Energy Expenditure Estimation During Daily Military Routine With Body-Fixed Sensors

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ABSTRACT The purpose of this study was to develop and validate an algorithm for estimating energy expenditure during the daily military routine on the basis of data collected using body-fixed sensors. First, 8 volunteers completed isolated physical activities according to an established protocol, and the resulting data were used to develop activity-class-specific multiple linear regressions for physical activity energy expenditure on the basis of hip acceleration, heart rate, and body mass as independent variables. Second, the validity of these linear regressions was tested during the daily military routine using indirect calorimetry ($n = 12$). Volunteers' mean estimated energy expenditure did not significantly differ from the energy expenditure measured with indirect calorimetry ($p = 0.898$, 95% confidence interval = −1.97 to 1.75 kJ/min). We conclude that the developed activity-class-specific multiple linear regressions applied to the acceleration and heart rate data allow estimation of energy expenditure in 1-minute intervals during daily military routine, with accuracy equal to indirect calorimetry.

INTRODUCTION

In physically demanding occupations such as those in a military setting, an optimal balance between physical job requirements, and individual physical capability is crucial in terms of injury prevention, unit performance, and morale.[1–4] The first step in ensuring this balance is obtaining an accurate description of the physical job requirements.[1,4] Procedures commonly used to assess military- or firefighting-specific job requirements include self-report questionnaires, interviews, observations, and physical measurements, such as heart rate (HR), energy expenditure, and oxygen (O_2) consumption.[1,4–6] Bos et al[7] and Almeida et al[8] recommended assessing the exposure to work demands objectively in terms of duration, frequency, and intensity. Each of the methods mentioned earlier has some limitations. Although self-report questionnaires and interviews have low objectivity, observations are not feasible in large study groups, and heretofore used physical measurements yielded no information on characteristics of the activities or on the distribution during the daily military routine. Therefore, Wyss and Mäder[9] recently adapted a new method to the military setting, using body-fixed sensor data to identify and measure the duration and frequency of the 6 most common physically demanding, military-specific activities (walking, marching with backpacks, lifting and lowering loads, lifting and carrying loads, and digging and running[1,2,10–13]). This method does not completely describe exposure to work demands because it fails to assess the intensity of activities. However, the same data signals (hip acceleration (H-ACC) and HR) collected for this method of military-specific activity recognition have previously been applied to estimate intensity of activities. Algorithms from these earlier studies[14,15] or newly developed, military-specific algorithm for energy expenditure estimation (EEE) requires validation in a military setting before being routinely applied to obtain more complete descriptions of work-related physical demands.

The aim of this study was to develop and validate activity-class-specific multiple linear regressions (AS-MLRs) to estimate physical activity energy expenditure (PAEE) during the daily military routine, using easy-to-handle body-fixed sensors. Further, the accuracy of EEE with AS-MLRs was compared with the algorithms presented in earlier studies,[14,15] developed in a different setting. For AS-MLRs, the activity class will be assigned first on the basis of Wyss and Mäder's algorithm.[9] Second, for every activity class, a specific MLR with HR, H-ACC, and body mass as the independent variables will be applied for EEE.

METHODS

Participants

All participants were male recruits from the Swiss Army (Table I). All were volunteers recruited from 2 selected military occupational specialties (reconnaissance and fusilier infantry training schools). The age, weight, and height of the volunteers in the 2 parts of data acquisition of this study did not differ ($p = 0.323$, 0.679, and 0.823, respectively, see Table I). The volunteers received comprehensive information about the study and provided written informed consent for their participation as approved by the Cantonal Ethics Committee of Bern, Switzerland, and from the Swiss Army Sports and Preventions Competence Center.

The sample size for the development of the regression equations was calculated according to the spreadsheet provided by Soper.[16] For this calculation, 2 independent variables (accelerometer counts and HR), an alpha level of 0.05, and a desired statistical power of 0.8 were set. The variance explained is assumed to be at least 0.85 (based on the results of Corder et al[17] and Zekeri et al[18]), which then results in an anticipated effect size (f^2) of 5.667. Therefore, a minimum sample size of 6 subjects is required. On the basis of this power calculation,

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TABLE I. Volunteers' respective age, body mass, height, and military training school in the 2 parts of data acquisition

Part of the Study	*n*	Military Training School	Age (*y*)	Body Mass (kg)	Height (cm)
Development of AS-MLRs for EEE	8	Swiss Army Reconnaissance Infantry	21.0 ± 0.9	72.1 ± 7.0	178.8 ± 4.3
Testing of AS-MLRs for EEE During Daily Military Routine	12	Swiss Army Fusilier Infantry	21.1 ± 3.0	72.6 ± 10.7	179.3 ± 4.5

8 volunteers in the first part and 12 volunteers in the second part of the study were investigated.

Study Design and Protocol

In both parts of data acquisition, volunteers were equipped with a portable spirometer and body-fixed sensors. First, 8 volunteers performed isolated, military-specific activities in a laboratory setting according to the protocol described later. Their data were used to develop AS-MLRs with PAEE as the dependent variable and HR, H-ACC, and body mass as the independent variables. Second, 12 volunteers were investigated during the daily military routine to validate the accuracy of AS-MLRs for EEE (Fig. 1).

In a laboratory setting, 8 volunteers (Table I) completed 6 military-specific, physically demanding activities, namely, walking, marching with a backpack (10–15 kg), lifting and lowering loads (30 kg), lifting and carrying loads (30 kg and 10–40 m), and digging and running. Further, other less demanding activities such as sitting, office work, cleaning dishes, mopping the floor, cleaning shoes, or manipulating a weapon were investigated. The order and duration (3–7 minutes) of the activities were randomized. Data were used to develop AS-MLRs for PAEE estimation based on sensor data.

During the daily military routine, the energy expenditure of 12 randomly chosen volunteers (Table I) from 2 different occupational specialties was recorded with an indirect calorimetry (portable spirometer) over a 90-minute period for each volunteer. Data were used to assess the accuracy of the sensor-based PAEE estimation. With daily military routine, all the tasks and activities in a soldier's military service from waking up in the morning until going to sleep in the evening are meant.

Measurements and Instruments

Age, body mass, and height data were collected during the first 2 weeks of military service. Therefore, a measuring tape and a calibrated balance (Seca model 877; Seca GmbH, Hamburg, Germany) were used.

ActiGraph uniaxial accelerometers (GT1M; ActiGraph LLC, Fort Walton Beach, FL) were used to monitor volunteers' H-ACC in the vertical direction and step frequency. A second accelerometer was mounted on the backpack to register backpack carrying. The intermonitor variability between different GT1Ms is very small (<1%).[19] The GT1M is lightweight (27 g), compact (3.8 x 3.7 x 1.8 cm^3), and splash proof. Its rechargeable battery is capable of providing power for more than 14 days without recharging and has a memory capacity of 1 MB. More detailed specifications have been described elsewhere.[20] In this study, the accelerometers were wrapped in waterproof plastic and were placed in a belt pouch on the waist over the right anterior axillary line and on the side strap of the personal backpack. The GT1Ms were programmed to record acceleration and step-count data in 2-second intervals so that data could be gathered over 6 continuous days.

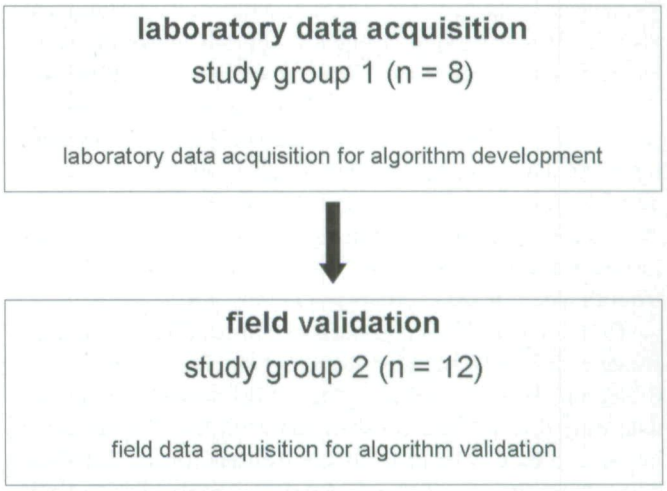

FIGURE 1. Two steps to the data acquisition in this study.

A Suunto monitor (Suunto Smartbelt, Suunto, Vantaa, Finland) was used to record HR. It is a lightweight (61 g) and waterproof standalone monitor worn on the chest. The monitor's exchangeable battery is capable of providing power for more than 4 weeks of continuous measurement. One million heartbeats can be stored in the internal memory, enough for more than 1 week of continuous measurement. A Suunto Smartbelt registers the HR as long as the chest strap is worn. In this study, data were transferred to a computer after a 5-day monitoring period at 2-second intervals using Suunto Training Manager Version 2.2.0.

Indirect calorimetry (METAMAX; Cortex Biophysik GmbH, Leipzig, Germany) was used to analyze the energy expenditure. The reliability and validity of this specific, mobile spirometric system have been shown to be very good (intraclass reliability of O_2 uptake, carbon dioxide (CO_2) output, and minute ventilation: $r > 0.973$[21]; no significant output differences were found compared with a stationary spirometric system [Oxycon Gamma, Mijnhardt, The Netherlands].[22] The turbine flowmeter was calibrated with a 3-liter calibration syringe, and the O_2 and CO_2 sensors were calibrated with room air and calibration gas (16% O_2, 5% CO_2, and 79% N_2) before each testing session.

Analysis

The assessed data were H-ACC, backpack acceleration (BP-ACC), HR, energy expenditure measured by indirect calorimetry, body mass, height, and age. Data were synchronized for every volunteer by a self-programmed application using Matlab (Matlab 5.3; MathWorks, Natick, MA).

Military-specific activities were classified into 1-minute sequences on the basis of Wyss and Mäder's[9] algorithm using H-ACC, BP-ACC, step frequency, and HR above the resting HR (HRaR). To assess the HRaR, first the mean HR in a sliding window with a duration of 2 minutes was calculated. This process was repeated for every 2 seconds on 5 days of continuous HR data. Finally, the lowest value found in such a window was used as the resting HR. Implausible data, caused by short duration artifacts in the signal, were detected by visual inspection of the plotted raw data. These data were excluded from the identification process of resting HR.

To estimate PAEE on the basis of comparative algorithms of Brage et al[14] (without individual calibration) and Swartz et al[15] (based on H-ACC data only), the GT1M acceleration monitor data were divided by a constant factor (0.91). This factor was introduced by Corder et al[23] to compensate for the differences in the data output of 2 generations of Actigraph accelerometers. In the studies by Brage et al[14] and Swartz et al,[15] an earlier generation of Actigraph accelerometers (Model 7164) was used.

The measured PAEE was calculated as total energy expenditure (TEE) minus resting energy expenditure (REE) values. TEE was assessed with indirect calorimetry using Péronnet and Massicotte's formula.[24] Their table indicates that, for a given ratio (CO_2 produced/O_2 utilized), the percentage of energy provided from carbohydrate vs. fat oxidation and the energy equivalent of O_2. The protein oxidation is not considered in that formula, assuming that its amount is small and negligible. After the findings of Jeukendrup and Wallis,[25] the equations of Peronnet and Massicotte are the most favorable in terms of fat oxidation and comparable to other published equations in terms of carbohydrate oxidation. REE was calculated using anthropometric data and the formula for men by Mifflin et al.[26] According to the review study of Frankenfield et al,[27] this formula is more accurate than other equations to estimate REE.

Statistical Analysis

SPSS version 16.0 for Windows (SPSS, Chicago, Illinois) was used for all statistical analyses, with an alpha level of 0.05 to indicate statistical significance.

MLRs between PAEE as the outcome variable and HRaR, H-ACC, and body mass as the independent variables were calculated separately for walking, marching with backpack, cumulative materials-handling class (lifting and lowering loads, lifting and carrying loads, and digging), running, and "other activities" class. Lifting and lowering loads, lifting and carrying loads, and digging were merged in 1 activity class, called material handling, because those activities can often hardly be separated. For the MLRs, HRaR, H-ACC, and body mass data were included only when they had a significant relationship to PAEE.

A Shapiro–Wilk test ($n < 50$) and a Kolmogorov–Smirnov test ($n > 50$) were conducted to determine whether the data were normally distributed. A paired t-test was used to examine differences in normally distributed anthropometric data between the study groups in the 2 parts of data acquisition and between the volunteers' estimated and measured mean PAEE values. Differences are presented as means ± standard deviations. Errors of estimated mean PAEE values were quantified as the root mean sum of squared errors (RMSE) and 95% confidence intervals (95% CI). Bland–Altman plots were used to visualize systematic errors in PAEE predictions.[28] A Wilcoxon signed-rank test was used to examine the differences between not normally distributed data. In some single activity classes, PAEE values of all assessed 1-minute sequences were not normally distributed. Therefore, the Wilcoxon signed-rank test was applied on all comparisons between the estimated and measured PAEE values within single activity classes. Differences were presented as the median and interquartile range (IQR) of differences.

RESULTS

Development of AS-MLRs for EEE

Investigated isolated activities collected for 8 volunteers added up to a total time of 284 minutes of PAEE and sensor data (25–50 minutes per volunteer). Derived AS-MLRs are presented in Table II. In this group of volunteers, body mass had no significant relationship to PAEE.

Testing of AS-MLRs for EEE During the Daily Military Routine

For 12 volunteers, 757 minutes, of a total of 1,080 investigated minutes, of energy expenditure data were collected. One to 64 minutes of the spirometer data for 10 of the 12 volunteers

TABLE II. MLRs, respective correlations (r), and RMSE for PAEE as the dependent variable and the HRaR and H-ACC as the independent variables for 5 different activity classes

Activity Class	Linear Regression	r	p	RMSE (kJ/min)
Walking	PAEE (kJ/min) = HRaR (bpm) × 0.5859 – 5.1508	0.701	0.000	5.7
Marching With Backpack	PAEE (kJ/min) = HRaR (bpm) × 0.7810 – 15.9337	0.848	0.000	6.6
Materials Handling	PAEE (kJ/min) = HRaR (bpm) × 0.4485 + H-ACC (cpm) × 0.0023 – 1.5166	0.705	0.000	6.4
Running	PAEE (kJ/min) = HRaR (bpm) × 0.7542 – 8.7800	0.877	0.000	9.2
Other Activities	PAEE (kJ/min) = HRaR (bpm) × 0.4840 + H-ACC (cpm) × 0.0010 – 4.7964	0.800	0.000	6.1

were lost due to technical problems. The volunteers' mean estimated PAEE (20.97 ± 8.31 kJ/min), based on AS-MLRs, did not differ from the mean measured PAEE (21.08 ± 8.00 kJ/min, $p = 0.898$, RMSE = 2.21 kJ/min, and 95% CI = −1.97 to 1.75 kJ/min). The correlation between the estimated and the measured mean PAEE values in the 12 volunteers was high ($r = 0.936$ and $p < 0.001$). The correlation between the alternatively estimated PAEE values (with algorithms from Brage et al[14] and Swartz et al[15]) and the measured PAEE values was large as well ($r = 0.915$, $p < 0.001$ and $r = 0.705$, $p = 0.011$, respectively). However, these algorithms resulted in a significant underestimation of PAEE (−25.12% and −32.47%, respectively; $p = 0.002$ and $p < 0.001$; RMSE = 5.29 and 6.84 kJ/min; and 95% CI = −7.42 to −3.16 and −10.45 to −3.23 kJ/min, respectively). The Bland–Altman plot (Fig. 2A) shows that no systematic error was found with AS-MLRs for PAEE estimation. By contrast, using the algorithms of Brage et al[14] and Swartz et al[15], volunteers' mean PAEE was systematically underestimated (Figs. 2B and 2C).

Activity classification showed that not every volunteer participated in all military-specific activity classes during the randomly chosen period of daily military service. The median of the differences between estimated and measured PAEE, of a total of 43 minutes assessed of the walking activities of 10 volunteers, was −4.419 kJ/min ($p = 0.002$ and IQR = 11.85 kJ/min). The median of the differences between estimated and measured PAEE, of a total of 84 minutes assessed of marching with backpack sequences by 6 volunteers, was −0.436 kJ/min ($p = 0.046$ and IQR = 9.74 kJ/min). Between estimated and measured PAEE, of a total of 90 minutes assessed of material-handling activities investigated among 12 volunteers, no significant difference was registered (median of differences = −0.652 kJ/min, $p = 0.941$, and IQR = 16.40 kJ/min). Only 4 volunteers ran for a short period while wearing the portable spirometer (13 minutes total). The respective median of the differences between estimated and measured PAEE was 1.193 kJ/min ($p = 0.917$ and IQR = 15.58 kJ/min). Between estimated and measured PAEE, during a total of 527 minutes of other activities investigated among 12 volunteers, no significant difference was registered (median of differences = −0.421 kJ/min, $p = 0.270$, and IQR = 7.57 kJ/min).

DISCUSSION

The AS-MLRs developed in this for PAEE estimation have been shown to be accurate and without systematic error. Meanwhile, the estimations according to Brage et al[14] and Swartz et al[15] have been shown underestimated PAEE during the military routine (see Figs. 2A–2C). However, in these researchers' studies, other activities were investigated, and these algorithms are thus probably less adequate for the specific military setting. Many military-specific activities, especially those resulting in high HR but low H-ACC data such as material-handling classes, are less frequent in other settings. Therefore, we conclude that it is reasonable to develop and use setting-specific algorithms for EEE. Further, we conclude

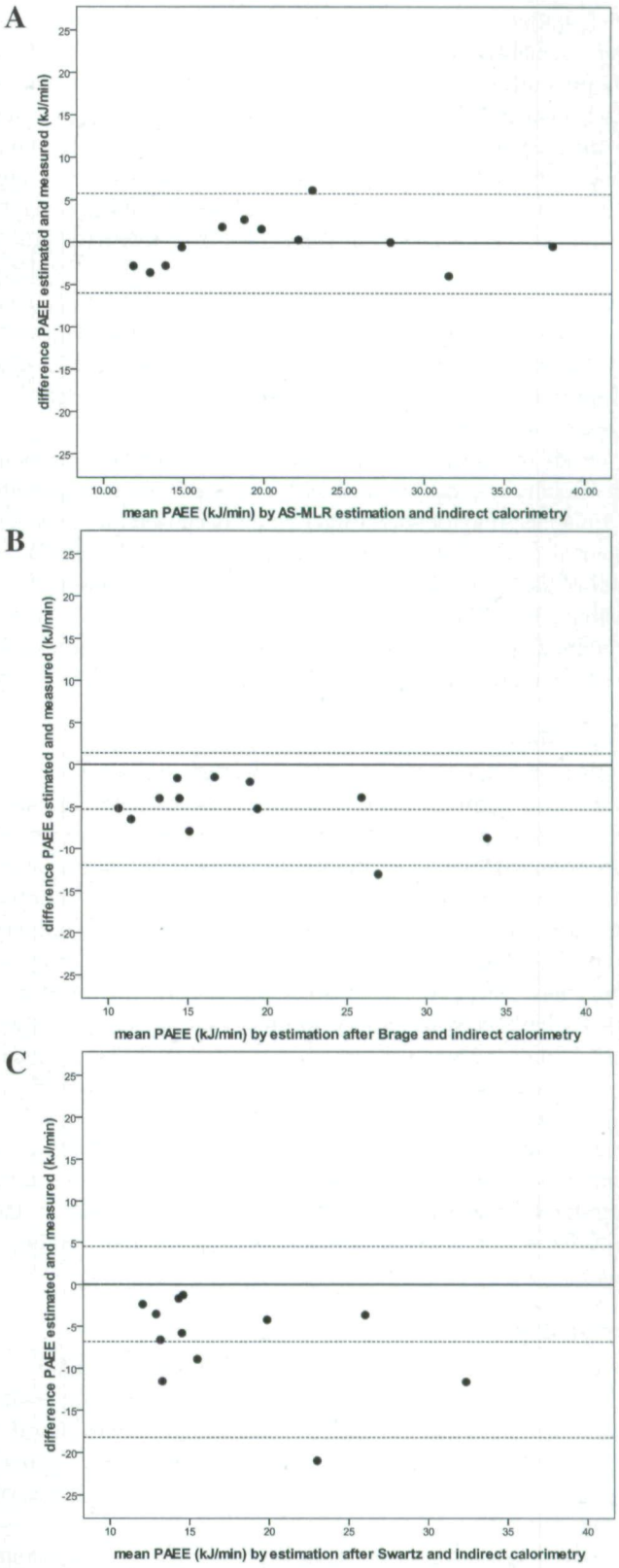

FIGURE 2. Bland–Altman plots on the average PAEE of 12 volunteers measured with indirect calorimetry and estimated using body-fixed sensor data for (A) AS-MLRs, (B) Brage et al's algorithm,[14] and (C) Swartz et al's[15] algorithm. The thin lines represent the mean and ± 2SD of the difference between the measured and estimated PAEE values; the broad line represents the zero line.

that continuous information about the current activity class is very valuable for precise EEE. This conclusion is supported by previous studies showing that the rates of the linear relation between H-ACC or HR and PAEE may differ if assessed in different activity classes. Collins et al[29] studied the relationship between HR and O_2 uptake (VO_2) during weight lifting. They concluded that the HR/VO_2 relationship during weight lifting exercise is linear but is different from that reported for dynamic low-resistance exercise such as running or cycling. Choi et al[30] found that PAEE increases as the intensity of activities (H-ACC) increases with different rates depending on the type of activity. The researchers suggested that new algorithms estimating PAEE on the basis of H-ACC data will depend on the types of activity.

Body mass had no significant influence on PAEE in any of the activity classes. This is most likely due to the homogeneity within the group of volunteers randomly chosen for the development of the EEE algorithm (see Table I). Although Wyss and Mäder[9] showed that H-ACC data are more important for activity recognition than HR data, this study demonstrated that for estimating activities intensity in a military setting, HR data are more powerful than H-ACC data (see Table II).

Implication

Direct observation,[31] EEE by doubly labeled water,[32,33] and self-report questionnaires[34,35] are the most common methods of assessing physical job requirements in the armed forces. Unfortunately, direct observations are not feasible for large-scale studies, doubly labeled water does not give any information about the distribution of PAEE during the daily military routine, and self-report questionnaires have low objectivity. In this study, established body-wearable sensors were used, and MLRs have been developed to objectively assess the intensity of military-specific physical activities in 1-minute intervals during the daily military routine. Combined with Wyss and Mäder's activity-recognition algorithm,[9] the duration, frequency, and intensity of military-specific physical activities can be assessed; therefore, physical job requirements can be registered objectively, feasibly, and with information on the distribution of physical demands during the daily military routine.

Limitations

Because of technical problems with the internal memory of the portable spirometer, only data transferred wirelessly to the examiners' computer on-site were saved. This transition did not always work from the beginning of the 90 minutes of data acquisition. Therefore, the dataset for 10 volunteers was of reduced duration.

Activity misclassifications by Wyss and Mäder's[9] algorithm can lead to reduced accuracy in the presented activity-class-specific PAEE estimation. However, misclassifications within the 3 material-handling classes are not relevant for PAEE estimation because the same regression model was used for these 3 classes. The residual activity misclassifications did not lead to a significant deviation between the estimated and the measured mean PAEE values. For PAEE estimation within single activity classes, activity misclassifications might have had a negative influence on the accuracy of the estimation.

In this study, volunteers were investigated during randomly chosen 90 minutes of their daily military routine. The disadvantage of this approach is its unequal outcome in duration, frequency, and intensity of different military-specific activities. Unfortunately, the dataset sampled during the daily military routine contained only 4 volunteers who did some running. Additionally, the respective periods were short (13 minutes in total, 1.3% of the registered activity time). However, the primary interests and the study design were configured to analyze accuracy of the estimation of cumulative energy expenditure over investigated time frames for every subject and not to analyze the energy expenditure during specific single physical activity classes.

Strengths

The developed AS-MLRs for PAEE estimation was validated during a daily military routine and not in a laboratory setting. Therefore, the results are more meaningful for future applied studies. Another strength of this study is that the method was developed particularly for the military setting. This fact and its combination with activity recognition allow good accuracy in PAEE estimation during the daily military routine of recruits and soldiers.

CONCLUSION

Established, easy-to-handle, body-fixed sensors deliver valid data for PAEE estimation in a military setting. With the discussed sensors and the developed MLRs, PAEE can be investigated objectively in 1-minute intervals over 6 continuous days during the daily military routine. Additionally, activities' duration and frequency can be estimated with the algorithm from an earlier study.[9] Therefore, the combination of both methods is ideal for quantifying physical job requirements in terms of the type, duration, frequency, and intensity of military-specific physical activities. Further, we conclude that knowing the activity class may provide important information for high precision in sensor-based PAEE estimation.

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