Journal of Sports Sciences

ISSN: 0264-0414 (Print) 1466-447X (Online) Journal homepage: http://www.tandfonline.com/loi/rjsp20

Development of an accelerometer-based multivariate model to predict free-living energy expenditure in a large military cohort

Fleur Horner , James L. Bilzon , Mark Rayson , Sam Blacker , Victoria Richmond , James Carter , Anthony Wright & Alan Nevill

To cite this article: Fleur Horner , James L. Bilzon , Mark Rayson , Sam Blacker , Victoria Richmond , James Carter , Anthony Wright & Alan Nevill (2013) Development of an accelerometer-based multivariate model to predict free-living energy expenditure in a large military cohort, Journal of Sports Sciences, 31:4, 354-360, DOI: 10.1080/02640414.2012.734632

To link to this article: https://doi.org/10.1080/02640414.2012.734632

Published online: 05 Nov 2012.

Journal of Sports Sciences, 2013
Vol. 31, No. 4, 354–360, http://dx.doi.org/10.1080/02640414.2012.734632

Development of an accelerometer-based multivariate model to predict free-living energy expenditure in a large military cohort

FLEUR HORNER[1,2], JAMES L. BILZON[1], MARK RAYSON[2], SAM BLACKER[2], VICTORIA RICHMOND[2], JAMES CARTER[2], ANTHONY WRIGHT[3], & ALAN NEVILL[4]

[1]*University of Bath, Department for Health, Bath, United Kingdom,* [2]*Optimal Performance Ltd, Clifton, Bristol, United Kingdom,* [3]*MRC Human Nutrition Research, Human Nutrition Research, Cambridge, United Kingdom, and* [4]*University of Wolverhampton, Research Institute of Healthcare Studies, Walsall, United Kingdom*

(Accepted 21 September 2012)

Abstract

This study developed a multivariate model to predict free-living energy expenditure (EE) in independent military cohorts. Two hundred and eighty-eight individuals (20.6 ± 3.9 years, 67.9 ± 12.0 kg, 1.71 ± 0.10 m) from 10 cohorts wore accelerometers during observation periods of 7 or 10 days. Accelerometer counts (PAC) were recorded at 1-minute epochs. Total energy expenditure (TEE) and physical activity energy expenditure (PAEE) were derived using the doubly labelled water technique. Data were reduced to $n = 155$ based on wear-time. Associations between PAC and EE were assessed using allometric modelling. Models were derived using multiple log-linear regression analysis and gender differences assessed using analysis of covariance. In all models PAC, height and body mass were related to TEE ($P < 0.01$). For models predicting TEE ($r^2 = 0.65$, SE = 462 kcal $\cdot$ d^{-1} (13.0%)), PAC explained 4% of the variance. For models predicting PAEE ($r^2 = 0.41$, SE = 490 kcal $\cdot$ d^{-1} (32.0%)), PAC accounted for 6% of the variance. Accelerometry increases the accuracy of EE estimation in military populations. However, the unique nature of military life means accurate prediction of individual free-living EE is highly dependent on anthropometric measurements.

Keywords: *accelerometry, doubly labelled water, military, free-living*

Introduction

Measuring the activity profile and energy demands of different populations is important in evidence based research and development of policy. This is particularly important in military organisations for two main reasons. Firstly to ensure that physical training and military field exercises can best match the physical demands experienced by soldiers in operational theatres. Secondly, because the successful quantification of energy expended during operations could better inform military feeding strategies. The energy demands of training and field exercise have been estimated as approximately 4500 kcal $\cdot$ day^{-1} (Tharion et al., 2005), However, there are little empirical data available documenting the energy demands of operations upon which to form evidence-based feeding strategies. This may, in part, be due to the difficulty of using common experimental techniques to measure energy expenditure (EE) in this unique setting.

The doubly labelled water (DLW) method is considered the gold standard for determination of free-living EE in humans (Ainslie, Riley & Westerterp, 2003). The use of DLW is often limited to small experimental studies due to resources and financial costs. Furthermore, DLW only provides a mean estimate of EE over a series of days (usually 7–14), and no pattern of activity over time can be determined (Campbell, Crocker, & McKenzie, 2002). While the deployment of a research team, to directly assess the energy demands of such operations is possible, on a large scale this is impractical, potentially dangerous and intrusive for the soldiers concerned. Movement sensing devices such as accelerometers may offer a practical compromise whereby EE can be predicted unobtrusively without the need for deployment of a large research team.

Body-borne accelerometers are now widely used for objectively assessing frequency, duration and intensity of activity (Chen & Bassett, 2005). It is still difficult however, to accurately use the dimensionless physical activity counts (PAC) to predict units of expended energy (Chu, McManus, & Yu, 2007); particularly as it is recognised that accelerometry

Correspondence: James L. Bilzon, University of Bath, Department for Health, Bath, United Kingdom. E-mail: j.bilzon@bath.ac.uk

tends to underestimate EE associated with load carriage, upper body movements and changes in terrain (Hendelman, Miller, Baggett, Debold, & Freedson, 2000).

Many laboratory-derived prediction equations are developed using a series of scripted activities such as walking, stepping, sweeping and deskwork (Chen et al., 2003). However, such equations may not accurately translate to activities of daily living. An alternative and, arguably, more ecologically valid approach is to derive a prediction equation from relevant free-living data in a population that is to be observed in future studies. During such a study, physical activity should ideally be accurately determined over a period of time representative of habitual activity (Bonomi, Plasqui, Goris, & Westerterp, 2010). Past validation studies that have been conducted in a free-living cohort often use accelerometer data from periods substantially shorter than the DLW observation period (Colley, Gorber, & Tremblay, 2010). Trost, Pate, Freedson, Sallis, and Taylor (2000) recommended that over a 7-day measurement period, 4–5 days of monitoring including a weekend day (i.e. 2–3 missing or incomplete days) returns sufficient reliability to characterise an individual's typical weekly activity profile. This is of relevance when developing prediction models in military cohorts where the waking day has been previously reported as $\sim$17 h on camp and up to 24 h during military exercise when military activities are continued throughout the night (Wilkinson, Rayson, & Bilzon, 2008). In this scenario the variable physical activity patterns observed over 7–10 days would unlikely be characterised by a subsample of 4–5 days of accelerometer data.

Carter et al. (2008) demonstrated the capability of accelerometry to predict total energy expenditure (TEE) in two free-living cohorts and reported explained variance of up to 35% using accelerometer counts alone and up to 78% when accelerometer counts were combined with body composition variables. However, the models presented by Carter et al. (2008) were divided into two groups; young adults and adolescents. When considered as independent cohorts, the young adult military-based prediction equations were developed using only 12 data points. Furthermore, a prediction equation developed in a single platoon of trainee guardsmen may not be applicable to other military groups, particularly female personnel.

This study aims to firstly test the hypothesis that PAC are independently associated with TEE and physical activity energy expenditure (PAEE), and secondly to develop a multivariate model to predict free-living EE in a pooled dataset from a number of independent cohort studies. This will be achieved using a stringent data reduction method returning a model which is based upon a large, highly compliant sample, developed using DLW as a gold standard criterion measure. The inclusion of a range of cohorts would make the resultant mathematical model more generic, at least within the military context.

To our knowledge, this will be the largest independent evaluation of the efficacy of an accelerometer to predict EE against the DLW method in multiple cohorts.

Methods

General approach

Over a six-year period from 2004 to 2010, 10 data collection periods with military cohorts in the UK and the Gulf Cooperation Council (GCC) produced 288 individual datasets where average daily 3DNX accelerometer counts (PAC) and average daily EE using the DLW technique were measured simultaneously. In all studies, written informed consent was provided and where necessary countersigned by a legal guardian following a full explanation of procedures. Ethical approval for each study was sought and obtained from the most appropriate research ethics committee, including the UK Ministry of Defence Research Ethics Committee and the School of Sport and Exercise Sciences Ethics Committee at the University of Birmingham.

Despite small methodological differences between each study, DLW and accelerometry techniques remained constant throughout.

Preliminary measures

Stature (Leicester Stadiometer, Seca, Hamburg, Germany) and body mass (Alpha 770, Seca, Hamburg, Germany) were measured on the day prior to the start of each observation period. Body composition was calculated from total body water using the average deuterium and 18-oxygen dilution spaces from the DLW measurements. Total body water was corrected by 1.04 and 1.01 respectively to account for non-aqueous exchange of the two isotopes within the body. Fat free mass was calculated using a hydration factor of 73% with fat mass as the difference between body mass and fat free mass.

Isotope dosing and sampling

The DLW method used was previously described by Bluck (2008). Briefly, each participant provided baseline urine samples before ingesting a weighed oral dose of $^2H_2{}^{18}O$ (day 0). The doses were 80 mg $\cdot$ kg^{-1} deuterium oxide and 145 mg $\cdot$ kg^{-1} $H_2{}^{18}O$. Post-dose urine samples were collected daily for 7–

10 days depending on the study (see below) and the time of day noted. Urine samples were subsequently frozen at -20°C and later analysed in duplicate using isotope-ratio mass spectrometry by a third party independent and blinded to the study (MRC, Human Nutrition Research, Elsie Widdowson Laboratory, Cambridge, UK). Using this dosing regime, TEE can be measured with a coefficient of variation lower than 5% (Bluck, 2008). A sample of drinking water was also collected to correct for the natural abundance of $^{2}H_{2}{}^{18}O$ at each study location.

Energy expenditure calculations

Energy expenditure was calculated, as previously described by Schoeller and van Santen (1982), from the slopes and intercepts of isotope disappearance curves, based on samples collected at the first two, middle and last two days of the study. For all participants the respiratory quotient was assumed to have a daily average value of 0.85 and resting metabolic rate (RMR) was estimated using the Schofield (1985) equations. Physical activity energy expenditure (PAEE) was calculated as (TEE x 0.9) – RMR, assuming that diet-induced thermogenesis was 10% of TEE (Plasqui, Joosen, Kester, Goris, & Westerterp, 2005).

Accelerometry

The triaxial 3DNX model v3 (BioTel Ltd, Bristol, UK) is sensitive to movements in three axes: X (anteroposterior), Y (mediolateral) and Z (vertical). The unit measures 54 x 54 x 18 mm, and weighs 70 g including a 3.6 v lithium battery (Saft Ltd., UK). The unit contains two ADXL321 biaxial micro-electro-mechanical sensors (Analog Devices Ltd., Surrey, UK) positioned orthogonally to measure acceleration in three movement axes. The sample frequency of the 3DNX is 100 Hz with a low pass filter set at 0.2 Hz and a high pass filter set at 20 Hz which ensures that most non-human movement, such as vibration, is not registered. Accelerometers were set to record at one-minute epochs. The reliability and validity of this device was examined by Horner, Rayson and Bilzon (2011).

In studies 5, 6, 7 and 8 an earlier version of the 3DNX accelerometer (v2) was used. For a full description of the 3DNX v2 see Carter et al. (2008). Slight differences in the unit software meant that a conversion factor was applied in order to standardise the activity counts between unit versions. This conversion factor was developed by simultaneously shaking both versions on a multi-axis shaker table (MAST-9720, Instron Structural Testing Systems Ltd., UK) at a range of accelerations and producing an ordinary least product linear regression equation (Ludbrook, 1997). The relationship between v3 and v2 units is given by $y = 0.224\,x - 5.703$, where y is v2 counts and x is v3 counts. This relationship was confirmed during unpublished observations in free-living human data where both versions of the accelerometer were worn simultaneously and showed close agreement once converted ($r^2 = 0.97$ SE = 3.9%).

Participants were given the accelerometers on waking and instructed to wear the unit in the small of the back (attached to an elastic belt) during the whole of the waking day except during water-based activities. A typical waking day was approximately 16 hours long (unless during military exercise) and collection periods ranged from 7–10 days depending on the study protocol. Maximum possible waking hours over the observation period were calculated for each cohort and actual wear time expressed as a percentage of the maximum. Data were downloaded on collection of the unit using dedicated software (BioTel, UK) and imported into Microsoft Excel for further analysis.

Actual wear time and daily PAC for each individual were calculated and the dataset was reduced as follows. A period of 11 hours monitoring was chosen as a threshold that included as many participants as possible whilst capturing most of the waking day. Any days where the accelerometer was worn for less than 11 hours (including removal for water activities) were coded as "missing". An individual was excluded from the analysis if they had more than one "missing" day. Overall wear time compliance based on each cohort's maximum possible waking hours before imputation was 93.5 ± 5.6% (i.e. participants wore the activity monitors for an average of 93.5% of the time between the distribution of the monitors in the morning and their collection at night). For those individuals with no more than one "missing" day, a group mean value was imputed. Imputation is encouraged when incomplete accelerometer data are observed (Catellier et al., 2005).The imputation method for this study was chosen due to the military nature of the participant population. Minimal between-participant variation was observed in the type and pattern of activities performed on a daily basis as groups often performed activities as a platoon. Using a group mean to impute only one missing day was deemed an acceptable method for retaining an individual dataset. The inconsistent nature of physical activity patterns between days could have led to an artificial increase or decrease in the mean PAC had a day simply been excluded. In total, PAC for 30 individual days were imputed out of 1349 days measured (2.2%).

Statistical analysis

As EE, along with other physiological variables, is known to increase with body size (Nevill, Bate, &

Holder, 2005), a multiplicative allometric modelling approach was used as detailed by Nevill and Holder (1995).

$$Y = a \cdot X^b \cdot \varepsilon \qquad (1)$$

Support for the use of this method was obtained as heteroscedasticity was observed when plotting size-related independent variables such as body mass and height against TEE and PAEE, i.e. when the residual errors are proportional to the size of the dependent variable (Nevill & Holder, 1995). This was overcome by log-transforming both the dependent and independent variables. Analysis of covariance (ANCOVA) was then used to identify any categorical differences (e.g. sex differences) by defining $\log_e$(TEE) and $\log_e$(PAEE) as dependent variables and using $\log_e$(PAC), $\log_e$(Mass) and $\log_e$(Height) as covariates. The log-linear model used to investigate the relationship between EE (Z) and PAC (Y), mass (X) and height (W) is given by

$$Z = a \cdot Y^b 1 \cdot X^b 2 \cdot W^b 3 \cdot \varepsilon \qquad (2)$$

The coefficient of determination (r^2) was used to describe the association between PAC and dependent variables. The partial r^2 value is reported to indicate how much variance is explained by the PAC variable alone above that which is explained by the combination of other variables in the model. The standard error (SE) is reported for all models. All measured variables are reported as mean $\pm$ standard deviation (s). All statistical analysis was conducted using SPSS (version 16.0, SPSS inc., Chicago, IL). The significance level was set *a priori* at $P < 0.05$.

Results

Following application of the exclusion process, the final dataset was reduced to $n = 155$. Participant characteristics are presented by study in Table I. Physical activity counts alone, expressed as $\log_e$(PAC), was associated with $\log_e$TEE ($r^2 = 0.08$, $P < 0.01$) and $\log_e$PAEE ($r^2 = 0.07$, $P < 0.01$).

General linear modelling (Equation 1) using multiple log-linear regression revealed a difference ($P < 0.01$) between the male and female models for height a and b parameters. Therefore, two separate models were developed for the prediction of TEE and PAEE, allowing the intercepts and height exponents to vary with gender. In all models PAC, height and body mass were related to EE ($P < 0.01$).

Prediction of TEE

The power function model relating TEE (Z) to PAC (Y), mass (X) and height (W) for males is given by

Table I. Physical characteristics of participants.

Study	Study duration (days)	Study Description	N (M/F)	Age (years)	Body Mass (kg)	Height (m)	RMR (kcal · day^{-1})	TEE (kcal · day^{-1})	PAEE (kcal · day^{-1})	PAC (counts · day^{-1})
1	7	GCC officer cadets	29 (29/0)	19.2 ± 1.9	70.0 ± 14.4	1.69 ± 0.06	1769 ± 239	3270 ± 489	1174 ± 340	657379 ± 66437
2	7	GCC officer cadets	15 (15/0)	20.5 ± 1.9	67.2 ± 7.7	1.72 ± 0.03	1701 ± 116	3278 ± 476	1249 ± 356	587763 ± 64524
3	7	GCC officer cadets	6 (6/0)	21.1 ± 1.8	68.3 ± 9.0	1.71 ± 0.06	1716 ± 136	3010 ± 442	993 ± 324	510268 ± 80513
4	10	Advanced field training	6 (6/0)	29.5 ± 4.1	72.2 ± 2.7	1.74 ± 0.06	1748 ± 30	4946 ± 224	2704 ± 216	667570 ± 58585
5	10	GCC military college	6 (6/0)	16.0 ± 1.3	67.3 ± 21.7	1.66 ± 0.02	1806 ± 293	3233 ± 451	1104 ± 220	476570 ± 111492
6	10	Recruits in training	21 (8/13)	19.4 ± 2.4	64.0 ± 10.8	1.71 ± 0.10	1571 ± 249	3426 ± 760	1512 ± 496	578904 ± 109242
7	10	Recruits in training	9 (4/5)	18.7 ± 1.9	64.3 ± 10.1	1.70 ± 0.10	1601 ± 249	3612 ± 428	1650 ± 245	610079 ± 107619
8	10	Infantry training	10 (10/0)	19 ± 2.0	71.0 ± 9.2	1.78 ± 0.06	1806 ± 148	4502 ± 378	2426 ± 251	669529 ± 61372
9	10	Recruits in training	27 (14/13)	21.8 ± 4.4	67.9 ± 12.4	1.71 ± 0.10	1621 ± 285	3580 ± 704	1600 ± 387	536342 ± 55144
10	10	Recruits in training	20 (10/10)	22.6 ± 4.4	68.5 ± 12.9	1.73 ± 0.10	1639 ± 291	3625 ± 771	1623 ± 470	536040 ± 62304
Overall			**155 (111/41)**	**20.6 ± 3.9**	**67.9 ± 12.0**	**1.71 ± 0.10**	**1679 ± 246**	**3553 ± 725**	**1531 ± 546**	**586388 ± 93457**

Note: GCC, Gulf Cooperation Council; RMR, predicted resting metabolic rate; TEE, total energy expenditure; PAEE, physical activity energy expenditure; PAC, 3DNX output.

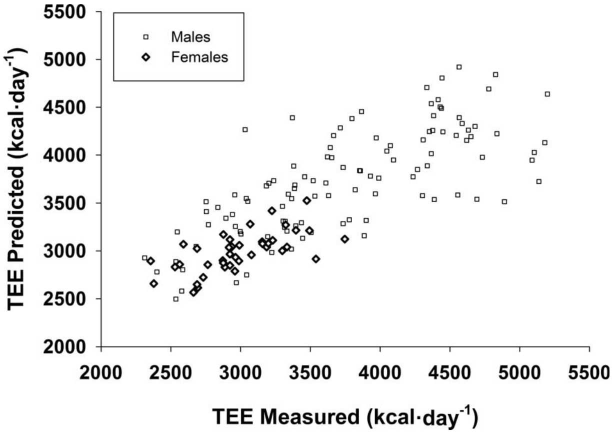

Figure 1. Regression plot of the prediction models of TEE based on 3DNX output (PAC), body mass, height and gender.

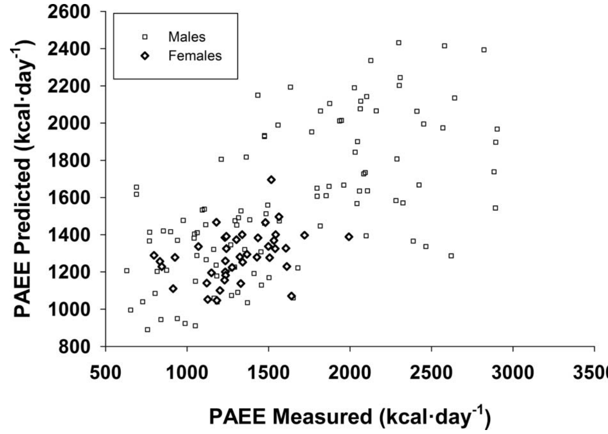

Figure 2. Regression plot of the prediction models of PAEE based on 3DNX output, height and gender.

$$TEE(kcal) = 1.67 \cdot PAC^{0.257} \cdot Mass^{0.434} \cdot Height^{2.322} \quad (3)$$

The power function model relating TEE (Z) to PAC (Y), mass (X) and height (W) for females is given by

$$\mathrm{TEE(kcal)} = 2.666 \cdot \mathrm{PAC}^0 \cdot 257 \cdot \mathrm{Mass}^0 \cdot 434 \cdot \times \mathrm{Height}^0 \cdot 364 \quad (4)$$

These models displayed a strong positive relationship with TEE ($r^2 = 0.65$, SE = 462 kcal · day^{-1} (13.0%)). Physical activity counts contributed significantly to the prediction of TEE explaining 4% of the total variance (Figure 1).

Prediction of PAEE

Body mass did not make a significant contribution to the prediction of PAEE and was removed from the model, hence the power function model relating PAEE (Z) to PAC (Y) and height (X) for males is given by

$$PAEE(kcal) = -3.755 \cdot PAC^{0.59_0} \cdot Height^{5.85_6} \quad (5)$$

The power function model relating PAEE (Z) to PAC (Y) and height (X) for females is given by

$$PAEE(kcal) = -1.227 \cdot PAC^{0.59_0} \cdot Height^{1.21_7} \quad (6)$$

These models showed a moderate positive relationship with PAEE ($r^2 = 0.41$, SE = 490 kcal · day^{-1} (32.0%)). Physical activity counts contributed significantly to the prediction of PAEE explaining 6% of the total variance (Figure 2).

Discussion

Triaxial accelerometry has emerged as a useful tool for assessing physical activity and its associated EE in large scale epidemiological studies (Vanhelst et al., 2012). In order to translate PAC into more meaningful units of expended energy, statistical models must be developed using an appropriate criterion measure such as DLW. In the present analysis, 10 independent cohort studies, using the same methodological approach, were combined with the aim of developing a generic model for the prediction of both TEE and PAEE in free-living military populations. Allometric modelling was used to provide a biologically plausible method of fitting the data. The relatively poor fit of the models in this study suggest that it may not be appropriate to use a generic prediction equation for different military populations and that careful consideration must therefore be given to generalising such models across other diverse sub-populations.

The prediction models showed that PAC measured by the 3DNX accelerometer explained significant, albeit small, amounts of variance in TEE and PAEE for both genders. PAC accounted for between 4% and 6% of the variance in TEE and PAEE respectively for both male and female models.

Overall, 3DNX (v3) output explained 65% of the variance in TEE when combined with body composition variables. When combined with RMR, the Tracmor explained 76% of the variance in TEE and the 3DNX (v2) explained 78% of the variance in TEE when combined with body composition variables (Bonomi et al., 2010; Carter et al., 2008).

On a basic level, it is difficult to compare the individual contribution of accelerometry to the estimation of EE between other studies in the extant literature as few report these data. The results of the present study are similar to the early work of Bouten, Verboeket-van de Venne, Westerterp, Verduin, and

Janssen (1996) who reported that the output from the triaxial Tracmor explained 6% of the variance in TEE measured by DLW (SEE = 18%). More recently, Bonomi et al. (2010) compared TEE measured by DLW and PAC measured by the Tracmor and reported explained variance of 16% (SE = 7.4%) when combined with body mass. This study reports a higher degree of predictive validity, with lower prediction error, compared to the present study. Although it is not readily apparent why the present study reports less favourable results for the predictive validity of 3DNX PAC, differences in study populations and the very high EEs (up to 5199 kcal $\cdot$ day^{-1}) reported for some participants may have been accumulated during activities which the accelerometer failed to quantify sufficiently. This is likely comprised of the frequent load carriage and uneven terrain encountered as part of military exercise (Knapik, Harman, & Reynolds, 1996; Pandolf, Givoni, & Goldman, 1977).

In the model to predict PAEE, PAC accounted for 6% of the variance in PAEE (SE = 32%). In comparison to the results of Bouten et al. (1996) and Plasqui et al. (2005) the 3DNX appears to poorly predict PAEE. Bouten et al. (1996) reported that 22% of the variance in PAEE could be explained by Tracmor PAC alone (SEE = 12%) and Plasqui et al. (2005) reported an increase in the explained variance of PAEE measured by DLW from 48 to 81% (SEE = 17%) when Tracmor PAC were added to a model containing body composition variables. The poorer prediction of PAEE than TEE may be in part due to the military populations studied. As well as frequent load carriage and ambulation on uneven terrain, the majority of military training is conducted in groups (i.e. platoons), where recruits largely complete the same physical activity, particularly during transits and drill. It is unsurprising therefore that mean PAC $\cdot$ day^{-1} does not accurately predict PAEE when there is such little variation in PAC between participants in a cohort.

Unfortunately due to the nature of the studies combined in this analysis it was not possible to directly measure RMR. As a result, RMR was estimated using the equations of Schofield (1985) incorporating age, gender, body mass and height. Such an equation is widely used despite concerns that it may not be appropriate for all populations. However, the population used to develop the equation contained a number of conscripts making it more relevant to this study population than other equations. Despite this limitation, Carter et al. (2008) contend that it may be just as appropriate to validate prediction equations in a field-based setting as accurate measures of RMR are rarely possible.

The reduction of variance in TEE and PAEE explained by 3DNX (v3) compared to the 3DNX (v2) is not easily accounted for but is most likely due to the combination of a number of different populations. It seems that there may have been different sources of unexplained variance for each population leading to a cumulative reduction in the common explained variance. This indicates that a generic equation for predicting EE in different free-living populations may not be appropriate particularly when researchers seek to combine cohorts with different physiological characteristics and physical activity patterns. To address some of these problems, we contend that some form of calibration should be undertaken, any proprietary equations should be refined and specific prediction equations should be developed for each free-living population studied.

This is the first large-scale study where the DLW technique has been used as a criterion measure to assess the accuracy of an accelerometry-derived multivariate model to predict free-living TEE and PAEE within a military population. We have used a highly compliant participant sample and provided a transparent and open account of the methodological issues surrounding the pooling of different populations. The results of this study demonstrate that 3DNX (v3) does marginally improve the estimation of free-living EE in sub-groups of military populations when combined with anthropometric variables. However, the accurate prediction of individual free-living EE requires careful consideration of multiple variables such as anthropometric measurements as well as the type of activities undertaken.

For populations such as the military, where day-to-day soldiering includes large amounts of resistance-style activity such as load carriage; a more accurate estimate of PAEE could be achieved if time spent performing such activities could be identified and appropriate relationships with VO_2 attributed. The recent shift in accelerometer-based research towards using the rich, raw accelerometer signal to identify activities of daily-living (Heil, Brage, & Rothney, 2012) could be a suited to identifying common soldiering activities that traditional accelerometry methodologies cannot, at present, fully detect. The exploitation of raw accelerometry signals for the identification of common military tasks such as load carriage warrants further investigation.

References

Ainslie, P., Reilly, T., & Westerterp, K. (2003). Estimating human energy expenditure: A review of techniques with particular reference to doubly labelled water. *Sports Medicine*, *33*(9), 683–698.

Bluck, L. (2008). Doubly labelled water for the measurement of total energy expenditure in man – progress and applications in the last decade. *Nutrition Bulletin*, *33*, 80–90.

Bonomi, A.G., Plasqui, G., Goris, A.H., & Westerterp, K.R. (2010). Estimation of Free-Living Energy Expenditure Using a Novel Activity Monitor Designed to Minimize Obtrusiveness. *Obesity (Silver Spring)*, *18*(9), 1845–1851.

Bouten, C.V., Koekkoek, K.T., Verduin, M., Kodde, R., & Janssen, J.D. (1997). A triaxial accelerometer and portable data processing unit for the assessment of daily physical activity. *IEEE Transactions on Biomedical Engineering*, *44(3)*, 136–147.

Campbell, K.L., Crocker, P.R., & McKenzie, D.C. (2002). Field evaluation of energy expenditure in women using Tritrac accelerometers. *Medicine and Science in Sports and Exercise*, *34*(10), 1667–1674.

Carter, J., Wilkinson, D., Blacker, S., Rayson, M., Bilzon, J., Izard, R., et al. (2008). An investigation of a novel three-dimensional activity monitor to predict free-living energy expenditure. *Journal of Sports Sciences*, *26*(6), 553–561.

Catellier, D.J., Hannan, P.J., Murray, D.M., Addy, C.L., Conway, T.L., Yang, S., … Rice, J.C. (2005). Imputation of missing data when measuring physical activity by accelerometry. *Medicine and Science in Sports and Exercise*, *37*(Suppl. 11), S555–562.

Chen, K.Y., & Bassett, D.R., Jr. (2005). The technology of accelerometry-based activity monitors: Current and future. *Medicine and Science in Sports and Exercise*, *37*(Suppl. 11), S490–500.

Chu, E.Y., McManus, A.M., & Yu, C.C. (2007). Calibration of the RT3 accelerometer for ambulation and nonambulation in children. *Medicine and Science in Sports and Exercise*, *39*(11), 2085–2091.

Colley, R., Gorber, S.C., & Tremblay, M.S. (2010). Quality control and data reduction procedures for accelerometry-derived measures of physical activity. *Health Reports*, *21*(1), 63–69.

De Lorenzo, A., Bertini, I., Candeloro, N., Piccinelli, R., Innocente, I., & Brancati, A. (1999). A new predictive equation to calculate resting metabolic rate in athletes. *Journal of Sports Medicine and Physical Fitness*, *39*(3), 213–219.

Heil, D.P., Brage, S., & Rothney, M.P. (2012). Modeling physical activity outcomes from wearable monitors. *Medicine and Science in Sports and Exercise*, *44*(Suppl. 1), S50–60.

Hendelman, D., Miller, K., Baggett, C., Debold, E., & Freedson, P. (2000). Validity of accelerometry for the assessment of moderate intensity physical activity in the field. *Medicine and Science in Sports and Exercise*, *32*(Suppl. 9), S442–449.

Horner, F.E., Rayson, M.P., & Bilzon, J.L. (2011). Reliability and validity of the 3DNX accelerometer during mechanical and human treadmill exercise testing. *International Journal of Obesity*, *35*(Suppl. *1*), S88–97.

Knapik, J., Harman, E., & Reynolds, K. (1996). Load carriage using packs: A review of physiological, biomechanical and medical aspects. *Applied Ergonomics*, *27*(3), 207–216.

Ludbrook, J. (1997). Comparing methods of measurements. *Clinical and Experimental Pharmacology and Physiology*, *24*(2), 193–203.

Nevill, A.M., Bate, S., & Holder, R.L. (2005). Modeling physiological and anthropometric variables known to vary with body size and other confounding variables. *American Journal of Physical Anthropology*, (Suppl. 41), 141–153.

Nevill, A.M., & Holder, R.L. (1995). Scaling, normalizing, and per ratio standards: An allometric modeling approach. *Journal of Applied Physiology*, *79*(3), 1027–1031.

Pandolf, K.B., Givoni, B., & Goldman, R.F. (1977). Predicting energy expenditure with loads while standing or walking very slowly. *Journal of Applied Physiology*, *43*(4), 577–581.

Plasqui, G., Joosen, A.M., Kester, A.D., Goris, A.H., & Westerterp, K.R. (2005). Measuring free-living energy expenditure and physical activity with triaxial accelerometry. *Obesity Research*, *13*(8), 1363–1369.

Schoeller, D.A., & van Santen, E. (1982). Measurement of energy expenditure in humans by doubly labeled water method. *Journal of Applied Physiology*, *53*(4), 955–959.

Schofield, W.N. (1985). Predicting basal metabolic rate, new standards and review of previous work. *Human Nutrition. Clinical Nutrition*, *39*(Suppl. 1), 5–41.

Tharion, W.J., Lieberman, H.R., Montain, S.J., Young, A.J., Baker-Fulco, C.J., Delany, J.P., & Hoyt, R.W. (2005). Energy requirements of military personnel. *Appetite*, *44*(1), 47–65.

Thompson, J., & Manore, M.M. (1996). Predicted and measured resting metabolic rate of male and female endurance athletes. *Journal of the American Dietetic Association*, *96*(1), 30–34.

Trost, S.G., Pate, R.R., Freedson, P.S., Sallis, J.F., & Taylor, W.C. (2000). Using objective physical activity measures with youth: How many days of monitoring are needed? *Medicine and Science in Sports and Exercise*, *32*(2), 426–431.

Vanhelst, J., Beghin, L., Duhamel, A., Bergman, P., Sjotrom, M., & Gottrand, F. (2012). Comparison of uniaxial and triaxial accelerometry in the assessment of physical activity among adolescents under free-living conditions: The HELENA study. *BMC Medical Research Methodology*, *12*(1), 26.

Wilkinson, D.M., Rayson, M.P., & Bilzon, J.L. (2008). A physical demands analysis of the 24-week British Army Parachute Regiment recruit training syllabus. *Ergonomics*, *51*(5), 649–662.