Original research

# Inertial sensors to estimate the energy expenditure of team-sport athletes 

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#### Abstract

Objectives: To quantify the energy expenditure of Australian Football training and matches and the total daily energy expenditure of Australian Football players using tri-axial accelerometers. Design: Cross sectional observation study. Methods: An algorithm was developed for the MiniMax 4.0 (Catapult Innovations, Scoresby Australia) using measured oxygen uptake and accelerometer data to estimate energy expenditure of 18 Australian Football players during training and matches. The algorithm was used to validate a metabolic power calculation used by Catapult Innovations (Scoresby Australia) in their proprietary GPS software. The SenseWear ${ }^{\text {TM }}$ (Model MF-SW, Bodymedia, Pittsburgh, PA) armband was used to determine non-exercise activity thermogenesis and was worn for 7 days leading into a match. Training, match and non-exercise activity thermogenesis data was summed for total daily energy expenditure. Results: Energy expenditure for field training was estimated to be $2719 \pm 666 \mathrm{~kJ}$ and for matches to be $5745 \pm 1468 \mathrm{~kJ}$. The estimated energy expenditure in the current study showed a large correlation ( $r=0.57,90 \% \mathrm{CI} 0.06-0.84$ ) with the metabolic power calculation. The mean total daily energy expenditure for an in-season main training day was approximately $18,504 \mathrm{~kJ}$ and match day approximately $19,160 \mathrm{~kJ}$ with non-exercise activity thermogenesis contributing approximately $85 \%$ and $69 \%$ on training and match days, respectively. Conclusions: The MiniMax 4.0 and SenseWear ${ }^{\mathrm{TM}}$ armband accelerometers provide a practical, noninvasive and an effective method to successfully measure training and match energy expenditure, and non-exercise activity thermogenesis in field sport athletes. Taking methodological limitations into consideration, measuring energy expenditure allows for individualised nutrition programming to enhance performance and achieve body composition goals.


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## 1. Introduction

Quantifying the total daily energy expenditure (TDEE) of an athlete allows individualised nutrition programming for sufficient energy supply. Whilst the activity profile of team-sport athletes is well established ${ }^{1-3}$ few studies have measured the TDEE of these athletes ${ }^{4}$ or quantified the energy expended during training and matches. ${ }^{5-7}$

The measurement of energy expenditure (EE) in team-sport and/or under free-living conditions has not received much attention due to difficulty in measurement. Traditional methods of EE assessment require metabolic analysis that restricts typical

[^0]movement and activities of daily living (ADL). ${ }^{8}$ The doubly labelled water (DLW) method is considered 'gold standard' ${ }^{9}$ for measuring TDEE, and estimated TDEE at $\sim 14,000 \mathrm{~kJ}$ in professional soccer players. ${ }^{4}$ However, the DLW method does not differentiate between tasks and their relative contribution to TDEE, thus not allowing quantification of discrete tasks such as training or competition. ${ }^{8}$ Heart-rate monitoring has also estimated the EE of professional soccer, and rugby players during matches as being between 5700 and 7100 kJ ,6,10 but likely overestimates EE by $15-20 \%{ }^{11,12}$ Thus, little is known of the EE in training and matches, nor the relative contribution of these to TDEE in team-sport athletes.

Global Positioning Systems (GPS) and inertial sensors may provide the practical solution to measuring physical activity (PA) of team-sport athletes. ${ }^{13,14}$ Researchers have used GPS and metabolic power calculations in professional soccer and Australian football
(AF) to estimate EE of activities involving accelerations and decelerations during intermittent activity. ${ }^{3,7}$ In soccer EE was $\sim 61 \mathrm{~kJ} \mathrm{~kg}^{-1}$ and AF ranged from 57 to $67 \mathrm{~kJ} \mathrm{~kg}^{-1}$, or $\sim 4200 \mathrm{~kJ}$ to 5200 kJ in absolute terms. This method has not been validated and does not take into account the direct impacts associated with contact sports such as AF .

Tri-axial accelerometers measure acceleration in three dimensions, and therefore all physical activity can be captured. ${ }^{15}$ Sport-specific accelerometers are a reliable tool for measuring PA in team-sport athletes ${ }^{13}$ while other devices such as the SenseWear ${ }^{\mathrm{TM}}$ Armband (Model MF-SW, Bodymedia, Pittsburgh, PA) have been used to measure PA at low to moderate intensities ${ }^{16}$ common in ADL. Energy prediction equations can be developed from the linear relationship between accelerometer data, $\mathrm{VO}_{2}{ }^{14}$ and estimated EE during a treadmill test ${ }^{15}$ which show reasonable concordance with DLW and calorimetry methods. ${ }^{16-18}$ It is possible that two or more accelerometers with established reliability for different intensity tasks could be used synergistically to measure specific EE of tasks but also TDEE.

The activity profile of AF is greater than other team-sports with an average $12.6 \mathrm{~km}, 82$ bouts of high velocity running, ${ }^{2}$ and 150 accelerations, ${ }^{2,19}$ thus ensuring a large metabolic cost. It is, therefore, likely that AF players have a higher match EE, potentially higher training EE and TDEE than other team-sport athletes, but this is yet to be quantified.

The aims of this study were, to develop an algorithm utilising oxygen uptake and accelerometer data from the MiniMax 4.0 (Catapult Innovations, Scoresby Australia) to measure the EE of AF players during training and matches and against this, validate the MiniMax metabolic power calculation. In addition, the SenseWear ${ }^{\mathrm{TM}}$ armband will be used to determine non-exercise activity thermogenesis (NEAT) from ADL. This data would then be used to address the secondary aim of the study which was to quantify the TDEE of professional AF players.

## 2. Methods

Eighteen professional AF players ( $22 \pm 3$ years, weight $89.2 \pm 6.2 \mathrm{~kg}$, height $1.89 \pm 0.07 \mathrm{~m}$ and body fat $9.9 \pm 2.7 \%$, mean $\pm$ SD) gave written informed consent to participate in this study. The study was approved by the University Human Research Ethics committee; and conformed to the Declaration of Helsinki. Body composition was assessed by Duel Energy X-ray Absorptiometry (DEXA, Hologic QDR).

Maximal aerobic power $\left(\dot{\mathrm{VO}}_{2}\right.$ max $)$ was determined in participants using an incremental exercise test completed on a motorised treadmill in a laboratory at $20.0 \pm 1.0^{\circ} \mathrm{C}$ and humidity $51 \pm 2.7 \%$. Testing was conducted in weeks 14 and 15 of the pre-season, $3-4$ weeks prior to the start of the competitive AF season when players would be considered at or close to peak match fitness. A metabolic measurement cart (S-3A/II and CD-3A analysers, Ametek, Pittsburgh, USA), calibrated before each test, measured oxygen uptake and estimated EE at each stage. After a 2 min warm up at $10 \mathrm{~km} \mathrm{~h}^{-1}$ the treadmill speed was increased by $1 \mathrm{~km} \mathrm{~h}^{-1}$ every minute until volitional fatigue. Maximum $\dot{\mathrm{V}}{ }_{2}$ was considered when the participant reached volitional exhaustion and maximum oxygen consumption was reached with increasing work rate. For the duration of the test, the MiniMax was worn in a vest and positioned between the shoulder blades as worn during matches and training. Accelerometer data were used to calculate Playerload ${ }^{\mathrm{TM}}$ (Catapult Innovations, Scoresby Australia) for each stage of the maximal test. Playerload ${ }^{\mathrm{TM}}$, expressed as arbitrary units (au) is a modified scaled vector magnitude and is a measure of total effort, expressed as the square root of the sum of the squared instantaneous rate of change in each of the three vectors divided by $100 .{ }^{13}$

Playerload ${ }^{\mathrm{TM}}$ was plotted against the corresponding estimated EE for $\dot{\mathrm{VO}}_{2}$ for each minute of the test. Correlation analysis was performed and individual regression equations were developed for each participant. These equations were then used to estimate EE of training and matches.

To calculate the EE of training and matches, Playerload ${ }^{\mathrm{TM}}$ was collected in players for the first six matches of the competitive season and in the main training session of the week. Each device was synchronised for starting time, time off the field of play and mandated breaks in play. ${ }^{19}$ The resulting EE regression equation was then applied to Playerload ${ }^{\mathrm{TM}}$ for each session and a correction factor of 1.29 applied to calculate final EE. This was needed to correct for the additional energy cost of running on grass compared to a firm surface. ${ }^{3}$

The EE calculated in this study was correlated with the metabolic power algorithm incorporated in the MiniMax software. The algorithm assumes sagittal plane acceleration and deceleration are primary drivers of energy cost. ${ }^{3}$ Two components of acceleration are considered. The 'equivalent slope' of an inclined terrain and the vertical orientation of the athlete is similar to that of accelerated running at a constant speed and the 'equivalent mass' where during a sprint an athlete exerts greater force than their body weight. Additional force is required to overcome acceleration. ${ }^{3}$ Energy cost is calculated as the function of the equivalent slope by the equivalent mass by a grass environment constant of 1.29. Metabolic power is derived from the energy cost of acceleration and running speed. ${ }^{3}$

The SenseWear ${ }^{\text {TM }}$ Armband was used to determine EE outside of field training and for ADL and will be reported as NEAT. The device is a tri-axial accelerometer and integrates sensors for heat flux, skin temperature and galvanic skin response. The SenseWear ${ }^{\mathrm{TM}}$ software acceptably calculates resting metabolic rate (RMR) ${ }^{20}$ and EE based on a proprietary algorithm including height, weight, age, sex accelerometer and skin temperature. Participants wore the armband on the right upper arm for seven days leading into a match and were instructed to remove the armband while showering, swimming and during contact training sessions (field based training and matches) to avoid damaging the device.

Total daily EE, NEAT, match EE and training EE are presented as absolute values (mean $\pm$ SD) and relative to body mass ( $\mathrm{kJ} \mathrm{kg}^{-1}$ ) and time ( $\mathrm{kJ} \mathrm{kg}^{-1} \mathrm{~min}^{-1}$ ). Regression analysis was used in development of EE equations for individual participants and has been presented with the coefficient of determination $\left(R^{2}\right)$ and typical error (TE) with $90 \%$ confidence intervals (CI). Pearson's correlation was performed between EE methods and presented as change in the mean and $90 \% \mathrm{Cl}$. Magnitude of correlations are reported as; 0.1 small, 0.3 moderate, 0.5 large, 0.7 very large and 0.9 extremely large.

## 3. Results

Descriptive results for participants are presented in Table 1. Injury, team selection and device malfunction resulted in only 12 full data sets from participants being collected for training and match data. Data collected from armband accelerometers to determine daily EE, resulted in 17 full data sets.

Regression equations were developed for each participant. Regression equations, correlations with TE and CV with $90 \%$ CI for each participant are in Table 1 and an example of a typical plot is presented in Fig. 1a. Overall, $r=0.73$ with $90 \%$ CI 10.7-13.6\%.

The length of matches played was $121 \pm 3.5$ min with players participating in $64-96 \%$ of the total playing time. The average PlayerLoad ${ }^{\mathrm{TM}}$ for this time was $1235 \pm 222$ au resulting in an absolute corrected EE of $5745 \pm 1468 \mathrm{~kJ}$ (range: $4097-8621 \mathrm{~kJ}$ ) or $64.7 \pm 16.5 \mathrm{~kJ} \mathrm{~kg}^{-1}$ or $0.66 \pm 0.16 \mathrm{~kJ} \mathrm{~kg}^{-1} \mathrm{~min}^{-1}$ per match. Variability between matches was $0.41 \mathrm{~kJ} \mathrm{~kg}^{-1} \min ^{-1}$ ( $0.29-0.69$ ). Using the metabolic power calculation, absolute EE was $5118 \pm 588 \mathrm{~kJ}$ for a

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