TITLE

Metabolic power method underestimates energy expenditure in field sport movements using a GPS tracking system

Abstract

The purpose of this study was to assess the validity of a GPS tracking system to estimate energy expenditure (EE) during exercise and field sport locomotor movements. Twenty-seven participants each completed one 90 minute exercise session on an outdoor synthetic futsal pitch. During the exercise session participants wore a 5 Hz GPS unit interpolated to 15 Hz (SPI HPU, GPSports Pty Ltd, Australia) and a portable gas analyser (Metamax® 3B, Cortex Pty Ltd, Germany) which acted as the criterion measure of EE. The exercise session was comprised of alternating five minute exercise bouts of randomised walking, jogging, running or a field sport circuit (x3) followed by 10 minutes of recovery. One-way ANOVA showed significant ($p<0.01$) and very large underestimations between GPS metabolic power derived EE and VO_2 derived EE for all field sport circuits (% difference ≈ -44%). No differences in EE were observed for the jog (7.8%) and run (4.8%) while very large overestimations were found for the walk (43.0%). The GPS metabolic power EE over the entire 90 minute session was significantly lower ($p<0.01$) than the VO_2 EE, resulting in a moderate underestimation overall (-19%). The results of this study suggest that a GPS tracking system using the metabolic power model of EE does not accurately estimate EE in field sport movements or over an exercise session consisting of mixed locomotor activities interspersed with recovery periods; however is able to provide a reasonably accurate estimation of EE during continuous jogging and running.

Keywords: criterion validity, intermittent exercise, excess post-exercise oxygen consumption, energy cost, time-motion analysis

Introduction

The use of global positioning system (GPS) tracking technology is now commonplace in professional and semi-professional field sports around the world including cricket,[1] rugby,[2,3] soccer [4] and Australian (Rules) football.[5-7] Small, lightweight and non-invasive, GPS tracking systems provide information relating to training load and performance during competition.[5] Time-motion analysis has subsequently been used to evaluate the movement demands of field sport participation and to guide training prescription.[8] Despite considerable time spent completing low intensity activities (e.g., standing, walking, jogging), it is the high intensity activities (e.g., running, sprinting, change of direction) that have been shown as critical to performance.[9,10] Furthermore, these high intensity activities also contribute greatly to the energy demand. The energy expenditure associated with acceleration and deceleration, often at low movement velocities, may be underestimated when using time-motion analysis approaches based on velocity alone.[11]

The assessment of energy expenditure (EE) in the field is of both theoretical and practical importance. The total energy cost of a training session or match has implications for recovery, including nutrition strategies to meet or manipulate desired energy balance. Unfortunately the assessment of the energy cost of high intensity exercise is problematic due to the contribution of both aerobic and anaerobic metabolism. While several indirect methods have been proposed to estimate energy cost, these approaches are not without their limitations. Most notably, these are typically laboratory based and performed during continuous and controlled exhausting bouts of exercise.[12] Team sports such as soccer, rugby and Australian football, however, are played in the field and are characterised by frequent intermittent high-intensity running efforts.[13] In an attempt to overcome some of these challenges, di Prampero and colleagues[14] proposed a theoretical model to estimate energy expenditure (EE) during sprint running using uphill running at a constant velocity as an analogue and as the basis for calculating instantaneous metabolic power. Accelerated running on flat terrain is considered energetically equivalent to running at a constant velocity up an equivalent slope. If acceleration is known, then energy cost can be determined. Measures of velocity and acceleration can subsequently be used to calculate metabolic power output at any given moment.[14,15]

The metabolic power model takes into account the acceleration of the athlete to give a more complete assessment of the demands of field sport by incorporating the energy cost, compared to traditional time-motion analysis which describes and summarises the movement demands but not the energy cost. The potential benefit of using EE to provide a more complete assessment of field sport demands is evident during sprinting from a stationary start. Initially velocity is low, yet acceleration and therefore EE is high. As such, traditional time-motion analysis based upon velocity alone would underestimate EE. An accurate estimation of EE would provide a more comprehensive method of measuring the demands of field sport.

Several recent studies have investigated the ability of the metabolic power model to estimate EE compared to a direct measure of EE.[16-18] Buglione and di Prampero[17] as well as Stevens et al.[18] compared EE during continuous and shuttle runs and found an overestimation of EE during constant velocity running and an underestimation during shuttle running, particularly over a short distance and at high velocity. In a more applied context, the metabolic power model has been adapted to provide an estimation of EE in soccer,[4,19,20] rugby league[21] and Australian football.[22] Based on instantaneous GPS derived velocity data, Gaudino et al.[4] and Osgnach et al.[19] found that the distance covered in soccer competition and training at a high intensity using a metabolic power definition was greater than distance covered at a high intensity based upon a velocity based threshold. This was in contrast to Coutts et al.[22] who found that distance covered in Australian football competition at high intensity was less when using a metabolic power definition compared to a velocity based threshold. Buchheit et al.[16] have recently investigated the validity and reliability of the metabolic power model during soccer drills with the ball, concluding that EE was largely underestimated, especially during the recovery phases. As such, the authors questioned the usefulness of the method, preferring locomotor data to describe the mechanical demands of training and competition, and to subsequently guide training prescription related to distance, speed and acceleration/deceleration.

These conflicting results, both in movement context and sports, suggest that further investigation is warranted. The recent introduction of metabolic power estimates in some commercially available GPS time-motion analysis software (GPSports, Canberra, Australia; GPEXE©, Exelio srl, Udine, Italy) further support the need to assess the usefulness of the metabolic power model to estimate EE in exercise and field sport locomotor movements. Therefore, the aim of this study was to assess the validity of a GPS tracking system, with software implementation of the metabolic power model,[14,19] to estimate EE during continuous walking, jogging and running, and typical field sport movements. Validity was assessed using measures of accuracy, agreement and precision in comparison to a criterion measure.

Methods

Twenty-seven healthy adults (15 males and 12 females, age 21.6 ± 2.7 years; height 173.8 ± 11.6 cm; mass 69.2 ± 11.6 kg) were recruited for this study. To be eligible, participants were required to be engaged in field sport activity at least once per week. Ethical approval for the study protocol was granted by the University Human Ethics Committee and written informed consent was obtained from all participants.

Each participant completed one 90 minute exercise session on an outdoor pitch. To measure velocity and acceleration, participants wore a 5 Hz GPS unit interpolated to a 15 Hz sampling rate (SPI HPU, GPSports Pty Ltd, Australia) for the duration of the exercise session. To reduce inter-unit variability the same unit was used for all participants. The SPI HPU was worn in a manufacturer supplied harness on the upper back. During collection of data, reception from at least six satellites was maintained to ensure acceptable accuracy. The data from the GPS unit was downloaded into proprietary software (Team AMS, version R1_2014_3, GPSports Pty Ltd, Australia) and a player profile, which included body mass, was created for each participant. Energy expenditure was calculated within the software from GPS derived velocity data and metabolic power estimates based on the di Prampero model,[14] with adaptations from Osgnach et al.[19] Energy expenditure data for each minute was exported from Team AMS software to Microsoft Excel.

Indirect open-circuit calorimetry (Metamax® 3B, Cortex Pty Ltd, Germany) was used to measure VO_2 derived EE to validate the GPS tracking system. The Metamax® 3B was worn for the duration of the exercise sessions and did not restrict or burden the participant. During the exercise session the Metamax® 3B was fastened to the chest with a harness and attached via a facemask. Prior to the beginning of each session the Metamax® 3B was calibrated according to manufacturer instructions. Breath-by-breath data was summarised into five second intervals using Metasoft® Studio. The data was then exported to Microsoft Excel and from this the EE in kJ for each minute was derived. The one minute sample intervals for the GPS and VO_2 derived EE were synchronised using Microsoft Excel.

The test protocol was completed in one 90 minute session on an outdoor synthetic futsal pitch. Participants refrained from eating and consuming caffeine for at least 2 hours prior to the exercise session and refrained from exercise for 12 hours prior. Prior to the beginning of the exercise session, the participant was required to be seated for 10 minutes to determine resting measurements of EE for the VO_2 derived EE. Mean resting EE was calculated from this 10 minute period, which was subtracted from all subsequent measures of EE during the 90 minute exercise session. Removing resting EE in this way ensured that all subsequent data used for analysis were directly related to the exercise undertaken, and is consistent with the approach used by Buglione and di Prampero.[17]

The exercise session comprised of six bouts of exercise, each followed by 10 minutes of rest. The exercise bouts were 5 minutes each of walking, jogging, running and three bouts of a simulated field sport circuit. In total, 30 min of exercise (distance = 2460 m) was completed with 60 min of recovery. The order of exercise bouts was randomised for each participant. The walk, jog and run bouts were designed to replicate continuous exercise. Participants were required to move in an anti-clockwise direction around the pitch for the entire five minutes at a dictated velocity. The velocity of the walk, jog and run were 4 $km \cdot h^{-1}$, 8 $km \cdot h^{-1}$ and 12 $km \cdot h^{-1}$, with total distance covered in each 5 min bout equal to 333.3, 666.7 and 1000 m, respectively. Velocities were based upon standardised ranges developed by previous work for field sport athletes.[23] The field sport circuit used in this study (Figure 1A) was a modified version of a circuit[24] designed to replicate the intermittent movement patterns of field sports. Movements in the circuits were performed at self-selected speeds, guided by movement descriptors (i.e., walk, jog, stride, sprint) and required acceleration and deceleration (Figure 1B). Five repetitions of the circuit were completed in each five minute bout (5 x 92 m = 460 m), with a short rest period (approximately 10 - 15 s) at the end of each circuit before the commencement of the next repetition on the minute.

To evaluate the GPS metabolic power method for estimation of EE, the total energy cost of the exercise needed to be measured to provide a valid criterion method. The contribution of both aerobic and anaerobic energy metabolism therefore needed to be considered. It is acknowledged that the time course of oxygen consumption will lag behind the instantaneous metabolic power requirement and will be different dependent on the locomotor activity at any given time. At the commencement of even submaximal exercise, anaerobic metabolism will contribute to the energy supply until such time as a steady state VO_2 is reached. In the case of higher intensity intermittent exercise, with movements that include acceleration and deceleration, the contribution of anaerobic metabolism will be greater, but also more difficult to measure. To account for this methodological problem, the EE during 10 min of recovery after each 5 min exercise bout was included in the VO_2 derived EE. While the mechanisms and contributing components of the excess post-exercise oxygen consumption (EPOC)[25] are not completely agreed upon,[26] it is reasonable to assume that any elevation in VO_2 above rest during the 10 min recovery period was a result of the preceding exercise bout.[27] As such, the overall energy cost of each exercise bout was taken as the EE expenditure (minus resting VO_2) during the 5 minutes of exercise and the 10 minutes of recovery. Data were therefore combined as exercise plus recovery (15 min in total) to account for the overall energy cost associated with the exercise interval, and overcome the limitation of non-steady state during intermittent, high intensity exercise.

Statistical analysis

Data were analysed in two formats as i) total session EE (90 min) and ii) six bouts of 15 min (walk, jog, run, 3 x circuit). All data analysed and reported relates to the cost of exercise above resting values (i.e., average resting baseline EE subtracted from minute-by-minute exercise and recovery data). Energy expenditure values for GPS metabolic power derived EE and VO_2 derived EE for the entire 90 minute session were compared using a paired samples t-test. Level of agreement, accuracy and precision were obtained by calculating the 95% limits of agreement (95% LoA), mean bias, percent (%) difference and effect size (Cohen's *d*, with associated descriptors),[28,29] and root mean square error (RMSE), respectively. To determine whether differences between mean biases existed between the six exercise bouts, a one-way ANOVA was conducted. Games-Howell post hoc tests (due to heterogeneity of variance) were used to identify where these differences lay.

To determine whether differences between device precision (RMSE) were evident between exercise bouts, Hartley's F-max tests[30] were undertaken. Due to the multiple comparisons being conducted for the F-max test and ANOVA the alpha level was adjusted to 0.01 and critical values determined from existing reference tables.[30]

Analyses were performed using Microsoft Excel (Microsoft, Washington, USA, 2013), SPSS (IBM, New York, USA, version 22.0) and Prism software (GraphPad Software, Inc, version 6, 2014). Data are reported as mean and standard deviation.

Results

The GPS metabolic power derived EE for the 90 minute session (1244.8 ± 226.1 kJ) was significantly lower ($p < 0.01$) than the VO_2 derived EE (1511.5 ± 271.3 kJ). There was a mean bias toward the VO_2 derived EE (266.7 ± 151.0 kJ, RMSE = 305.1 kJ, % difference = -19.4%), representing a moderate effect ($d = 1.07$). The 95% LoA for the session ranged from -562.7 to 29.3 kJ. Figure 2A (raw data) and 2B (corrected for resting metabolism) illustrates minute by minute data for the 90 min session.

The EE (above resting) associated with each exercise bout for both GPS metabolic power derived EE and VO_2 derived EE is presented in Figure 3. Table 1 presents indices of accuracy, agreement and precision for each of the six bouts. Results from the ANOVA revealed that EE was significantly higher for the GPS metabolic power compared to the VO_2 derived EE during the walk (% difference = 43.0%, *d* = 2.11), however it was significantly lower in each of the circuit bouts (-42.2 – -45.8%, *d* = 1.97 – 2.24). There were no significant differences between EE measured using the GPS metabolic power and VO_2 derived EE for the jog (7.8%, *d* = 0.44) or run (4.8%, *d* = 0.28).

Hartley's test's revealed that RMSE values for all three circuit bouts were significantly higher compared to the walk, jog and run. There were no significant differences in RMSE between circuit bouts or between the walk, jog and run. The mean bias for all three circuits was significantly higher than the walk, jog and run. The walk had a significantly higher mean bias compared to the run and jog, but a significantly lower mean bias compared to the circuits. There were no significant differences in mean bias between the jog and run, and between the three circuit bouts.

Bland-Altman plots (Figure 4) highlight the improved accuracy and agreement between GPS metabolic power derived estimation of EE and VO_2 derived EE during the jog and run, and to a lesser extent the walk, compared to the circuit bouts.

Discussion

The purpose of this study was to assess the validity of a GPS tracking system, with associated software implementation of the metabolic power model,[14,19] to predict EE during exercise and field sport locomotor movements. The major finding was that the GPS metabolic power model was unable to accurately estimate EE during walking (a very large overestimation) or intermittent movement patterns that are typical of field sports (a very large underestimation). However, the GPS derived estimation of EE was reasonably accurate during steady state jogging and running.

Two previous studies have assessed the validity of the metabolic power model for the estimation of EE during continuous and intermittent shuttle runs.[17,18] These reports concluded that there was an underestimation in EE during shuttle running, particularly over short distances at higher velocities.[17,18] In a more applied approach, Buchheit et al.[16] recently reported an underestimation in EE during soccer training drills with the ball (23% lower during the soccer circuit and 85% lower during recovery). These findings are all consistent with our results for the intermittent, variable intensity field sport circuits. In contrast, however, Stevens et al.[18] found that the metabolic power model overestimated EE (6 – 11%) during steady state continuous running at velocities between 7.5 $km \cdot h^{-1}$ and 10 $km \cdot h^{-1}$ whereas no differences were observed at velocities of 8 $km \cdot h^{-1}$ and 12 $km \cdot h^{-1}$ in the current study. Figure 2 suggests we may have reached a similar conclusion (i.e., the estimated EE being greater than the measured VO_2) had the recovery EE not been included in our calculations.

The difficulty associated with a validation study of this nature is the measurement of EE during exercise that includes intermittent high intensity exercise and acceleration and deceleration during running and sprinting. Stevens et al.[18] used steady state oxygen consumption for the measurement of EE, and while appropriate for continuous running at submaximal running velocities, the approach may not be suitable for shuttle running. Buglione and di Prampero[17] used oxygen consumption and blood lactate levels to give a measurement of aerobic and anaerobic EE during non-steady state exercise. To overcome the estimation of EE during non-steady state exercise in our study, 10 minutes of recovery was included in the data analysis to capture the EPOC and to account for the overall EE associated with each 5 minute exercise bout. At the completion of the 10 minute recovery bout, the EE was found to be plateauing and nearing baseline levels (Figure 2B). Therefore, including the 10 minutes of recovery represented a direct measure of the EE associated with the exercise bout. Not measuring blood lactate levels may be considered a limitation of the current study, although to include two measures that might simultaneously account for anaerobic non-oxidative metabolism during exercise would not be appropriate. While the EPOC is greater than the O_2 deficit (i.e., a result of metabolic factors in addition to phosphagen restoration and lactate removal),[25] its occurrence and magnitude can be directly attributed to the exercise performed[26,27] and therefore represents a necessary component of the energy cost associated with each exercise bout. From a practical perspective, if the energy cost of exercise is to be estimated (e.g., for the purposes of energy balance and nutrition strategies), the total energy consumption linked to the physical activity needs to be accounted for, irrespective of its source of origin. Therefore, on the basis that this is a reasonable assumption and that the measured energy cost is accurate, there are likely to be two main factors that would lead to the results found in this study; the ability of the GPS device to measure velocity and acceleration accurately and / or the ability of the metabolic power model to accurately estimate EE.

As the estimation of EE is based upon GPS data, the validity of this estimation may be limited by the GPS tracking system's ability to measure velocity and acceleration accurately.

Recent studies investigating the validity and reliability of GPS tracking systems incorporating faster sampling rates (e.g. 10 Hz) to measure velocity have reported improved accuracy[31,32] compared to previous investigations,[33,34] especially with regards to movements performed at higher speeds. Despite this, the intermittent and variable nature of the acceleration and velocity within the field sport circuit will influence the ability of the GPS tracking system to accurately estimate EE based on these measures[11,35]. However the magnitude of the errors observed in the current study are unlikely to be explained by possible errors in GPS accuracy. The very large overestimation of EE during the walk and the very large underestimation during the field sport circuit suggests a level of systematic bias in the metabolic power method.

There are a number of assumptions and limitations outlined by di Prampero et al.[14,15] that may impact the validity of the metabolic power model. Firstly it is assumed that the biomechanics (e.g. movements of the limbs, stride frequency, mechanical efficiency) of accelerated running are similar to constant speed running up an incline and the economy of accelerated and decelerated running is similar between individuals, including body inclination. Secondly, it is assumed that the overall mass of the runner is concentrated in the centre of mass, which disregards the variable contribution of the limbs. Finally energy estimates are based on reference values associated with running on flat terrain and do not take into account air resistance or changes of direction. The metabolic power method represents a theoretical model and as such attempts have been made to both justify[14,15,17,19] and challenge[16] these assumptions. Of primary interest to the practitioner, however, is whether the approach provides a reasonably accurate estimate of EE in situations of practical importance. Our results suggest this may not be the case.

Practical Applications

The GPS metabolic power approach used to estimate EE in this study demonstrated unacceptable accuracy during intermittent and variable intensity movements. Consequently, this approach appears to have limited utility in field sports where movements require frequent changes in velocity, acceleration and direction. In contrast, the approach seems to be more suitable to continuous steady state activities such as jogging and running. While the method has some appeal in that it can provide a single estimate of exercise session load and the associated energy expenditure, both of which can guide exercise prescription, recovery and nutrition strategies, further improvements are required before the method can be used with confidence in the field.

Metabolic power has been reported in the literature to describe and quantify movement demands[19-22] and may be considered another example of an arbitrary measure of external load available to practitioners. However the potential loss of the underlying mechanical origins of the load (i.e., speed vs acceleration/deceleration)[16] as well as compounding errors (i.e., those associated with both GPS technology and the metabolic power method) advise caution in its use at this time. Future research should investigate whether the poor validity in field sport movements observed in the current study is due to the ability of the GPS tracking system to accurately measure velocity and acceleration, the ability of the metabolic power model to estimate EE or a combination of both. The use of other criterion measures that are able to measure both aerobic and anaerobic EE directly may also help with assessing the validity of the approach.

Conclusion

The results of the current study suggest that a GPS tracking system incorporating the metabolic power model is unable to provide an accurate estimation of EE during field sport movements or during an exercise session consisting of mixed locomotor activities interspersed with recovery periods. Despite some concerns regarding the accuracy of GPS technology, the shift from very large overestimations (i.e., the walk) to very large underestimations (i.e., the circuit) with increasing intensity suggest a systematic error in the metabolic power method. Further developments in GPS hardware and software, including increased sampling rates, and developments and improvements in the metabolic power model used to estimate EE may improve the estimation of EE in field sports in the future.

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Table 1. Accuracy (mean bias, % difference, effect size (Cohen's *d*), agreement (95% LoA) and precision (RMSE) of energy expenditure measurements for each 15 minute bout (5 minute exercise plus 10 minute recovery). Data compare GPS metabolic power derived energy expenditure against VO_2 derived energy expenditure as the criterion measure. Positive values indicate an overestimation by the GPS metabolic power model and negative values an underestimation.

Exercise Bout	Mean Bias (± SD diff) (kJ)	% Difference (%)	Effect Size (*d*)	95% LoA (kJ)	RMSE (kJ)
Walk	40.7 ± 18.0^	43.0	2.11	5.4 to 76.0	44.4
Jog	17.1 ± 27.9#	7.8	0.44	-37.6 to 71.7	32.3
Run	15.6 ± 27.8#	4.8	0.28	-38.8 to 70.0	31.4
Circuit 1	-102.3 ± 33.4*	-42.2	1.97	-167.7 to -36.9	107.4†
Circuit 2	-111.4 ± 35.1*	-45.8	2.24	-180.3 to -42.6	116.6†
Circuit 3	-106.5 ± 33.4*	-44.0	2.07	-172.0 to -40.9	111.4†

^ indicates significant difference from jog, run and circuit 1, circuit 2 and circuit 3, p <0.01
* indicates significant difference from walk, jog and run, p <0.01
# indicates significant difference from walk, circuit 1, circuit 2 and circuit 3, p <0.01
† indicates significant difference from walk, jog and run, p <0.01
SD diff, standard deviation of the difference; 95% LoA, 95% limits of agreement; RMSE, root mean square error
Cohen's *d* interpreted as small (>0.2 – 0.6), moderate (>0.6 – 1.2), large (>1.2 – 2.0), very large (>2.0 – 4.0)[29]

Figure Legends

Figure 1. A. Field sport circuit designed to replicate the intermittent movement patterns of field sports. Modified from Bishop, Spencer, Duffield, & Lawrence, (2001); B. Speed profile (GPS data) of the field sport circuit over five repetitions.

Figure 2. GPS metabolic power (GPS-MP) estimate of minute by minute energy expenditure (kJ) compared against indirect calorimetry (VO_2) for the 90 minute exercise session. A. Total energy expenditure including resting energy expenditure; B. Energy expenditure minus resting values. Exercise bouts were randomised, yet are ordered here for ease of interpretation.

Figure 3. Comparison between GPS metabolic power (GPS-MP) estimates of energy expenditure (kJ) and indirect calorimetry (VO_2) for each 15 minute bout (5 minute exercise plus 10 minute recovery) for exercise and field sport circuits. Data are Mean ± SD. * significant difference ($p < 0.01$).

Figure 4. Bland-Altman plots illustrating the difference between energy expenditure (kJ) determined by the GPS metabolic power model and VO_2 (y-axis), and the criterion measure of energy expenditure (VO_2; x-axis) for each 15 minute bout (5 minute exercise plus 10 minute recovery). Dotted lines: mean bias; dashed lines: 95% limits of agreement.