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Full Length Article

Profiling movement quality and gait characteristics according to body-mass index in children (9–11 y)

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ABSTRACT

Obese children move less and with greater difficulty than their normal-weight counterparts. Whilst the effect of high BMI on cardiovascular fitness is well known, the effect on movement quality characteristics during a standardised fitness test has not been investigated. The aims of this study were, to characterise the movement quality of children performing the multi-stage fitness test (MSFT), and, report how movement quality characteristics cluster according to weight status. One hundred and three children (10.3 ± 0.6 y, 1.42 ± 0.08 m, 37.8 ± 9.3 kg, BMI; 18.5 ± 3.3 kg m^2) performed the MSFT whilst wearing an ankle mounted accelerometer. BMI groups were used to classify children as underweight (UW), normal weight (NW), overweight (OW) and obese (OB). Characteristics of movement were profiled using a clustering algorithm. Spearman's rho was used to assess relationship with BMI group, and a Mann-Whitney *U* test was used to assess differences between BMI groups. Obese children had significantly lower spectral purity than every other group and significantly lower time to exhaustion (TTE) than UW and NW children ($P < 0.05$). BMI was clustered with stride profile and TTE with spectral purity. Significant negative correlations ($P < 0.05$) were found between BMI and TTE ($r = -0.25$), spectral purity ($r = -0.24$), integrated acceleration ($r = -0.22$), stride angle ($r = -0.23$) and stride variability ($r = -0.22$). This was the first study to report the spectral purity of children's gait. Further analysis unveiled key performance characteristics that differed between BMI groups. These were (i) representative of children's performance during the MSFT and, (ii) significantly negatively correlated with BMI.

1. Introduction

Physical inactivity is one of the most widespread non-communicable diseases worldwide (WHO, 2010), and despite recognition of the importance of physical activity, the use of the appropriate measurement and analytical techniques is currently limited, especially with regard to gait and movement quality characteristics that make up physical activity.

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Accelerometers are the *de facto* standard in objectively measuring physical activity (Mathie, Coster, Lovell, & Celler, 2004; Van Hees et al., 2012) that cover the range of acceleration amplitudes and frequencies required to capture human movement (Bhattacharya, McCutcheon, Shvartz, & Greenleaf, 1980). However commercial accelerometers have limitations, for example high frequency movement and noise information can escape the bandpass filter which in turn adds unexplained variation in activity counts (Brond & Arvidson, 2015). In addition, variations in epoch length, cut points and device type further add to the lack of clarity in the literature (Bassett, Rowlands, & Trost, 2012; Edwardson & Gorely, 2010; Strath, Bassett, & Swartz, 2003). This is further confounded by the fact that commercially available accelerometers only provide manufacturer-dependent output values that are computed by unpublished and proprietary signal processing techniques, resulting in a unit of measure termed, 'activity counts'. Activity counts summarize data in an epoch, reducing the burden of data management, analysis, and interpretation; however, information about the raw accelerometer signal is irretrievably lost and a full picture of physical activity overlooked. In the assessment of human movement a central body position is the best accelerometer placement for capturing overall quantity of activity and best predicts energy expenditure (Boerema, van Velsen, Schaake, Tonis, & Hermens, 2014; Crouter, Churilla, & Bassett, 2008). However, the location of an accelerometer should be dependent on what researchers are attempting to investigate. Mannini, Intille, Rosenberger, Sabatini, and Haskell (2013) asserted that for gait quality characteristics, an ankle-mounted monitor had greatest validity, with a classification accuracy of 95%. Furthermore detailed information about gait quality during ambulation, gait phase detection, walking speed estimation, with an ankle mounted device would be far more revealing (Clark et al., 2016; Mannini et al., 2013).

The quantity of physical activity has been linked to various comorbidities, such as hypertension and obesity. (Katzmarzyk et al., 2015; Vale, Trost, Rego, Abreu, & Mota, 2015). The quantity of physical activity is useful in studies interested in measuring energy expenditure. The problem is that energy expenditure takes one simple measure from the accelerometer trace, the area under the curve. In contrast, there are numerous other features that can be derived from accelerometer data. For example quality characteristics can provide specific, contextualised feedback, but these have not been well utilised. The best known use of raw accelerometry to ascertain qualities of movement is in fall detection and the mobile gait analysis of older adults (Aziz, Park, Mori, & Robinovitch, 2014; Aziz & Robinovitch, 2011; Kangas, Korpelainen, Vikman, Nyberg, & Jamsa, 2015) whereby specific monitoring of walking and balance quality has been used to determine patients' safety and control during ambulation. As novel and robust analytics develop quantity and quality data will be derived from accelerometer traces (Clark et al., 2016).

For example fast Fourier transformation (FFT), has been used to process the accelerometer signal and identify gait qualities; walking smoothness, walking rhythmicity, dynamic stability and stride symmetry (Bellanca, Lowry, Vanswearingen, Brach, & Redfern, 2013; Brach et al., 2011). While FFT is an analytical technique used to characterise accelerometer data, cluster analysis involves the use of algorithms to separate a population into clusters or groups based on various parameters, such as activity behaviours, gait or movement qualities, stride profile, and BMI. Cluster analysis uses an iterative process of interactive, multi-objective optimization and has been used to inform animal movement and behaviour theory (Braun, Geurten, & Egelhaaf, 2010) and to identify and track cells (Tonkin et al., 2012). Given the nature of human movement, cluster analysis could be of great use in the understanding and analysis of gait and movement quality characteristics at a group level (Clark et al., 2016).

Fast Fourier transformation and cluster analysis can be combined to analyse movement in standardised settings. Moreover sensors can be attached to whole groups undertaking the same movement task. The multi-stage fitness test (MSFT) is a globally utilised test of cardio-respiratory, particularly used within school aged children, and is a component of the European battery of cardiorespiratory and motor tests (Eurofit, 1983). It is well reported that obese children move less and with much greater difficulty than normal-weight counterparts (Blakemore, Fink, Lark, & Shultz, 2013; McNarry, Boddy, & Stratton, 2014; Nantel, Brochu, & Prince, 2006; Nantel, Mathieu, & Prince, 2011; Shultz, Hills, Sitler, & Hillstrom, 2010; Stratton, Ridgers, Fairclough, & Richardson, 2007). This compromised movement is attributed to greater force through joints, decreased mobility, modification of gait pattern, and changes in the absolute and relative energy expenditures for a given activity. Further, detrimental changes in gait pattern have been demonstrated at the ankle, knee, and hip, and modifications at the knee level affecting articular integrity (Nantel et al., 2011; Shultz, D'Hondt, Lenoir et al., 2014). Although some recent work has examined the relationship between gross motor and fundamental movement skills and physical activity, in a standardised setting (incorporating accelerometry) (Laukkanen, Finni et al., 2013; Laukkanen, Pesola et al., 2013), however, there has been no attempt in the literature to use clustering algorithms to profile and compare derivatives of a raw acceleration trace signal during standardised fitness tests. There is clearly potential to derive more information from the signal from accelerometers to address current gaps in scientific knowledge. The aims of this study were first, to apply automated, novel analyses to characterise the movement quality of children during the MSFT (Clark, Barnes, Mackintosh, Summers, & Stratton, 2015; Mannini et al., 2013; Tonkin et al., 2012), and second, to report how movement quality characteristics of gait cluster according to BMI.

2. Methods

2.1. Participants and settings

One hundred and three children (10.3 ± 0.6 y, 1.42 ± 0.08 m, 37.8 ± 9.3 kg, body mass index; 18.5 ± 3.3 kg m^2) volunteered to take part in this study. Participants were a representative sub-sample of 822 children (10.5 ± 0.6 y, 1.42 ± 0.08 m, 27.3 ± 9.6 kg, body mass index; 18.7 ± 3.5 kg m^2) from 30 schools in the City and County of Swansea. Mean and variance data