Quantitative Time Profiling of Children's Activity and Motion

Claire Barnes, Cain Clark, Mark Holton, Gareth Stratton and Huw Summers

Original citation:
Barnes, Claire M., et al. "Quantitative time-profiling of children's activity and motion." *Med Sci Sports Exerc* (2016).
http://dx.doi.org/10.1249/MSS.0000000000001085

ISSN: 0195-9131

Publisher: Lippincott, Williams and Wilkins

Medicine & Science in Sports & Exercise
The Official Journal of the American College of Sports Medicine
www.acsm-msse.org

. . . Published ahead of Print

Quantitative Time-Profiling of Children's Activity and Motion

Claire M. Barnes[1,3], Cain C. T. Clark[2,3], Mark D. Holton[1,3],
Gareth Stratton[2,3], and Huw D. Summers[1,3]

[1]Centre for Nanohealth, College of Engineering, Swansea University, Singleton Park, Swansea, Wales, United Kingdom; [2]Applied Sports Science Technology and Medicine Research Centre (A-STEM), College of Engineering, Bay Campus, Swansea University, Fabian Way, Swansea, Wales, United Kingdom; [3]Engineering Behaviour Analytics in Sport and Exercise (E-BASE) Research group, College of Engineering, Bay Campus, Swansea University, Fabian Way, Swansea, Wales, United Kingdom

Accepted for Publication: 10 August 2016

Medicine & Science in Sports & Exercise, Publish Ahead of Print
DOI: 10.1249/MSS.0000000000001085

Quantitative Time-Profiling of Children's Activity and Motion

Claire M. Barnes[1,3], Cain C. T. Clark [2,3], Mark D. Holton[1,3],

Gareth Stratton [2,3], and Huw D. Summers[1,3]

[1]Centre for Nanohealth, College of Engineering, Swansea University, Singleton Park, Swansea, Wales, United Kingdom; [2]Applied Sports Science Technology and Medicine Research Centre (A-STEM), College of Engineering, Bay Campus, Swansea University, Fabian Way, Swansea, Wales, United Kingdom; [3]Engineering Behaviour Analytics in Sport and Exercise (E-BASE) Research group, College of Engineering, Bay Campus, Swansea University, Fabian Way, Swansea, Wales, United Kingdom

Running title: Profiling of children's activity and motion

Corresponding author:

Claire Marie Barnes

College of Engineering,

Swansea University, Bay Campus

Fabian Way, Crymlyn Burrows

Swansea, SA1 8EN, U.K.

637351@swansea.ac.uk

07809284648

During this work PhD scholarship funding was provided to Claire Barnes from the Engineering and Physical Science Research Council, U.K. and Swansea University Scholarship fund and to Cain Clark from the College of Engineering, Swansea and the Swansea University Scholarship fund. None of the authors or anyone involved with this research had a conflict of interest and the results of this study do not constitute endorsement by ACSM.

ABSTRACT

Introduction: The aim was to establish children's mechanical movement patterns during a standardised assessment of fitness by means of an accelerometer. Further to this, our objective was to use the information from the accelerometer to profile individual time courses of exercise, across the cohort. **Methods**: A multi-stage fitness test study was performed with 103 children, aged 10.3 years ± 0.6y. Children wore an ankle mounted accelerometer and gait data was collected on radial acceleration traces obtained at a frequency of 40 Hz. Time resolved metrics of foot impact force, maximum leg lift angle and stride frequency were used to profile children's performance across the test duration. A whole-history metric of stride quality, based on the changing ratio of stride length to stride frequency, was used in bivariate analyses of physical performance and body metrics. **Results**: Stride angle derived by our protocol was found to have a strong positive correlation with integrated acceleration, synonymous with counts, widely used in the sport science community ($r = 0.81$, $r = 0.79$ and $r = 0.80$ across different stages of the multi-stage fitness test). Accelerometer data show that differing performance in the test is related to the children's ability to accurately control their gait, with high performers displaying a linearly increasing speed, delivered through stride extension and well matched to the demand level of the test. A negative correlation was found between stride quality and body measures of BMI ($r = -0.61$), body mass ($r = -0.60$). **Conclusion**: Profiles of the gait parameters provide information on the mechanics of child's motion, allowing detailed assessment of multiple parameter during increasing intensities of exercise.

Key Words: Physical activity, Population Profiling, Accelerometry, Time series analysis, Gait analysis.

INTRODUCTION

Physical activity levels, particularly in children, are an important, well established area of research (20, 21). Much of the literature up to this point has focused on the correlation between quantity of physical activity and outcomes such as obesity, depression or anxiety (2). However, applying this approach to child populations is problematic as few have multiple risk factors and so these correlations become less important. Of equivalent interest to the quantity is the quality of physical activity. Qualitative aspects of physical activity are more akin to child development and can give a meaningful picture. We consider any measure of how much activity a child has done to be quantity measures whilst measures pertaining to how they performed the activity (the mechanics of exercise) to be quality measures. In this study we record the quantity of activity as this is a valuable metric, but we supplement this with a wider collection of more informative descriptors that may be referred to as 'quality' metrics, e.g. the mechanics of gait, agility, balance and co-ordination. Indeed there is a growing body of research which suggests that promoting an increase in the quality of physical activity is as important, if not more so, than simply increasing amount (6, 7). At present there is no established protocol to define quality of movement in the field that has been validated for use in populations.

Accelerometers have become the *de facto* standard for objectively measuring physical activity (16, 20) with the Actigraph (ActiGraph, LLC, Fort Walton Beach, FL) being the most commonly used, commercially available device. A major limitation with commercially available accelerometers is that they provide manufacturer-dependent output values commonly referred to as 'counts' (22). These are integrative values that sum up activity levels (integrated acceleration) usually averaged over user defined time periods, resulting in activity being quantified. However, the raw data is typically collected at frequencies of 10-100 Hz and so contains sufficient detail to resolve components within typical movement cycles such as gait or radial acceleration and so report on the kinetics of motion. Use of this high density time data together with data logging allows a transformation in the study of activity patterns.

The aim of this work is to derive a series of robust measures that could give accurate information on the quantity and quality of a child's physical activity within a semi-controlled environment (i.e. outside of a testing laboratory). Further to this, we wanted to quantify multiple time-dependent activity metrics, within large cohort studies ($n > 100$). Accurate and objective quantification of activity from a raw acceleration trace provides a rich data set that is robust enough to allow multi-dimensional profiling. The motion metrics describing gait may be correlated to measures of physiologic importance or profiled against socio-economic factors as well as psychological factors that have been derived through health and lifestyle questionnaires. Previous research has undertaken detailed analyses of accelerometer traces taken from subjects whilst walking and running and much of this work has involved measures of gait (18, 19) and foot impact (9). While these reports clearly show the depth of information available from a raw accelerometer trace; it is important to note that there is often a considerable computational load as complex models based on multiple accelerometers are used to reconstruct walking or running motion (3). The associated algorithms require exhaustive human input along with significant amounts of computer time and memory. Thus to date activity profiling has had to rely on broad based measures of physical activity due to the fact that detailed analysis of gait has been confined to studies involving small cohorts in controlled settings (5, 16). In this study our aim was to demonstrate the use of ankle-worn accelerometers in a semi-controlled activity environment: within the framework of a 20-m multi-stage fitness test (11). The objective being to deliver a detailed quantitative analysis of the relation between the mechanics of the children's motion and their overall performance. Staged fitness tests such as this provide in-field information on the quantity and intensity of activity but to date they have not been used to investigate the mechanics of how the children adapt their physical motion in response to changing demands in performance.

METHODS

Participants and Settings

103 children volunteered to take part in this study (average age = 10.3±0.6y, height = 1.42±0.08m, mass = 37.8±9.3kg, BMI = 18.5±3.3 $kg \cdot m^{-2}$, boys = 58 and girls = 45). Participants were required to attend an indoor training facility, have anthropometric measurements recorded and take part in the Multi-stage fitness test (MSFT). Further, BMI centiles were used to classify children as either underweight (<5^{th} percentile, n = 7), normal weight (5^{th} to 85^{th} percentile, n = 73), overweight (>85^{th} to <95^{th} percentile, n = 14) or obese (≥ 95th percentile. n = 9) (5). This research was conducted in agreement with the guidelines and policies of the institutional ethics committee and parents/guardians gave full written informed consent and children gave full written informed assent to take part in the study.

Instruments and Procedures

After standard familiarisation and five minute warm-up, children performed the MSFT (10), whilst wearing a custom built motion tracking and recording device (figure 1a), which incorporated a tri-axial accelerometer with a +/- 16g dynamic range, 3.9mg point resolution and a 13 bit resolution (with an amplitude coefficient of variation of 0.004 at 40hz) (ADXL345 sensor, Analog Devices). The device was housed in a small plastic case. As we are assessing gait we decided to affix via a Velcro strap to the lateral malleolar prominence of the fibula of the right leg. There is a body of work that suggests that this is the best location to assess gait patterns (4, 8). A co-ordinate system referenced to the lower leg was used (motion space rather than absolute space), in which acceleration in the axis along the lower leg towards the origin of motion (knee or hip), A_{radial} is used for all measurements - termed the radial axis, (figure 1b). The device was set to record at 40 Hz and data were recorded onto a microSD card (figure 1c).

Twenty-metre Multi-Stage Fitness Test

Participants completed the MFST by running back and forth along a 20m course, and were required to touch the 20m line at the same time that a sound signal was emitted from a pre-recorded audio disk. The frequency of the sound emissions increased to produce a corresponding increase in running speed. The test stopped when the participant reached volitional exhaustion and was no longer able to follow the set pace, or participants were withdrawn after receiving two verbal warnings to meet the required pace (12).

Data extraction and analysis

Data extraction and analysis was carried out using custom algorithms written in the MATLAB software environment. Low and high frequency device noise was removed by passing the raw data through a broadband-pass filter (0.5Hz to 12 Hz) i.e. only frequencies within the normal range of walking and running frequencies were accepted. To remove breaks in the signal caused by participants stopping at the end of each 20 metre shuttle and before the next bleep trigger a simple process of data removal from redundant time periods was used. To this end, the acceleration trace was integrated to give an activity ‘count’, when a child’s reading dropped below a threshold, twenty five percent or lower of the average ‘count’ level during the main activity of running they were deemed to be inactive and waiting at the end of one of their 20 metre shuttle runs. This period of trace was then deleted from that which is analysed.

The radial acceleration trace for one stride is shown in figure 2. There are three regions corresponding to the push-off, leg swing and foot impact phases of the stride. A number of defining metrics were extracted from the traces. The maximum impact force generated upon foot strike, F_{max}, corresponds to the peak positive value of acceleration (force vector pointing from foot to knee). When converting the force data to absolute values the background static signal of 1g is subtracted and the remaining signal converted to a force through multiplication by the subject's body mass. Confirmation of the accuracy of the impact force value, F_{max}, derived from the accelerometer was obtained by comparison to that measured by a Kistler force platform, model number 9286AA which uses piezoelectric sensors to determine force applied in multiple-axes (figure 3a and 3b). The force plate was set to sample at 1000Hz and is calibrated to give a value of the force applied in Newtons.

The maximum angle of foot lift, α_{max} is obtained from the peak acceleration value in the negative direction. At this point of maximum leg lift the dynamic acceleration is zero and the radial acceleration is wholly determined by the vector component of the gravitational field, as determined by the angle of the accelerometer relative to the vertical axis. Thus to determine the angle to which the subject's leg swings the minimum point during the acceleration trace of the stride, A_{radial} is used in the following expression:

$$\boldsymbol{\alpha}_{max} = acos(A_{radial}/g) \qquad [1]$$

To validate the accelerometer-derived value of maximum angle of foot lift, α_{max}, comparison was made to a video analysis (figure 3c). A video sequence was recorded for a subject running on a treadmill at speeds ranging from 7 $km \cdot h^{-1}$ to 13 $km \cdot h^{-1}$. Manual measurement of the leg position from the image frames was then used to determine angle. It is important to note that the angle of foot lift is defined to be that of the lower leg as it rotates around the knee position. To derive measures from the frequency domain a discrete Fast Fourier Transform was applied to the data. The stride frequency, f is identified as the first amplitude maxima.

RESULTS

Analysis of an individual's activity profile

The participants were classified into 3 groups (low, moderate or high performers) according to their performance in the shuttle run test. The 'low' performers were the first third of the group to drop out of the test. 'Moderate' performers were the middle third of the group whilst the top third of the group, staying in the test the longest were classified as the 'High' performers. To demonstrate the potential of our accelerometer-derived metrics for detailed assessment of activity we present a sample comparison between 2 children with differing performance. The response profiles from the children are shown in figures 4a and 4b, these represent typical individuals from the 'moderate' and 'high' performance categories. Data is shown for a number of metrics, across the duration of each child's test. All measures are normalised to the value obtained in the first running section and illustrate how gait and activity level are altered in response to the increasing demands of the test. The 'demand line' is the normalised running speed imposed and thus the speed at which the children should be running. Alongside this are plotted the response metrics of integrated acceleration, α_{max}, F_{max} and f. The high performer (figure 4a) has a consistent approach, increasing the work done per stride as they progress through the exercise, whilst maintaining a constant stride frequency. This results in linearly increasing impact force and foot lift angle. The close alignment of the gait metrics and overall physical effort to the demand line indicate an efficient expenditure of energy for this individual. In contrast the profile for a lower performance child (figure 4b) is more erratic indicating a less controlled and hence less energy efficient response to the test. There is no clear trend in stride extension or frequency and the overall work rate (integrated acceleration) remains constant after the first MSFT section. As soon as the relative demand of the test passes this fixed work rate (at section 4) the child dropped out of the test. Further evidence of the poor physical control exhibited here can be obtained by analysing the raw acceleration trace for the low performer. This child is representative of many in their performance group who, early on in the exercise, ran at a higher speed than required and then took extended breaks in activity at each end of their twenty-meter shuttle.

Analysis of activity across a cohort

A bivariate analysis of integrated acceleration and α_{max}, was performed for a single exercise section, at three key-time points in the fitness test; i. the first section of running (all children active), ii. the section at which two thirds of the original cohort remain in the activity (2/3 active, 3rd out of 8 sections of running) and iii. the section of running at which just one third of the original cohort remain active (1/3 active, 5th out of the 8 sections). Correlation plots of the data are shown in figure 5a-c. These relate the work done within a level of the test (equivalent to counts in standard accelerometry) to α_{max}, a metric that is a surrogate of stride length. From the outset of the activity session there is a significant 'strong' correlation between the α_{max}, and integrated acceleration, with increasing activity being linearly related to an increased stride length. This correlation holds throughout the activity (all active, $r = 0.81$, p-value < 0.01; 2/3 active, $r = 0.79$, p-value < 0.01; 1/3 active, $r= 0.80$, p-value < 0.01). As the activity progresses the increased running speed translated to a shift of the data set to the upper right quadrant of the plots.

Profiling the correlation between activity and body metrics

To describe a child's overall performance in the test a summative quality measure was extracted from plots of mean stride frequency versus mean foot lift angle from each section of the test. Two examples, chosen to indicate differing responses from 2 children, are shown in figure 6a. The line defined by this series of data points tracks the changes in gait and so describes the physical response of the child to the demands of the MSFT. More specifically the performance line indicates the relative weighting of increased stride frequency to increased stride length, made in response to the need for increased running speed. This response is parameterised using the angle, α of the data line relative to the x-axis to define a *stride profile quotient*, $Q = \sin \alpha$. This ranges in value according to the activity profile of the child with extreme values of 0 (constant stride frequency with increasing stride length) and 1 (constant stride length with increasing stride frequency).

The correlations between a child's stride profile quotient and their body measures are shown in figures 6b-d. Only those children who had remained in the test for over 350 seconds were compared as this set have a sufficiently long time trace from which to make an accurate determination of Q (measured over 8 sections). The comparison of stride profile to BMI percentile resulted in a 'moderate' negative correlation (r value of -0.61, p-value = 0.11), indicating that as body mass index increases, stride extension is favoured over increased frequency when adjusting to the increased speed demand (resulting in a lower quotient value). The negative correlation remains when splitting the BMI into its component metrics although the correlation between height and stride profile (r = -0.22, p-value = 0.60) is much weaker than that between mass and stride profile (r = -0.60, p-value = 0.12).

DISCUSSION

Physical activity assessment for groups of children is typically limited to measurements of duration or intensity (15, 20), thus a single, end –point total or quantity of activity is obtained allowing the researcher to answer the question of - *how much?* In this work we present an approach which provides a much richer data set, reporting on *how* an activity was completed and *when* physical motion was undertaken. The main aim of the study was to derive a set of robust measures capable of accurately detailing both the work done in physical exercise – *activity quantity*, and the mechanics of the physical motion involved – *activity quality*. These measures were also quasi-continuous and logged so that an unbroken historical assessment of performance could be made.

We provide validation evidence that these measures can be obtained, in quantified units, from ankle worn acceleration sensors and that they allow multi-parameter analysis of children's activity within the semi-controlled environment of a standard multi-stage fitness test. Accelerometer data traces, recorded at rates of 10's of Hz adequately capture the kinetics of physical motion allowing us to differentiate stride patterns as they alter during an activity sequence and vary between children. The study demonstrates that through the adoption of low cost, wearable sensors allied to automated data analysis, investigations of the kinetics of motion can be undertaken outside of a sports performance laboratory, within a field setting. The technology platform and protocols are also robust enough to implement in large cohort studies. Thus our approach bridges the disciplines of gait biomechanics and exercise science; introducing for the first time *in field,* detailed motion analysis into studies of children's activity.

The usual result of the multi-stage fitness test is a duration – time spent in the test. Thus as an activity assessment this present a 'black-box' approach in which the mechanisms influencing a child's performance and the causes that lead them to drop-out from the test remain hidden. Here we show that by recording physical motion through accelerometry we can reveal the driving influences on performance. Time-resolved gait analysis, based on multiple metrics of foot impact force, leg lift angle and stride frequency, provides a record of the physical responses made in reaction to the work load demands of the test. This temporal profiling provides a holistic assessment of performance as it describes the accuracy with which an individual can control their physical exertion to meet a specific performance level. This reveals the influence of physical competence, taken in their totality and relate to 'physical literacy' which is an important area of research. Our results demonstrate that high performers exhibit a tight and accurately controlled increase in work rate to match the running speed of the test whilst poor performers displayed widely varying gait speed often mismatched to the test level. The frequency spectra of the running traces did also show a gender difference. Boy and girl subgroups were compared by means of cross-correlation of their frequency spectra to form a correlation matrix for the population. Statistical differences between girl and boy subgroups were present ($p = 0.05$).

This work brings together measures of aerobic fitness and physical literacy and enables the assessment of both from the multi-stage fitness test which has historically only been used to assess the former. The quantitative description of physical activity provided by the accelerometer data also allows profiling across a cohort. The physical motion history recorded within the fitness test can be used to parameterise each child's performance in terms of their adaptation to the intervention of increased running speed. We use this to rank the children according to their use of increased stride length or stride frequency. Bivariate analysis of this physical performance parameter to BMI demonstrates a significant negative correlation between the two. Further analysis of the shows that body mass is the primary determining factor in this correlation (17).

Literature has highlighted limitations associated with the Multi-stage fitness test, particularly when used for assessing children and a case for submaximal testing has been made (1, 14). Measures of gait along with descriptive measures of how an individual performs in a running test such as these derived as part of this protocol may go on to inform the design of better submaximal tests in the future.

These findings are novel in that they report quality metrics of children’s physical activity in a field setting. Moreover this approach takes gait analysis to a population level allowing movement quality to be added to the widely reported metric of movement quantity at scale. Further these findings have demonstrated that movement quality differs according to body weight adding more detail to factors that contribute to movement. This is important in children’s studies where the development of quality as well as quantity of movement is apparent in clinical groups (13, 23) but is largely missing from the descriptive and intervention literature. Further investigations are required to apply this approach to other frequently occurring fundamental movements that can be measured at a population level.

Acknowledgments

During this work PhD scholarship funding was provided to Claire Barnes from the Engineering and Physical Science Research Council, U.K. and Swansea University Scholarship fund and to Cain Clark from the College of Engineering, Swansea and the Swansea University Scholarship fund. None of the authors or anyone involved with this research had a conflict of interest and the results of this study do not constitute endorsement by ACSM.

References

1. Andersen LB, Andersen TE, Andersen E, Anderssen SA. An intermittent running test to estimate maximal oxygen uptake: the Andersen test. *J Sports Med Phys Fitness*. 2008; 48: 434–437.

2. Biddle SJH, Asare M. Physical activity and mental health in children and adolescents: a review of reviews. *Br J Sports Med.* 2011; 45: 886-8953. Cain KL, Sallis JF, Conway TL, Van Dyck D, Calhoon L. Using Accelerometers in Youth Physical Activity Studies: A Review of Methods. *Journal of Physical Activity and Health*. 2013; 10: 437-450

3. Djurić-Jovičić MD, Jovičić NS, Popović DB. Kinematics of Gait: New Method for Angle Estimation Based on Accelerometers. *Sensors.* 2011; 11: 10571-10585

4. Dobkin BH, Xu X, Batalin M, Thomas S. Kaiser W. Reliability and validity of bilateral ankle accelerometer algorithms for activity recognition and walking speed after stroke. *Stroke*. 2011; 42, 2246-50.

5. Friederichs SAH, Bolman C, Oenema A, Lechner L. Profiling physical activity motivation based on self-determination theory: a cluster analysis approach. *BMC Psychology.* 2015; 3: 1

6. Garber CE, Blissmer B, Deschenes MR,. et al. Quantity and Quality of Exercise for Developing and Maintaining Cardiorespiratory, Musculoskeletal, and Neuromotor Fitness in Apparently Healthy Adults Guidance for Prescribing Exercise. *Medicine and Science in Sports and Exercise*. 2011; 43: 1334-1359.

7. Gordon PM, Heath GW, Holmes A, Christy D. The quantity and quality of physical activity among those trying to lose weight. *American Journal of Preventive Medicine.* 2000; 18(1): 83-86.

8. Kuo YL, Culhane KM, Thomason P, Tirosh O, Baker R. Measuring distance walked and step count in children with cerebral palsy: an evaluation of two portable activity monitors. *Gait Posture*. 2009; 29: 304-310

9. Lafortune MA, Henning E, Valiant GA. Tibal Shock Measured with Bone and skin mounted transducers. *Journal of Biomechanics.* 1995; 28: 989-993.

10. Lee PH, Yu Y, McDowell I, Leung GM, Lam TH. A cluster analysis of patterns of objectively measured physical activity in Hong Kong. *Public Health Nutr.* 2013; 16(8):1436-44

11. Leger LA, Lamber J. A maximal multistage 20-m shuttle run test to predict $\dot{V}O_2$ max. *European Journal of Applied Physiology*. 1982; 49 (1): 1-12.

12. Leger LA, Mercier D, Gadoury C, Lambert J. The multistage 20 metre shuttle run test for aerobic fitness. *Journal of Sport Sciences.* 1988; 6: 93-101.

13. Lowry KA, Vanswearingen JM, Perera S, Studenski SA, Brach JS. Walking smoothness is associated with self-reported function after accounting for gait speed. *J Gero Biol Sci Med Sci.* 2013; 10:1286-90.

14. Noonan V, Dean E. Submaximal Exercise Testing: Clinical Application and Interpretation. *Phys Ther.* 2000; 80(8): 782-807.

15. Pate RR, McIver KL, Colabianchi N,. et al.Physical Activity Measures in the Healthy Communities Study. *Am. J. Prev. Med.* 2015; 49,653-9.

16. Sanchez A, Norman GJ, Sallis JF, Calfas KJ, Cella J, Patrick K. Patterns and correlates of physical activity and nutrition behaviors in adolescents. *American Journal of Preventive Medicine.* 2007; 32: 124–130.

17. Shultz SP, D'Hondt E, Lenoir M, Fink PW, Hills AP. The role of excess mass in the adaptation of children's gait. *Hum Mov Sci* [Internet]. 2014; *36*: 12-19

18. Takeda R, Tadano S, Todoh M, Morikawa M, Nakayasu M, Yoshinari S. Gait analysis using gravitational acceleration measured by wearable sensors. *Journal of Biomechanics*. 2009; 42: 223-233.

19. Tao W, Liu T, Rencheng Z, Feng H, Gait Analysis Using Wearable Sensors. *Sensors*. 2012; 12: 2255–2283.

20.Trost S G, McIver KL, Pate RR. Conducting accelerometer-based activity assessments in field-based research. *Medicine and Science in Sports Exercise.* 2005; *37* (11),: S531-543.

21. Trost S G, Pate R R, Dowda M, Saunders R, Ward D S, Felton G Gender differences in physical activity and determinants of physical activity in rural fifth grade children. *Journal School Health.* 1996; 66(4),:145-150.

22. Van HeesVT, Gorzelniak L, Leon E,. et al. A method to compare new and traditional accelerometry data in physical activity monitoring. *World of Wireless Mobile and Multimedia Networks. Montreal, QC, Canada.* 2012; 1 - 6

23. Warren JM, Ekelund U, Bessond H, Mezzani A, Geladas Vanhees L. Assessment of physical activity – a review of methodologies with reference to epidemiological research: a report of the exercise physiology section of the European Association of Cardiovascular. *Prevention and Rehabilitation European Journal of Cardiovascular Prevention and Rehabilitation*. 2010; 17: 127–139

Figure Legends

Figure 1. a.) An image of the accelerometer system. b.) Measurement co-ordinate reference system in which the radial axis is along the line of the lower leg, the transverse axis is perpendicular to the leg in the plane of motion and the lateral axis is perpendicular to the leg and the direction of whole body motion. c.) A typical acceleration trace from the radial axis, recorded at a data collection frequency of 40 Hz for 300 seconds.

Figure 2. a.) The radial acceleration trace for a single stride can be divided into a 'push off', a 'foot impact' and a 'leg swing' section. b.) The integrated acceleration metric quantifies the amount of activity and corresponds to the commonly used, 'count' measure. c.) Transformation of the radial acceleration into the frequency domain readily identifies the fundamental frequency of the gait cycle. Spectra derived for a trace incorporating running over one minute.

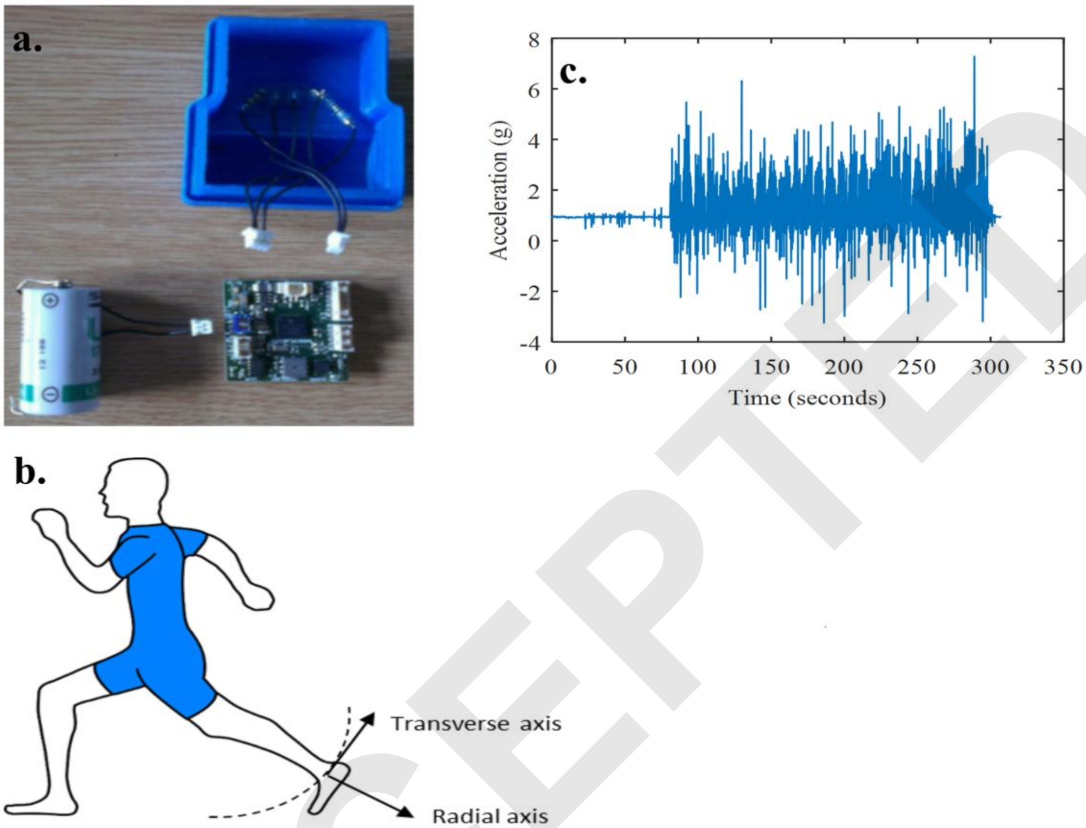
Figure 3. a.) force profiles generated by foot impact during running, force plate (solid line), accelerometer (dashed line). b.) correlation plot of peak impact force as measured by force plate and accelerometer. c.) Correlation plot of maximum foot lift angle, measured by accelerometer and video sequence.

Figure 4: a.) Typical activity profile of a high performance child. The normalised bleep frequency (solid line), integrated acceleration (dashed), peak impact force (triangles), maximum angle of inflexion (stars) and stride frequency (circles) are shown for the first 8 sections of the test. b.) Typical activity profile of a moderate performance child.

Figure 5: a.) Correlation plot of α_{max} versus integrated acceleration for the 1st running section of the fitness test. b.) Correlation plot of α_{max} versus integrated acceleration for the 3rd section. c.) Correlation plot of α_{max} versus integrated acceleration for the 5th section. The 95% confidence ellipse shown on each graph is constructed such that the major and minor axis are determined by the variation in X and Y directions of the plots and the angle at which the ellipse sits in relation to the X axis is determined by the covariance between the variables. The ellipse is shown in all sub-plots for the specific section (solid line) and for the other two analysed sections (dashed line).

Figure 6: a.) Stride frequency versus α_{max} of two children as they progress through the sections of activity. Solid lines indicate lines of best fit. b.) Stride profile quotient versus BMI percentile of 8 children taking part in the test. c.) Stride profile quotient versus height. d.) Stride profile quotient versus weight.

Figure 1



a.
b.
Transverse axis
Radial axis
c.
Acceleration (g)
Time (seconds)
8
6
4
2
0
-2
-4
0
50
100
150
200
250
300
350

Figure 2

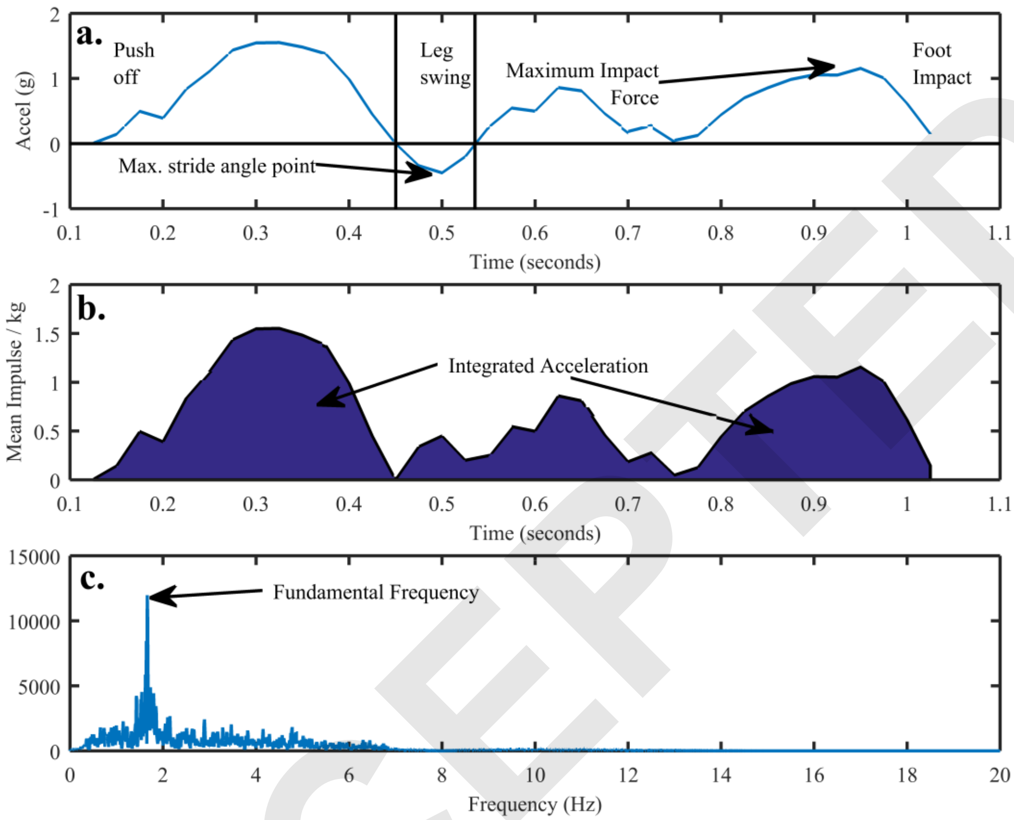
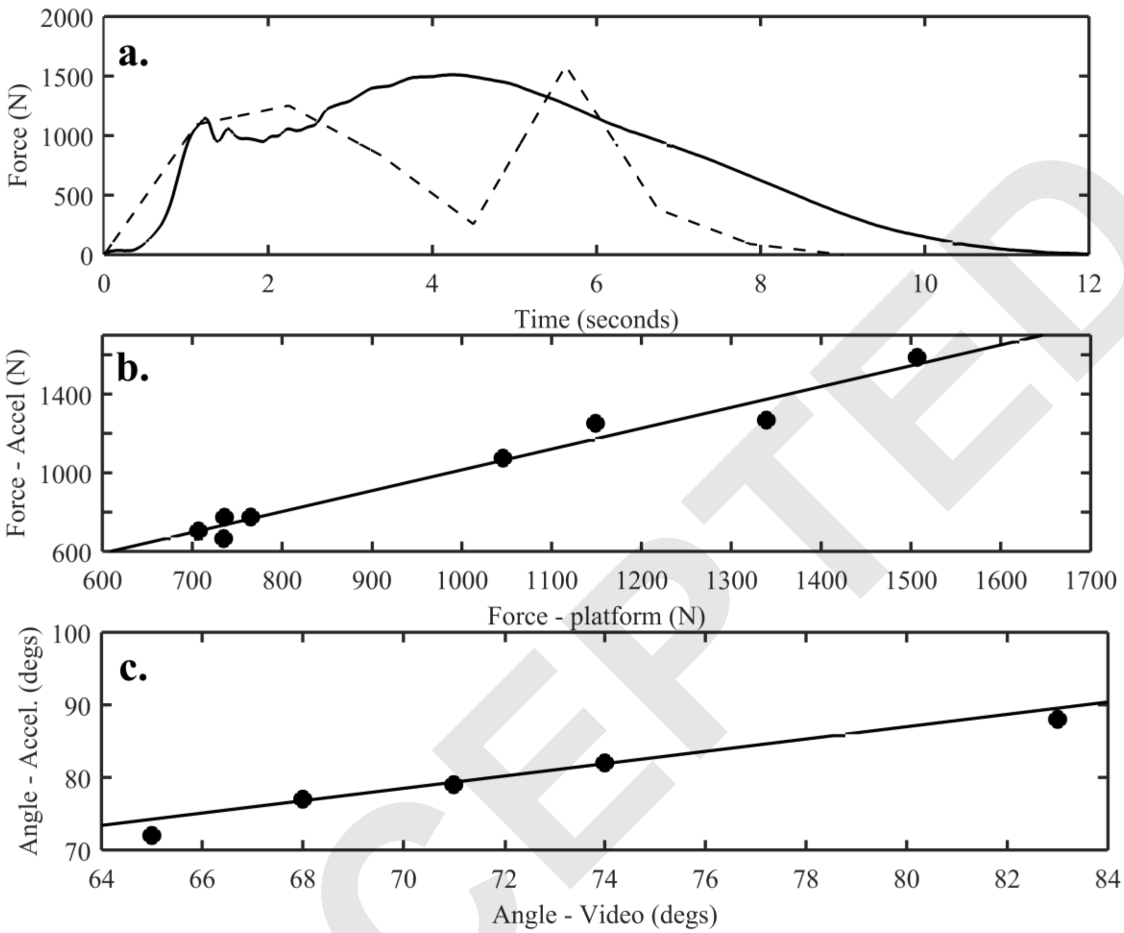

a.
Push
off
Leg
swing
Maximum Impact
Force
Foot
Impact
Max. stride angle point
Accel (g)
Time (seconds)
b.
Integrated Acceleration
Mean Impulse / kg
Time (seconds)
c.
Fundamental Frequency
|Y|
Frequency (Hz)

Figure 3



a.
Force (N)
2000
1500
1000
500
0
0
2
4
6
8
10
12
Time (seconds)
b.
Force - Accel (N)
1400
1000
600
600
700
800
900
1000
1100
1200
1300
1400
1500
1600
1700
Force - platform (N)
c.
Angle - Accel. (degs)
100
90
80
70
64
66
68
70
72
74
76
78
80
82
84
Angle - Video (degs)

Figure 4

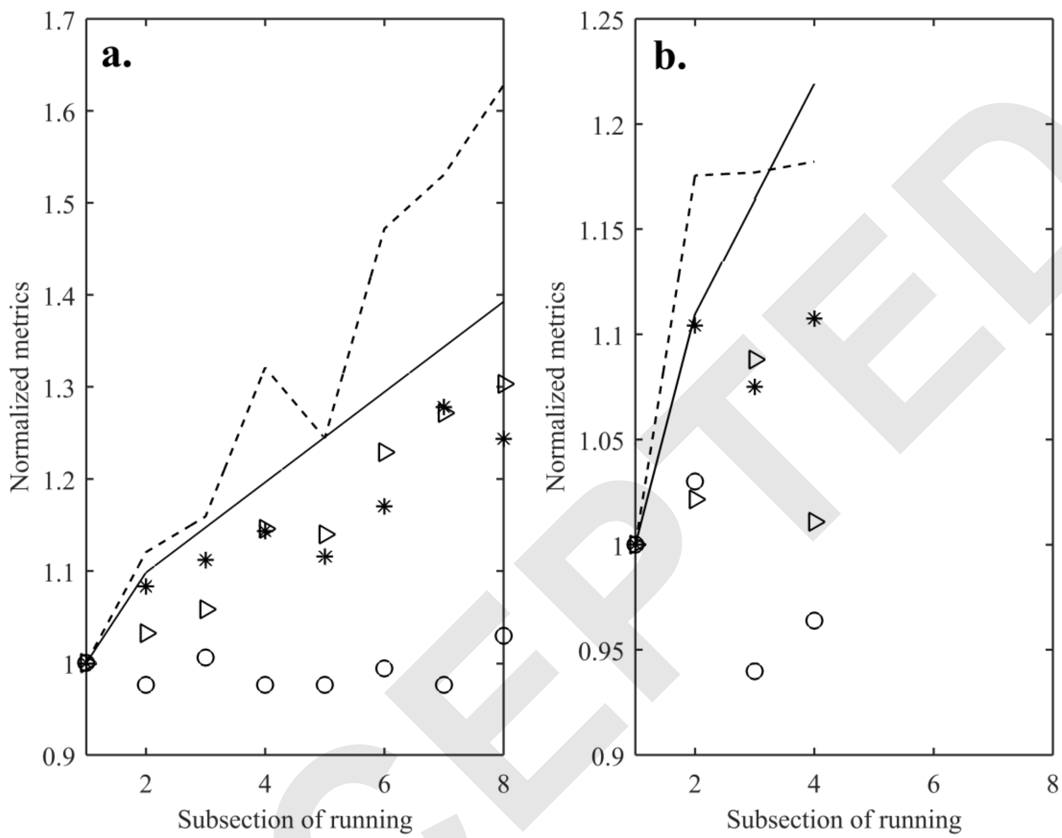
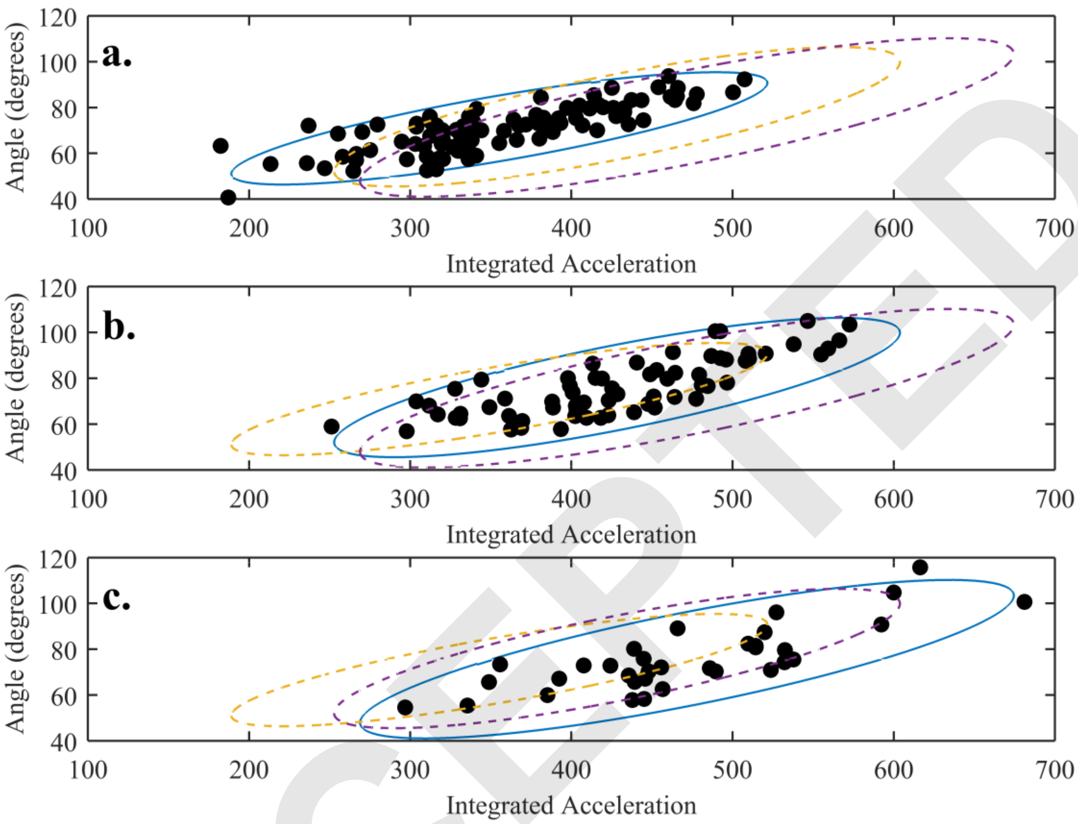
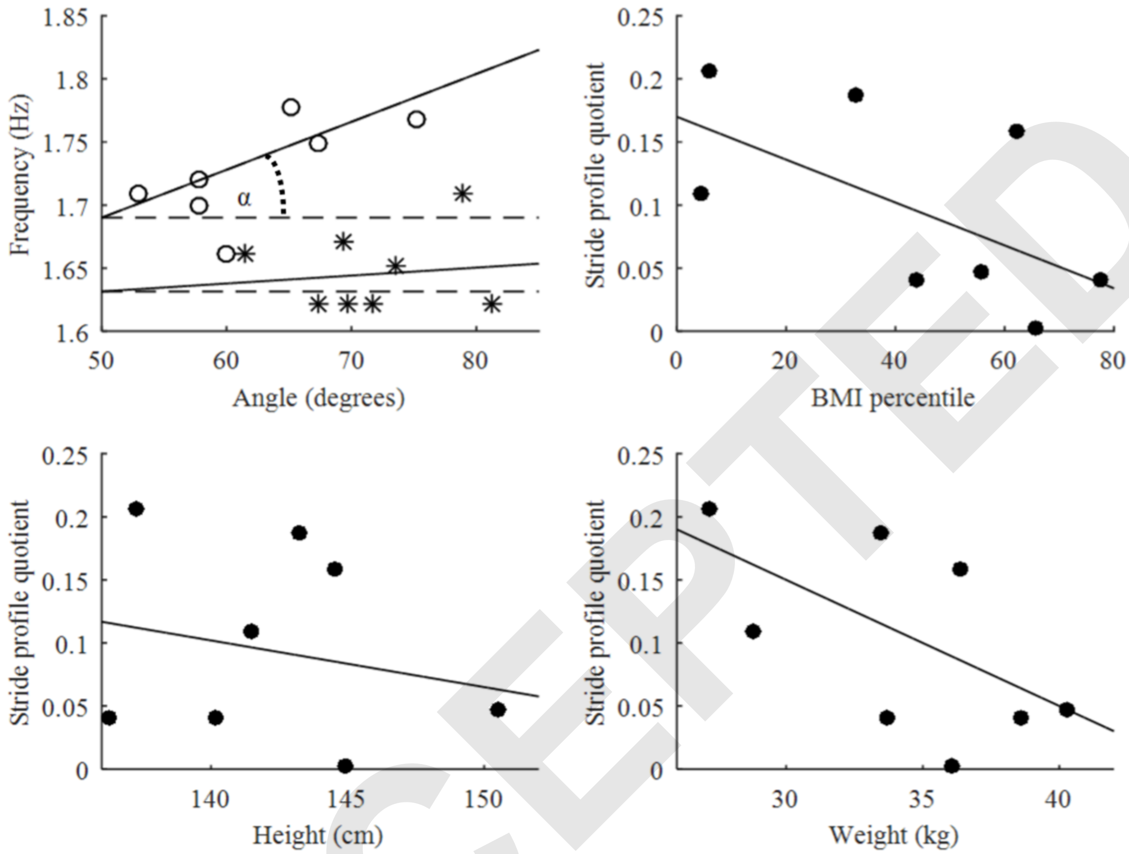

a.
b.
Normalized metrics
Subsection of running
1.7
1.6
1.5
1.4
1.3
1.2
1.1
1
0.9
2
4
6
8
1.25
1.2
1.15
1.1
1.05
1
0.95
0.9
2
4
6
8

Figure 5



a.
b.
c.
Angle (degrees)
Integrated Acceleration
120
100
80
60
40
100
200
300
400
500
600
700

Figure 6



1.85
1.8
1.75
1.7
1.65
1.6
Frequency (Hz)
α
50
60
70
80
Angle (degrees)
0.25
0.2
0.15
0.1
0.05
0
Stride profile quotient
0
20
40
60
80
BMI percentile
0.25
0.2
0.15
0.1
0.05
0
Stride profile quotient
140
145
150
Height (cm)
0.25
0.2
0.15
0.1
0.05
0
Stride profile quotient
30
35
40
Weight (kg)