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PAPER

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Wrist-worn accelerometers in assessment of energy expenditure during intensive training

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Abstract
We assessed the ability of the Polar activity recorder (AR) to measure energy expenditure (EE) during military training. Twenty-four voluntary male conscripts participated in the study and wore an AR on the non-dominant wrist 24 h a day for 7 d. The AR analyzed and stored the frequency of hand movements (*f*_hand) into memory at 1 min intervals. The relationship between *f*_hand and EE was studied over a 7 d period of military training using the doubly labeled water (DLW) technique. In addition, the relationship between *f*_hand and EE was analyzed during walking and running on a treadmill with an indirect calorimeter (IC), and *f*_hand was measured during a supervised 45 min field march test where the conscripts carried combat gear. EE was expressed as physical activity level (PAL), total energy expenditure (TEE), and activity-induced energy expenditure adjusted for body mass (AEE/BM). Over the 7 d period, *f*_hand alone explained 46% of inter-individual variation in PAL_{DLW}. After inclusion of body height and mass in the model used to predict PAL_{DLW} from *f*_hand, a very high positive correlation and a low standard error of estimate (SEE) were observed between the AR and DLW techniques: for TEE $r = 0.86$ ($p < 0.001$), the SEE was 6.3%, and for AEE/BM $r = 0.84$ ($p < 0.001$), the SEE was 12.8%. In the treadmill exercise, *f*_hand correlated highly with PAL_{IC} ($r = 0.97 \pm 0.02$). In the 45 min field march test, the AR measured similar *f*_hand as on the treadmill at the same speed. In conclusion, the wrist-worn AR can be regarded as a reliable and valid method for assessing EE during intensive training.

Keywords: accelerometers, doubly labeled water, energy expenditure, military training, physical activity

(Some figures may appear in colour only in the online journal)

1. Introduction

Military service includes physically demanding tasks both indoors and outdoors and involves carrying loads and using various pieces of equipment and tools. The range of fitness levels among conscripts has widened (Santtila *et al* 2006), and the ability to tolerate intensive military training may be affected by increased body mass (BM) and lower fitness level (Tanskanen *et al* 2009). Subsequently, it would be important to have practical and reliable tools to monitor physical activity and energy expenditure (EE) in soldiers. During heavy training periods in the military and among endurance athletes, knowledge of EE could help in adjusting the training volume as well as controlling adequate energy availability. In order to be acceptable for the military, the methods need to be robust and unobtrusive.

EE is an important training parameter, since many measures of training load are associated with total energy expenditure (TEE). Physical activity level (PAL), defined as TEE divided by basal metabolic rate (BMR), has been used to classify occupational workload and leisure-time physical activity. PAL among North American and European adult population is typically 1.6–1.7 (Westerterp and Speakman 2008, Speakman and Westerterp 2010). An upper limit of PAL that can be maintained for a longer period of time has been determined to be about 2.5 within the general population (Black *et al* 1996, Westerterp and Plasqui 2004) while professional endurance athletes may reach higher PAL values (Westerterp 1998). Another measure for describing EE is activity-induced energy expenditure (AEE) with corrections for differences in body size (Ekelund *et al* 2004). AEE arises from muscular activity, including shivering and fidgeting as well as purposeful physical exercise (Poehlman 1989), and it is affected by the intensity and duration of activity as well as by individual differences in movement efficiency (Ainsworth *et al* 1993).

The doubly labeled water (DLW) technique is considered the golden standard for measuring EE under free-living conditions. Since the DLW technique is expensive, it is most often used in small study populations. While this technique provides an accurate measure of TEE, it gives no information on physical activity in terms of frequency, duration, and momentary intensity. Nevertheless, it is the only method available for accurately measuring TEE under free-living conditions (Plasqui and Westerterp 2007). In short-term measurements, indirect calorimetry (IC) has been extensively used as the reference method for assessing the validity of accelerometers in various sports and non-sports activities.

An accelerometer is the small instrument designed to register movement data at a high frequency over days or weeks. Accelerometers are typically uniaxial or triaxial, of which the latter are generally accepted as providing more information and a better relationship to AEE than uniaxial ones (Bouten *et al* 1994). Previously validated accelerometer applications (CSA/MTI/Actigraph and Tracmor) are worn close to the center of the body (hip, waist, or lower back), and they are designed to integrate the total amount of acceleration in one or three dimensions (Plasqui and Westerterp 2007). In contrast to these devices, Polar activity recorders (AR) utilize frequency and regularity of hand movements with adjustment for body parameters (Kinnunen *et al* 2009). This method requires little computational power, which has enabled its use in battery-operated wrist-worn devices (Polar AW200, FA20 and Active, Polar Electro Oy, Kempele, Finland).

Wrist-worn motion sensors were introduced in a research setting already in the 1950s, but until a recent study by van Hees *et al* (2011), there have been no validation data available from wrist-worn accelerometers with respect to TEE under free-living conditions (Plasqui and Westerterp 2007). Van Hees *et al* (2011) used a linear model to analyze the role of wrist acceleration in explaining variations in AEE, and they found that a wrist-worn three-dimensional accelerometer explained 24% of variation in AEE in 73 non-pregnant women.

In short-term recordings, activity monitoring from the wrist has been found to be accurate in measuring EE while walking and hiking (Bouten *et al* 1997, Brugniaux *et al* 2010). In daily tasks and sports activities, a minimal prediction improvement has been reported when a wrist accelerometer has been added to the center of body measurement (Swartz *et al* 2000, Tanaka *et al* 2007). However, Kinnunen *et al* (2009) have reported a reasonably high accuracy with the present methodology. Modern signal processing technology has allowed more complex analysis methods to improve the accuracy of accelerometer applications. For example, automatic activity classification has been widely studied in recent years with machine learning procedures or hierarchical algorithm structures, among other methods (Siirtola *et al* 2009, Yang and Hsu 2010, Zhang *et al* 2012).

In normal walking and running, the frequency of hand movement (f_hand) is linked with stride frequency (Wagenaar and van Emmerik 2000), and stride frequency is associated with walking and running speeds. Wixted *et al* (2007) described an EE estimator in walking and running based on step frequency modified by anthropometric measures. Anthropometrics such as leg length, body height (BH) and BM affect self-selected step length and stride frequency at a given speed. Walking cadence has also been successfully used to determine the lower limit for moderate-intensity activity (Tudor-Locke and Rowe 2012). Another recent paper by Cheng *et al* (2009) describes an algorithm for estimation of exercise rate, i.e. stride rate in walking or running, pedaling cadence in cycling or stroke rate in rowing. All of these approaches have used waist mounted accelerometers, and apparently none of them has been validated in the long-term field setting so far.

The aim of this study was to assess the validity and reliability of the wrist-worn AR in measuring EE in a military environment. Because of usability issues and extreme measurement conditions, simple and robust methods were preferred. Firstly, a piece-wise linear relationship between f_hand and intensity of exercise was determined so that the best match was attained with AR and DLW regarding TEE and AEE during 7 d of intensive military training. Secondly, the relationship between f_hand and intensity of exercise was determined with IC in treadmill walking and running on a minute-by-minute basis. Finally, the effect of carrying 20 kg of extra military equipment on f_hand was studied when walking or running at a constant speed on flat terrain covered by fine gravel.

2. Methods

2.1. Subjects

Twenty-four voluntary male conscripts, age 19–20 years, mean ± SD BM 77 ± 15 (range 57–111) kg, BH 178 ± 8 (153–187) cm, and maximal oxygen uptake (VO_{2max}) 47 ± 6 (30–59) ml kg^{-1} min^{-1}, participated in the study. The selection of subjects from a group of voluntary subjects is explained in detail by Tanskanen *et al* (2009). The subjects' physical fitness characteristics were representative of young Finnish men (Santtila *et al* 2006). All the subjects were informed of the experimental protocol and they gave their written consent to participate in the study. They were also advised of their right to withdraw from the investigation at any time. The study protocol was approved by the Finnish Defense Forces and the Ethics Committees of the University of Jyväskylä and the Kainuu region.

2.2. Study protocol

The experimental protocol, timing of the tests, and main daily program with respect to the DLW assessment period, are illustrated in table 1. The study protocol included a treadmill

Table 1. Experimental protocol and main daily program during the DLW assessment period.

	Days										
	$-9, \ldots, -5$	0	1	2	3	4	5	6	7	8	+1
VO_{2max} test on a treadmill	×										
DLW (doubly labeled water) dose		×									
Urine sample		×	×							×	
Combat shooting exercise		×	×								
Overnight field exercise				×	×	×	×				
Long-distance skiing									×		
Shooting exercise										×	
45 min march test											×

test about 1 week before the DLW assessment period, and a 45 min field march test on the following day after the DLW period. The data collection took place during the winter when the ambient temperature varied between −2 and −23 °C.

2.3. Polar AR

Each conscript wore an AR (prototype of Polar FA20, Polar Electro Oy, Kempele, Finland) on the non-dominant wrist 24 h a day. As the sensing element, the AR included a capacitive 1D accelerometer. In the signal processing, the AR utilized a patented movement counting and filtering procedure (Kinnunen and Miettinen 2005). The acceleration signal was band-pass filtered (0.3–3.0 Hz) and the device counted hand movements if acceleration exceeded a preset threshold. The device did not register hand movements that appeared too soon after the previously detected movement, and the rejection time was longer in non-rhythmic activities. The number of registered hand movements was stored in the memory of the device at 1 min intervals, and this is referred to as f_hand_{AR}. The prototype had a 24 h running memory, so the AR were collected every evening for data download and redistributed within 30 min. If the AR had registered 30 consecutive zeros during the day (between 8 a.m. and 9 p.m.) and 300 consecutive zeros during the night (between 9 p.m. and 8 a.m.), the corresponding time was considered to be non-wear and left out of the analysis.

2.4. Military training and DLW measurement

Description of the 7 d military training. The measurement period was one of the most intensive training weeks during 8 week basic military training. The conscripts were involved in typical physically demanding military tasks, such as marching, material handling, and shooting exercises, and in several unsupervised activities of varying intensity in the garrison area and in the field. During the 7 d measurement period, the main events included a 1 d combat shooting exercise, 4 d of overnight field training, and 1 d of long distance skiing (table 1).

DLW experimental design. Reference EE for the 7 d period (TEE_{DLW}) was measured with DLW according to the Maastricht Protocol (Westerterp *et al* 1995). Briefly, at 10 p.m. on day 0 after collecting a baseline urine sample, the subjects drank a weighed mixture of ^2H_2O (99.9 atom%) and $H_2{}^{18}O$ (10 atom%), resulting in an initial excess total body water enrichment of 150 ppm for deuterium and 300 ppm for oxygen-18. Total body water was estimated from calculated body composition based on BH, BM, age, and gender with the equation from Deurenberg *et al* (1991), assuming 73% hydration of fat-free mass. The subjects consumed no foods or fluids for 10 h after dose administration during overnight equilibration of the isotopes with body water. Subsequent urine samples were collected from the second and third voiding on the morning of day 1, and from the first and second voiding on the morning of day 8. Isotope quantities (deuterium and oxygen-18) in the urine were measured with an isotope ratio mass spectrometer (Optima, VG Isogas, Middlewich, UK), and CO_2 production was calculated from isotope ratios at the baseline and days 1 and 8 using the equations from Schoeller *et al* (1986). CO_2 production was converted to daily metabolic rate using an energy equivalent based on the individual macronutrient composition of the diet (Black *et al* 1986). AEE_{DLW} was calculated as $TEE_{DLW} \times 0.9 - BMR$, assuming diet-induced thermogenesis of 10% (Poehlman 1989). To remove the confounding effect of body size (Ekelund *et al* 2004), AEE_{DLW} was adjusted for BM (AEE/BM_{DLW}). BM was measured on days 1 and 8, and the average of these two measurements was used as individual BM.

Sick leave, substitution of lost AR data. Sick leave was non-attendance in daily service because of illnesses or injuries examined by a physician. Three of the subjects had a maximum of a 24 h period when they did not wear the AR because of sick leave. During that time their wrist activity counts were set to a very low level in the daytime (corresponding to PAL = 1.6), and to zero activity at night (10 p.m.–7 a.m.). Other non-wear time was excluded from further analysis and we assumed that the individual average PAL of the analyzed wear time represented the entire 7 d period. In order to be included in further analysis, the subjects had to have successfully recorded AR data from a minimum of 4 d.

2.5. Treadmill test

To determine VO_{2max} and to observe the relationship between f_hand_{AR} and the intensity of exercise in treadmill walking and running, the conscripts performed a maximal treadmill test. The test was performed in 3 min stages starting by walking at 4.6 km h^{-1} (1.0° inclination). Thereafter, treadmill speed and inclination were increased gradually every 3 min to induce an increase in intensity up to maximal effort. The procedure was the following: second stage: 6.3 km h^{-1} (1.0°), third stage: 7.7 km h^{-1} (1.4°), fourth stage: 9.0 km h^{-1} (1.9°), fifth stage: 10.3 km h^{-1} (2.3°), sixth stage: 11.3 km h^{-1} (3°), seventh stage: 12.6 km h^{-1} (3.2°), and eighth stage: 13.2 km h^{-1} (4.2°). Pulmonary ventilation and respiratory gas exchange data were measured online by using the breath-by-breath method (Jaeger Oxygen Pro, VIASYS Healthcare GmbH, Hoechberg, Germany), and mean values were calculated at 1 min intervals for later analysis. Heart rate was continuously recorded at 5 s intervals using a heart rate monitor (Polar810i, Polar Electro Oy, Kempele, Finland). Blood lactate was determined 1 min after completion of exercise from a fingertip blood sample using a lactate analyzer (LactatePro®, Arkray, Japan). The criteria used to determine maximal effort were: VO_2 and heart rate did not increase despite an increase in inclination and speed of the treadmill, a respiratory exchange ratio higher than 1.1, and a post-exercise blood lactate higher than 8 mmol l^{-1} (ASCM 2001).

Median f_hand_{AR} from each 3 min stage, as well as oxygen consumption (VO_2) and carbon dioxide production (VCO_2) from the final minute of each stage were extracted from the measured data. Only those 3 min stages that the subjects were able to finish were included in the analysis. A reference value (PAL_{IC}) was calculated from respiratory gases and BM as follows: $EE = 3.8149 * O_2 (l) + 1.2321 * CO_2 (l)$ (Lusk 1924), $BMR = 15.1 * BM + 692$ (Schofield 1985), and finally, $PAL_{IC} = EE/BMR$.

2.6. Field march test

To assess the validity of the AR in quantifying the intensity of a typical military activity, f_hand_{AR} was determined during a 45 min field march test while the subjects carried a total of 20 kg of military equipment. The subjects marched in small groups at a constant speed in an indoor hall on a fine gravel surface. The speed was individually selected for each subject to match about 70% of measured VO_{2max}. Five subjects marched at 6 km h^{-1}, 12 at 7 km h^{-1}, and 2 subjects at 8 km h^{-1}. Constant and precise speed was ensured by a group leader who monitored the speed using a Polar S625X training computer (Polar Electro Oy, Kempele, Finland) equipped with an individually calibrated foot pod. The average f_hand_{AR} measured during the march test was compared with the f_hand_{AR} value measured during treadmill walking and running at the same speed. The average frequency was calculated over the 45 min march excluding 2 min from the beginning and the end. Because the speeds on the treadmill were not exactly the same as during marching, the treadmill data were individually interpolated between two treadmill stages to achieve f_hand_{AR} that would best correspond to the same speed.

2.7. Statistical analysis

Customized model between the AR and PAL. Post-processing of the measured AR data was performed using Matlab software (The Mathworks Inc., Natick, MA). In order to derive EE parameters from the AR data, the first step was to model a piece-wise linear relationship between f_hand_{AR} and PAL. Four pairs of f_hand_{AR} and PAL were determined: two intermediate points and the extreme values of f_hand_{AR} (0 and 100 movements min^{-1}). As the second step, two per-cent-wise factors were determined to adjust PAL based on differences in BH and BM compared with the group mean values. The model parameters were selected so that the model would yield a best fit between the AR and DLW over the 7 d period. PAL_{AR} was determined as the average of the minute-by-minute values over the 7 d period. TEE_{AR} was calculated as $PAL_{AR} \times$ BMR, and AEE/BM_{AR} as ($TEE_{AR} \times 0.9$ – BMR)/BM. Minimal 95% limits of agreement between TEE_{AR} and TEE_{DLW} and a lack of trend in a Bland–Altman plot (Bland and Altman 1986) were used as the criteria of the best model.

Linear regression models. The statistical analyses were performed using PASW Statistics, version 18.0.0 (SPSS Inc). A Shapiro–Wilk test was used to verify that the data were normally distributed. In order to allow comparison with earlier studies and to identify the predictors of PAL_{DLW}, TEE_{DLW}, and AEE/BM_{DLW} in the 7 d assessment, stepwise multivariate linear regression analysis was used with f_hand_{AR}, BH, and BM as independent variables. In order to account for the effects of nonlinearity observed between f_hand_{AR} and PAL, minute-by-minute f_hand_{AR} values were normalized based on the best piece-wise linear model so that the original range between 0 and 100 was maintained. The average normalized frequency of hand movements for the whole 7 d period is later referred to as $f\_hand\_n_{AR}$.

A paired-samples t-test was used to compare the measures of the AR (PAL_{AR}, TEE_{AR}, AEE/BM_{AR}) with the reference DLW values (PAL_{DLW}, TEE_{DLW}, AEE_{DLW}) and to compare f_hand_{AR} between the march and treadmill tests. Pearson correlation coefficients were computed to determine the linear relationships between the parameters studied. The level of statistical significance was set at $p < 0.05$. Unless otherwise mentioned, all data are presented as mean $\pm$ SD.

3. Results

3.1. Military training and DLW measurement

Accomplishment of activity measurement. Two of the subjects had the AR data collected from 3 d only, and thus they were excluded from the analysis of the 7 d period. The remaining

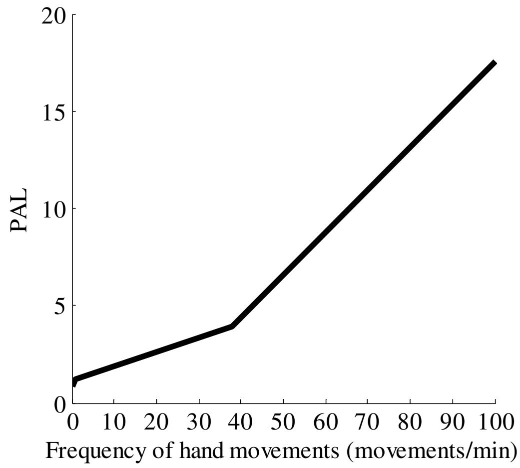

Figure 1. Customized four-point linear model between the frequency of hand movements and physical activity level (PAL, solid line) in 7 d of military training ($N = 22$).

Table 2. EE measured by the AR and DLW, $N = 22$. With the AR, a customized model predicted PAL using frequency of hand movements, BH, and BM.

	AR	DLW	*t*-test	*r* (*p*)	SEE	SEE (%)
PAL	2.17 ± 0.19	2.17 ± 0.23	0.984	0.80 (<0.001)	0.136	6.3%
TEE (MJ d^{-1})	16.6 ± 1.80	16.6 ± 2.1	0.991	0.86 (<0.001)	1.05	6.3%
AEE/BM (kJ kg^{-1} d^{-1})	98.3 ± 19.9	98.1 ± 23.5	0.977	0.84 (<0.001)	12.5	12.8%

SEE: standard error of estimate. SEE (%): standard error of estimate in per cents. PAL: physical activity level (multiple of BMR). TEE: total energy expenditure (MJ d^{-1}). AEE/BM: activity energy expenditure adjusted with body mass (kJ kg^{-1} d^{-1}).

22 subjects' activity measurements were accomplished successfully, and the percentage of measured time share was similar during the days and at night (80% ± 19% and 78% ± 12%, respectively, $p = 0.499$). When comparing 24 h periods with each other, the measured time share varied between 59% and 96% and was not associated with average PAL_{AR}. Between the subjects, the measured time varied from 51% to 97%, and it was not associated with the individual differences between AR and DLW in PAL, TEE, or AEE/BM.

Customized model between the AR and PAL. The four-point piece-wise linear model that yielded the best fit between TEE_{AR} and TEE_{DLW} is presented in figure 1. The best BH adjustment factor was 1.00% of the minute-by-minute PAL above resting value per 1 cm difference from the group mean BH, and the BM adjustment factor was −0.65% of the minute-by-minute PAL above resting value per 1 kg difference from the group mean BM.

Figure 2 shows physical activity graphs over the 7 d measurement period derived from the AR and anthropometric parameters from two different subjects. During the 7 d measurement period, no statistical differences were found in PAL, TEE, and AEE/BM measured with the AR and DLW techniques (table 2, figure 3). A Bland–Altman plot of TEE and AEE/BM showed no significant trend between the mean and the difference of the two methods, and the 95% confidence intervals were −2.1–2.1 MJ d^{-1} in TEE and −25.1–25.2 kJ kg^{-1} d^{-1} in AEE/BM (figure 4).

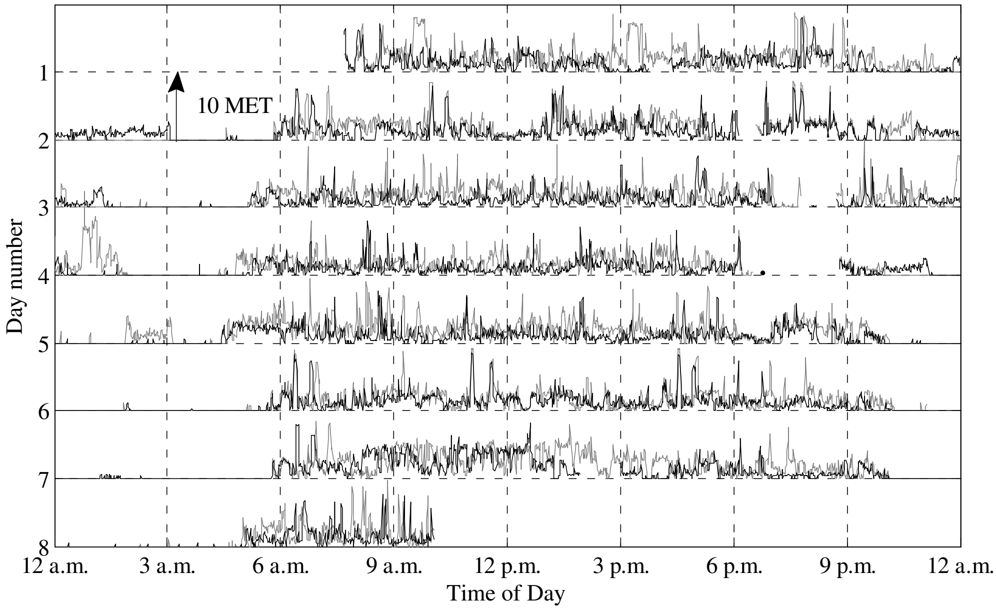

Figure 2. Physical activity of two example subjects measured by the AR during 1 week of military training. The average PAL of the two subjects was 2.41 and 1.90 (gray and black, respectively). The dashed horizontal lines for each day represent full rest and the gap between successive days is scaled to 10 metabolic equivalents. Subject in gray: BM 87.4 kg, BH 187 cm, f_hand 14.0 mov. min^{-1} (12.3 n.u.), TEE 20.3 MJ d^{-1}. Subject in black: BM 98.8 kg, BH 183 cm, f_hand 11.0 mov. min^{-1} (10.0 n.u.), TEE 17.4 MJ d^{-1}. f_hand: average frequency of hand, n.u.: nonlinearity normalized units, TEE: total energy expenditure.

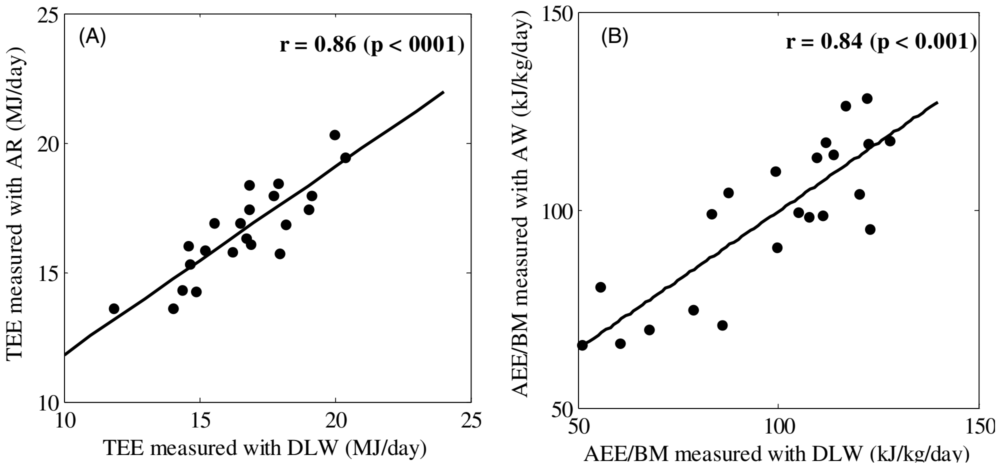

Figure 3. Total energy expenditure (TEE, (A)) and activity-induced energy expenditure adjusted for body mass (AEE/BM, (B)) measured by the AR and DLW technique over the 7 d period of military training ($N = 22$).

Linear regression models. AR-measured f_hand_n_{AR} explained 46% of the variation in PAL_{DLW} with no significant additional contribution by inclusion of BH and BM in the model. In the TEE model, BM explained 29% of the variation in TEE_{DLW} with a significant added contribution by inclusion of f_hand_n_{AR} (58%) and BH (70%). Regarding AEE/BM_{DLW},

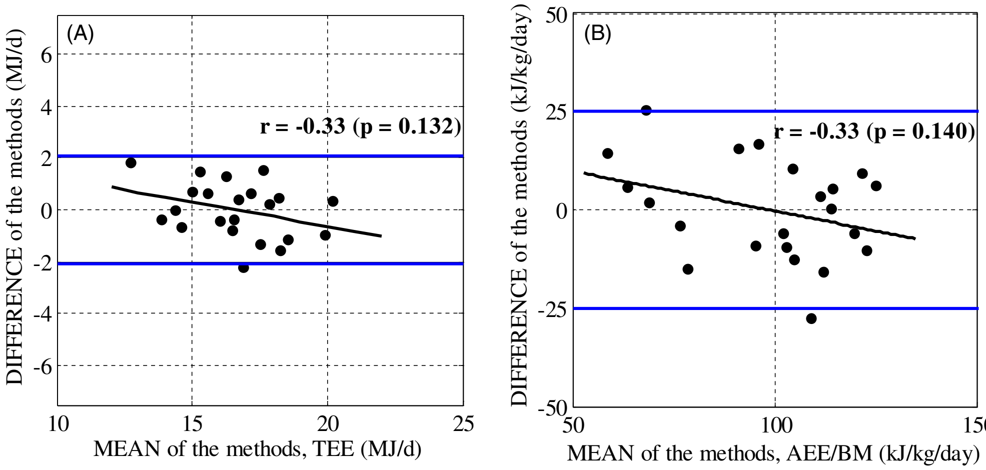

Figure 4. Bland–Altman plots of total energy expenditure (TEE, (A)) and activity energy expenditure adjusted for body mass (AEE/BM, (B)) measured by the AR and DLW technique over the 7 d period of military training ($N = 22$).

Table 3. Multivariate regression models for explaining the variation in EE parameters ($N = 22$).

Prediction equation	Adjusted r^2	r	p	SEE	SEE (%)
$PAL_{DLW} = 0.153 * f\_hand\_n_{AR} + 0.531$	0.46	0.69	<0.001	0.172	7.9
$TEE_{DLW} = 0.064 * BM + 1.25 * f\_hand\_n_{AR} + 0.120 * BH - 22.9$	0.70	0.86	<0.001	1.168	7.0
$AEE/BM_{DLW} = 15.2 * f\_hand\_n_{AR} - 1.01 * BM + 1.30 * BH - 213$	0.70	0.86	<0.001	12.96	13.2

SEE: standard error of estimate. SEE (%): standard error of estimate in per cents. PAL_{DLW}: physical activity level (multiple of BMR). TEE_{DLW}: total energy expenditure measured with DLW (MJ d^{-1}). DLW: double labeled water. AEE/BM_{DLW}: activity energy expenditure adjusted with body mass (kJ kg^{-1} d^{-1}). BM: body mass (kg). BH: body height (cm). $f\_hand\_n_{AR}$: frequency of hand movements registered by Polar AR, normalized for nonlinearity, and averaged over the 7 d period.

$f\_hand\_n_{AR}$ explained 41% of the variation with a significant added contribution by inclusion of BM (59%) and BH (70%). The prediction equations are shown in table 3.

3.2. Treadmill test

All 24 subjects performed the treadmill test and reached the criteria set for maximal effort. The subjects were able to walk and run 5.3 ± 1.1 three-minute stages on the treadmill (range 3–7). In 2 subjects the AR apparently failed to detect all steps at the lowest walking speed (<45 counts min^{-1} at 4.6 km h^{-1}); they were excluded from the analysis. On an individual level, measured f_hand_{AR} correlated strongly with PAL_{IC}, $r = 0.97 \pm 0.2$ (range 0.93–1.00). There was, however, some individual variation in the relationship between f_hand_{AR} and intensity of exercise (figure 5).

During walking ($f\_hand_{AR} = 60$ mov. min^{-1}, corresponds to 120 steps min^{-1} and about 6 km h^{-1}) and running (80 mov. min^{-1} and about 11 km h^{-1}), BH correlated with PAL_{IC} ($r = 0.60$, $p = 0.002$ and $r = 0.65$, $p = 0.001$, respectively). At the mentioned levels of f_hand_{AR}, a 1 cm change in BH increased PAL_{IC} by 1.3% in walking and 1.1% in running.

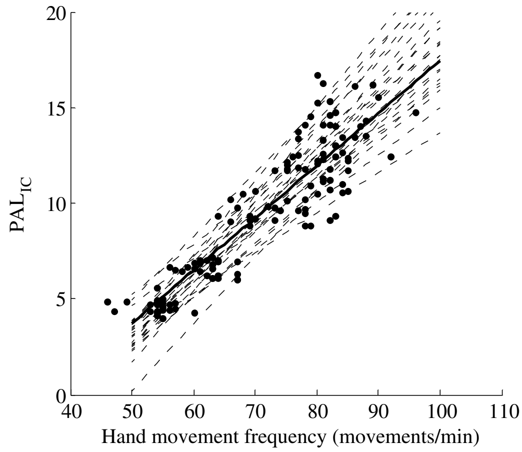

Figure 5. Hand movement frequency registered by a Polar AR and PAL measured by an indirect calorimeter (PAL$_{IC}$) during treadmill walking and running ($N = 24$). The average individual coefficient of correlation was 0.97 ± 0.02 (dashed lines), and for combined data the coefficient of correlation was 0.90 (solid line).

3.3. Field march test

From a total of 24 subjects, 4 subjects did not participate in the field march test because of being sick. On an individual level, f_hand_{AR} was very constant during the 45 min march (SD 2.3 ± 1.0 movements min^{-1}). The average f_hand_{AR} of marching was not different from f_hand_{AR} measured in treadmill walking or running at the same speed ($p = 0.256$), and the frequencies correlated with each other ($r = 0.77$, $p < 0.001$). Bland–Altman plot showed no trend between the mean and the difference of the two methods ($r = 0.03$, $p = 0.916$), and the 95% confidence intervals were −7.4–5.6 movements min^{-1}.

4. Discussion

The main focus of this study was to investigate the reliability and validity of the new and practical AR method during military training. During the 7 d measurement period, AR-derived parameters of EE were compared with those measured with the DLW technique, and a very low standard error of estimate (SEE) and a high positive correlation were found. A Bland–Altman plot showed no trend between the mean and difference of the two methods, indicating that the accuracy of the AR was equal independent of the level of EE. In the treadmill exercise, hand movement frequency correlated highly and positively with PAL$_{IC}$, and the correlation improved further by inclusion of BH in a regression model. In the field marching test, the AR measured similar hand movement frequencies as on the treadmill with the same speeds.

In the signal processing, the main outcome of this research was the determination of a relationship between f_hand_{AR} and PAL$_{DLW}$ which may provide a reliable and robust method for estimating the EE of military training. This was accomplished iteratively by searching for a best fit between the estimated 7 d TEE and the corresponding value measured with the DLW technique. Furthermore, during the 45 min march on a flat surface with 20 kg of military equipment, similar f_hand_{AR} was measured as on the treadmill at the same speed. Comparison between the march and treadmill tests needs to be interpreted with caution because subjects had freedom to select between walk and run in both tests, and we did not account for the apparent nonlinearity in the relationship between speed and stride frequency that takes place in transition from walk to run. However, the fact that individual variability in $f\_\mathrm{hand}_{\mathrm{AR}}$ was very low during marching confirmed that the AR was able to register stride frequency of walking or running correctly even though the hands were not able to move freely during the field march test—the subjects held the rifle in front of them. If the speed is maintained, carrying 20 kg of extra weight increases metabolic requirements significantly (Bilzon *et al* 2001). Altogether, these results indicate that the AR did not account for the extra amount of load carried. This is an expected finding because accelerometers are, in general, insensitive to extra load carried. This implies that the accuracy of the AR might be improved further by including the amount of extra weight as supplemental data input into the AR.

Use of a wrist-worn accelerometer was shown to be a practical approach in monitoring military training even though the 7 d period included high-intensity activities under extreme winter conditions. The subjects had no need to remove the device at any time except for data download, and they were able to wear it during days and nights. Some activity data were missed because of difficulties in organizing data downloading during overnight field training and due to sick leave. Nevertheless, activity data were successfully recorded 79% of the time, which can be considered high enough for reliable comparison of the EE measures of the AR and DLW techniques. A similar percentage of data (8.2 out of 10 d) was recently measured in the only study on a wrist-worn device that is available for comparison (van Hees *et al* 2011).

Comparison of the results obtained from the 7 d military training period and the treadmill exercise indicates that at the same $f\_\mathrm{hand}_{\mathrm{AR}}$, the intensity of physical activity was higher during the 7 d period than in the treadmill test which included walking and running. The magnitude of the difference was largest at movement frequencies typical of normal walking. As discussed above concerning the 45 min march test, part of the difference can be attributed to the insensitivity of the accelerometers to extra load carried during military service. Different modes of activities (skiing, fighting) and terrain factors (snow, hills, etc) included in military training may also induce higher energy requirements at the same movement frequencies. The 7 d military service included cross-country skiing during several days. In skiing data measured by Vähäsöyrinki *et al* (2008), the poling frequency was 43 cycles min^{-1} at slow speed and 61 cycles min^{-1} at maximal skiing speed, which represent a smaller range and lower maximal value than in walking and running.

The presented approach to assessing human EE—a wrist-worn 1D accelerometer and a special movement counter—is a most simple and practical way to monitor activity and can be seen as a successor to traditional wrist-worn motion sensors (Montoye *et al* 1983). The current study is the first one which has compared exercise rate or hand movement frequency with DLW. Van Hees *et al* (2011) recently compared a wrist-worn 3D accelerometer with DLW by utilizing a more complex signal processing method, and found a significant but clearly smaller contribution of wrist acceleration to AEE (24%) than what was found in the present study. The partly divergent results obtained therefore deserve methodological discussion.

It is clear that movements of the hands only cause a fraction of AEE. However, in this study $f\_\mathrm{hand}_{\mathrm{AR}}$ strongly predicted $\mathrm{PAL}_{\mathrm{DLW}}$ measured over a 7 d period and $\mathrm{PAL}_{\mathrm{IC}}$ measured during treadmill walking and running. In walking and running, the strong prediction can be explained by the linkage between hand movement frequency and walking cadence, which was also confirmed in this study. Spontaneous choice of running cadence has been associated with optimization of running economy (Cavanagh and Williams 1982), a fact that apparently stabilizes hand movement frequency during walking and running and makes measurement of hand movement frequency more reliable. A wrist-worn accelerometer may underestimate TEE in high-intensity activities, but these usually cover only short periods of time over the whole day and therefore do not contribute strongly to TEE (Westerterp and Plasqui 2004). If wrist-worn accelerometers are used to measure the intensity of structured exercise sessions, more complex signal processing methods, including activity classification, may certainly improve prediction accuracy (Siirtola *et al* 2009). In activities including standing and slow motion, hand movements have a role in maintaining the balance of the body and subsequently may also reflect the whole body's activity level. It is also possible that behavioral aspects, such as the number of restless hand movements within sedentary and standing activities, are also reflected in both estimated and measured TEE. The independent role of the regularity of hand movements, which affects the determination of f_hand_{AR} (Kinnunen and Miettinen 2005), was not examined in the present study; nevertheless, use of regularity may prevent overestimation of light-intensity activities, because repetitive hand movements are ignored within a longer time window in the case of an irregular movement pattern.

Different parameters of TEE are supposed to strongly depend on each other: TEE = PAL * BMR, AEE/BM = (0.9 * TEE − BMR)/BM, and BMR = 15.1 * BM + 692. Nevertheless, the stepwise multivariate linear regression analysis illustrated different contributions of accelerometer data, BH, and BM for each dependent parameter. A reader might wonder why BM was included as a predictor of AEE/BM. Inclusion was considered reasonable because BM may affect not only AEE, but also the relationship between exercise rate and intensity of exercise. In the customized piece-wise linear model designed to predict PAL_{DLW}, we decided to include BH and BM as correcting factors even though the corresponding multivariate linear regression model was not significantly improved by inclusion of the body parameters. The use of the anthropometric parameters can be justified with both mechanical considerations and a desire to be systematic. It is apparent that mechanical gait characteristics, including step length and cadence, depend on body dimensions (Wixted *et al* 2007). Systematically thinking, one cannot affect AEE without affecting PAL and TEE—unless there is a compensating change in BMR. Another advantage of our customized equation is that it can also be applied to short periods of time. In addition, the method can be developed further in different groups of people and different activities in the future, even if the DLW technique is not available. Using the customized model, TEE_{AR} and AEE/BM_{AR} were derived systematically from PAL_{AR} and estimated BMR, and the accuracy compared well with the separate multivariate regression models.

Measurement of EE during an intensive training week of basic military training would be challenging for any wearable monitor technology and post-processing method. Regardless of the challenges, the magnitude of correlation between AEE/BM_{AR} and AEE/BM_{DLW} ($r = 0.86$) and the contribution of wrist accelerometer measures alone to AEE/BM_{DLW} (41%) and PAL_{DLW} (46%) were among the highest that have been reported in the literature with any accelerometer approaches (Plasqui and Westerterp 2007). However, none of the studies available for comparison have been carried out in military training. The most straightforward applications of this study include estimation of PAL and TEE in soldiers and athletes in order to give feedback on training volume. The average 7 d activity level ($PAL_{DLW} = 2.17$) indicated a very high training volume that is comparable to that of endurance athletes. In conclusion, compared to the DLW technique, the wrist-worn AR method estimated TEE accurately with SEE of 6.3%. Thus the present method can be regarded as a reliable and valid way to assess EE during intensive training.

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