NRC Research Press

ARTICLE

Fully automated waist-worn accelerometer algorithm for detecting children's sleep-period time separate from 24-h physical activity or sedentary behaviors

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Abstract: Analysis of 24-h waist-worn accelerometer data for physical activity and sedentary behavior requires that sleep-period time (from sleep onset to the end of sleep, including all sleep epochs and wakefulness after onset) is first identified. To identify sleep-period time in children in this study, we evaluated the validity of a published automated algorithm that requires nonaccelerometer bed- and wake-time inputs, relative to a criterion expert visual analysis of minute-by-minute waist-worn accelerometer data, and validated a refined fully automated algorithm. Thirty grade 4 schoolchildren (50% girls) provided 24-h waist-worn accelerometry data. Expert visual inspection (criterion), a published algorithm (Algorithm 1), and 2 additional automated refinements (Algorithm 2, which draws on the instrument's inclinometer function, and Algorithm 3, which focuses on bedtime and wake time points) were applied to a standardized 24-h time block. Paired *t* tests were used to evaluate differences in mean sleep time (expert criterion minus algorithm estimate). Compared with the criterion, Algorithm 1 and Algorithm 2 significantly overestimated sleep time by 43 min and 90 min, respectively. Algorithm 3 produced the smallest mean difference (2 min), and was not significantly different from the criterion. Relative to expert visual inspection, our automated Algorithm 3 produced an estimate that was precise and within expected values for similarly aged children. This fully automated algorithm for 24-h waist-worn accelerometer data will facilitate the separation of sleep time from sedentary behavior and physical activity of all intensities during the remainder of the day.

Key words: measurement, youth, physical activity, sedentary behavior.

Résumé : L'analyse pendant 24 h des données d'un accéléromètre porté à la taille afin d'étudier les comportements kinésiques et sédentaires doit d'abord prendre en compte la durée de la période de sommeil (du début à la fin) en incluant tous les épisodes de sommeil et d'éveil suivant l'endormissement. Cette étude 1) évalue la validité d'un algorithme automatisé et publié requérant l'entrée sans accéléromètre du temps de sommeil et éveil vs l'analyse visuelle critériée par un expert des données minute par minute d'un accéléromètre porté à la taille pour la détermination du temps de sommeil des enfants et 2) valide un meilleur algorithme totalement automatisé. Trente élèves de 4^{e} année (50 % de filles) fournissent les données d'un accéléromètre (ActiGraph GT3X+) porté à la taille durant 24 h. On applique sur une période standard de 24 h l'analyse visuelle de l'expert (critériée), l'algorithme publié (Algorithme 1) et deux raffinements automatisés additionnels (Algorithme 2, d'après la fonction inclinométrique de l'instrument et l'Algorithme 3 plus centré sur les périodes de sommeil et d'éveil). On utilise des tests t pour mesures appariées afin d'analyser les différences de durée moyenne du temps de sommeil (critères de l'expert – estimation selon l'algorithme). Comparativement à l'approche critériée, l'Algorithme 1 et l'Algorithme 2 surestiment significativement le temps de sommeil de 43 min et 90 min respectivement. L'Algorithme 3 procure la plus petite différence moyenne (2 min) et ne diffère pas significativement de l'approche critériée. Comparativement à l'analyse visuelle d'un expert, notre Algorithme 3 automatisé procure une estimation d'une précision comparable et se situe dans l'intervalle des valeurs prédites chez des enfants du même âge. L'algorithme totalement automatisé pour l'analyse pendant 24 h des données de l'accéléromètre porté à la taille permet de séparer facilement le temps de sommeil du temps consacré à des comportements sédentaires et kinésiques de toutes intensités durant le reste de la journée. [Traduit par la Rédaction]

Mots-clés : mesure, jeunesse, activité physique, comportement sédentaire.

Introduction

Waist-worn accelerometers are recommended for the objective measurement of physical activity and sedentary behavior in children (Freedson et al. 2005; McClain and Tudor-Locke 2008). Protocols have traditionally asked participants to remove instruments at bedtime and replace them upon awakening in the morning (Troiano et al. 2008). Unfortunately, this "waking hours protocol" has led to overall concerns about compliance with wearing regimens (Masse et al. 2005) and, specifically, with continued concerns about the requisite duration of wear time necessary to represent a valid day of measured habitual behavior (Cain et al. 2013). To address this problem, a few studies (Butte et al. 2007; Treuth et al. 2003) have successfully implemented a 24-h monitoring protocol and have demonstrated noticeable improvements in wearing time.

To measure physical activity and sedentary behavior during the awake portion of the 24-h day with waist-worn accelerometers, time spent in the sleep period must first be identified and accounted for. "Sleep-period time" has been defined in polysomnography research as the "time of sleep onset to the end of sleep, including all sleep epochs and wakefulness after onset" (Scholle

Received 25 April 2013. Accepted 12 June 2013.

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Published at www.nrcresearchpress.com/apnm on 26 June 2013.

et al. 2011). Actigraphy can be used to estimate sleep–wake cycles from recorded differences in movement and nonmovement (Meltzer et al. 2012). The first automated scoring algorithm was developed by Sadeh et al. (1994) for a wrist-worn device, the AMA-32 (Ambulatory Monitoring Inc., Ardsley, N.Y., USA), which was only worn overnight in a sleep laboratory. Another automated scoring algorithm developed for the Actilume wrist-worn accelerometer (Cole et al. 1992) is still used today, and only minor changes have been recommended for evaluating night-time wear, compared with 24 h-wear, and for evaluating younger adults, compared with older adults (all sleeping periods were originally evaluated in a sleep laboratory) (Jean-Louis et al. 2001).

The ActiGraph (ActiGraph LLC, Pensacola, Fla., USA) is a waist-worn accelerometer widely used to study the free-living behavior of children and adults (Troiano et al. 2008) outside of potential laboratory influences. Previous work by Kinder and colleagues (2012) validated the use of the Sadeh et al. (1994) published algorithm with a waist-worn ActiGraph accelerometer, compared with a wrist worn Mini-MotionLogger (Ambulatory Monitoring Inc.) accelerometer, for estimating sleep-period time in free-living children. However, the final algorithm requires diary accounts of bed and wake times, which can be more difficult to record and report accurately for younger children. Missing bed- and wake-time data is an acknowledged limitation of the original research, and required laborious individual data-point manual replacement by researcher estimates drawn from raw data (Kinder et al. 2012). Further improvements are needed to fully automate an algorithm (by also automating determination of bed and wake times) that is applicable to large-scale epidemiologic studies of children's 24-h waist-worn ActiGraph accelerometry.

Thus, the purpose of this study was 2-fold: to continue to evaluate the validity of a published automated algorithm (Sadeh et al. 1994) previously applied to waist-worn accelerometry that required nonaccelerometer bed- and wake-time inputs (Kinder et al. 2012), compared with a criterion expert visual analysis of minute-by-minute waist-worn accelerometer data, for the identification of sleep-period time in children; and to validate a refined and fully automated algorithm to determine bedtime and wake time and refine estimates of sleep-period time in children.

Materials and methods

Participants

Thirty grade 4 schoolchildren (15 boys, 15 girls; descriptive characteristics in Table 1) were randomly drawn from a larger sample of grade 4 children that represents multiple schools participating in the Baton Rouge, Louisiana site of the International Study of Children's Obesity, Lifestyle, and Environment (Katzmarzyk et al., in press[1]). Written informed consent from a parent or guardian and written assent from each child were obtained prior to any data collection. The study protocol and procedures were approved by the Pennington Biomedical Research Center's Institutional Review Board.

Instrumentation

The ActiGraph GT3X+ is a triaxial accelerometer capable of collecting raw acceleration data over a dynamic range of ±6*g* at sampling frequencies up to 100 Hz. Device data are downloaded using ActiLife software (ActiGraph LLC), and activity counts are recorded for each axis and for the combined vector of all 3 axes (vector magnitude). Step counts and inclinometer position (off, lying, sitting, or standing) are available for each epoch (selected time interval) of output. When processing raw ActiGraph data, users can choose to enable the low-frequency extension filter, which increases sensitivity; this feature has been suggested for new waist-worn accelerometer-based sleep algorithms (Hjorth et al. 2012).

Table 1. Descriptive characteristics of the study sample (n = 30).

Age, y	9.9±0.2 (9.5, 10.5)
Body mass, kg	39.6±11.6 (27.5, 80.0)
Height, cm	141.1±5.8 (132.4, 153.3)
Body mass index, kg·m^{-2}	19.6±4.3 (15.0, 34.1)
Race–ethnicity, %	
Caucasian	43
African-American	57

Note: All values except race–ethnicity are presented as means ± SD and range (min, max).

Procedures

Each child's body mass and height were measured, without shoes, prior to accelerometer monitoring. Body mass index was calculated by dividing body mass by height squared. The age and race or ethnicity of each child were obtained from the child's parent or guardian.

Children were then instructed to attach and wear an ActiGraph GT3X+ accelerometer snugly at their right hip on an elasticized waist belt at all times (24 h per day) for 7 days, except while bathing or during water-based activities. Accelerometers were distributed on a weekday at the child's school at approximately 1000 h and initialized to collect raw data at a frequency of 80 Hz at 1200 h the following day. Accelerometers were retrieved after 7 days of wear and the data were downloaded. Raw accelerometer data were integrated into 60 s epochs, with the low-frequency extension filter enabled.

Data treatment

Expert visual inspection (criterion), a published algorithm, and 2 additional automated refinements to this algorithm were applied to a selected 24-h time block (1159 h of day 2 to 1158 h of day 3) from each child's data to estimate their sleep-period time.

Expert analysis of minute-by-minute accelerometer data

The research team met a priori on several occasions to view accelerometer data patterns collectively, and set decision rules for directing visual inspection of minute-by-minute waist-worn accelerometry data and identifying bedtimes and wake times that could be used to ultimately calculate sleep-period time. Inclinometer output that indicated a change from the sitting or standing position to the lying or off position served as an initial data flag. Then, "bedtime" was identified having satisfied 2 additional conditions: the first minute with a recorded vector magnitude of <1000, followed by at least 4 min of a vector magnitude of <500 and <10 steps per min; and at least 90 min needed to elapse between bedtime and wake time. "Wake time" was first located with inclinometer output, again indicating a change from the lying or off position to the sitting or standing position, and then defined as the first minute with either of the 2 following data patterns: a high amount of activity (>1500 vector magnitude), accompanied by >20 steps per min and at least 4 min with a vector magnitude of >0; or at least 10 consecutive minutes with a vector magnitude of >0. These decision rules were applied to practice datasets until the research team was satisfied with their utility.

Subsequently, 2 well-trained accelerometry experts — T.V.B. and J.M.S. — independently reviewed the study dataset and identified bedtime, wake time, and sleep-period time (duration between bedtime and wake time, including all sleep epochs and

[1]Katzmarzyk, P.T., Barreira, T.V., Broyles, S.T., Champagne, C.M., Chaput, J.-P., Fogelholm, M., et al. The International Study of Childhood Obesity, Lifestyle and the Environment (ISCOLE): Design and Methods. BMC Public Health. In press.

wakefulness after onset) on 2 occasions separated by 1 week. Upon completion of both sets of individual scoring, the experts met to come to a consensus (where differences of any magnitude were noted) on the bedtimes, wake times, and sleep-period times that were to be used as criterion values in all subsequent computer-driven analyses.

Computer algorithms

The algorithms were created in a stepwise fashion, with each algorithm building on the previous one. All algorithms were implemented in SAS (version 9.3; SAS Institute Inc., Cary, N.C., USA), and are publically available at http://www.pbrc.edu/pdf/PBRCSleepPeriodTimeMacroCode.pdf.

- *Algorithm 1.* Sadeh et al. (1994) used discriminant analysis techniques to develop a sleep–wake scoring algorithm for wrist-worn accelerometers, relative to polysomnography, and others (Hjorth et al. 2012; Kinder et al. 2012) have successfully applied this algorithm to waist-worn accelerometer data (Kinder et al. 2012). Basically, for each minute (i.e., epoch) of data, a probability of sleep is rendered and a binary indicator variable is assigned to identify each epoch as sleep (1) or wake (0). This algorithm does not specifically identify bedtime or wake time. The sum of all minutes identified as sleep in the 24-h period for each child was originally considered the total sleep time, which we used as an indicator of sleep-period time. Others have urged caution when applying this algorithm directly to waist-worn accelerometry data, and have called for improved algorithms (Hjorth et al. 2012). Kinder et al. (2012) reported that it performs well with a waist-worn accelerometer "when bedtimes and final wake times can be reasonably documented" (p. 130).
- *Algorithm 2.* A second algorithm was created to refine sleep-period time estimates by making use of the instrument's inclinometer function. Specifically, Algorithm 2 redefines the wake minutes assigned in Algorithm 1 as sleep minutes when the inclinometer is in the off position. Again, the sum of all minutes identified as sleep for each child was considered an indicator of sleep-period time.
- *Algorithm 3.* A third algorithm was created that built onto Algorithm 2 by modifying a commonly used and publicly available nonwear algorithm developed by the National Cancer Institute (http://riskfactor.cancer.gov/tools/nhanes_pam/). In this instance, we fully automated the algorithm by identifying "bedtime" and "wake time." Bedtime is identified as the first 5 consecutive minutes defined as sleep in Algorithm 2. Similarly, wake time is identified as the first 10 consecutive minutes defined as wake after a period of sleep defined in Algorithm 2. Bedtime and wake time are only identified when at least 160 min has elapsed between these 2 time points. An unlimited number of nonconsecutive wake minutes are allowed between bedtime and wake time, in keeping with the definition of sleep-period time that includes all sleep epochs and wakefulness after onset (Scholle et al. 2011). Multiple sleep periods (≥160 min) are allowed during each 24-h day. The algorithm was constructed to output the beginning and ending minutes for each sleep period identified, but ultimately retains only the beginning minute of the first period (bedtime) in the time block studied and the final minute of the last period (wake time). Sleep-period time is ultimately calculated as the number of minutes between bedtime and wake time.

Statistical analysis

Reliability analyses

Coefficients of variation (CV) ((SD/mean)× 100, where SD is standard deviation)) and intraclass correlation coefficients (ICC) were calculated to assess intra- and inter-rater reliability for sleep-period time estimates derived from the expert visual analyses. Intra-rater CVs and ICCs were computed for each expert using data from the 2 sleep-period time scoring occasions. The inter-rater CV and ICC were calculated using mean values (across the 2 occasions) for each expert. Intra- and inter-rater CVs were calculated for each occasion (30 CVs each for the 2 intrarater and 1 inter-rater analyses) and presented as the mean ± SD from the individual CVs. As described by Shrout and Fleiss (1979), ICC method (3,1) was used to calculate ICCs for intrarater reliability and ICC method (2,2) was used to calculate the ICC for inter-rater reliability.

Table 2. Mean sleep-period time estimates for each sleep identification method.

Sleep identification method	Mean sleep-period time ± SD (min)	95% confidence interval
Expert criterion	555±98	519–592
Algorithm 1	599±110	558–639
Algorithm 2	645±110	604–687
Algorithm 3	553±100	516–590

Comparison of expert criterion and computer algorithms

Pearson's product–moment correlations were calculated to assess the magnitude of the association between the experts' consensus estimate of sleep-period time and that derived from each of the computer algorithms. Mean absolute error (mean of the absolute errors = |expert criterion − algorithm estimation|), mean absolute percent error (mean of absolute percent error expressed as a percentage = (absolute error/expert criterion) × 100), and the mean difference in sleep-period time (mean of the difference scores = expert criterion − algorithm estimation) between the expert criterion and each of the computer algorithm's estimates were calculated. Paired *t* tests were used to compare mean sleep-period time between the expert criterion and each algorithm estimate, and bedtime and wake time differences between the expert criterion and Algorithm 3. Cohen's *d* effect sizes (Cohen 1988) were computed to provide a context for the magnitude of differences between the expert criterion and each computer algorithm-generated estimate. All statistical analyses were conducted using R (version 2.15.2; R Foundation for Statistical Computing, Vienna, Austria), and the level of significance α was set to 0.05.

Results

Reliability analyses

Intrarater sleep-period time estimates were highly consistent for expert T.V.B. (mean CV ± SD = 0.45% ± 0.97%, ICC = 0.99) and expert J.M.S. (mean CV ± SD = 0.72% ± 2.58%, ICC = 0.94). Similarly, a high degree of agreement was observed for inter-rater sleep-period time estimates between T.V.B. and J.M.S. (CV = 0.18% ± 0.65%, ICC = 0.99).

Comparison of expert criterion and computer algorithms

Mean sleep-period time and 95% confidence intervals for the expert criterion and each computer algorithm estimate are presented in Table 2. Sleep-period time from the expert criterion was moderately correlated with Algorithm 1 (r = 0.70) and Algorithm 2 (r = 0.69), and strongly correlated with Algorithm 3 (r = 0.97).

Comparisons between the expert criterion of sleep-period time and each computer algorithm estimate are shown in Table 3. When compared with the expert criterion of sleep-period time, the mean absolute and absolute percent errors associated with Algorithm 1 were substantial; Algorithm 1 significantly overestimated sleep-period time by 43 min. Similarly, the mean absolute and absolute percent errors associated with Algorithm 2 were large; Algorithm 2 significantly overestimated sleep period time by approximately 90 min. Algorithm 3 produced the smallest mean absolute and absolute percent errors in sleep-period time,

Table 3. Sleep-period time comparisons between expert criterion and computer algorithms.

Sleep identification method	Mean absolute error ± SD (min)*	Mean absolute percent error ± SD (%)*	Mean difference ± SD (min)*	$p^{\dagger}$	Cohen's d*
Algorithm 1	75±52	14.0±10.2	−43±82	0.01	−0.5
Algorithm 2	97±74	18.4±14.5	−90±82	<0.01	−1.1
Algorithm 3	16±18	3.0±3.6	2±24	0.61	0.1

*Compared with expert criterion.
†Corresponding to paired t test with 29 df.

Table 4. Bedtime and wake time comparisons between expert criterion and Algorithm 3.

Variable	Expert criterion time ± SD (min)	Algorithm 3 time ± SD (min)	Mean difference ± SD (min)	p*	Cohen's d
Bedtime	2218h±65	2220h±63	−2±12 min	0.32	−0.2
Wake time	0733h±86	0732h±91	1±23 min	0.80	0.1

*Corresponding to paired t test with 29 df.

compared with the expert criterion. Additionally, a nonsignificant 2 min difference in sleep-period time between Algorithm 3 and the expert criterion was observed. Algorithm 3 also produced the smallest effect size (0.1).

Further comparison of expert criterion bedtimes and wake times and those identified from Algorithm 3 are presented in Table 4. No significant differences were observed, and effect sizes were small.

Discussion

The original Sadeh algorithm was developed to identify sleep–wake cycles for wrist-worn actigraphy validated against polysomnography in a laboratory setting (Sadeh et al. 1994), and was shown subsequently to provide similar estimates, whether applied to wrist- or waist-worn accelerometry in free-living children (Kinder et al. 2012), but only "when bedtimes and final wake times can be reasonably documented" (p. 130). We observed that, relative to expert visual analysis of minute-by-minute accelerometer data, the Sadeh algorithm overestimated sleep period by approximately 43 min; however, it also included potential sleep episodes outside of the sleep-period time defined herein (e.g., during daytime hours). We improved on this algorithm by fully automating it for the express purpose of identifying a nocturnal sleep-period time anchored by accelerometer-derived estimates of bedtime and wake time, and ultimately demonstrated only a 2 min mean difference between our automated Algorithm 3 and a criterion of expert visual analysis of children's 24-h waist-worn accelerometer data. Because there was no significant difference between these 2 approaches, combining the expert criterion and the algorithm-generated estimate allows us to conclude that, on average, the studied children went to bed at 2218 to 2220 h and woke up at 0732 to 0733 h the next morning, accumulating approximately 9.2 h, on average, over the course of their total sleep period. This is in keeping with expected (i.e., normative) amounts of sleep time for this age group (Scholle et al. 2011), which lends support to the veracity of our final algorithm. However, it is less than the 10–11 h of sleep that the National Sleep Foundation suggests that children of this age actually need (National Sleep Foundation).

Through a collective and iterative process, we established decision rules to guide expert visual analysis of minute-by-minute accelerometry data in the determination of sleep-period time, and demonstrated consistent application between and within experts. If children fail to accurately record bed- and (or) wake times (i.e., in the case of missing data), a similar manual method is the ultimate recourse needed prior to applying the Sadeh algorithm (Kinder et al. 2012). However, this is a tedious and time-consuming process, and an automated algorithm for sleep-period time identification is preferable. As a single example, Butte et al. (2007) instructed 897 participants 4–19 years of age, with parent support, how to wear an Actiwatch accelerometer at their waist for 24 h per day over 3 consecutive days. Prior to processing, the accelerometer data were manually compared with participant-recorded times for instrument removal, napping, sleep, and awakening. Sleep time averaged 529–539 min per day, and was significantly lower in overweight than in nonoverweight children. Although the exact details of how sleep times were verified or adjusted, relative to self-reported records, were not reported, it should be evident that the individual scrutiny, processing, and quality control of manifold lines of accelerometer data can and should be facilitated with the application of an automated algorithm for detecting and representing sleep time in children's 24-h waist-worn accelerometer data.

We identified sleep-period time as the duration accruing between bedtime and wake time, identified by accelerometer movement and nonmovement meeting various criteria. Between these 2 time points, however, there were frequently minutes of movement, suggesting repositioning, restlessness, or wakefulness. Our definition of "sleep-period time" reflects the time of sleep onset to the end of sleep, including all sleep epochs and wakefulness after onset, as defined by Scholle et al. (2011). Published normative polysomnography data for sleep-period time among similarly aged children averages 504–540 min, with extremes as low as 388–692 min (Scholle et al. 2011). Our own estimates are within these normative values. Future researchers might be interested in quantifying the number (equivalent to the total time detected in 1-min epochs) of non-0 epochs or total accumulated activity counts detected between bedtime and wake time as potential indicators of wakefulness and (or) disrupted sleep; such an analytic foray was beyond the intended scope of this study.

Although this study was carefully conducted, it is not without limitations that impair our ability to make firm conclusions. All data analyses were applied to the same 24-h waist-worn accelerometer data. There was no separate measurement of sleep or sleep-period time; this should be directly addressed in future research. Because of the laborious nature of expert visual inspection of minute-by-minute data, we focused our analysis on a single selected 24-h time block. We used a sample with a very narrow age range (9.5–10.5 years), and the results should not be generalized to other age groups. We also cannot make assertions about the applicability of the final algorithm to other accelerometer-based instruments or other sites of attachment (e.g., wrist). We processed the accelerometry data using the manufacturer's low-frequency extension filter in an effort to increase sensitivity, and did not analyze the data using the regular filter. Our criterion measure of sleep period was based on expert visual inspection of minute-by-minute waist-worn accelerometry, which we believe is an improvement over a comparison to only wrist-worn accelerometry (Hjorth et al. 2012; Kinder et al. 2012). However, we did not concurrently measure sleep with polysomnography. Future research focused on 24-h waist-worn accelerometry should test the algorithm created in this study in other age groups and validate it against polysomnography. Any comparison is likely to be imperfect, however, because polysomnography provides estimates of sleep architecture that go beyond inferring sleep and wake patterns from time-stamped accelerometer records of movement and nonmovement. The advantages of accelerometry over polysomnography for large-scale epidemiologic study include its convenience and the ability to record multiple 24-h days.

Although Algorithm 3 provided estimates within 2 min of the expert criterion, achieved a level of accuracy better than that previously reported (Kinder et al. 2012), had a level of error much lower than that considered clinically irrelevant (i.e., 10%) in physical activity measurement studies (Kang et al. 2009), and provided estimates on par with those considered indicative of acceptable pedometer performance during short walks (i.e., 3%) (Crouter et al. 2003; Hatano 1997), there is no set standard to facilitate an interpretation of the level of accuracy when estimating bedtime, wake time, or sleep-period time with accelerometry. Despite these limitations, this algorithm facilitates large-scale 24-h waist-worn accelerometer data treatment to identify bedtime and wake time and rank children's sleep-period time for epidemiologic study. The study of children's sleep duration has relevance to obesity, metabolic syndrome, and growth hormone deficiency, among other health concerns, and is therefore of significant clinical importance to children's health (Lazaratou et al. 2012).

In summary, we improved upon a published algorithm for ascertaining sleep-period time when applied to children's 24-h waist-worn minute-by-minute accelerometer data. Relative to a criterion of expert visual inspection and analysis of the same data, our automated algorithm produced an estimate that was similarly precise (a nonsignificant difference of 2 min) and well within expected values for similarly aged children. Moving forward, standardized application of this automated algorithm to 24-h waist-worn accelerometer data will facilitate separation of sleep-period time from sedentary behavior and physical activity of all intensities performed during the remainder of the day. Sleep is a potential contributor to the development of obesity; however, more objective data are needed to address measurement concerns in this area (Guidolin and Gradisar 2012). This data treatment approach provides a unique opportunity to study how sleep also interacts with physical activity and sedentary behavior.

Acknowledgements

This research was funded by The Coca-Cola Company. We acknowledge the contributions of the International Study of Children's Obesity, Lifestyle, and Environment Coordinating Center at the Pennington Biomedical Research Center; Gina Pennington, who is coordinator of the Baton Rouge site; and our local data collection team.

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