Moving forward with accelerometer-assessed physical activity: Two strategies to ensure **Meaningful, Interpretable & Comparable** measures

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Abstract

Significant advances have been made in the measurement of physical activity in youth over the past decade. Monitors and protocols promote very high compliance, both night and day, and raw measures are available rather than 'black box' counts. Consequently, many surveys and studies worldwide now assess children's physical behaviours (physical activity, sedentary behaviour and sleep) objectively 24 h a day, 7 days a week using accelerometers. The availability of raw acceleration data in many of these studies is both an opportunity and a challenge. The richness of the data lends itself to the continued development of innovative metrics, while the removal of proprietary outcomes offers considerable potential for comparability between datasets and harmonising data. Using comparable physical activity outcomes could lead to improved precision and generalisability of recommendations for children's present and future health. I will discuss two strategies that I believe may help ensure comparability between studies and maximise the potential for data harmonisation, thereby helping us capitalise on the growing body of accelerometer data describing children's physical behaviours.

Where we are

Back in the early to mid- 1990's, there were only a handful of papers published per year relating to physical activity and accelerometry. Post 1997, this increased steadily to 28 publications in the year 2000, then gathered pace rapidly with over 300 papers published in 2010 and more than 1100 papers published in 2017. From around 2000, accelerometry has been used to objectively assess children's physical activity in large-scale surveys (e.g. National Health and Nutrition Examination Survey (NHANES) 2003-4 and 2005-6 (36), Avon Longitudinal Study of Parents and Children (ALSPAC) 2003-5 (25), the European Youth Heart Survey (EYHS) 2006 (1), Canada Health Measures Survey (CHMS) 2007-9 (6) and the Health Survey for England (HSE) 2008 (7)). Studies predominantly used the ActiGraph or Actical monitor worn on a belt at the waist and removed for water-based activities and sleep.

Until 2010, output from these accelerometry-based activity monitors was provided in proprietary counts. Counts are an arbitrary dimensionless unit that depend on the specifications of the accelerometer, and therefore cannot be compared between different brands of accelerometer. The accumulated counts per day are indicative of the daily volume of activity. Additionally, to give biological meaning to the output, cut-points were developed to calibrate accelerometer output, typically using regression or ROC (Receiver Operating Characteristic) curves to convert accelerometer counts to estimates of time spent at a given activity intensity, e.g. time spent in moderate-to-vigorous physical activity (MVPA) (3).

There are a number of cut-points available for use with each of the various accelerometer brands; which of the available cut-points are selected can have a large effect on activity outcomes. For example, Bornstein et al. (4) reported that minutes recorded in MVPA for a sample of 419 children aged 3–6 y varied from 39 to 269 min per day depending on the cut-points used with ActiGraph data. Similarly, in 2043 adolescents, Vanhelst et al. (44) reported that the percentage of adolescents meeting the recommendation of 60 min per day of MVPA varied from 6% to 37% depending on the ActiGraph cut-points used.

International Children's Accelerometry Database (ICAD)

To address the lack of comparability in accelerometer output variables, in 2008 the International Children's Accelerometry Database (ICAD) was initiated (http://www.mrc-epid.cam.ac.uk/research/studies/icad/): ICAD is a compilation of waist-worn ActiGraph accelerometer-derived estimates of children's physical activity from a range of studies and settings across Europe, the US, Brazil and Australia (33). Crucially, ICAD obtained the epoch level count data for each of the studies so was able to process data from all studies using consistent rules for classifying wear-time and time spent in activity intensities making the outputs comparable. This harmonising of waist-worn ActiGraph data from over 37000 children across >20 studies worldwide has facilitated the investigation of diverse questions across international datasets. For example, findings from studies using ICAD include: across countries children get more active as it gets warmer, but only up to about 20^{o} C (14); children in Northern Europe and South-East Australia are more active on average than children in the US and Western Europe, but also more active given the weather conditions they experience (14); and that shifting the clocks forward in Europe and Australia, and consequently having more evening daylight, could potentially increase mean population child physical activity levels in a single stroke (13).

A full list of publications can be found on the ICAD website (http://www.mrc-epid.cam.ac.uk/research/studies/icad/), where details on how to apply to use ICAD data can also be found. Recently ICAD2 was released, further increasing the potential of this valuable resource by including longitudinal data and access to a wider range of non-accelerometer data.

Raw acceleration accelerometry-based activity monitors

In 2009 there was an Objective Measurement of Physical Activity Expert Consensus Meeting co-sponsored by the American College of Sports Medicine and the National Institute for Health. A key recommendation of this meeting was that monitor data should be collected and saved as raw signals, rather than proprietary counts. This would remove the proprietary nature of accelerometer output by enabling data transformation to be carried out post-processing using transparent replicable methods, potentially facilitating comparisons between output regardless of which brand of monitor was used to collect data (46). Following this GENEActiv, ActiGraph and Axivity raw acceleration research-grade monitors became commercially available. All are waterproof and suitable for wear at multiple wear-sites but have been primarily marketed for wrist-wear.

Capture of physical behaviours across the 24 h day

These properties make them suitable for wear day and night meaning physical behaviours (sleep, sedentary behaviour and physical activity) across the 24 h day can be assessed. Further, 24 h wear protocols appear to lead to greater adherence with studies reporting average wear-times approaching a full 24 h day (23, 29). In contrast, in the US National Health and Nutrition Examination Survey (NHANES) 2003-2006, 40-70% of participants wore a hip-worn ActiGraph for 10 h/day for 6+ days, whereas when NHANES 2011-2014 switched to a wrist-worn ActiGraph 70-80% of participants wore the monitors for 21-22 h/day for 6+ days (12). The higher compliance persists even across multiple measurement points (23, 29). Greater wear-times and fewer instances of non-wear reduce the risk of misclassification due to incomplete capture of physical activity and selection bias due to exclusion of participants who do not wear monitors for sufficient time (34).

The International Study of Childhood Obesity, Lifestyle and the Environment (ISCOLE) deployed raw acceleration waist-worn ActiGraphs in a 24 h a day wear protocol in an ambitious multi-national cross-sectional study. Over 7000 children, aged about ten, were recruited from 12 countries between 2011 and 2013 (17, 38). Major strengths of this study were the purposeful inclusion of low-, medium- and high-income countries spread across the five major regions of the world (Europe, Africa, the Americas, South-East Asia and the Western Pacific) and use of a 24 h accelerometer wear protocol, facilitating the measurement of all physical activity, sedentary behaviour and sleep over the 24 h day. This is the first study to show that children who meet 24 h movement guidelines (35) for MVPA ($\geq$60 min/day), recreational screen time (<2 h/day) and sleep (9-11 h/night) are 72% less likely to be obese (26) and more likely to have better health-related quality of life (HRQoL, 32) than those who do not meet any of the guidelines. For obesity, similar results were observed across countries, but for HRQoL this was not consistent across study site. However, only 7% of children met all three physical behaviour guidelines across the 12 countries, with the highest proportion in Australia and Canada (14-15%) and the lowest in China, Portugal and USA (2%) (26).

The ongoing research outputs from ICAD and ISCOLE clearly demonstrate the value in harnessing accelerometer data across studies and/or populations (2, 33, 38).

There is now an increasing number of large-scale studies deploying raw acceleration wrist-worn accelerometers to assess children's physical activity including NHANES 2011-2014, the Pelotas Birth Cohort (8), the Melbourne Child Health Checkpoint (45), the Millennium Cohort Study (16) and the Cork Children's Lifestyle Study (18). It would be beneficial to ensure data and results from studies deploying these wrist-worn raw accelerometers are comparable.

What (I think) we need to know

The studies use one of the three research-grade accelerometers which give acceleration units in *g* (GENEActiv, ActiGraph or Axivity) and use the wrist wear-site. This theoretically makes the studies comparable (30). However, the availability of raw acceleration data also presents researchers with a new and different challenge; without the 'black box' generation of proprietary counts, the researcher is now responsible for processing and analysing huge amounts of data; one week of measuring at 100 Hz, as in most of these studies, generates over 180 million data points for each person. Consequently, physical activity research benefits from an increasing number of researchers with backgrounds in mathematics, computer science, engineering and statistics as well as sports science.

One of the stated aims of using raw acceleration monitors was to facilitate comparisons between output regardless of which brand of monitor was used to collect data. However, with researchers now having the responsibility for processing raw acceleration data to generate activity metrics, there is a risk that this will not be achieved unless some form of standardisation is agreed on. The challenge is twofold: 1) to develop innovative methods that take advantage of the richness of the data to classify behaviours, while 2) also ensuring accelerometer output measures that are comparable (so avoiding a repeat of the cut-point conundrum).

1) Classification of behaviours

Examination of features of the raw acceleration signal can facilitate classification of types or clusters of physical behaviours. For example, if the acceleration signal is cyclic it indicates a behaviour with repeating patterns, e.g. walking or running. It is also possible to determine the orientation of the monitor, and therefore the position of the wrist. The latter has been used to classify sleep (42) and posture (31).

There is a considerable amount of research into using supervised machine learning (e.g. 21) that uses labelled data (i.e. where the activity the child is doing is known) to learn to classify types of behaviours from features of the acceleration signal (e.g. sedentary, walking, running). These data are typically collected during prescribed or short free-living protocols; however, transferring the methods to classification of types of physical behaviours in free-living data is challenging, perhaps particularly in children given the transitory nature of their activity patterns. More recently, unsupervised machine learning approaches (e.g. 43) have been used with free-living data. These methods do not use labelled data (i.e. the activity the child is doing is not known), instead they are data-driven and allow the identification of clusters or characteristic states present in the data. It may then be possible to explore the physical behaviours these states likely represent, how they differ between groups, how they change over time and how they associate with health.

2) Maximising data comparability and the potential for data harmonisation

The removal of proprietary outcomes offers considerable potential for comparability between datasets and harmonising data. The ability to compare and harmonise these data would lead to improved precision and generalisability of recommendations for health.

While the first of these two challenges (classification of behaviours) requires specialist mathematical expertise, everyone assessing physical activity with a raw acceleration device can contribute to the second (maximising data comparability). By reporting comparable accelerometer metrics, we will also maximise opportunities for data harmonisation moving forward. ICAD has demonstrated what can be achieved when children's physical activity accelerometer data can be harmonised across studies and /or countries. Making data and outcomes from the many studies now using wrist-worn raw accelerometers comparable and harmonisation-ready would help us capitalise on the wealth of children's (and adult's) accelerometer data being collected globally.

Maximising data comparability - How (I think) we should get there

Individual studies will use a variety of approaches and outcome measures to address specific research questions and/or employ innovative metrics. To aid comparability it would be beneficial if, where possible, researchers could also make key standardised physical activity metrics available, much as other standard information such as age, height and mass is always given.

In this paper, I propose two strategies that I believe may help ensure comparability between studies and maximise the potential for data harmonisation moving forward.

1) *Agree on and present key standardised accelerometer metrics that are **Meaningful, Interpretable** and **Comparable**.*

Comparable across populations, yet interpretable for a given population, can seem contradictory. However, the metric itself need not be population-specific; instead:

2) *Move population-specific translation and interpretation to post processing/analysis.*

Strategy 1: Agree on and present key standardised metrics that are Meaningful, Interpretable and Comparable.

Meaningful in relation to associations between the metric and children's health (or performance);
Interpretable, so can be translated, e.g. in public health messages;
Comparable with other studies, populations and monitors.

In addition, the key metrics should:

- Reflect directly measured acceleration. The further we move from the measured variable, i.e. acceleration, the greater the scope for error (5).
- Include a single metric for 'How much?' or the volume of activity, and a single metric for 'How hard?' the intensity of activity.
- The metric for volume should not be highly correlated with the metric for intensity; this is necessary to facilitate investigation into the relative importance of intensity and volume for a given health outcome.
- The metric for intensity should reflect the entire intensity profile. Typically measures of MVPA and/or VPA are used for intensity, this is not ideal as it only covers a very small percentage of the amount of activity. Further, time accumulated above acceleration thresholds is highly correlated with volume of activity (e.g. counts per day) meaning that it is not possible to explore relative contributions of volume and intensity of activity to health outcomes.
- Both metrics should be possible to produce simply using open-source freely available software that works with all the three key brands of raw acceleration accelerometers (GENEActiv, ActiGraph and Axivity). This enables the same accelerometers metrics to be produced that are theoretically equivalent, regardless of device.

How much? Volume metric: Proposed metric - Average dynamic acceleration (Average acceleration)

This is the component of the acceleration signal due to movement, i.e. corrected for acceleration due to gravity (static acceleration). It is **meaningful** as it is correlated with energy expenditure (15, 39) and associated with health outcomes, e.g. adiposity (28). While not immediately interpretable (see Strategy 2) it is standardised and thus **comparable** between populations (Figure 1, upper panel). It is already widely used and is the metric reported in the Pelotas birth cohort (8) and Girls Active (10) as well as adult surveys, e.g. UK Biobank (9) and Whitehall II (19). It reflects **directly measured dynamic acceleration** over the whole measured time-period, is a **single metric for volume of**

activity, and can be produced using the **open-source freely available** GGIR R-package (https://cran.r-project.org/web/packages/GGIR/index.html, van Hees et al. (40, 41, 42) for the GENEActiv, ActiGraph and Axivity). Published evidence suggests that average acceleration can be considered equivalent between the GENEActiv and Axivity but is approximately 10% lower for the ActiGraph (30). More recent data considering longer free-living periods indicates average acceleration from all three monitors can be considered equivalent for monitors worn on the non-dominant wrist (unpublished data from our laboratory).

Insert Figure 1

How hard? Intensity metric: Proposed metric - Intensity gradient

As well as the confusion in intensity estimates resulting from the multiple cut-points available, intensity metrics tend to focus on parts of the intensity range, e.g. time spent in MVPA or time spent sedentary. This means that several metrics are needed to cover a range of intensities; ideally, a single metric that reflects the entire intensity profile is needed.

Most of a child’s day is spent in very low intensity activities, somewhat less time in light activities, less in moderate- and little in vigorous- and high-intensity activities, such that if you plot time accumulated against intensity you get a curvilinear plot (Figure 2). If you take the natural logs of time and intensity this becomes a straight-line graph. The intensity gradient describes the slope of this (28). The steeper it is (the more negative), the worse the intensity profile, the shallower it is (the less negative) the better the intensity profile. It reflects the whole profile of acceleration, rather than just a small fraction of it like MVPA.

Insert Figure 2

The intensity gradient is a new metric so not widely used. But, as with the average acceleration metric, it is **meaningful** in that it is related to measures of health, e.g. adiposity (28) and shows the known age-related decline in children’s physical activity (Figure 1, lower panel). While again not immediately interpretable (see Strategy 2), it is standardised and thus **comparable** between populations. It also reflects **directly measured dynamic acceleration** over the whole measured time-period, is **a single metric that reflects the intensity profile**, and can be produced using the **open-source freely available** GGIR R-package for the GENEActiv, ActiGraph and Axivity. Importantly, within a population, **the intensity gradient is not highly correlated with average acceleration**, meaning the two metrics can be used to investigate the relative importance of intensity and volume of activity for a given health or performance outcome. For example, in adolescent girls (28) and 10-y old children (personal communication Dr Stuart Fairclough), we have shown that the intensity profile is associated with body fatness independent of the volume of activity, but conversely the volume of activity is not associated with body fatness after controlling for the intensity profile. Further, recent free-living data from our laboratory (unpublished) suggests that the intensity gradient can be considered equivalent between all three brands of monitor and between wrists.

Strategy 2: Move population-specific translation and interpretation to post processing/analysis.

While average acceleration and intensity gradient are standardised and comparable between populations, e.g. age, they are not immediately interpretable in the same way as e.g. minutes of MVPA or minutes spent walking. However, both metrics do lend themselves to the creation of population-specific physical activity percentiles that would facilitate interpretation in relation to norms, as Wolff-Hughes and colleagues (47) have done with US children's age- and sex-specific percentile curves for total activity counts per day (TAC/d) for ActiGraph counts.

To give accelerometer outputs biological meaning while maintaining comparability, cut-point translation could be applied either at the time, or a later date. The time spent above incremental acceleration thresholds, e.g. 50 m*g*, is also easily available through GGIR. Reporting these data would enable people reading the paper to apply any cut-points to the data. In Figure 3 the time spent above incremental 50 m*g* thresholds is shown, with MVPA and VPA determined from both Hildebrand et al. (15) and Phillips et al. (22) children's cut-points.

Insert Figure 3

A recent paper showed how presenting the time spent above these incremental thresholds could also facilitate a 'ball-park' comparison to time spent in MVPA reported from children's studies using count cut-points with hip-worn ActiGraphs (27). For example, Figure 4 shows that time spent above 150 m*g* compares well to hip-worn ActiGraph MVPA estimates using the age-specific criteria of the Freedson group, published by Trost et al. (37), time spent above 200 m*g* to the Pate et al. (20) cut-points (all epochs), time above 250 m*g* to the Evenson et al. (11) cut-points (5 & 15 s epochs), and time above 400 m*g* for the Puyau et al. (24) cut-points (60 s epochs).

Insert Figure 4

Alternatively, it would be possible to use accelerations elicited by walking or running for a given age-group to translate the findings, see Figure 3 showing the acceleration associated with typical children's activities taken from Hildebrand et al (15) and Phillips et al (22). This type of translation may aid public health messages and intervention strategies.

Conclusion

The benefits of comparable children's waist-worn accelerometer data have been clearly demonstrated by ICAD and ISCOLE, both of which have significantly advanced the use of accelerometry to assess children's physical activity in large studies. Numerous studies worldwide, including large-scale surveys, are now measuring children's physical activity objectively using wrist-worn raw acceleration accelerometers. It is desirable to be able to directly compare and/or harmonise these data, while not interfering with innovation. This paper presents two standardised accelerometer metrics that could be presented in research papers alongside sample descriptors (e.g. age, height, mass) and in addition to physical activity outcomes specific to the research question addressed. Together, the proposed metrics capture the volume and intensity profile of physical activity and could allow children's physical activity studies to be instantly comparable, regardless of age-group and potentially across the three research-grade accelerometers. If, in addition, time above incremental 50 m*g* acceleration thresholds were presented, post-hoc population specific interpretation would be possible. In any given paper, if preferred, these metrics could be presented as additional online material, so as not to interfere with the message of the overall paper.

As suggested by Professor Tom Rowland many years ago, population referenced age- and sex-specific percentiles for physical activity, as have proved valuable for BMI, fitness, height and weight, would be extremely beneficial to clinicians and researchers alike. Wolff Hughes and colleagues (47) have produced such charts for US youth using TAC/d as a measure of volume of physical activity from the ActiGraph that is not dependent on cut-points. It would be possible to use two accelerometer metrics (average acceleration and intensity gradient) to do the same for the volume and intensity profile of children's physical activity for the many studies globally using wrist-worn accelerometry. Potentially these could become valuable to clinicians and researchers in the future. If a sufficient number of researchers bought into these strategies, it may help us capitalise on the growing body of accelerometer data describing children's physical behaviours 24 hours a day, 7 days a week.

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List of figures

Figure 1

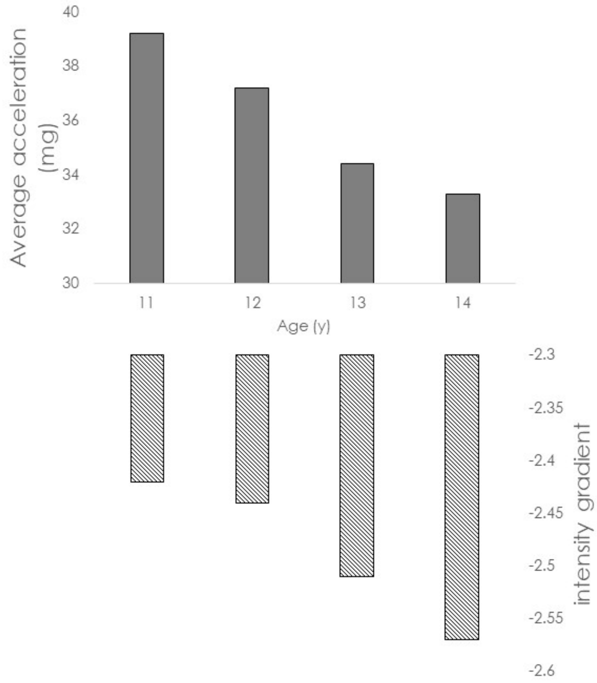

Figure 2

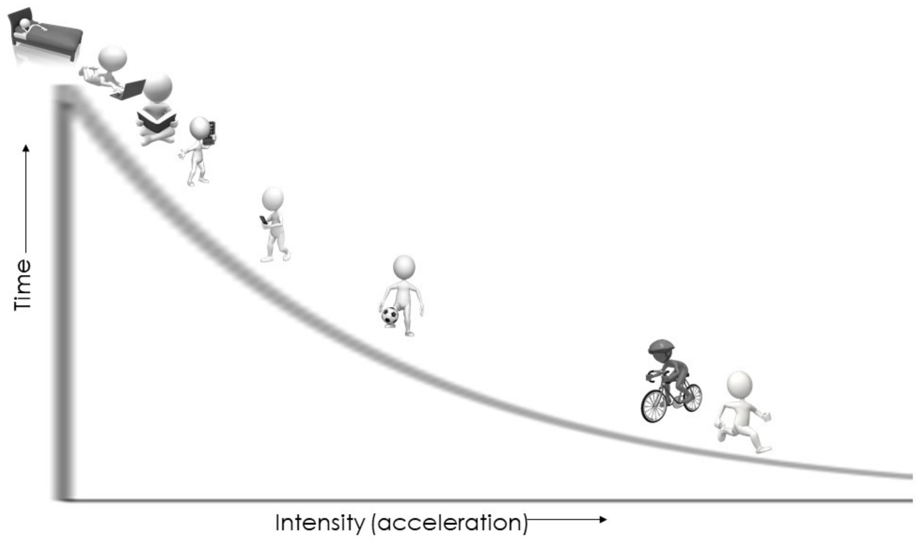

Figure 3

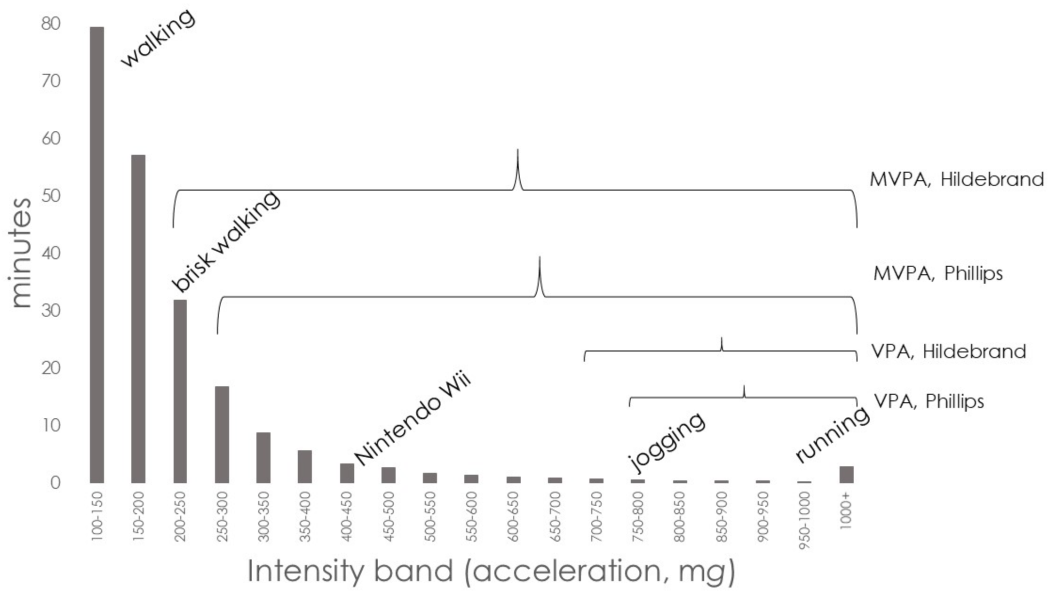

Figure 4