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Activity Mapping of Children in Play Using Multivariate Analysis of Movement Events

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ABSTRACT

Purpose: i. To develop an automated measurement technique for the assessment of both the form and intensity of physical activity undertaken by children during play. ii. To profile the varying activity across a cohort of children using a multivariate analysis of their movement patterns. **Methods**: Ankle-worn accelerometers were used to record 40-minutes of activity during a school recess, for 24 children over 5 consecutive days. Activity events of 1.1 s duration were identified within the acceleration time trace and compared to a reference motif, consisting of a single walking stride acceleration trace, obtained on a treadmill operating at a speed of 4 km h^{-1}. Dynamic time warping (DTW) of motif and activity events provided metrics of comparative movement duration and intensity, which formed the data set for multivariate mapping of the cohort activity using a principal component analysis (PCA). **Results:** The 2-D PCA plot provided clear differentiation of children displaying diverse activity profiles and clustering of those with similar movement patterns. The 1^{st} component of the PCA correlated to the integrated intensity of movement over the 40 min. period whilst the 2^{nd} component informed on the temporal phasing of activity. **Conclusion:** By defining movement events and then quantifying them by reference to a motion-standard, meaningful assessment of highly varied activity within free play can be obtained. This allows detailed profiling of individual children's activity and provides an insight on social aspects of play through identification of matched activity time profiles for children participating in conjoined play.

Key Words: CHILDREN'S PHYSICAL ACTIVITY, INERTIAL SENSORS, DYNAMIC TIME WARPING, MULTIVARIATE CLUSTERING, ACTIVITY PROFILING.

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INTRODUCTION

Physical inactivity is one of the major causes of death worldwide (1) and so exercise and activity programmes, designed to avoid sedentary lifestyles, are increasingly prevalent and have been shown to reduce risk factors such as type 2 diabetes, heart disease and even some cancers (2). For these reasons, it is important for children to develop the healthy habit of frequent physical activity (3,4) and considering that children spend a large amount of their day at school, recess becomes a natural time to encourage this. A wide range of factors determine children's propensity for activity (5), however it is clear that good playground design can have a positive effect (6,7). There is also a growing realisation that the quality of activity, as reflected in the movement competence of individuals is as important as the quantity of exercise undertaken (8,9).

Given this importance of exercise to a healthy lifestyle, detailed and quantitative assessment of activity frequency and intensity is a well-established research area (10,11). Measurement is often by wearable, inertial sensors (i.e. accelerometers) (12,13), placed at various locations on the body (14), to give signals that are proportional to the intensity and direction (magnetometer) of movement (15). Whilst the implementation of this technology to obtain a faithful record of body acceleration is relatively straightforward, the interpretation of the data to inform on activity is more difficult. In particular, the wide range of movements and irregular intensity of activity displayed by children during free play (16) present a demanding challenge to quantitative analysis. The commonly used metric for assessment of activity is 'counts' – integrated acceleration-magnitude during a defined epoch (17). This gives a ready measure that directly correlates to energy expenditure, however it conveys no information on the form of movement undertaken and by definition is insensitive to rapid changes in activity level.

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We therefore present a technique, based on the raw acceleration trace and the use of a standardized reference signal - a ‘movement motif’, which is a data sequence corresponding to a known motion such as a walk step or run stride. The movement motif provides a time-series template (18,19) to which movement events within the acceleration trace can be compared, using pattern matching implemented with a dynamic time warping algorithm (20). The evaluation of activity through analysis of specific movement features and patterns is well established, with many variations of machine learning approaches reported (21). The aim in these studies is to classify activity into identifiable phenotypes such as walking, running, standing, etc. (22,23). Our approach differs in that whilst a reference motif is classified (a walking stride), individual movement events are not. We compare rather than classify. This removes any restriction on the form of movement, thus avoiding mis-classification errors, whilst maintaining the context that a known movement type provides. Each comparison of a movement event with the motif quantifies the intensity and duration of the movement relative to the reference point of the motif sequence. This provides quantitative assessment of both quantity and form of motion undertaken during an activity session. The definition of specific movement categories for traditional pattern classification necessitates the use of extended time-sequences (multiple strides) to ensure that example sets are uniform enough to describe a single class (17,24–26). In the approach presented here there is no such restriction and event-motif comparisons are made with accelerometer time-sequence data acquired at 40 Hz. Implementation of the technique on children’s motion data obtained from a 40 minute school play period, allows high resolution temporal profiling of their activity (27,28). Participant profiling, based on the multi-parameter movement metrics is presented and used to assess variation within the cohort (29) and day to day trends across a week of measurements.

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METHODS

Participants and settings. The study was based on a set of 24 children, whose motion was recorded for one school-week (5 days), in a primary school in the U.K., 2 children were absent on one of the days and so the total data set included 118 motion records. In the participant sample set, 12 of the children were in year 5 and 12 in year 6, 18 children were boys and the summary statistics of the cohort are - age 10.5±0.6y, height 1.44±0.09m, mass 39.6±9.5kg, body mass index; 18.8±3.1 kg.m^2. The participants wore ankle-mounted accelerometers during school recess for 5 days. The participants' BMI, height, weight, gender, and school year were registered and the distributions of these metrics were typical for the age group of children. A stadiometer (Holtain, Crymych, UK) and digital scales (SECA, Hamburg, Germany) were used to measure stature (to the nearest 0.01m) and body mass (to the nearest 0.1kg) respectively, following standard procedures. Furthermore, children were classified as either underweight (< 5th percentile) (n = 1), normal weight (5th to 85th percentile) (n= 16), overweight (> 85th to < 95th percentile) (n = 5) or obese (≥ 95th percentile) (n= 2). (For more information about the participants, see Supplemental Digital Content 1, Appendix – supplementary information, http://links.lww.com/MSS/B710). The data were recorded with consent from the legal guardians and assent from the children, following the guidelines and policies of the institutional ethics committee and the Declaration of Helsinki.

Instruments. The children's motion was evaluated during normal time school-time recess (40 ± 4 min/day) for 5 days. A custom Micro Electro-Mechanical System (MEMS) based device was used to measure their physical activity at a frequency of 40 Hz and record it onto a microSD card (30). The sensor system incorporated a tri-axial accelerometer with a +/- 16 g dynamic range, 3.9

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mg point resolution (with an amplitude coefficient of variation of 0.004 at 40hz) (ADXL345 sensor, Analog Devices). It was housed in a small plastic case and affixed via a Velcro strap to the lateral malleolar prominence of the fibula of the right leg (see additional images, Supplemental Digital Content 1, Appendix – supplementary information, http://links.lww.com/MSS/B710).

Data extraction and analysis. All data handling and analysis was done in the *Matlab 2016b* environment. The total duration of play varied between 42-50 minutes, only the first 40 minutes of activity were analyzed, this ensured that all traces studied were of the same duration. The methods described in this section were applied to all the children's measurements along the five days, unless stated otherwise. Data acquired in the radial acceleration axis was selected for analysis as this had proven to be highly informative in previous work (30), with information being contained on push-off impulse, force of heel and toe impact and angle of leg lift. The raw acceleration time signal, with no filtering or smoothing applied, was used in all analyses. The extraction of movement metrics is based on the use of a 'movement motif'. This is a short, 1.1 s accelerometer sequence from a single stride, taken by a 27 year old male walking on a treadmill at a speed of 4 km hr^{-1}, with the same sensor system and attachment as used in the children's play study. This motif sequence, of a known and well understood biomechanical movement, provides a standard reference to which all of the children's movements can be compared. This choice of movement motif was based on a requirement for a known and well understood motion pattern that was distinct from those of the children to avoid biasing of any comparative analyses. We need a reference that is known and unchanging. This is difficult to obtain from a child as there is high variability due to the different states of physical maturity within the chosen age

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group. Also, the reference comes from outside of the group and so we get a comparison to an independent reference rather than self-referencing within the study cohort. Selected sequences of the acceleration signal, corresponding to movement events within each child's trace, were extracted using a threshold demarcation of 1.5 g. Comparison of each movement event with the motif was done using the Matlab dynamic time warping algorithm – '*dtw'*. This provides metrics on time difference, Δt and amplitude difference, Δd. A full mathematical description of Δt and Δd is given in the results section. Dimensional reduction of 80 metrics obtained from the time dependence of Δd and clustering of the 24 children into similar groups was done using Matlab functions for principal component analysis – '*pca'*, and dendrogram clustering – '*dendrogram'*.

EXPERIMENTAL PROCEDURES AND RESULTS

Signal processing and data extraction. An example of a raw acceleration trace is shown in figure 1. This is typical for a child at play, displaying variable and interrupted movement across the play session and complex acceleration features at short timescales, with no discernible regularity. Commonly used analyses of acceleration data take a time-averaged approach, defining 'counts' and categorizing activity level by the use of signal cut-points (31). In implementing time-integration, some knowledge of the form of the movement is inevitably lost. To avoid this, we take an alternative approach and implement an event-based analysis that highlights the temporal shape of the short, often sub-second, acceleration features. This provides metrics that can inform on the type of movement undertaken, with a time resolution that is consistent with biomechanical and musculoskeletal control dynamics. The challenge in doing this for children's play data is to find a robust method for defining motion events within non-uniform acceleration traces. Our solution is to use a movement 'motif' – a well understood,

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standard motion pattern. This sets a reference to which the acceleration signal can be compared, and events identified as data sequences with similar amplitude and duration as the motif. Essentially the raw acceleration trace is sectioned into events through a loose pattern matching to the motif standard. The movement motif is shown in figure 2a and is the acceleration trace from a single stride taken by an adult (male, age 27) on a treadmill walking at a speed of 4 km h^{-1}. Motion events are located using a peak detect algorithm with an imposed peak threshold of 1.5 g and a minimum peak-to-peak distance of 40 samples (1 sec.). Thus, a series of short sections within the signal trace are identified, within which the acceleration is similar to or greater than that imposed when walking. The identification process also ensures that no two events temporally overlap. A short trace section with 5 events identified, is shown in figure 2b.

Once motion events have been identified a secondary challenge arises as to how these are to be parameterized? As figure 1b shows, they vary considerably in shape, duration and magnitude, thus it is difficult to capture this heterogeneity with a tractable number of consistent metrics that can be easily extracted. We therefore, choose to characterise each event by comparison to the motif rather than by direct measurement of the event acceleration values. Each motion event is assessed by asking the question – ‘how close is it to a walk step?’. This produces correlation metrics that are quantitative, robust and which provide context to the movement undertaken. The event to motif correlation is done using a dynamic time warping algorithm (32). The dynamic time warping between event and motif signals introduces time steps in the data sequence in order to achieve optimum matching between traces (33,34). Basically, the two signals are stretched at various time points to create ‘warped’ sequences, these stretches are imposed in a way that achieves the best match between the pair of traces. Two parameters are

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extracted from each of these event-motif comparisons – the fractional change in time, Δt and the magnitude of the acceleration difference between the time warped signals, Δd, measured as the mean per sample point. These result from summation over the full trace and are mathematically defined as:

$$\Delta t = \frac{\sum_i \delta t_i}{t_{motif}} \qquad [1]$$

$$\Delta d = \frac{\sum_i |\delta d_i|}{n_{DTW}} \qquad [2]$$

$$if \int accel_{event} > \int accel_{motif} \quad then \quad \Delta d{+}'ve$$

$$if \int accel_{event} < \int accel_{motif} \quad then \quad \Delta d{-}'ve$$

Where δt_i and δd_i are the time and amplitude differences respectively (see figure 2c), t_{motif} is the duration of the motif signal and n_{DTW} is the total number of samples in the time warped signals. These event parameters can be displayed for a complete activity session in the form of a simple scatter plot. The plot obtained from the sample trace in figure 1 is shown in figure 2d. This provides an individualized, contextual map of movement and a ready visualization of the child's activity during play. Each point identifies a movement event, thus their density quantifies the amount of activity undertaken and corresponds to the information gathered in a traditional approach, where activity counts are recorded. Here, however there is also information on the form of each movement, captured in the x and y-coordinate values. The Δd value gives an immediate indication as to the intensity of the movement with the zero point being the reference level of walking (~3 METs hr^{-1} for the 4 km hr^{-1} motif (35)). The Δt value informs on how close

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the time phasing of acceleration is to a walk step. Values of $\Delta t > 0$ indicate the magnitude of the fractional difference in duration of each movement event to that of the walking stride motif. This is an absolute number and so does not differentiate between shorter or longer duration. Comparison to the motif standard also allows benchmarking of the child's activity to that undertaken in a controlled environment. The areas outlined in red in figure 2b indicate the range of values obtained when the motif is compared to other events in the treadmill-study acceleration signal, from which it is extracted. This shows the evolution from walk areas (low Δt, 3-5 km hr^{-1}) to running (high Δt, 9-13 km hr^{-1}). The red shaded area centered at zero Δd is the parameter state space covered by multiple step events acquired at 4 km hr^{-1} (i.e. stride-to-stride variability in the motif itself). The overlay of data from a staged walk to run exercise of the treadmill (red sections) onto the map of the child's movement (black circles) provides an immediate visual assessment of their activity in the 40 minutes of play. The spread of data gives shows the range of activity intensity and indicates the degree of variability compared to the controlled movement on a treadmill running through a sequence of set speeds. A number of features are evident in the child's movement map: i. a majority of low intensity events have greater Δt values than the motif sequence (3-5 km hr^{-1} section), this reflects the shorter stride duration relative to the adult walk motif; ii. there is a wide range of movement profile with events (black circles) spanning a continuous area that encompasses the 3-13 km hr^{-1} treadmill reference set; iii. there are ultra-high intensity outlier events which reflect movement for which the sum acceleration is well above that within a gait step produced by an adult running at high speed (13 km hr^{-1}).

Multivariate profiling. The extraction of multiple parameters for profiling of children from their activity profile was based on the time dependent values of Δd (figure 3a) as this gave a

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much greater discrimination that the Δt metric. The total number of events plus the summed value of the positive and negative Δd metric within a sliding, 2 minute time window provided 80 measures per child over the 40 minute activity sequence. Dimensional reduction was implemented using PCA; the 2-D plot for all 118 activity traces is shown in figure 3b. To interpret the PCA plot three regions were identified: L – low axis 1 and 2; M – medium axis 1, high axis 2; H – high axis 1, low axis 2 (figure 4a). Representative plots of the acceleration trace (magnitude) from each of these regions, are shown in figure 4b-g. Inspection of these shows that component 1 of the PCA correlates to activity intensity, measured as mean acceleration over the duration of the activity session (Pearson, r = 0.54), (for correlation plot, see Supplemental Digital Content 1, Appendix – supplementary information, http://links.lww.com/MSS/B710), whilst component 2 reflects differences in the time-staging of activity during play. Closely located points in the PCA plot indicate children with highly similar motion variables.

Figure 5a shows an expanded view of the PCA plot (shaded area in figure 4a). The raw traces from two children juxtaposed in the PCA plot, indeed confirm that their acceleration profiles are highly correlated across the whole of the play duration (figure 5c & d). Dendrogram plots provide an alternative to PCA for identifying hierarchical clustering of children based on their activity profiles. Figure 5b shows the dendrogram for all traces, sorted into 30 clusters using a weighted method with arithmetic mean (WPGMA), operating on the pairwise distance matrix between all points in the multivariate space (Euclidean distance). This provides information on groups of children with similar activity, e.g. cluster 17 encompasses the children shown in the red square on the PCA plot. It also allows quantitative assessment of similarity/dissimilarity using the cluster separation metric.

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Longitudinal study of the PCA plot provides insight on the daily activity patterns of the children. As an example, two children with differing patterns of play are shown highlighted in figure 6. Child A exhibits highly varied activity profiles with large day-to-day variance in the level and the time-pattern of physical motion, whilst child B displays a tight cluster of points from consistent daily activity patterns. Analysis of the varying activity profiles across a week also point to social influences on play. The extremely consistent play pattern of child B is disrupted on the Friday of the study week and they have a much reduced activity level on this day. Inspection of the PCA plot shows that the upper left region, in which the Friday play data of child B sits, is dominated by a cluster of other data points from Friday activity traces for children from the same class. The time-dependent acceleration traces for all of this group show an extended period of inactivity between the 15 minute and 25 minute points of the play session (see additional figures, Supplemental Digital Content 1, Appendix – supplementary information, http://links.lww.com/MSS/B710). Thus, there is strong circumstantial evidence that the altered play pattern of child B is due to the influence of their peer group.

DISCUSSION AND CONCLUSIONS

The aim of this study was to demonstrate automated, quantitative assessment of children's movement during play. There is a growing appreciation of the importance of the quality of activity in developing movement competence (9) and automated assessment of various movement tasks, based on signal feature extraction from wearable sensors, has been reported (36,37). Recognition and classification of activity type has also been achieved using Machine Learning algorithms (38,39). Whilst these approaches provide enhanced metrics on activity, over and above simple quantification, they are based on a premise that there exists a stable and

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recognizable movement pattern associated with each activity category, e.g. walk, run, skip etc. For children at play it is debatable whether such pattern standards exist. They exhibit an almost unlimited range of movement and even in core motions such as walking will display highly varied patterns, both at an individual level in step-to-step variance and at population level in the changing walk style across the cohort. In recognition of this we have developed an alternative method for activity profiling, based on identifying when movement takes place rather than when acceleration is produced. This follows other quantitative techniques in being focused on discrete motion events rather than continuous acceleration-based metrics. However, it offers a novel alternative when characterizing these events as it implements indirect measurement by comparison to a reference standard, rather than direct extraction of data from the child's motion signal. The advantage here is that because the acceleration patterns displayed by the children can be of any form, movement is no longer constrained to fit to a pre-ordained pattern. Benchmarked quantification is maintained as the extraction of metrics is always in reference to the known motif, which becomes the yardstick for interpretation.

As all metrics stem from comparison to a single motif this approach provides robust data that support comparison across a cohort and across different study days. By resolving movement into motion-events of short duration the technique also provides multi-parameter descriptions of each child's play session and this allows multivariate profiling of the cohort. All of the moment-to-moment detail of the varied play activity is captured and can be mapped, using a dimensional reduction algorithm, into a map of all activity profiles. This allows visual inspection of the variation or uniformity in activity level and identification of clusters of like-individuals who display similar activity patterns. This clustering may also point to social influences upon play, as

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closely mapped children have very similar acceleration time-traces, and this suggests common play during the measured time period. The activity map also shows temporal change across a longitudinal study and could be a powerful analysis tool in the case of intervention, where coordinate position on the map shows comparative performance between individuals, pre and post intervention.

In the work presented the reference standard chosen was a walk step, but other motifs could be used to give activity profiling in relation to a running stride, hop step, arm movement or similar. It is important to note that the motif determines the values of the extracted activity parameters but does not change the form of the measured motion signal. Thus, if an alternative motif pattern is used the values of Δd and Δt for each event will be different but the density of movement events and the comparative relationships between children will be unaltered. In this respect the motif acts as a filter through which we view the children's movement; changing it provides a different perspective of the same underlying activity topography.

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ACCEPTED

FIGURE CAPTIONS

Figure 1: a. Typical radial acceleration trace from a child wearing an ankle-mounted sensor for a 40-minute play session. b. expanded view of a 5-second play sequence.

Figure 2: a. radial acceleration trace of the walk-step motif. b. short sample of typical acceleration trace showing event peaks detected, the motif signal is compared to each of these using DTW. c. DTW traces for a motif-event comparison with instantaneous time warps, δt_i *and acceleration amplitude difference,* δd_i*. d. Scatter plot of all events within a single 40 minute playground session,* Δd *– magnitude of fractional event-to-motif acceleration difference,* Δt *– fractional extension of signal due to time-warping. Red areas indicate parameter space occupied by reference data obtained from participant walking and running on a treadmill with a unit incremented speed of 3 to 13 km* hr^{-1}.

Figure 3: a &b. Time-dependent measures for +'ve Δd *(a) and –'ve* Δd *(b); cumulative movement-event count - blue circles,* $\sum \Delta d$ *within 2-minute time window – black bars. c. Motion-metrics PCA for all children, the day of activity is indicated by the color shading (Monday – red, Tuesday – green, Wednesday – blue, Thursday – black, Friday – magenta).*

Figure 4: a. Motion-metrics PCA for all children with highlighted areas. b.-g. Typical acceleration magnitude traces for children within the highlighted areas of the PCA plot – L (b & e), M (c & f) and H (d & g).

ACCEPTED

Figure 5:a. Expanded view of the grey shaded area in PCA plot of figure 3, with similar pair (black line) and similar group (red dash line) of children highlighted. b. dendrogram plot showing cluster relationships, cluster 17 corresponds to the red-dash highlighted area of the PCA plot. c. & d. acceleration magnitude plots for the pair of children highlighted by the black outline in the PCA plot.

Figure 6: motion-metrics PCA with daily activity of two children highlighted (child A – red, child B – green). Black-filled circles represent Friday activity points of 6 children in same year (year 6) as child B.

Supplementary Digital Content

Physical-activity-playgroung-Appendix.docx

ACCEPTED

Figure 1

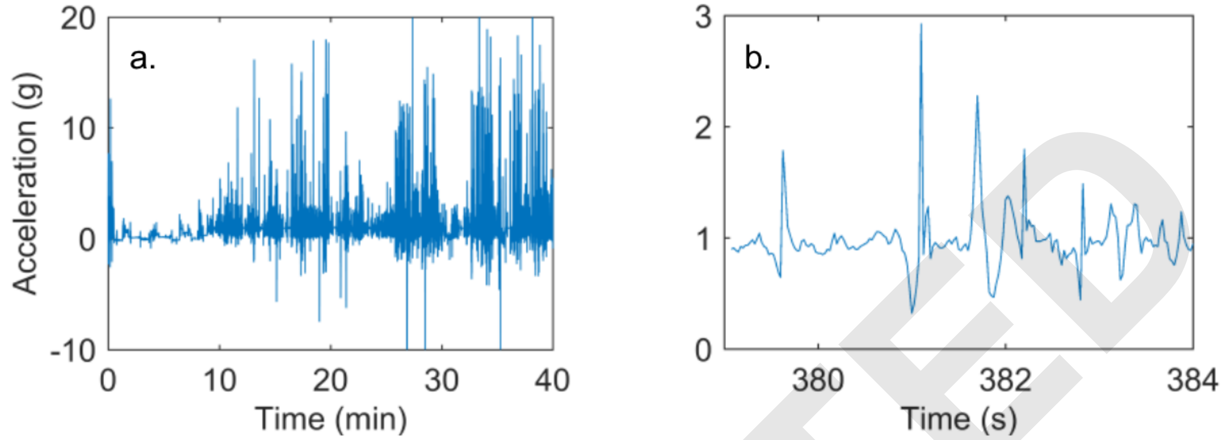

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Figure 2

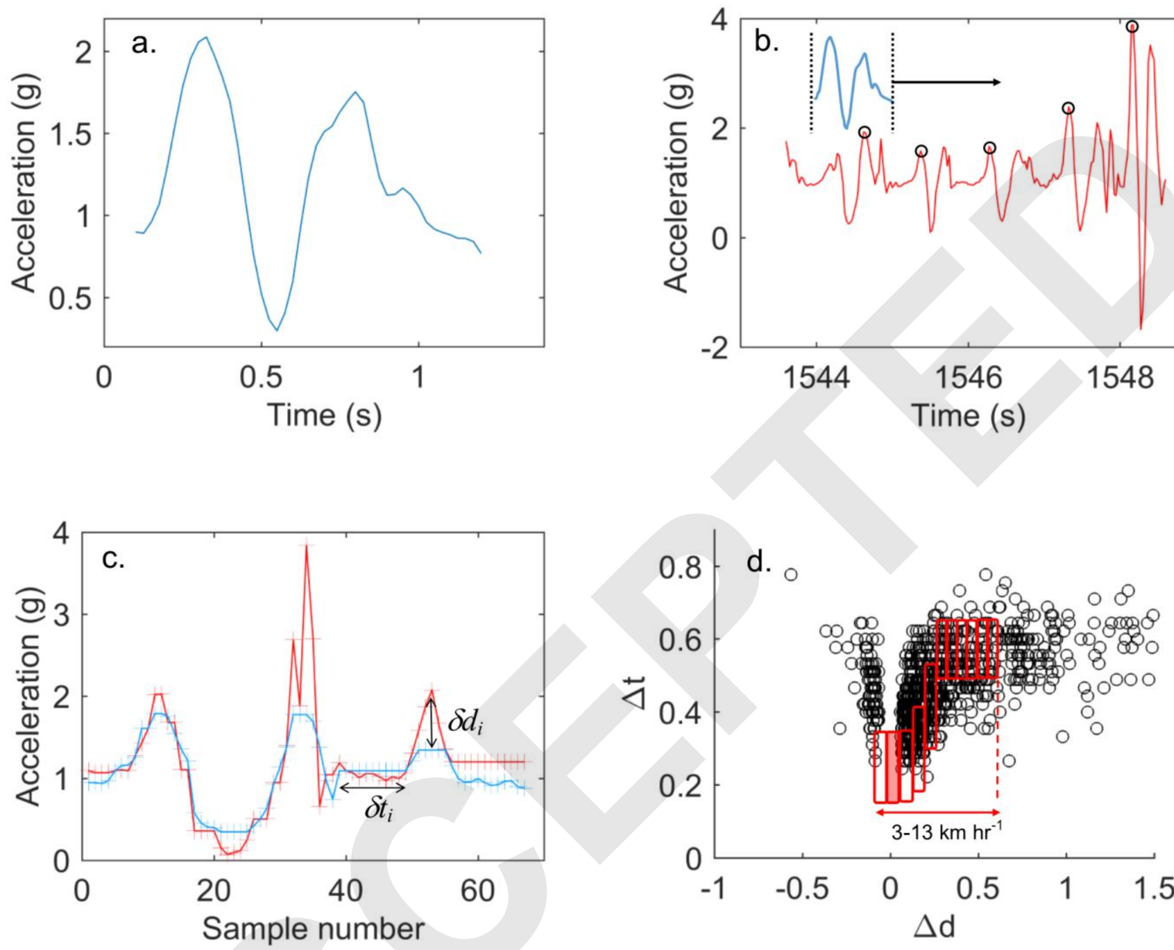

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Figure 3

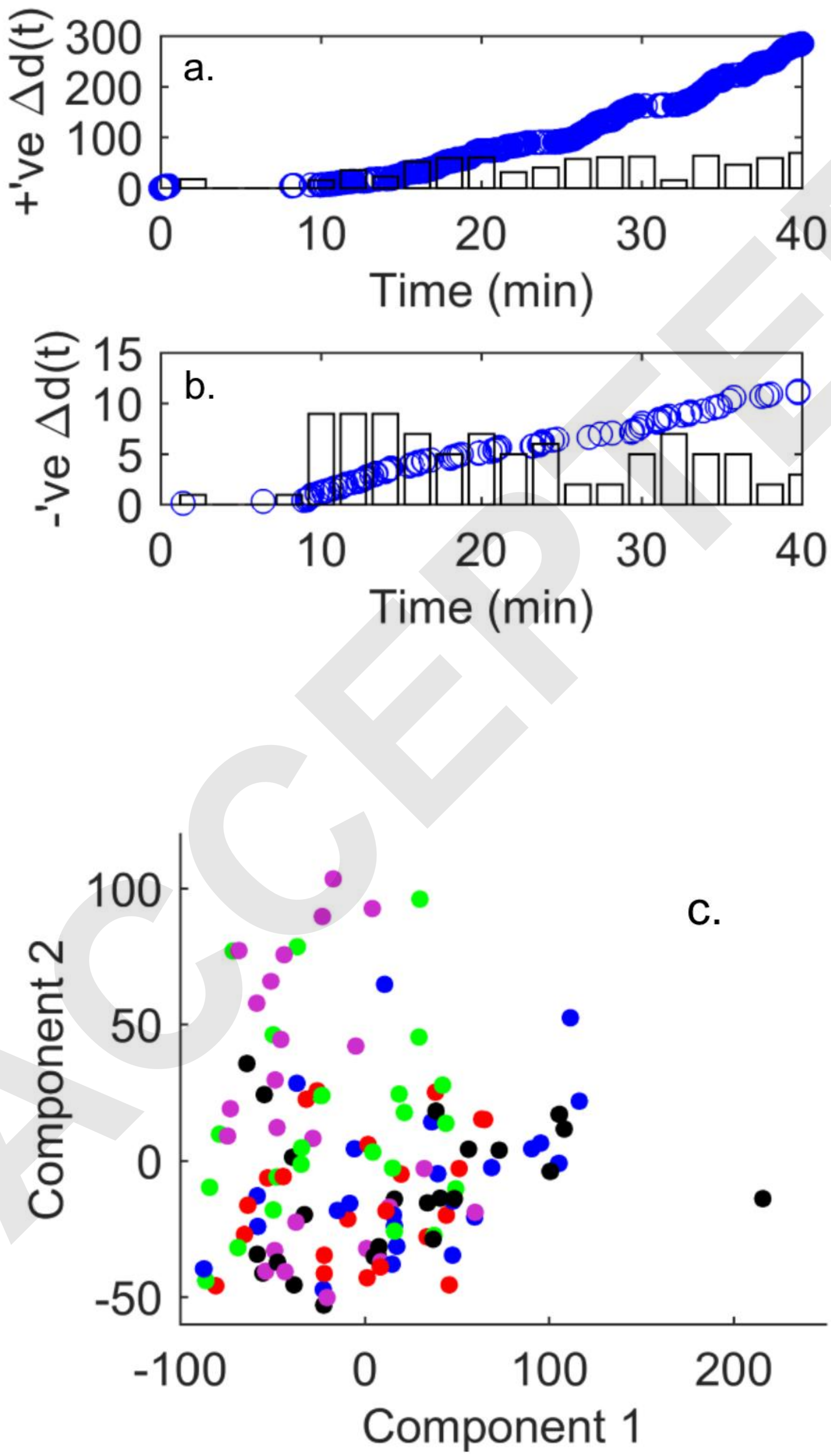

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Figure 4

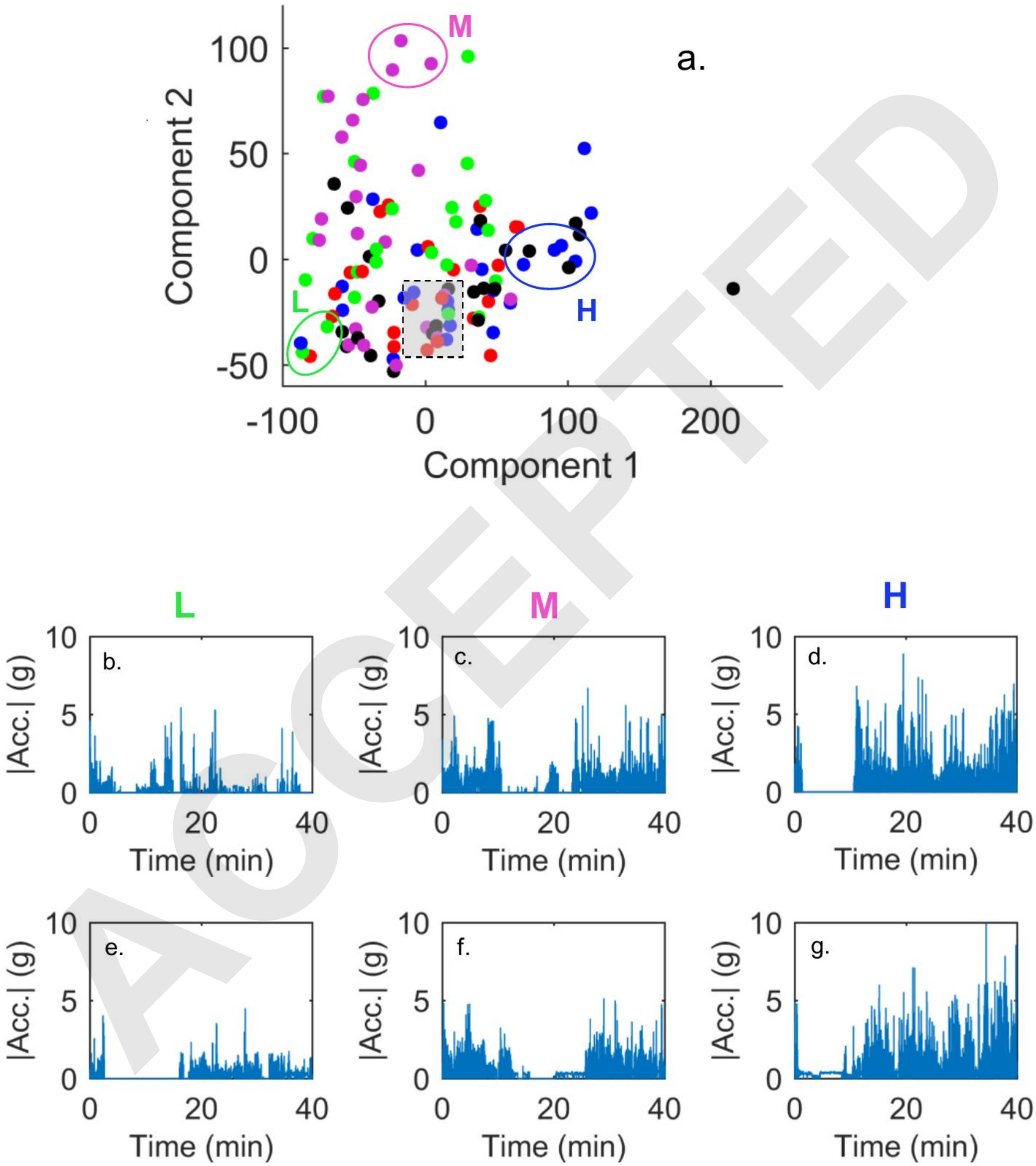

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Figure 5

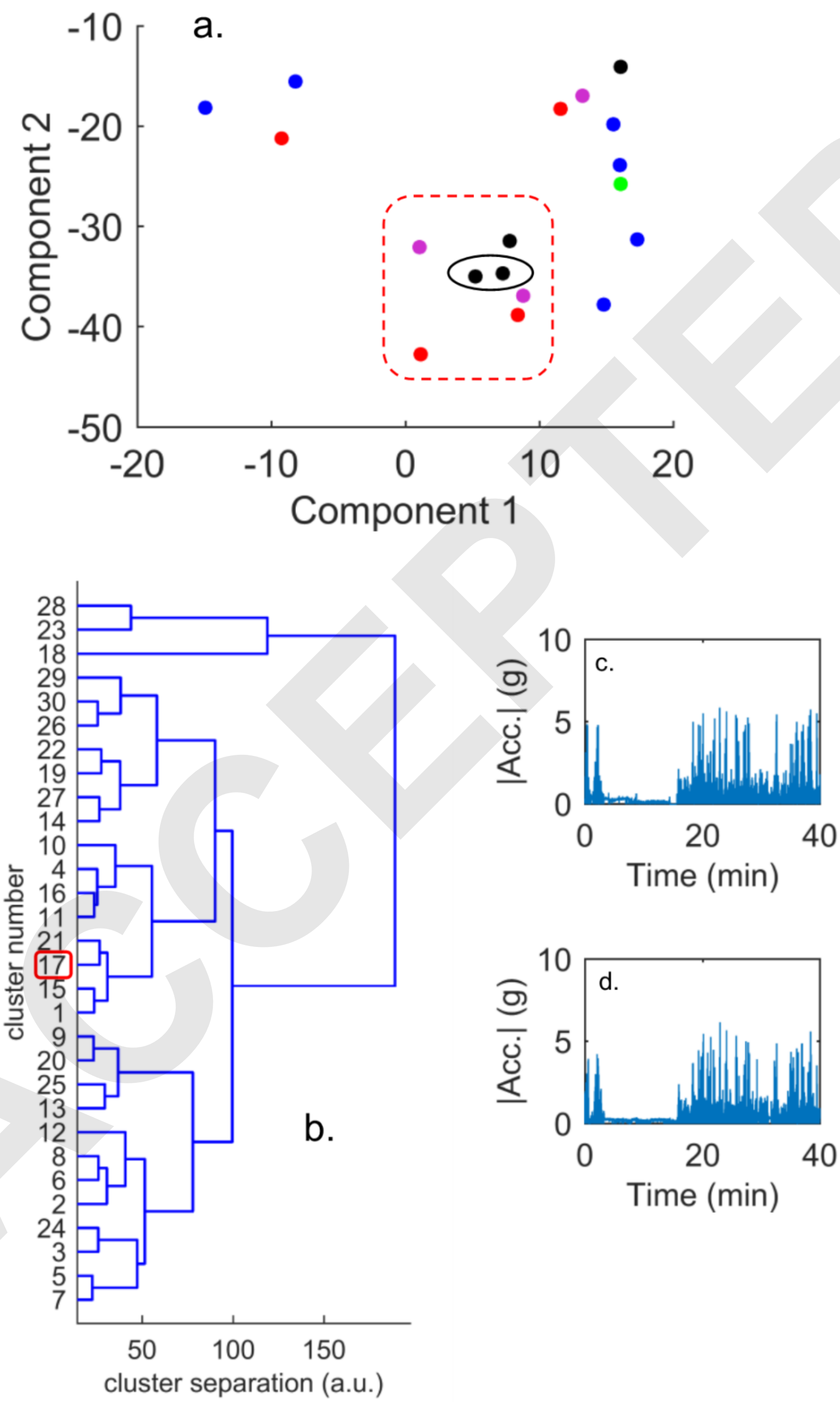

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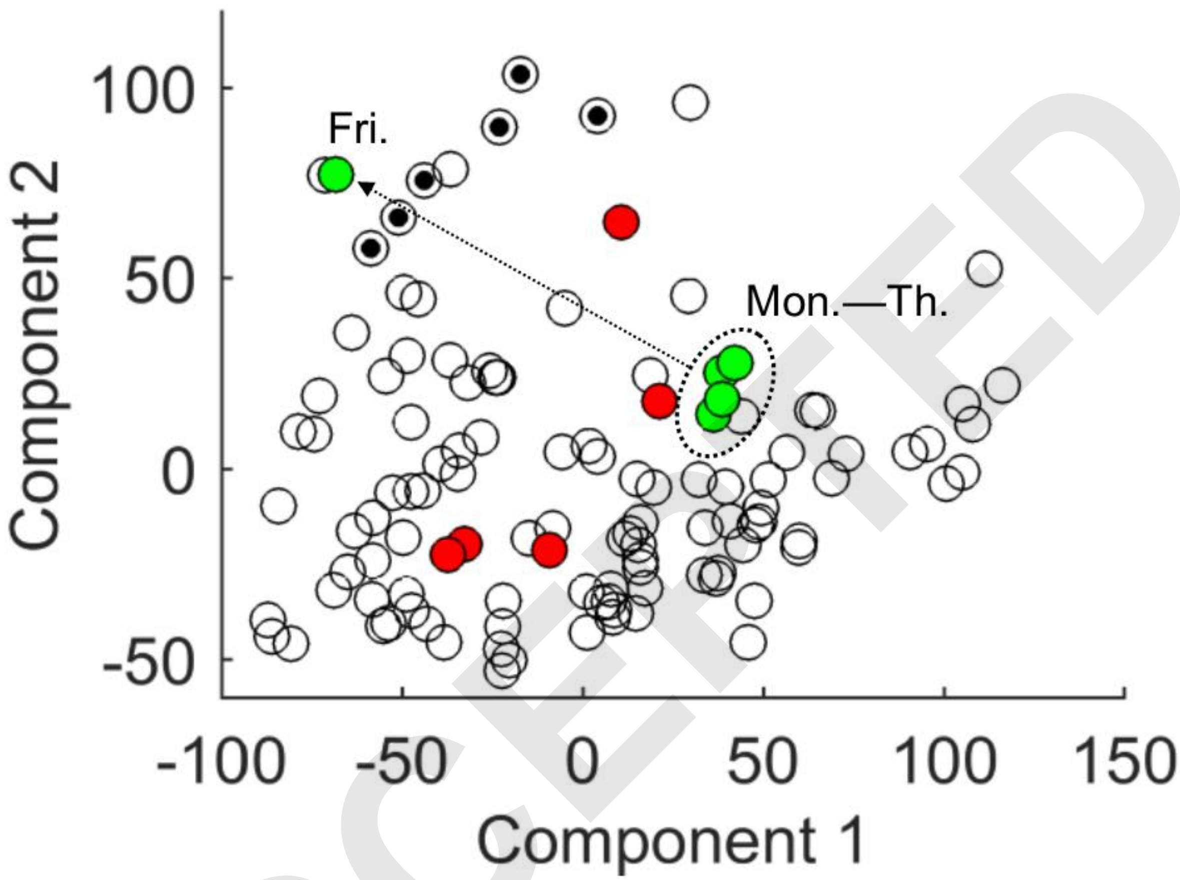
Figure 6



ACCEPTED

ACTIVITY MAPPING OF CHILDREN AT PLAY USING MULTIVARIATE ANALYSIS OF MOVEMENT EVENTS

J N Rocha[1], C M Barnes[2], P Rees[2], C.T. Clark[3,*], G. Stratton[3] and H D Summers[2].

ACCEPTED

APPENDIX: supplementary information and additional data-plots

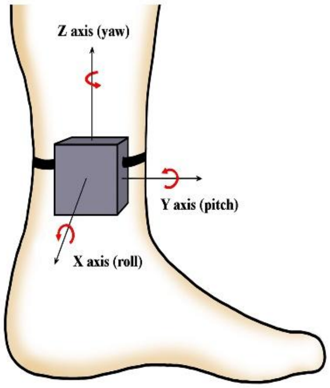
1. Table of health and fitness statistics for the 24 participants.

Table 1.

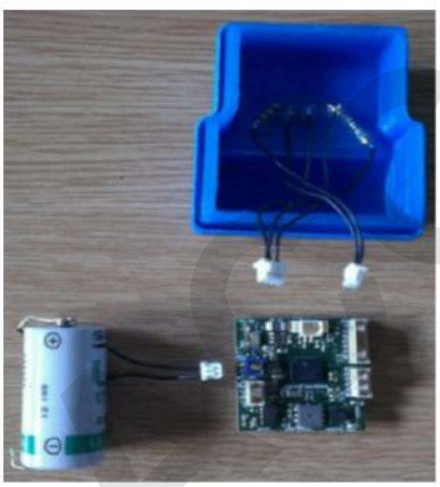
Self-assessed Health and Fitness scores range from 1 (poor) to 5 (excellent). BMI classification - UW (underweight), NW (normal weight), OW (overweight), or OB (obese).

Child	Mean Acceleration (arb. units)	Coefficient of Variation	Self Health	Self Fitness	Gender	BMI %	BMI Class
1	6,627	0,086	1	2	F	98	OB
2	10,082	0,181	4	4	F	42	NW
3	10,034	0,256	5	5	M	55	NW
4	8,191	0,137	5	4	M	59	NW
5	8,340	0,271	4	5	F	50	NW
6	12,059	0,398	5	5	M	51	NW
7	10,862	0,373	4	3	M	89	OW
8	8,621	0,279	3	5	M	94	OW
9	10,890	0,199	4	5	M	61	NW
10	6,112	0,231	2	2	M	96	OB
11	12,349	0,399	5	5	M	37	NW
12	7,537	0,212	5	4	M	86	OW
13	8,087	0,212	5	4	M	41	NW
14	10,705	0,135	4	5	M	26	NW
15	9,491	0,261	4	5	M	14	NW
16	11,283	0,232	4	5	M	71	NW
17	9,830	0,385	5	5	M	81	NW
18	13,036	0,062	4	5	M	59	NW
19	11,837	0,308	4	4	M	60	NW
20	6,653	0,516	1	1	M	98	OB
21	10,062	0,188	4	2	F	92	OW
22	11,376	0,227	4	3	F	35	NW
23	9,343	0,416	4	5	F	56	NW
24	7,292	0,392	4	5	M	89	OW

2. Images and placement of the movement sensor.



Placement on the lateral malleolar prominence of the fibula of the right leg

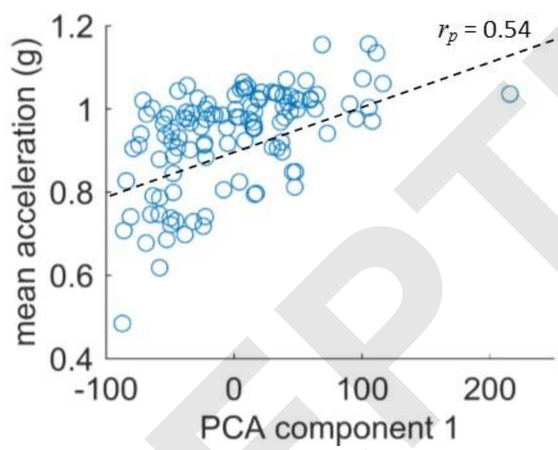


Device sensor board with housing and battery

ACCEPTED

3. Correlation of PCA component and activity level.

Mean acceleration, averaged over the 40 minute play session, for all 118 data sets and the corresponding values for Principal Component Axis 1 (see figure 3c in paper).

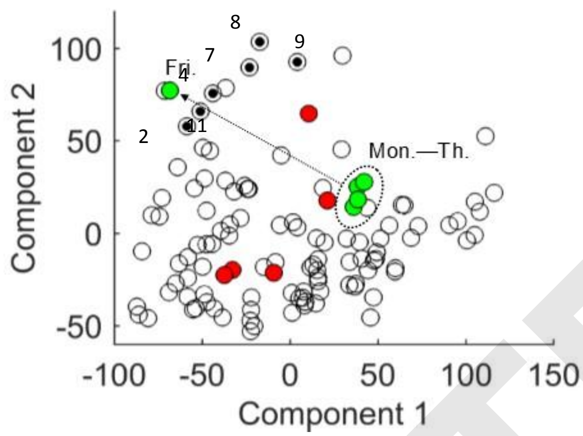


Correlation plot of mean acceleration versus PCA component 1.

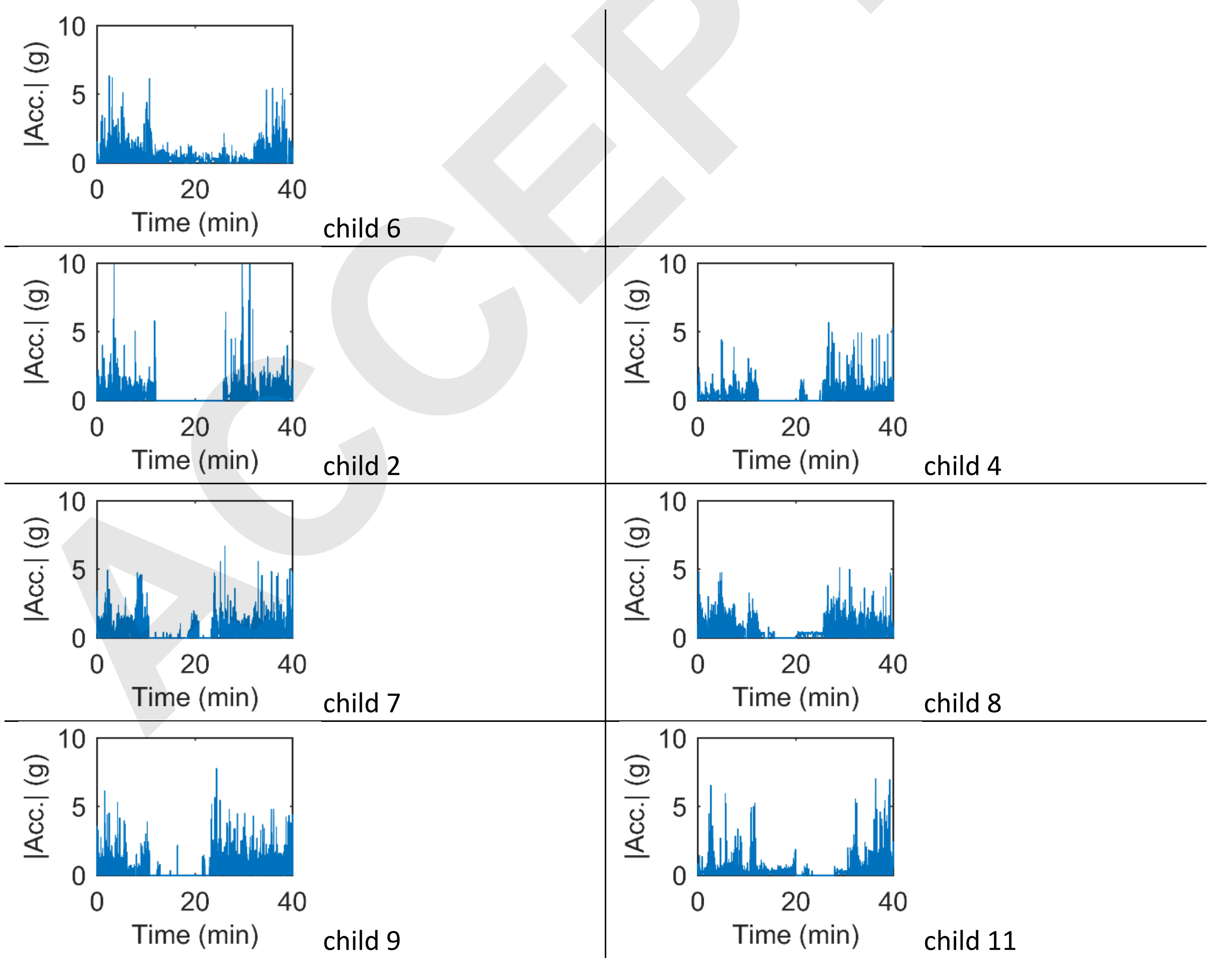
ACCEPTED

4. Additional raw-data traces from the 5-day longitudinal study.

Acceleration data traces, acquired on Friday of the study week for the cluster of year 6 children identified in the PCA plot. Black-filled circles and number identifiers indicate the 6 children. The data points for child 6, for all 5 days are identified by green-filled circles.



PCA plot in figure 6 of paper - re-presented.



Friday acceleration traces corresponding to the children identified in the PCA plot

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