggest that recess interventions comprised of curriculum, environmental changes or the combination are not sufficient to increase the amount of MVPA that children accumulate. Future studies may consider a more tailored approach for recess curriculum to target children who are at risk for low activity (e.g., girls). Results also suggest that children may be more active than previously thought, based on our high free-living daily estimates of PA.

CHAPTER 5: OVERALL CONCLUSIONS

Accurate, objective physical activity (PA) monitoring is critical to understanding current physical activity levels, as well as in evaluating the effectiveness of interventions aiming to increase PA. Accelerometers (ACC) are the most widely used objective measure of PA in both children and adults (54).

In the first study, using ROC curves, the calibration of the wrist-mounted GENEActiv in elementary school-aged children resulted in intensity cutpoints of .019, .314 and .998 SVM_g for sedentary, moderate and vigorous activity, respectively. Importantly, these data were processed using a band pass filter. MVPA intensity classification accuracy was moderately good (~70%). When applied to a free-living data set, we estimated 308 minutes of MVPA/day, suggesting that perhaps children move frequently and intermittently throughout the day. As we continue to move toward raw data collection, researchers will need to explore how to interpret the physiological meaningfulness of these very short bouts of activity.

In our second study, a more in-depth examination of methods used to process the raw acceleration signal was undertaken. This was the first study to independently validate methodologies for processing (i.e. filtering) high-frequency acceleration data to quantify MVPA in children. Our results suggest that the methodologies by which researchers elect to filter high-frequency acceleration data impacts the ability of the signal to correctly classify activity intensity. Compared to direct observation, unfiltered (ENMO) and low-pass filtered (LPENMO) cutpoints achieved higher accuracy (~85%) in estimating MVPA in the school day sample compared to band pass filtered data (BPEN, 77%). The resulting accumulated daily MVPA in the multi-day sample was 282, 143 and 137 minutes using BPEN, ENMO and LPENMO, respectively. This was an important finding, given that our first study attempted to establish cutpoints with band pass –filtered data, the method associated with the lowest accuracy in predicting MVPA. Standardizing processing methodologies is a critical next step to accurately interpret high-frequency acceleration data in children, and this study established a framework to do so.

Because of findings from our second study, we abandoned the band pass methodology for processing our raw acceleration data and adopted the low pass Euclidian norm minus one (LPENMO) procedure. In the third study, we used this methodology in a large sample of free-living multi-day data to evaluate the effects of a novel curricular and environmental intervention aimed at increasing PA in elementary school children. Results from the IPLAY study suggested that neither recess curriculum (SPARK) nor a novel playground environment (Learning Landscapes), nor the combination of the two resulted in meaningful increases in PA during any period of the day (i.e., lunch recess, school day or full day). An additional important finding from these results is that children are accumulating relatively more MVPA than previously reported. Finally, we observed no effect of BMI z-score on accumulated MVPA across any time point. This finding challenges the current paradigm that low PA is associated with childhood obesity. These results suggest that a more in-depth examination of children’s PA habits is necessary to understand when, how and how much activity children accumulate.

In order to better understand children’s activity patterns, future studies should be conducted that incorporate multiple methods to quantify PA. For example, direct observation data ought to be collected over full days to examine activity accumulation at various time points throughout the day. Additionally, calibration studies need to be conducted outside the laboratory in order to effectively capture real-world situations in which children play and develop free-living based intensity/activity classification. The gathering of contextual information will also be important in order to assess PA accumulation in children. For example, the social environment may play a critical role in how much and when children accumulate activity. Therefore, utilizing methods that may capture social interactions within a space (e.g., GPS and Radio Frequency Identification, RFID) will provide necessary information to researchers and program planners to help design and evaluate novel intervention strategies. In sum, in order to capture a comprehensive picture of children's PA habits and patterns, researchers must begin to combine multiple assessment methodologies. As we gain this improved understanding, more effective programs may be developed to impact children's PA.

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APPENDIX

We have included the following files in the appendix material:

1) BINREAD, CONVERTBIN, FILTERBIN .m files

    - These are the three pieces of Matlab (.m extension) code that are used to read the bin file (binread), convert it from a .bin to a .csv file (convertbin), and apply the band pass filter (filterbin).

BINREAD

```
function [header, time, xyz, light, button, prop_val] = binread(filename, 
varargin)
% BINREAD Reads GENEActive .bin files
%
% [hdr, time, xyz, light, but] = binread(fname)
% [hdr, time, xyz, light, but, prop_val] = read(fname, 'key1', 'key2',...)
%
% Where
%
% FNAME is the file name
%
% HDR is a Mx1 cell array containing M header pages (each of them a struct)
%
% TIME is an Nx1 vector of measurement times. The times are expressed as
% serial date numbers (see help datenum)
%
% XYZ is a Nx3 matrix of calibrated accelerometer measurements. The columns
% correspond to the x, y and z axes
%
% LIGHT is a Nx1 vector of calibrated light measurements
%
% BUT is a Nx1 vector of button status values (1 on / 0 off)
%
% 'key1', 'key2' are names of page properties that should be extracted (and
% interpolated) from each data page. For instance
%
%
% (c) German Gomez-Herrero
% german.gomezherrero@ieee.org

% Some constants
DATA_PAGE_NAME = 'Recorded Data';
```

```
NB_HEADER_PAGES = 7;
NB_DATA_PAGES = 100;
CALIBRATION_PAGE_NAME = 'Calibration Data';
TIME_NAME = 'Page Time';
TIME_FORMAT = 'yyyy-mm-dd HH:MM:SS:FFF';
DATA_PROPS = {'Battery voltage', 'Temperature'};
INTERPOLATE_PROPS = true;
MEASUREMENT_FREQ_NAME = 'Measurement Frequency';

if nargin < 2,
    data_props = DATA_PROPS;
else
    data_props = varargin;
end

fid = fopen(filename, 'r');

% Skip any blank line at the beginning of file
C = textscan(fid, '%[^\n]',1);
while isempty(C(39)),
    C = textscan(fid, '%[^\n]', 1);
end

% Read header pages
header = cell(NB_HEADER_PAGES, 1);
header_page_count = 1;
page_name = C(39);
while ~strcmpi(page_name, DATA_PAGE_NAME),
    C = textscan(fid, '%[^\n:*]: %[^\n]');
    header{header_page_count} = cell2struct(C{2}, ...
        strrep(C(39)(1:numel(C{2})), ' ', '_'), 1);
    header{header_page_count}.Page_Name = page_name;
    if strcmpi(page_name, CALIBRATION_PAGE_NAME),
        x_gain = str2double(header{header_page_count}.x_gain);
        y_gain = str2double(header{header_page_count}.y_gain);
        z_gain = str2double(header{header_page_count}.z_gain);
        x_offset = str2double(header{header_page_count}.x_offset);
        y_offset = str2double(header{header_page_count}.y_offset);
        z_offset = str2double(header{header_page_count}.z_offset);
        volts = str2double(header{header_page_count}.Volts);
        lux =  str2double(header{header_page_count}.Lux);
    end
    if numel(C{2})<numel(C(39)),
        page_name = C(39){end};
        header_page_count = header_page_count + 1;
    else
        % We have reached the end of the file
        xyz = [];
        light = [];
        button = [];
        prop_val = [];
        return;
    end
end
header(header_page_count+1:end) = [];
```

```
if isfield(header{end},'Number_of_Pages'),
    nb_pages_in_header = true;
    nb_pages = str2double(header{end}.Number_of_Pages);
else
    nb_pages_in_header = false;
    nb_pages = NB_DATA_PAGES;
end

% Read the data pages
data_page_count = 1;
page_name = DATA_PAGE_NAME;
xyz = nan(300*nb_pages, 3);
light = nan(300*nb_pages, 1);
button = nan(300*nb_pages, 1);
prop_val = nan(nb_pages, length(data_props));
time = nan(nb_pages, 1);
freq = nan(nb_pages, 1);
while strcmpi(page_name, DATA_PAGE_NAME),
    C = textscan(fid, '%[^\n:*]: %[^\n]');
    if numel(C(39)) ~= numel(C{2})+1,
        error('Invalid format in %dth data page', data_page_count);
    end
    % Get the numeric properties of that the user wants to get
    [prop_idx, prop_loc] = ismember(C(39)(1:end-1), data_props);
    [prop_loc, idx] = sort(prop_loc(prop_idx));
    prop_idx = find(prop_idx);
    prop_idx = prop_idx(idx);
    prop_val(data_page_count, prop_loc) = str2double(C{2}(prop_idx));

    % Get the measurement time
    time(data_page_count) = datenum(C{2}(ismember(C(39)(1:end-1),
TIME_NAME)), ...
        TIME_FORMAT);

    % Get the measurement frequency
    freq(data_page_count) = str2double(C{2}(ismember(C(39)(1:end-1), ...
        MEASUREMENT_FREQ_NAME)));

    % Get the measurements
    meas_idx = (data_page_count-1)*300+1:(data_page_count*300);
    [xyz(meas_idx,:), light(meas_idx), button(meas_idx)] =
hex2xyz(C(39){end});
    page_name =  textscan(fid, '%[^\n]',1);
    if ~isempty(page_name(39)),
        page_name = page_name(39);
        data_page_count = data_page_count + 1;
    else
        page_name = '';
    end
end
if ~isempty(page_name),
    warning('binread:unknownPageName', 'Unknown page name %s', page_name);
end
if nb_pages_in_header && data_page_count ~= nb_pages,
    warning('binread:unknownPageName', ...
```

```
        'Only %d data pages were found although %d pages are annotated in the
header', ...
        data_page_count, nb_pages);
end

% Interpolate the time
if any(diff(freq)),
    error('Not implemented yet');
else
    secs = 300/freq(1);
    msecs = round((secs-floor(secs))*1e3);
    secs = floor(secs);
    time_end = addtodate(addtodate(time(1), secs, 'second'), ...
        msecs, 'millisecond');
    offset = linspace(0, time_end-time(1), 300);
    time_interp = repmat(time(:), 1, 300) + repmat(offset, numel(time), 1);
    time_interp = time_interp';
    time_interp = time_interp(:);
end

% Intepolate the selected page properties
if INTERPOLATE_PROPS
    prop_val_interp = nan(numel(time_interp), size(prop_val, 2));
    for i = 1:size(prop_val, 2)
        prop_val_interp(:, i) = interp1(time, prop_val(:,i), time_interp,
'spline');
    end
    prop_val = prop_val_interp;
end
time = time_interp;

% Calibrate the data
xyz = (xyz*100 - repmat([x_offset, y_offset, z_offset], ...
    data_page_count*300, 1))./repmat([x_gain, y_gain, z_gain], ...
    data_page_count*300, 1);
light = floor(light*lux/volts);

end

function [xyz, light, button] = hex2xyz(hstr)
% Hexadecimal to decimal conversion of data values
n_bytes = floor(numel(hstr)/2);
n_meas = n_bytes/6;
hstr = reshape(hstr(1:n_bytes*2), 2, n_bytes)';
bin_values = dec2bin(hex2dec(hstr))';
bin_values = reshape(bin_values, 1, n_bytes*8);
idx = repmat((1:48:48*n_meas)', 1, 12) + repmat(0:11, n_meas, 1);
x = tc2dec(bin_values(idx),12);
y = tc2dec(bin_values(idx+12),12);
z = tc2dec(bin_values(idx+24),12);
idx = repmat((37:48:48*n_meas)', 1, 10) + repmat(0:9, n_meas, 1);
light = bin2dec(bin_values(idx));
button = bin_values((47:48:48*n_meas)')=='1';
f = bin_values((48:48:48*n_meas)')=='1';
if any(f),
    error('The (f) field is not zero!');
```

```
end

xyz = [x(:),y(:),z(:)];
button = button(:);
light = light(:);

end

function value = tc2dec(bin,N)
% Two-complement to decimal conversion

val = bin2dec(bin);
y = sign(2^(N-1)-val).*(2^(N-1)-abs(2^(N-1)-val));

value = y;
condition = (y==0 & val~=0);
value(condition) = -val(condition);

end
```

CONVERTBIN

```
clear all
clc

disp('Sampling Frequency is set at 75 hz')
disp(' ')
disp('File being processed:')

direc=dir('*.bin');
fnames={direc.name};
numfiles=length(fnames);


All_Data=[];
for t=1:numfiles
    filename=fnames {t};
    Name_1=filename;
    disp(Name_1);

    [hdr, time, xyz, light, but] = binread(filename); %Read in the bin file


[Name]=textscan(Name_1, '%s %s', 'delimiter','.'); %Seperates ID number from
.xls extension
ID=Name{1,1}; %Selects the ID number
Extension1='_filtered.csv';
New_Name1=char(strcat(ID,Extension1));
```

```
    [Filtered_data] = filterbin(xyz, time);%Apply Bandpass filter and
calculate signal vector magnitude

    dlmwrite(New_Name1,Filtered_data,'delimiter',',','precision',15);


clear xyz
clear time
clear Filtered_data


end
disp(' ')
disp('Columns 1:4 of the .csv are:[time, filt x, filt y, filt z]');
```

FILTERTBIN

```
function [Filtered_data] = filterbin(xyz, time)

%change sampling frequency here:
freq=75;

x=xyz(:,1);
y=xyz(:,2);
z=xyz(:,3);

[bx,ax]=butter(4,[.2,15]/(freq/2));
filtx=filter(bx,ax,x);

[by,ay]=butter(4,[.2,15]/(freq/2));
filty=filter(by,ay,y);

[bz,az]=butter(4,[.2,15]/(freq/2));
filtz=filter(bz,az,z);

filtered=[filtx,filty,filtz];
Filtered_data=[time,filtered];
```

2) Sample1_Filtered_Timestamp

- This is the output when the raw file is run through the .m files. Because of the size of this file, we included only a sample of one minute of values relevant for the calibration trial. (See Sample1_ActivityTimes file for relevant times).

Time Stamp	X axis	Y axis	Z axis
12:26:30.007	-0.04877	-0.02893	0.01303
12:26:30.020	-0.04933	-0.03181	0.024176
12:26:30.033	-0.04553	-0.02956	0.026131
12:26:30.047	-0.04161	-0.02319	0.016714
12:26:30.060	-0.03854	-0.01661	0.004891
12:26:30.074	-0.03511	-0.01311	0.000141
12:26:30.087	-0.03291	-0.01271	0.003261
12:26:30.100	-0.03232	-0.01326	0.008542
12:26:30.114	-0.03124	-0.01285	0.010741
12:26:30.127	-0.03083	-0.0096	0.009162
12:26:30.140	-0.03448	-0.00129	0.009198
12:26:30.154	-0.04013	0.010295	0.015463
12:26:30.167	-0.04111	0.016046	0.021764
12:26:30.181	-0.03615	0.009243	0.018225
12:26:30.194	-0.03176	-0.00256	0.008416
12:26:30.207	-0.03241	-0.00581	0.006116
12:26:30.221	-0.03533	0.001849	0.013169
12:26:30.234	-0.03664	0.011588	0.017739
12:26:30.247	-0.03584	0.016713	0.016153
12:26:30.261	-0.03489	0.01822	0.015256
12:26:30.274	-0.03595	0.018107	0.016414
12:26:30.288	-0.03708	0.01496	0.016194
12:26:30.301	-0.03466	0.009373	0.015405
12:26:30.314	-0.03135	0.006307	0.015147
12:26:30.328	-0.03306	0.008565	0.013077
12:26:30.341	-0.03897	0.012406	0.011155
12:26:30.355	-0.04214	0.013127	0.015564
12:26:30.368	-0.04009	0.01275	0.024601
12:26:30.381	-0.03763	0.014126	0.02891
12:26:30.395	-0.03626	0.012838	0.024873
12:26:30.408	-0.03204	0.005416	0.019448
12:26:30.421	-0.02656	-0.00395	0.020031
12:26:30.435	-0.0267	-0.00938	0.025068
12:26:30.448	-0.03295	-0.00884	0.029578
12:26:30.462	-0.03748	-0.00534	0.032383
12:26:30.475	-0.03501	-0.00352	0.032087
12:26:30.488	-0.02968	-0.00373	0.025449
12:26:30.502	-0.02647	-0.0035	0.015404
12:26:30.515	-0.02175	-0.00364	0.011
12:26:30.528	-0.01091	-0.00728	0.016351
12:26:30.542	2.84E-05	-0.01282	0.027329
12:26:30.555	0.001022	-0.01462	0.036092

12:26:30.569	-0.00747	-0.01116	0.036569
12:26:30.582	-0.01701	-0.00639	0.03073
12:26:30.595	-0.02371	-0.0035	0.026137
12:26:30.609	-0.02836	0.000381	0.024404
12:26:30.622	-0.02873	0.009947	0.020546
12:26:30.635	-0.02202	0.022847	0.015195
12:26:30.649	-0.01263	0.033355	0.014502
12:26:30.662	-0.00891	0.039543	0.018245
12:26:30.676	-0.01422	0.040557	0.020772
12:26:30.689	-0.02482	0.033938	0.019273
12:26:30.702	-0.03205	0.019908	0.013648
12:26:30.716	-0.02965	0.006316	0.006928
12:26:30.729	-0.02074	0.003637	0.00642
12:26:30.742	-0.01196	0.013801	0.015057
12:26:30.756	-0.0061	0.029708	0.026226
12:26:30.769	-0.00411	0.042839	0.031383
12:26:30.783	-0.00748	0.047914	0.02749
12:26:30.796	-0.01636	0.047079	0.01883
12:26:30.809	-0.02549	0.049074	0.014591
12:26:30.823	-0.02665	0.058754	0.023352
12:26:30.836	-0.02057	0.070919	0.045304
12:26:30.850	-0.01694	0.076013	0.066541
12:26:30.863	-0.01981	0.069795	0.070451
12:26:30.876	-0.02375	0.058732	0.058534
12:26:30.890	-0.02312	0.05368	0.0502
12:26:30.903	-0.01651	0.055959	0.058669
12:26:30.916	-0.00588	0.056917	0.071245
12:26:30.930	0.003461	0.053589	0.063796
12:26:30.943	0.006271	0.05299	0.035183
12:26:30.957	0.003014	0.059927	0.009078
12:26:30.970	-0.00091	0.071886	0.002827
12:26:30.983	-0.00178	0.083477	0.014061
12:26:30.997	-0.00172	0.089369	0.03129

3) Sample1_ActivityTimes

- These are the end times of each activity performed in the calibration study. We used the values from the previous two minutes for each trial to create the cutpoints.

End Time	Activity	Duration
12:20:30 PM	Rest	2 min.
12:27:30 PM	Coloring	2 min.
12:33:45 PM	Legos	2 min.
12:40:45 PM	Wii Tennis	2 min.
12:47:45 PM	Wii Boxing	2 min.
12:54:30 PM	0.75 m/s	2 min.
1:00:30 PM	1.25 m/s	2 min.
1:05:45 PM	1.75 m/s	2 min.
1:14:00 PM	2.25 m/s	2 min.
1:18:45 PM	Stairs	30 sec.