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PROFILING MOVEMENT QUALITY CHARACTERISTICS OF CHILDREN (9-11Y) DURING RECESS

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ABSTRACT

Introduction. Frequency spectrum characteristics derived from raw accelerometry, such as spectral purity, have the potential to reveal detailed information about children's movement quality, but remain unexplored in children's physical activity. The aim of this study was to investigate and profile children's recess physical activity and movement quality using a novel analytical approach. *Materials and Methods.* A powered sample of twenty-four children (18 boys) (10.5±0.6y, 1.44±0.09m, 39.6±9.5kg, body mass index; 18.8±3.1 kg·m^2) wore an ankle-mounted accelerometer during school recess, for one school-week. Hierarchical clustering, Spearman's rho and the Mann-Whitney U test were used to assess relationships between characteristics, and to assess inter-day differences. *Results.* There were no significant inter-day differences found for overall activity (P>0.05), yet significant differences were found for spectral purity derived movement quality (P<0.001). Overall activity was hierarchically clustered, and positively correlated, with spectral purity (P<0.05). Discussion. This is the first study to report spectral purity derived movement quality of children's physical activity in an uncontrolled setting and our results highlight potential for future research.

Key words: clustergram; accelerometer; spectral purity; movement quality; recess

PERFILES DE MOVIMIENTO DE CALIDAD DE LOS NIÑOS DE 9-11 AÑOS, DURANTE EL RECREO

RESUMEN

Introducción. Las características del espectro de frecuencias derivadas de la acelerometría en bruto, como la pureza espectral, tienen el potencial de revelar información detallada sobre la calidad del movimiento de los niños, pero permanecen inexploradas en la actividad física de los niños. El objetivo de este estudio fue investigar y describir la actividad física y la calidad de movimiento del recreo de los niños, utilizando un enfoque analítico novedoso. *Materiales y métodos.* Una muestra de veinticuatro niños (18 niños) (10.5 ± 0.6y, 1.44 ± 0.09m, 39.6 ± 9.5kg, índice de masa corporal, 18.8 ± 3.1 kg.m2) usó un acelerómetro montado en el tobillo durante el recreo escolar, durante una semana escolar. La agrupación jerárquica, la rho de Spearman y la prueba U de Mann-Whitney se usaron para evaluar las relaciones entre las características y para evaluar las diferencias entre días. *Resultados.* No se encontraron diferencias significativas entre días para la actividad general (P> 0.05), sin embargo, se encontraron diferencias significativas para la calidad del movimiento derivado de la pureza espectral (P <0.001). La actividad global se agrupó jerárquicamente y se correlacionó positivamente con la pureza espectral (P <0,05). *Discusión.* Este es el primer estudio que informa la pureza espectral de la calidad del movimiento derivado de la actividad física de los niños, en un entorno no controlado y nuestros resultados destacan el potencial para la investigación futura.

Palabras clave: análisis de cluster, acelerómetro, pureza espectral, calidad de movimiento, recreo

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INTRODUCTION

Regular physical activity during childhood is associated with a lower risk of obesity, insulin resistance, mental health problems, cardiovascular disease, and improved academic performance (Blair et al., 1992; Strong et al., 2005; Telama et al., 2013). However, a substantial number of children fail to engage in sufficient physical activity outside of the school setting (Centers for Disease et al., 2003; Erwin et al., 2014; Ridgers et al., 2012; van Sluijs et al., 2011). Children spend a significant proportion of their waking time at school, and noncurricular time, such as school recess periods, provide opportunities for children to be physically active within the school environment (Jago et al., 2006; Parrish et al., 2013). It is suggested that recess periods may provide the single greatest opportunity during the school day to impact on child physical activity levels (RWJF., 2007; Stratton et al., 2007; Yildirim et al., 2014).

A number of systematic reviews have examined correlates of children's physical activity (Hinkley et al., 2010; Ridgers et al., 2012; Van Der Horst et al., 2007), yet these have predominantly focused on factors associated with whole-day activity. Ridgers et al. (2006) and Brusseau et al. (2012) highlighted that overall recess physical activity remains statistically invariant day-to-day, whilst Fairclough et al. (2012) reported no significant differences in recess activity between *a priori* categorised low and high activity children. Physical activity is a multidimensional behaviour influenced by numerous factors across several domains (Hinkley et al., 2008), and Myer et al. (2015) suggested that focusing on overall physical activity quantity alone overlooks other potentially important information, like skill development, enjoyment, and importantly, movement quality

It has recently been asserted that frequency-domain analytics may bridge the gap between quality and quantity measures of human movement (Clark et al., 2016a). Accelerometers that record the raw signal without undergoing proprietary pre-processing have been used to provide additional information about ambulation (Aziz et al., 2014; Aziz et al., 2011; Kangas et al., 2015), and to assess characteristics such as ambulation smoothness, control, balance and rhythmicity, albeit in adults (Bellanca et al., 2013; Brach et al., 2011). Furthermore, frequency-domain features (how much of the signal lies within each given frequency band over a range of frequencies), extracted from the coefficients of raw accelerometry signals may be obtained by performing spectral analysis (fast Fourier transformation (FFT)), and have been used for physical activity energy expenditure estimation and activity type recognition (Bonomi, 2013; Bonomi et al., 2009a; Bonomi et al., 2009b, 2012; Liu et al., 2012). However, whilst novel measures have been used to quantify physical activity energy expenditure and its classification, less attention has been given to the *quality* of movement. Whilst quality may be a nebulous term, one operational and measurable definition is; the purity of the fundamental frequency spectra (or signal), during human movement (Clark, 2017; Clark et al., 2016b). Recently, Clark et al. (2017) demonstrated; movement quality in young children, defined as above, was hierarchically clustered with motor competence and overall activity, whilst significant differences were found in movement quality between motor competence classifications.

Movement quality characteristics are retrievable using the harmonic content of the accelerometer signal, by analysing the symmetry within a movement (Gage, 1964; Smidt et al., 1971). The resulting spectral purity and integrated accelerations of each movement can be analyzed to assess, and profile, movement quality in children (Bellanca et al., 2013; Clark et al., 2016b; Clark et al., 2015; Clark et al., 2017). This type of analysis is highly suggestive of a fundamental feature of the neural control of movement and development of motor control (Clark et al., 2017; Stergiou et al., 2011) and shown to be representative of movement quality in standardised settings (Clark et al., 2016b). However, this has not been investigated in an uncontrolled setting, such as school recess, in primary school children. The aim of this study was to investigate and profile children's recess physical activity and movement quality using a novel analytical approach.

MATERIALS AND METHOD

Participants and settings

A sample of 24 children (18 boys) (10.5±0.6y, 1.44±0.09m, 39.6±9.5kg, body mass index; 18.8±3.1 $kg{\cdot}m^2$) volunteered to take part in this investigative study from a primary school in the U.K. Participants were a voluntary sub-sample of 822 children (10.5±0.6y, 1.42±0.08m, 27.3±9.6kg, body mass index; 18.7±3.5 $kg{\cdot}m^2$) from 30 primary schools. Paired t-tests confirmed there were no significant differences for any participant characteristics (height, weight, BMI) between the whole and sub-sample (P>0.05). Sample size was calculated based upon the primary outcome variable (spectral purity derived movement quality), and assumes a mean spectral purity of 2.3 (see: (Clark et al., 2016b; Clark et al., 2017) with a generous standard deviation of 2.0 (alpha = 0.05, power = 0.90). The sample size estimation was based on the ability to detect a minimum 2.0 %-unit change in spectral purity and highlighted 18 participants would be required to find statistical significance. In order to account for potential attrition, 24 participants were recruited. Prior to research commencing, legal guardian informed consent and child assent was attained. This research was conducted in agreement with the guidelines and policies of the institutional ethics committee, and in accordance with the Declaration of Helsinki.

Instruments and procedure

Children took part in normal school-time recess (40 ± 4 minutes per day) for one school week (five days), and physical activity was recorded using a Micro Electro-Mechanical System (MEMS) based device (Wilson et al., 2007; Wilson et al., 2006), which incorporated a tri-axial accelerometer with a ± 16g dynamic range, 3.9mg point resolution and a 13-bit resolution (SlamTracker, ADXL345 sensor, Analog Devices, Norwood, Massachusetts, USA). The recording frequency was set to 40 Hz, and deemed appropriate based upon the work of Clark et al. (2016c), where amplitude coefficient of variation and inter-device reliability was optimal (0.004%) at 40 Hz. In order to standardise data collection, the MEMS device 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 of all participants. Mannini et al. (2013) highlighted that for movement quality characteristics related to ambulation, an ankle-mounted monitor may be most suitable, and Barnes et al. (2016) systematically demonstrated that ankle affixed accelerometers can be used to accurately compute gait. Data were stored locally on the device, with no incidences of data loss. Children were also asked to complete self-reported health and fitness questionnaires, administered and graded according to standardised procedures, outlined in Idler et al. (1997) and Marques et al. (2017) (Self-reported health) and Ortega et al. (2011) (Self-reported fitness). The assessment of self-reported health and fitness used in this study has been shown to be independently accurate and valid in children (Idler et al., 1997; Marques et al., 2017; Ortega et al., 2011).

Anthropometrics

Stature (measured to the nearest 0.01m) and body mass (to the nearest 0.1kg) were measured using a stadiometer and digital scales (SECA, Hamburg, Germany), respectively, using standard procedures (Lohmann et al., 1988). Additionally, 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) (Cole et al., 2012).

Data analysis

Raw acceleration data were extracted from the MEMS device and subsequently uploaded into MatLab (Mathworks, MATLAB version R2016a. Natick, MA), where integrated acceleration and spectral purity were derived. The characteristics used for analysis were derived from acceleration in the axis along the lower leg towards the origin of motion, termed the radial axis. Briefly, the integrated acceleration was determined using a full-wave rectification of the integrated raw acceleration signal and correspondent to the computation used to derive activity counts by other commercial devices (i.e ActiGraph, for a full description of the algorithm used see: van Hees et al. (2010)).

Accelerometer data taken from children performing varying forms of ambulation were converted from the time into the frequency domain. In order to convert the data into the frequency domain the Fast Fourier transform was applied to the data. The Fast Fourier Transform computes the discrete Fourier transform (DFT) of a sequence.

Let x_0,…,x_(N-1) be a sequence of N complex numbers. The Fast Fourier transform computes the Discrete Fourier transform,

$$X_k = \sum_{n=0}^{N-1} x_n . e^{-i2\pi kn/N} \quad k \in Z$$

EQUATION 1. Fast Fourier Transform.

Where, N = number of time samples, n = current sample under consideration (0 .. N-1), x_n = value of the signal at time n, k = current frequency under consideration (0 Hertz up to N-1 Hertz), X_k = amount of frequency k in the signal (amplitude and phase, a complex number), n/N is the percent of the time gone through, 2 * pi (π) * k is the speed in radians·sec^{-1}, e^-ix is the backwards-moving circular path.

In order to determine the quality of a child's movement - 'Spectral purity' was calculated from the cumulative distribution function (CDF) of the frequency spectrum. The CDF plot is used to generate a value for spectral purity. The empirical CDF *F(x)* is defined as the proportion of X values less than or equal to some value *x*. In this case, it is the number of values less than or equal to some frequency in a spectrum being considered. A measure for spectral purity is therefore considered to be the frequency at which the midway point of the CDF (0.5) occurs. As a result, spectra that is 'clean', i.e. consisting of a tall narrow peak at the fundamental frequency and only low amount of noise and small harmonics will have a different value to spectra where there is lots of noise, a shorter wider peak, and higher peaks at the harmonics. Spectral purity measures how tightly the frequency components of the raw accelerations are distributed using fundamental frequency to harmonics and the frequency spectrum analysis is directly related to the ambulation of a participant (Barnes et al., 2016; Clark et al., 2016b). Contextually, high spectral purity indicates that smooth or cyclical, high periodicity movement has occurred.

Cluster analysis

Cluster analysis is an analytic procedure that reduces complex multivariate data into smaller subsets or groups. Compared with other data reduction methods, such as factor analysis, clustering yields groupings that are based on the similarity of whole cases, as opposed to the individual variables that comprise those cases (Leonard et al., 2008). Cluster analysis is used for profiling, or in the development of classification systems or taxonomies (Leonard et al., 2008; Sokal et al., 1962). Numerous characteristics of movement and lifestyle in adults and children (9-11y) can be reliably analysed using cluster analysis (Clark et al., 2016b; Schonlau, 2002; Tonkin et al., 2012). Further, Clark et al. (2016a) highlighted that cluster analysis is an analytical tool that should be exploited in the analysis of human movement characteristics.

The derived characteristics (integrated acceleration, integrated acceleration coefficient of variation (CV), spectral purity, spectral purity CV, BMI percentile, self-perceptions of health and fitness, gender) were normalised to fall between the data range of 0 and 1, so that they could be compared and input into an in-built clustering algorithm (MATLAB version R2016a). This algorithm goes through multiple iterative processes to cluster the data along the columns of the dataset. The similarity or dissimilarity between metrics was determined by calculating the pairwise Euclidean distances between the values of the different metrics.

$$d_{2SD} = (x_s - x_t)(x_s - x_t)'$$

EQUATION 2. Euclidean distance.

Where, d is the Euclidean distance, x_s and x_t represent the data values being compared, SD represents standard deviations.

Once the distances between the characteristics for each child were derived, a linkage function was applied, to determine the proximity of the metrics to each other. The characteristics were paired into binary clusters, which were subsequently grouped into larger clusters until a hierarchical tree was formed. The resulting clustergram was displayed as a heat map and dendrogram and were displayed in terms of Z-score, derived using a standard formula: Z = (raw score - mean) / standard deviation. The height of the link at which two observations on the dendrogram were joined was analysed using cophenetic distance (Equation 3), to demonstrate the similarity between two clusters (Saracli et al., 2013; Schonlau, 2002; Sokal et al., 1962). The values for the dendrogram linkages were subsequently normalised (0 to 1). The cophenetic distance ratio for the overall clustergram was also measured to demonstrate how successfully the dendrogram preserved the pairwise distances between the original unmodeled data points (where 1 is maximum).

$$c = \frac{\sum_{i<j}(Y_{ij} - y)(Z_{ij} - z)}{\sqrt{\sum_{i<j}(Y_{ij} - y)^2 \sum_{i<j}(Z_{ij} - z)^2}}$$

EQUATION 3. Cophenetic distance equation.

Where Y_{ij} is the distance between objects i and j in Y. Z_{ij} is the cophenetic distance between objects i and j, from Z. y and z are the average of Y and Z, respectively.

The whole raw acceleration signal was analysed over the duration of each recess period, for each day (five in total), subsequently mean integrated acceleration and spectral purity values for each day were assessed for differences. A Shapiro-Wilk test was conducted to assess normality of distribution, and data were found to be significantly different from normal (all $P<0.05$). Therefore, non-parametric analyses were used, and were presented as mean, median and upper and lower quartiles. The Kruskall-Wallis (KW) and post-hoc Mann-Whitney U tests, with continuity correction and tie adjustment (Gibbons et al., 2011), were used to determine differences between days, where appropriate, whilst the Spearman's rho test was used to identify correlation coefficients between each characteristic. All inferential statistics were performed using MatLab (Mathworks, version R2016a, Natick, MA) and statistical significance was accepted at $P\leq0.05$. Data were reported in graphical and tabular format.

RESULTS

There were no significant inter-day differences found for integrated acceleration ($P>0.05$), however, significant inter-day differences were found for spectral purity derived movement quality ($P<0.001$). Post-hoc tests revealed significant differences between multiple days (detailed in Table 1). Significant positive and negative relationships were found between movement characteristics, and are detailed in Table 2.

The clustergram illustrated that integrated acceleration and mean spectral purity (cophenetic distance (CD): 0.22), integrated acceleration and self-perceived fitness/self-perceived health (both: CD: 0.22), mean spectral purity and self-perceived fitness/self-perceived health (both: CD: 0.13), self-perceived health and self-perceived fitness (CD: 0.02), gender and BMI percentile and integrated acceleration CV (CD: 0.90), and finally, BMI percentile and integrated acceleration CV (CD: 0.72), were clustered together (Figure 1), with a cophenetic distance ratio for the overall clustergram of 0.96.

TABLE 1
Descriptive data for integrated acceleration and spectral purity day-to-day variation.

	Measure	Day 1	Day 2	Day 3	Day 4	Day 5
IA	Mean	8.86	9.09	10.76	9.73	10.32
	Med	8.69	8.61	10.77	9.93	10.12
	UQ	11.71	9.97	13.71	12.19	12.78
	LQ	6.35	7.37	8.17	7.39	8.14
SP	Mean	2.38	2.46 *	2.41 #	2.47 *	2.67 *, #, Φ, ǂ
	Med	2.38	2.47 *	2.42 #	2.48 *	2.82 *, #, Φ, ǂ
	UQ	2.41	2.53 *	2.47 #	2.52 *	2.9 *, #, Φ, ǂ
	LQ	3.32	2.41 *	2.34 #	2.39 *	2.56 *, #, Φ, ǂ

*IA: mean Integrated acceleration (arbitrary unit), SP: mean Spectral purity (arbitrary unit), Med: Median, UQ: Upper quartile, LQ: Lower quartile. * denotes significant difference vs. day 1, # denotes significant difference vs. day 2, Φ denotes significant difference vs. day 3, ǂ denotes significant difference vs. day 4. Significance level: P≤0.05.*

TABLE 2
Correlation coefficient matrix for movement characteristics.

	IA	IA CV	SP	SP CV	BMI %	SH	SF	Gender
IA	-	-0.05 *(0.82)*	0.51 *(0.01)* #	0.12 *(0.58)*	-0.55 *(0.005)* #	0.54 *(0.009)* #	0.47 *(0.02)* *	-0.09 *(0.66)*
IA CV	-	-	-0.02 *(0.92)*	-0.07 *(0.75)*	0.06 *(0.77)*	-0.01 *(0.97)*	-0.001 *(0.99)*	-0.19 *(0.37)*
SP	-	-	-	0.19 *(0.39)*	-0.05 *(0.79)*	0.65 *(<0.001)* ǂ	0.50 *(0.01)* #	-0.32 *(0.13)*
SP CV	-	-	-	-	0.11 *(0.62)*	0.22 *(0.31)*	-0.13 *(0.53)*	-0.08 *(0.72)*
BMI%	-	-	-	-	-	-0.53 *(0.007)* #	-0.53 *(0.008)* #	-0.002 *(0.99)*
SH	-	-	-	-	-	-	0.68 *(<0.001)* ǂ	-0.22 *(0.31)*
SF	-	-	-	-	-	-	-	-0.28 *(0.19)*
Gender	-	-	-	-	-	-	-	-

*Data reported as r value (P value). * denotes significance at P≤0.05. # denotes significance at P≤0.01. ǂ denotes significance at P<0.001. IA: Integrated acceleration, IA CV: Integrated acceleration coefficient of variation, SP: Spectral purity, SP CV: Spectral purity coefficient of variation, BMI%: Body-mass index percentile, SH: Self-perceived health, SF: Self-perceived fitness.*

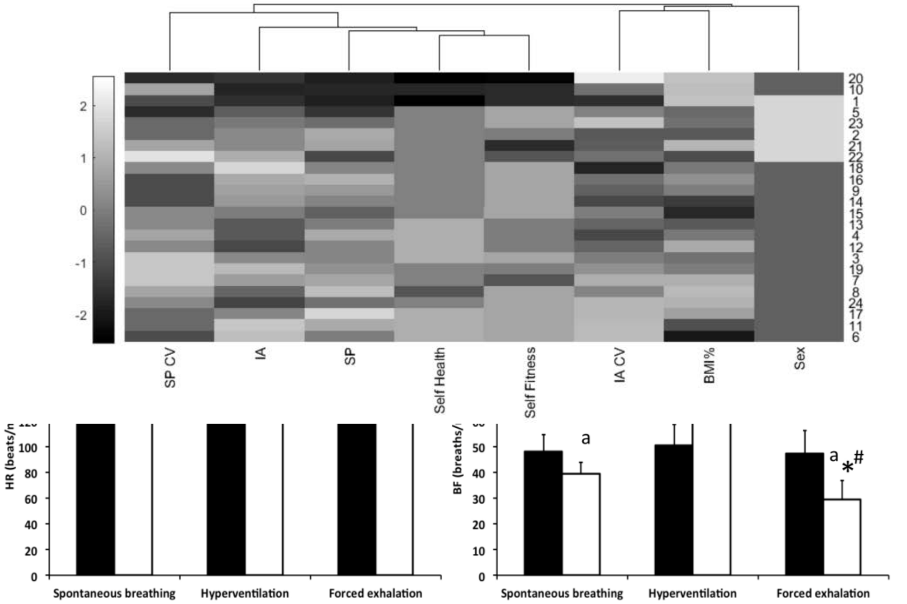

FIGURE 1. Colour gradation represent Z-scores in the Clustergram (for sex, grey denotes male and white, female). The Dendrogram highlights linkage between two or more characteristics. SP CV: spectral purity coefficient of variation, IA: integrated acceleration, SP: spectral purity, SH: self-perceived health, SF: self-perceived fitness, IA CV: integrated acceleration coefficient of variation, BMI%: body-mass index percentile.

DISCUSSION

Integrated acceleration and spectral purity

Novel characterisation of recess activity in this study, through spectral purity derived movement quality, highlighted significant day-to-day variance (Table 1). Congruent with previous research, the present study found that children's overall activity (integrated acceleration) during recess can be characterised as comparable across days (Fairclough et al., 2012; Ridgers et al., 2006). Importantly, recess activities are volitional, though results reported in the literature suggest that children are consistent in their choices due to factors such as playground hierarchies that dictate activity choices. Thus impacting upon the variability recorded, making recess characterisation using traditional methods relatively straightforward (Ridgers et al., 2006). Advancing on previous research, the present study utilised analyses of the entire raw accelerometry signal, rather than the use of long epochs (> 5 s). Long epochs may be too insensitive to accurately characterise sudden bouts of activity, and concomitant frequency spectrum characteristics, highlighting the potential of raw accelerometry (Barnes et al., 2016; Clark et al., 2016b).

In contrast to the lack of day-to-day variability of overall activity, movement quality characteristics have been shown to be significantly different between days in previous research in children (Clark, 2017; Clark et al., 2016b). Further, in controlled settings, it has been highlighted that spectral purity derived movement quality may be indicative of movement characteristics, such as time to exhaustion, overall activity, stride angle and stride frequency, all specifically relating to ambulation (Clark et al., 2016b). Recently, Clark et al. (2017) reported that in young children, spectral purity derived movement quality was significantly different between motor competency classifications ($P < 0.001$), i.e. children who scored lower in standardised motor competency assessment (MABC-2nd edition) also had a lower movement quality. However, the present study found that spectral purity derived movement quality was significantly different day-to-day ($P<0.05$) (Table 1). This novel finding demonstrates that the periodicity of the signal is variable day-to-day, indicating that the quality of activities and length of specific activities changes daily, even though overall activity remains invariant, offering novel insight into recess characterisation on a group and individual basis. Further, a tentative interpretation of spectral purity derived movement quality is that fundamental frequency and harmonic characteristics measured from an ankle worn accelerometer reflect the movement quality of children. Contextually, the signal characteristics of children's movement were significantly higher on Day 5 vs. Day 1, i.e. the raw accelerometric signals derived from movement were cleaner, indicating a 'higher' movement quality on this day, whilst overall activity remained invariant. This has important implications given variability is intrinsic in all biological systems (Stergiou et al., 2011) and has been asserted that an optimal state of variability that exhibits chaos is important for health and functional movement (Cai et al., 2006; Rosano et al., 2007), and therefore warrants a deeper investigation into signal characteristics of children's movement. In a comprehensive review, Stergiou et al. (2011) reported that variability has an optimal chaotic structure and deviations from this state can lead to biological systems that are either overly rigid and robotic or unstable. Both result in systems (humans) that are less adaptable to perturbations, such as those associated with unhealthy states or absence of skilfulness or control. It was also concluded that novel exploration of movement would provide a platform for better understanding human movement (Stergiou et al., 2011).

With regards to overall activity (integrated accelerations) and mean spectral purity, traditional analytics highlighted a significant relationship ($r=0.51$; $P\leq0.05$), whilst hierarchical clustering yielded a cophenetic distance of 0.22 (Figure 1). Based upon previously reported cophenetic distances between characteristics of movement (Clark et al., 2016b), and Clark et al. (2017) demonstrating spectral purity hierarchically clusters with motor competence at a cophenetic distance of 0.06, and integrated acceleration at 0.19, this indicates some congruence in the relationship between movement quality and overall activity in pre-adolescent children, and supports the notion that the underlying frequency spectrum may be fundamentally linked to overall activity levels. Table 1 highlighted that spectral purity derived movement quality may be significantly higher or lower daily, this finding has important practical implications related to physical activity intervention monitoring, at a group and individual level, and necessitates deeper investigation. Metcalf et al. (2013) reported that physical activity interventions, assessed using objective measures, were ineffective, however, no movement quality, nor frequency domain, measures were used in this meta-analysis. There is potential for future research to consider overall activity levels in conjunction with spectral purity (and other frequency spectra) derived movement quality measures to further interrogate intervention effectiveness and the underlying factors of human movement.

Body-mass index, gender and self-perception

Traditional analytics highlighted significant (P<0.05) relationships between overall activity (integrated acceleration) and, BMI percentile (r=-0.55), self-perceived health (r=0.52) and self-perceived fitness (r=0.47). Whilst BMI percentile was significantly correlated with, self-perceived health (r=-0.53) and self-perceived fitness (r=-0.53). Seabra et al. (2012) reported children with high BMI have lower levels of attraction to physical activity, lower perceived physical competence and less parental physical activity support, which puts them at greater risk of being physically inactive. Whilst, De Meester et al. (2013) asserted a combination of high actual and perceived motor competence is related to higher physical activity and lower weight status. Additionally, in the present study, self-perceived health was significantly correlated with self-perceived fitness (r=0.68), whilst being hierarchically clustered at a cophenetic distance of 0.02 (Figure 1). Although the low sample size utilised in this investigative study restricts direct comparisons, this is correspondent to the work of Peterson et al. (2003) who showed self-reported lifestyle and fitness were strongly positively correlated.

Spectral purity derived movement quality was found to have a stronger correlation and closer cophenetic distance (Figure 1) to self-perceptions of health and fitness, than overall activity. This novel finding tentatively indicates that movement quality may be more related to self-perceptions (of health and fitness) than overall activity (integrated acceleration). Clark et al. (2016b), Barnes et al. (2016) and (Clark et al., 2017)have previously demonstrated spectral purity is a measure of movement qualities in a standardised setting, and it is evident that this may translate to a measure of movement quality in uncontrolled physical activity.

Limitations

The sample size utilised within this study was acknowledgedly small, however was suitably powered to detect minimal changes in the primary variable of interest, movement quality, day-to-day, albeit the current bank of spectral purity derived movement quality data is low. Further, this study demonstrates a novel methodological analysis technique, setting a benchmark for further work. The authors recommend that a greater range of participants now be investigated to test the robustness of this novel technique, and to highlight whether school size and location impacts upon quality of movement derived from raw accelerometry. Although the accelerometers used within this study were custom-built, the protocol and analysis is repeatable using commonly used accelerometers, such as Actigraph or GeneActiv; the authors re-integrated the raw acceleration data in to, essentially, "counts" using a publicly available algorithm (van Hees et al., 2010), and because many commercial accelerometers have raw data available, researchers can begin to investigate movement quality in their studies as well (i.e., a specific accelerometer brand is unnecessary). The clustering algorithm used in this study was structured using hierarchical methods pairing characteristics by proximity, meaning inverse relationships may be difficult to highlight. On the other hand, this can be overcome with careful interpretation of the clustergram, in addition to other correlation analyses (i.e. Spearman's rho). This study employed novel accelerometer signal analytics i.e. spectral purity derived movement quality, however, there are additional approaches that could be employed, i.e. direct observational tools, and should be incorporated into future research. Thereby further refining the assessment of movement quality, in-field. The assessment of self-reported health and fitness used in this study, although not validated in combination, has been shown to be independently accurate and valid in children (Idler et al., 1997; Marques et al., 2017; Ortega et al., 2011), and was not a primary outcome of the study.

CONCLUSION

The aim of this study was to investigate and profile children's recess physical activity and movement quality using a novel analytical approach. In conclusion, this study found that spectral purity derived movement quality was significantly different between days, whilst also being hierarchically clustered with overall physical activity. Analyses of the frequency and harmonic content of movement quality, using raw accelerometry, is demonstrably sensitive and informative in investigating children's physical activity, and should be better exploited. This has important practical implications, particularly related to future intervention monitoring and assessing human movement. Researchers should consider exploring frequency spectrum derived quality and quantity of movement to further assess physical activity interventions, at a group and individual level. Further research should seek to better quantify and qualify physical activity in contextualised settings to enhance our understanding of specific movement and ambulation patterns, with emphasis on development through the ages and the utility of novel analytics.

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