Integration of Physiological and Accelerometer Data to Improve Physical Activity Assessment

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ABSTRACT

STRATH, S. J., S. BRAGE, and U. EKELUND. Integration of Physiological and Accelerometer Data to Improve Physical Activity Assessment. *Med. Sci. Sports Exerc.*, Vol. 37, No. 11, pp. S563–S571, 2005. **Purpose:** Accurate measurement of physical activity (PA) is a prerequisite to determine dose–response relationships between activity and health. The combination of HR and accelerometers (ACC) holds promise for improving the accuracy of PA assessment, but it is unclear how currently proposed modeling techniques compare and to what extent different levels of individual calibration (IC) of HR influence monitoring accuracy. **Methods:** A total of 10 men and women (25.8 ± 3.4 yr, 1.70 ± 0.1 m, 71.7 ± 11.8 kg, 24.4 ± 5.0 kg·m^{-2}) were recruited for this study, in which IC of HR to PA energy expenditure (PAEE) during both arm crank and treadmill activity were available. Participants completed 6 h of free-living activity, during which PAEE (obtained with indirect calorimetry), HR, hip ACC, arm ACC, and leg ACC were collected. PAEE was then modeled from two different methods of combining HR and ACC (arm-leg HR+M and branched model), both with IC and group-level calibration (GC) of HR, and also from hip ACC estimates alone. Estimates of PAEE were compared with criterion values for PAEE. **Results:** Combined estimates of PAEE from the arm-leg HR+M and the branched model were similar when IC was used (R^2 = 0.81, SEE = 0.55 METs and R^2 = 0.75, SEE = 0.61 METs, respectively). When using GC, all estimates of PAEE had larger error, but the performance of the branched model suffered less than the arm-leg HR+M model (R^2 = 0.75, SEE = 0.67 METs and R^2 = 0.67, SEE = 0.88 METs, respectively). Both combination modeling techniques were more precise than single-measure hip ACC estimates (R^2 = 0.41, SEE = 0.96 METs). **Conclusion:** The combination of HR and ACC improves the accuracy of PAEE estimates and could be applied in large-scale epidemiological studies. **Key Words:** ENERGY EXPENDITURE, HR, MONITORING, EXERCISE, BEHAVIOR

To fully understand and define relationships between physical activity (PA) and health, it is necessary to accurately quantify PA levels. Physical activity is a complex behavior, and identifying the most accurate way in which to assess PA remains a challenge. PA can be measured in a multitude of direct and indirect ways, including direct and indirect calorimetry, doubly labeled water, PA records and logs, direct observation, HR monitoring, electronic motion sensors, and self-report surveys. The choice of which PA assessment device to use is largely dictated by the exposure variable of interest and the feasibility and practicality of using the device.

Perhaps two of the most studied objective and direct PA monitoring devices of late have been the use of motion sensors and HR monitors. Considerable attention has been given to accelerometers (ACC), as many brands offer a relatively unobtrusive mechanism that can measure body movement while it is occurring and capture the spectrum of PA, namely, the intensity, frequency, duration, and total volume of activity. As already identified by Matthews (21) and other reviews (2,32,35), ACC have strengths as well as weaknesses for PA assessment. HR monitoring also has been well studied as a PA assessment tool (19,25,28,33) and is attractive because it is a physiological variable and it possesses the capability to capture the spectrum of PA. Different techniques in which to use HR monitoring, such as the FLEX HR technique, have been proposed and tested for validity and reliability (10,19,28). Similar to ACC, HR monitors have strengths as well as weaknesses as a PA assessment instrument. Other comprehensive reviews discuss advantages and disadvantages of activity assessment devices and HR monitoring (2,13,35).

Integrating physiological measures, notably HR monitoring, with ACC holds considerable promise to improve measurement precision, and a number of studies over the past decade have examined this combined innovative approach (1,6,11,14,20,23,26,27,31). Although empirical evidence is accumulating that integration has benefits, the best way to combine these two sources of activity measurement is still debatable. Adding to this complexity is the issue of individual calibration (IC). HR monitoring typically employs some level of IC, which may be performed during specific laboratory tests, or during a range of activities undertaken in a room calorimeter. IC removes the majority of measure-

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0195-9131/05/3711(Suppl)-S563/0
MEDICINE & SCIENCE IN SPORTS & EXERCISE®

DOI: 10.1249/01.mss.0000185650.68232.3f

TABLE 1. Demographic characteristics of secondary analysis sample.

	Men (N = 4) Mean ± SD	Women (N = 6) Mean ± SD	All (N = 10) Mean ± SD
Age (yr)	25.5 ± 4.0	26.0 ± 3.3	25.8 ± 3.4
Height (m)	1.85 ± 0.1	1.63 ± 0.1	1.70 ± 0.1
Weight (kg)	78.3 ± 7.1	67.2 ± 12.7	71.7 ± 11.8
BMI (kg·m^{-2})	22.9 ± 1.3	25.5 ± 6.4	24.4 ± 5.0

ment error that is caused by differences in age, sex, level of physical fitness, and possibly other factors. Although IC has been recommended for precision, it is less feasible in large-scale epidemiological studies or surveillance studies because of restrictions in time, resources, and setting. It can be done, however, as shown by the Ely study, which carried out baseline and follow-up IC in more than 800 individuals (9,34).

Recently, the authors of this paper proposed two different modeling techniques that combine ACC and HR in order to improve physical activity energy expenditure (PAEE) measurement (6,26,27). Strath et al. (26,27) followed up on original work performed by Haskell et al. (14) and examined the validity of developing individualized arm and leg HR–PAEE (oxygen uptake, $\dot{V}O_2$) calibration curves, and then used ACC placed on the arm and leg to determine which of the two calibration curves to use to estimate PAEE. Brage et al. (6) developed an elaborate weighting technique involving branched equation modeling for use with ACC and HR worn on the waist. Essentially, when both ACC and HR values are low, the ACC–PAEE relationship derived during walking and running has more weight, and when ACC and HR values are higher, the HR–PAEE relationship is the predominant contributor to the estimate of PAEE. Intermediate values of ACC and HR are quantified with more equal weightings of the two PAEE relationships.

This paper reports on a secondary data set analysis that we conducted to examine these two most recent modeling techniques against one another, with and without dynamic IC, and to compare PAEE estimates with both minute-by-minute measured PAEE, as assessed by indirect calorimetry, as well as to the accuracy of single-device, nonintegrated ACC predictions. The paper concludes with a brief review of the strengths and weaknesses, calibration needs and procedures, and future directions of these combined monitoring techniques.

METHODS

Participants

Data from 10 participants were included in this secondary data analysis. Study procedures were approved by the university's institutional review board. Before completing the protocol, all participants had their body mass and height measured, using a physician's scale (Health-O-Meter, Bridgeview, IL) and stadiometer (Seca Corp., Columbia, MD), respectively. Participant characteristics are shown in Table 1.

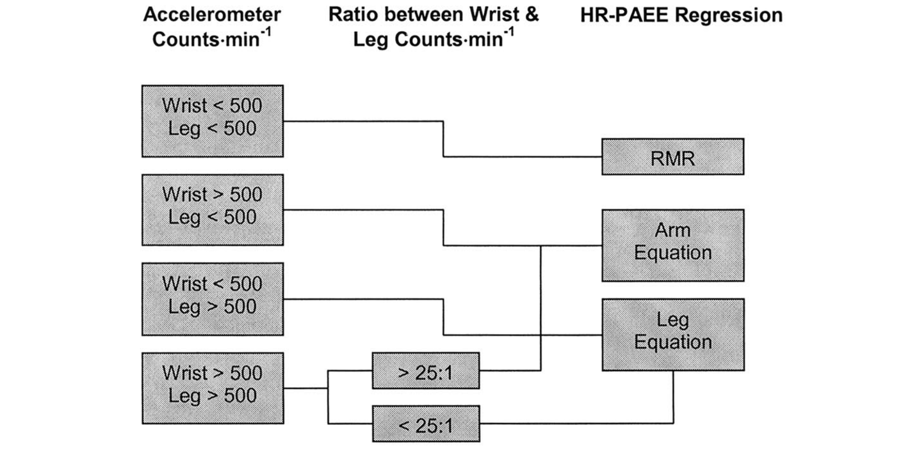
Study Protocol

The 6-h protocol has been described in detail previously (27). In brief, participants reported to a laboratory and were asked to wear a Polar HR watch and transmitter band (Polar NV, Polar Oy, Kempele, Finland) and a portable metabolic measurement system (Cosmed K4^2, Cosmed, S.r.L, Rome, Italy). Both of these devices have been shown to be valid for measurements of HR (16,18,29), and $\dot{V}O_2$ (22), respectively. Individuals then were asked to remain in supine, sitting, and upright positions, for 10, 5, and 5 min, respectively, while HR and $\dot{V}O_2$ data were collected. Following this, each individual completed a continuous submaximal (to 85% of age-predicted maximal HR) walking treadmill test, and a continuous submaximal arm ergometer test, performed in random order with a rest period in between. Physical activity energy expenditure was expressed in net METs as $\dot{V}O_2$ minus resting $\dot{V}O_2$ and divided by 3.5 mL O_2·min^{-1}·kg^{-1}. These exercise tests enabled individual HR–PAEE calibration curves for both leg (treadmill) and arm (arm ergometer) activity to be established. Within 1 wk of this laboratory calibration, individuals were monitored for 6 h during their normal daily routine. During this time, individuals wore ActiGraph model 7164 motion sensors (Actigraph was formerly known as Computer Science and Applications (CSA) and Manufacturing Technology Inc. (MTI), ActiGraph, LLC, Fort Walton Beach, FL) placed on their wrist, thigh, and hip as well as a HR watch and transmitting band, and the Cosmed K4b^2. Each piece of equipment was synchronized to the same time and was set to record in minute-by-minute increments. Following this testing, all data were downloaded and imported into a digital file. The ActiGraph has been shown to quantify acceleration in a frequency-dependent manner (7).

Estimations of Free-Living Physical Activity

Simultaneous arm-leg HR-motion sensor technique. The methodology pertaining to the simultaneous arm-leg HR-motion sensor technique (arm-leg HR+M) distinguishing between arm and leg work has been reported previously (26,27). Briefly, the arm and leg ACC outputs were used to establish whether primarily upper or lower body activity was taking place and whether meaningful activity was happening. If both devices recorded less than 500 counts per minute, PAEE was presumed to be zero (total energy expenditure (TEE) = resting energy expenditure (REE)), irrespective of HR. A ratio technique between arm and leg ACC activity was used to establish which HR–PAEE regression to use. A ratio of greater than 25:1 between arm and leg activity signified that predominantly arm activity was taking place, and the corresponding individualized arm HR–PAEE regression would be used to predict PAEE from measured HR. For a ratio of less than 25:1, the individualized leg HR–PAEE regression was used to predict PAEE from measured HR (Fig. 1).

To assess the precision of using nonindividually calibrated HR–PAEE relationships, we reanalyzed data and used permutations of the average HR–PAEE equation derived on the whole group, omitting the subject for whom the equation was



HR = heart rate, PAEE = physical activity energy expenditure, RMR = resting metabolic rate

FIGURE 1—Model structure for the arm-leg HR+M technique. PAEE, physical activity energy expenditure; RMR, resting metabolic rate.

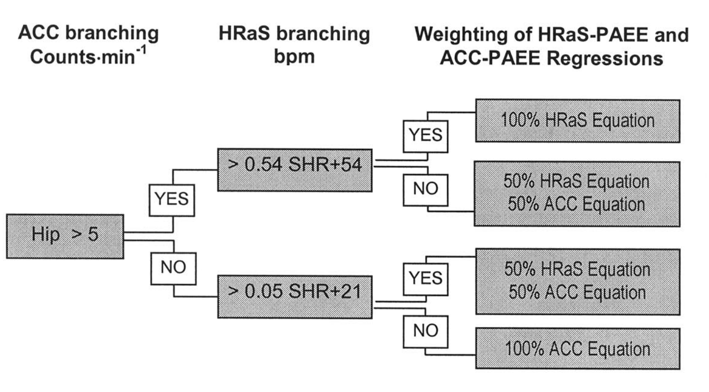
intended (Student's jackknife approach). For example, to derive a nonindividual equation for participant 1, we used calibration data for all participants but participant 1. This was performed on HR data adjusted for resting HR (RHR).

Branched equation modeling technique of simultaneous accelerometry and HR monitoring. The branched equation model of simultaneous ACC and HR monitoring (branched model) applies different weightings (P_{1-4}) to the HR–PAEE and ACC–PAEE relationships (6) (Fig. 2). These can be derived on an individualized and nonindividualized level. The original calorimetry study (6) in which the branched model was first presented used individualized PAEE relationships for both HR and ACC. ACC–PAEE were not available on the individual level in the current data set. Thus, the MET-based equation by Freedson et al. (12) was used for both the individualized and nonindividualized version of the branched model. The Freedson equation was, however, slightly modified. First, we subtracted 1 MET from the intercept so as to return PAEE to net METs, and, second, we forced this equation through the origin by using a movement flex point of 497 counts per minute, as described previously (6). The individualized and nonindividualized HR–PAEE relationships were derived as described above for the arm-leg HR+M model, but we used only the treadmill test data. However, in keeping with the principle behind the models in the original calorimetry study, sleeping HR (SHR) was used as the basis for the HR–PAEE relationships and HR–PAEE relationships were forced through the origin to form PAEE = β_1·HRaS·HRaS + β_2·HRaS, where HRaS denotes HR above SHR. In the present data set, however, only RHR was available, and SHR was therefore calculated according to the formula SHR = 0.83·RHR (5). In terms of parameters for the branched model, we used values similar to the *a priori* parameters in the original study (6), that is., an X value = 5 cpm, Z_{1-2}, and Y_{1-2} values equal to flex HRaS and walking–running transition HRaS, respectively, (5) and P_1 = 100%, P_2 = P_3 = 50%, and P_4 = 0%. Using the method described previously, (6) these parameters are also fitted *post hoc* to minimize estimation error.

Single accelerometer technique. The predictive capabilities of the hip-worn ACC in isolation also were examined, using the treadmill walking and running equation by Freedson et al. (12). However, we subtracted 1 MET from the intercept to estimate PAEE, rather than TEE. The ActiGraph was placed on the hip over the midline of the thigh in a manufacturer supplied pouch and attached to a belt.

Data Analysis

All data are presented in PA levels above rest (i.e., net PAEE in METs). Minute-by-minute data were analyzed for



ACC = accelerometry, HRaS = heart rate above sleeping heart rate (SHR), bpm = beats/min, PAEE = physical activity energy expenditure

FIGURE 2—Model structure for the branched equation modeling technique. Note that the HR–PAEE equation is forced through the point sleeping HR (SHR) and PAEE = 0 METs (equal to resting metabolic rate (RMR)), and below 497 cpm, the ACC–PAEE equation is forced through the point 0 cpm and PAEE = 0 METs. ACC, accelerometry; HRaS, HR above sleeping HR (SHR); PAEE, physical activity energy expenditure.

TABLE 2. PAEE estimates from individual and group level calibrated arm-leg HR+M, branched equation model, and single-measure ACC in net METs.

		Estimated PA, Using Individual Calibration									Estimated PA, Using Group Calibration					
	Criterion	Arm-Leg HR+M			Branched Model			Arm-Leg HR+M			Branched Model			ACC		
ID	PAEE	PAEE	R^2	RMS	PAEE	R^2	RMS	PAEE	R^2	RMS	PAEE	R^2	RMS	PAEE	R^2	RMS
1	1.15	0.5	0.65	0.87	0.72	0.56	0.66	0.42	0.63	0.89	0.58	0.56	0.74	0.71	0.21	0.71
2	1.38	1.37	0.81	0.87	1.33	0.81	0.77	0.3	0.68	1.31	0.95	0.79	0.7	0.92	0.51	0.92
3	1.45	1.42	0.83	0.65	1.43	0.71	0.74	1.92	0.71	1.25	1.32	0.71	0.74	0.95	0.38	1.07
4	1.12	0.71	0.75	0.49	0.99	0.74	0.46	1.9	0.66	1.15	1.55	0.74	0.75	0.97	0.48	0.69
5	1.82	2.34	0.76	0.82	2.13	0.76	0.62	2.56	0.67	1.29	2.06	0.77	0.56	0.81	0.42	1.33
6	1.58	1.51	0.88	0.58	1.52	0.83	0.76	1.23	0.68	0.87	1.34	0.81	0.82	1.38	0.47	1.2
7	1.4	1.41	0.81	0.51	1.26	0.72	0.58	2.1	0.57	0.96	1.29	0.72	0.58	1.1	0.4	0.91
8	0.7	0.83	0.81	0.37	0.9	0.76	0.42	0.5	0.56	0.7	1.09	0.76	0.58	0.94	0.41	0.58
9	1.21	1.1	0.87	0.51	1.43	0.76	0.7	2.08	0.71	0.99	1.65	0.74	0.89	1	0.31	0.97
10	1.65	1.63	0.88	0.71	1.95	0.86	0.94	2.26	0.87	1.27	2.38	0.88	1.27	2.9	0.53	3.81
Mean	1.35	1.28	0.81	0.64	1.37	0.75	0.67	1.53	0.67	1.07	1.42	0.75	0.76	1.17	0.41	1.22
SD	0.32	0.53		0.18	0.44		0.15	0.84		0.21	0.52		0.21	0.63		0.94

PA, physical activity; PAEE, physical activity energy expenditure; M, motion sensor; RMS, rooted mean square.

all predictions of PAEE relative to the criterion standard. Agreement between criterion-measured PAEE and PAEE estimated from the five models (IC arm-leg HR+M; IC branched model; GC arm-leg HR+M; GC branched model; and individual ACC estimates) were assessed in a variety of ways. First, Pearson correlation coefficients were computed to assess the degree to which the PAEE models would explain variance in the criterion measure. Second, estimation error (criterion minus estimate) was expressed in METs and graphically represented with Bland–Altman plots (4) with 95% limits of agreement (LoA). Dynamic bias (intensity-dependent estimation error or *differential* error) was determined with Pearson correlation between error and criterion PAEE. In addition, estimation error was quantified as the square root of the mean squared differences between criterion and estimated PA (rooted mean square (RMS)). Lower RMS values indicate a "tighter fit" with the criterion measure, a higher level of estimation accuracy. RMS differences between models were tested with paired *t*-tests. Third, agreement between time spent in the two intensity categories of "moderate activity" (2–5 net METs) and "vigorous activity" (≥5 net METs) was analyzed with repeated-measures ANOVA. Bonferroni *post hoc* testing was performed to locate significant differences. Statistical significance was set at alpha = 0.05. All analyses were conducted with SPSS for Windows Version 12.0 (SPSS Inc., Chicago, IL).

RESULTS

Individually calibrated PAEE estimates. Measured minute-by-minute PAEE was significantly correlated with PAEE estimates from both IC arm-leg HR+M and branched model estimates ($R^2 = 0.81$, $P < 0.001$, SEE = 0.55 METs and $R^2 = 0.75$, $P < 0.001$, SEE = 0.61 METs, respectively). As previously reported (27), IC arm-leg HR+M estimates did not significantly differ from criterion PAEE (mean error: 0.07 METs; $P = 0.916$; +1.3, −1.3, 95% LoA). New results reveal that IC branched model estimates did not significantly differ from the criterion measure (mean error 0.02 METs; $P = 0.206$; +1.4, −1.3, 95% LoA). The proportions of observations quantified by the five pathways of the arm-leg HR+M model (low arm-ACC and leg-ACC, high arm-ACC and low leg-ACC, low arm-ACC and high leg-ACC, high arm-ACC and high leg-ACC with a ratio greater than 25, and finally high arm-ACC and high leg-ACC with a ratio smaller than 25) were on average (SD) 21 (7)%, 11 (3)%, 44 (12)%, 7 (3)%, and 17 (6)%, respectively. The proportions of observations quantified by the four pathways in the branched model (high ACC–high HR, high ACC–low HR, low ACC–high HR, and low ACC–low HR) were on average (SD) 3 (4)%, 69 (13)%, 12 (6)%, and 16 (13)%, respectively. Mean PAEE estimates from IC arm-leg HR+M and IC branched models are shown in Table 2. Percentage errors of the group mean for the IC arm-leg HR+M and branch estimates of PAEE (mean ± SE) were −6.3 ± 7.7%, and 1.4 ± 6.2%, respectively. Estimation accuracy (RMS values, Table 2) of the arm-leg HR+M and branched models using IC ($P = 0.602$) did not differ compared with the single ACC model ($P = 0.076$ and $P = 0.065$, respectively). *Post hoc* estimation of branched model parameters used in conjunction with IC HR–PAEE relationships revealed a minimum RMS of 0.60 METs with parameters X = 100 cpm, $Y_1 = 0.1$, $Y_2 = 82$ bpm, $Z_1 = 0.6$, $Z_2 = 58$ bpm, $P_1 = 100\%$, $P_2 = 64\%$, $P_3 = 54\%$, and $P_4 = 46\%$. The proportions of observations quantified by the four pathways in the branched model were on average (SD) 2 (4)%, 49 (13)%, 0.2 (0.5)%, and 49 (12)%, respectively.

The Bland–Altman plots (Fig. 3A and B) show the differences between estimated PAEE from IC arm-leg HR+M and IC branch model and criterion measured PAEE (i.e., estimation error) plotted against the mean of the methods. The 95% LoA were −1.3 to 1.3 METs and −1.35 to 1.32 METs, respectively. The IC arm-leg HR+M and IC branched model estimation errors were negatively correlated with PAEE, r = −0.35, $P < 0.01$; and r = −0.20, $P < 0.01$, respectively.

Table 3 shows the degree to which PA models correctly classified time spent in moderate and vigorous intensity categories. Both the IC arm-leg HR+M estimates and IC branched model estimates did not differ significantly from measured time spent in moderate ($P = 0.13$, $P = 0.20$) and vigorous activity ($P = 0.10$, $P = 0.10$, respectively).

Group-calibrated PAEE estimates. PAEE estimates for both arm-leg HR+M and branched model using GC equations were significantly correlated with criterion minute-by-minute PAEE values ($R^2 = 0.67$, $P = < 0.001$,

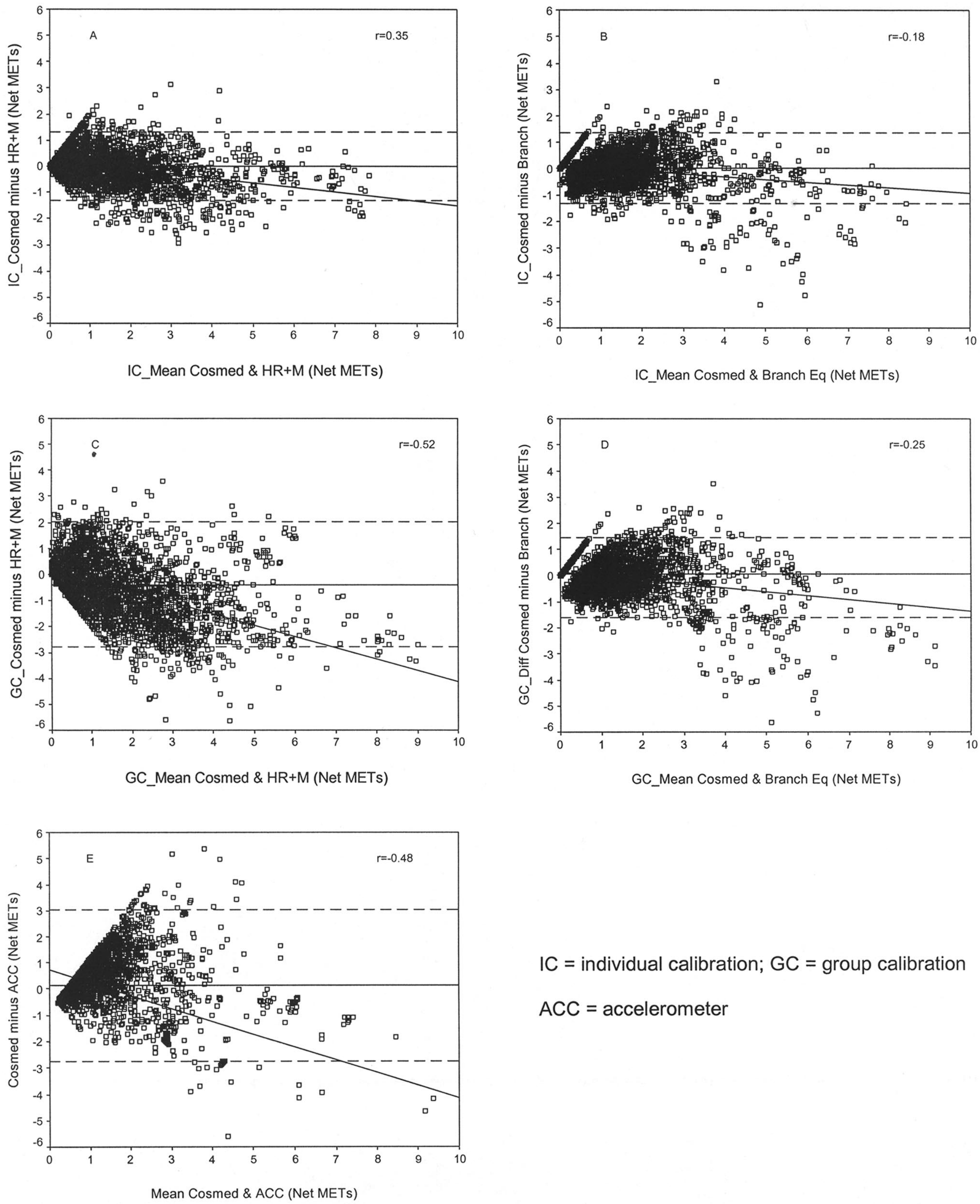


FIGURE 3—Bland–Altman plots depicting differences for minute-by-minute PAEE. A and B. Individual group estimates for arm-leg HR+M and branched model. C and D. Group calibration estimates for arm-leg HR+M and branched model. E. Single-measure ACC estimates using the equation of Freedson et al. (12). IC, individual calibration; GC, group calibration; ACC, accelerometer.

SEE = 0.88 METs, and R^2 = 0.75, P = <0.001, SEE = 0.67 METs, respectively). Corresponding single-measure ACC correlations with measured minute-by-minute PAEE was R^2 = 0.41 (P < 0.001, SEE = 0.96 METs). PAEE estimates from GC arm-leg HR+M, GC branched model, and single-measure ACC were all significantly different from criterion measured PAEE (mean errors: 0.4 METs, P < 0.001, +2.1, −2.8, 95% LoA; 0.1 METs, P < 0.001, +1.6, −1.4, 95% LoA; and 0.1 METs, P < 0.001, +3.0, −2.8, 95% LoA, respectively). Mean PAEE estimates from GC arm-leg HR+M, GC branched model, and single-measure ACC are shown in Table 2, alongside the estimates using IC. Percentage errors for the GC arm-leg HR+M and GC branched model estimates of PAEE were 18.2 ± 19.7%,

TABLE 3. Time spent in moderate and vigorous activity: mean error scores for individual- and group-level calibrated arm-leg HR+M, branched equation model, and single-measure ACC.

	Moderate Activity		Vigorous Activity	
	Mean Error	% Difference	Mean Error	% Difference
IC arm-leg HR+M	−9 ± 5	15.6 ± 12.1	−3 ± 2	84.6 ± 52.5
IC Branched model	+13 ± 7	−16.5 ± 8.6	−4 ± 2	71.7 ± 46.7
GC arm-leg HR+M	−27 ± 17	39.6 ± 24.5	−9 ± 5	163.6 ± 89.2
GC branched model	+13 ± 9	−3.9 ± 28.8	−5 ± 4	98.6 ± 54.7
Single ACC (hip)	+38 ± 12*	−44.4 ± 16.4	−4 ± 3	10.0 ± 35.8

Predictions in minutes.
* Significantly different from zero at 0.05 level.
IC, individual calibration; GC, group calibration; ACC, accelerometer.

and 7.5 ± 11.2%, respectively. ACC corresponding percentage errors were −11.6 ± 12.3%. As also indicated by the differences in RMS values (Table 2), the GC arm-leg HR+M and GC branched models performed better than the single-measure ACC predictions, but were less precise than IC estimates. Differences in RMS values between the single-measure ACC and GC arm-leg HR+M were not statistically significant ($P = 0.595$), nor were the single-measure ACC and GC branched model ($P = 0.095$). *Post hoc* estimation of branched model parameters used in conjunction with GC HR–PAEE relationships, revealed a minimum RMS of 0.72 METs with parameters X = 100 cpm, Y_1 = 0.5, Y_2 = 60 bpm, Z_1 = 0.1, Z_2 = 85 bpm, P_1 = 100%, P_2 = 59%, P_3 = 47%, and P_4 = 42%. These parameters resulted in average (SD) branched model pathway utilizations of 2 (4)%, 49 (13)%, 0.2 (0.5)%, and 49 (12)% for high ACC–high HR, high ACC–low HR, low ACC–high HR, and low ACC–low HR, respectively.

Graphical representations highlight the differences between GC arm-leg HR+M, GC branched model, and single-measure ACC estimates and criterion-measured values for PAEE (Fig. 3C–E). The 95% LoA were −2.8 to 2.1 METs, −1.63 to 1.46 METs, and −2.8 to 3.0 METs, respectively. The estimation errors from GC arm-leg HR+M and GC branched model were negatively correlated with PAEE ($r = -0.52$, $P < 0.01$ and $r = -0.25$, $P < 0.01$, respectively). Single-measure ACC estimation errors negatively correlated with PAEE ($r = -0.48$, $P < 0.01$).

For time spent in moderate activity and vigorous activity intensity categories (Table 3), GC for arm-leg HR+M estimates and GC branched model estimates did not significantly differ from measured time spent in moderate ($P = 0.09$, $P = 0.09$) and vigorous activity ($P = 0.19$, $P = 0.16$, respectively). Single-measure ACC significantly underestimated time spent in moderate activity ($P = 0.01$), but reflected vigorous activity not significantly different from the criterion ($P = 0.32$).

DISCUSSION

In this report, we conducted a secondary analysis and examined recently published combined monitoring modeling techniques to predict PAEE. The following discussion highlights past combination techniques, present combination techniques, calibration procedures, strengths and weaknesses, and future directions.

Past Work

Overview. HR monitoring and ACC monitoring used in isolation have limitations to predict PAEE. One main criticism of HR monitoring is that HR can be elevated due to nonactivity-related stressors. Moreover, that predicting PAEE from HR at low intensities is problematic because the HR–PAEE relationship is typically not linear at low intensities (19,25). Weaknesses surrounding ACC have focused on the inability of a single unit, typically worn on the hip, to account for all bodily movement and to account for external work performed, such as walking up an incline (3,17). Therefore, investigators have attempted to circumvent these limitations by combining methodologies, most typically combining HR monitoring and motion sensors.

Strengths. For the in-depth strengths of past work conducted up to 2000, we refer readers to work by Treuth (30). In brief, the strength of combining methodologies stems from an increase in PAEE prediction accuracy. To our knowledge, the study by Avons et al. (1) was the first to examine the value of combining HR and movement sensing to increase measurement precision of EE. Haskell et al. (14) performed multiple regression analyses to predict EE from arm and leg motion sensors and measured HR during different laboratory-based activities. Motion detection added to HR monitoring increased the accuracy of PAEE prediction. For instance, R^2 values were increased from 0.69 when activity was predicted from HR alone during Air-Dyne ergometer activity, to 0.82 when arm motion detection was added. Luke et al. (20) followed this work with an evaluation of laboratory-conducted simulated activities of daily living (ADL) and treadmill activities. They reported improvement in PAEE prediction when motion detection was added to HR monitoring, especially during ADL. Past studies also have examined modeling techniques and compared them to measured PAEE obtained from 24-h room calorimetry (23,31). Such studies have examined the utility of developing two regression lines, one for inactive time and the other for active time, and have shown such an approach to have a low percentage error (e.g., <3.3% error) for predicting PAEE.

Weaknesses. Although it has been established that combination approaches have increased accuracy (e.g., they can separate inactive and active relationships), their weaknesses stem from the complexity and sophistication often required for data analysis. If IC also is warranted for increased precision (see the following section), this also significantly reduces the application to large studies. This complexity is further escalated by the fact that no commercially available single unit devices capable of recording both HR and ACC were available in the past. However, the recent development of lightweight, combined HR and movement sensing devices may overcome this. For instance, preliminary studies indicate promising results for inter- and intrainstrument reliability and validity during walking and running of the Actiheart (Mini Mitter Co., Inc., Bend, OR) (5), but further work is necessary.

Calibration. Studies that have included some form of calibration for combined method approaches have done so in a nonunified manner. For instance, some studies employ the utility of a single dynamic activity in which to regress independent predictors to measured EE (24,26,27), whereas others have used multiple activities including some sedentary, low-level habitual activities and some exercise-related activities (6,23,31). Although the usefulness and robustness of multiple activity calibrations are acknowledged, this further increases complexity and reduces practicality. The accuracy of different levels of calibration has yet to be demonstrated when establishing the relationship between HR and activity counts and PAEE for use in free-living individuals. Perhaps a flexible consistency is needed, with different levels of calibration, ranging from IC including a number of activities with different intensities to some type of static calibration using parameters such as age, sex, and sleeping HR for PAEE estimation. In this approach, a set calibration level could be routinely employed or selected, depending on the type of study involved. With regard to which activities should be incorporated in calibration, this is most important for establishing the ACC–PAEE relationship, as the HR–PAEE relationship applies more universally across different activities within individuals. Further studies are underway to assess these issues.

What does appear to be consistent is that IC appears more accurate than pooled data that generate a GC. For instance, Haskell et al. (14) reported that combined HR and ACC R^2 estimates were 0.89, SEE 2.3 $mL^{-1} \cdot kg^{-1} \cdot min^{-1}$, for IC, versus $R^2 = 0.73$, SEE 5.2 $mL^{-1} \cdot kg^{-1} \cdot min^{-1}$, for GC. Additional work has corroborated such findings (20).

Present Work

Overview. For purposes of present work, we refer to published works after the review conducted by Treuth (30). Since that last review, Strath et al. (26,27) and Brage et al. (6) have examined additional modeling techniques to integrate physiological HR data and movement data. Separately these studies further highlight the increased accuracy of such combination techniques.

Strengths. The first of two papers by Strath et al. (26) compared motion sensor (hip-worn ACC), HR, and combined HR and motion sensor estimates of PAEE during 14 different simulated activities of daily living. Activities were conducted for 15 min each. IC were established for arm and leg activities between HR and EE, and motion sensors placed on the arm and leg were used to distinguish between upper and lower body activity. As previously discussed, a ratio of greater than 25:1 between arm and leg movement obtained from the motions sensors were used to see which regression to employ. Results showed that using motion sensors to discriminate between which HR–EE regression to use (arm or leg) resulted in greater EE estimation precision than when either HR or ACC were used in isolation ($R^2 =$ 0.81, 0.67, and 0.54, respectively). A follow-up study by the same investigators sought to examine the same technique during 6 h of free-living activity (27) (source of data for current secondary analysis). This time, the integration of physiological and ACC data were compared to HR monitoring in isolation using the FLEX HR method. The combination approach accounted for 81% of the shared variance in measured EE (SEE = 0.55 METs), compared with 63% of the shared variance (SEE = 0.76 METs) deduced from the FLEX HR method.

The recent paper by Brage et al. (6) examined a branched modeling technique that used the combination of HR monitoring and ACC and weighted each respective estimation based on the intensity of activity. This study used PAEE from direct whole-body calorimetry as the criterion standard. IC were established for both the HR–PAEE and ACC–PAEE relationships during treadmill walking and running. Results were examined for combination PAEE predictions as well as independent predictions from ACC and HR. Results found percent errors in the region of $-4 \pm 29\%$ for branched estimates, $-51 \pm 10\%$ for ACC estimates, and $39 \pm 58\%$ for HR estimates. GC estimates also were examined and, interestingly, found not to be significantly less precise than branched estimates using IC.

Both of these two latest modeling techniques have established accuracy for predicting PAEE. To further the examination of these methods, we performed a secondary analysis of a common data set. Within this secondary analysis, comparing the two techniques, it was further demonstrated that error margins are small. IC with the arm-leg HR+M and branched model accounted for 81 and 75% of the variance in criterion-measured PAEE, respectively. Both techniques also accurately reflected minute-by-minute PAEE, estimated within relatively narrow margins centered a round the mean (+1.5 to −1.4 METs, 95% LoA, Fig. 3A and B). Additionally, both techniques accurately assessed time spent in moderate and vigorous activity, with a range of error −9 to +13% when IC were used. Although not statistically significant, errors associated with IC arm-leg HR+M estimates were less than IC branched model estimates. When single-measure ACC predictions (12) were examined, the degree of error was considerably more, only accounting for 41% of the shared variance, with minute-by-minute PAEE estimates statistically different from the criterion measure ($P < 0.001$) and with a greater level of variance (+3.0 to −2.8 METs, 95% LoA, Fig. 3E), and significantly underestimating time spent in moderate activity (−44%, $P <$ 0.05, Table 3).

New information stemming from this secondary analysis shows the arm-leg HR+M technique estimates to become less precise for GC estimates compared with IC arm-leg HR+M estimates ($R^2 = 0.81$ and 0.67, respectively).

Minute-by-minute analysis revealed GC arm-leg HR+M estimates were significantly different from zero ($P < 0.001$, +2.1 to −2.8 METs, 95% LoA, Fig. 3C), but did not significantly differ from criterion measured time spent in moderate and vigorous activity (Table 3). This decrease in precision agrees with other literature that notes a decrease in precision when using GC (14,20). It is important to mention that the GC branched model estimates did not change much in precision from IC branched model estimates, both accounting for 75% of the shared variance compared with criterion measures. Minute-by-minute data did reveal GC branched model estimates to be significantly different from zero ($P < 0.001$), but within relatively narrow margins of error (+1.6 to −1.4 METs, 95% LoA, Fig. 3D). GC branched model estimates for time spent in different intensity categories also did not differ from the criterion measure. These results demonstrate the robustness of this model, by way of prediction accuracy not being tied to individual level calibrations. This agrees with previous findings from this modeling technique examined against whole-body calorimetry (6). Interestingly, the *post hoc* estimated parameters in the present study were fairly similar for the IC and GC versions of the branched model, and could broadly be summed up as a 60/40 weighting of the HR–PAEE and ACC–PAEE relationships when ACC was over 100 cpm, and a 40/60 weighting if ACC was below 100 cpm. Although it is tempting to then propose a simplification of this model, the results may reflect an absence of certain activities of daily living in the present data set.

Weaknesses. Similar to past studies, these latest combination modeling techniques require complex and sophisticated data analyses. Studies by Strath et al. (26,27) have added further complexity by having subjects wear multiple motion sensors and conducting two IC to discriminate between upper and lower body activity. Although such an approach has demonstrated precision at the individual level, feasibility may become an issue in larger studies. Both of the current modeling techniques examined used activity count thresholds to separate out inactivity and activity. Further examination of these thresholds is warranted for corroboration.

Current instrumentation. A variety of different methods have been proposed in recent years to examine combination techniques for HR and motion detection. Clearly, irrespective of the particular modeling technique employed, all serve to enhance PAEE prediction capabilities. Adding to this exciting line of research has been the addition of new technology that combines HR and ACC approaches into single-unit devices. Rennie et al. (24) reported on such a combined approach, and examined the accuracy of a combination unit but this device was never commercially available. Brage et al. (5) demonstrated the validity of a combined HR and movement sensor for predicting PAEE during walking and running. Further work by Hustvedt et al. (15) showed good agreement between a combined motion and HR unit and criterion values of PAEE obtained from both whole-body respiration chambers, and doubly labeled water. Other advances have seen devices worn on limbs that measure motion and other physiological markers (i.e., HR and heat flux) (8). Other combination, single-unit devices are rapidly flooding the market, similar to what has been witnessed with the evolution of accelerometry to objectively measure PA behavior. It is too early to assess the level of impact these devices will have, but they hold promise for the future advancement of the field of PA assessment. Two objectives for engineers when designing future devices will be to decrease study participant burden by developing a single-unit device and to improve data management capabilities.

SUMMARY AND FUTURE DIRECTIONS

This report shows that combination monitoring, irrespective of modeling technique employed, can accurately reflect PAEE levels when both individual and group level equations are used. Study design and magnitude will largely dictate the activity measure of choice, but with advances in combination monitoring, and data showing accuracy for group-based calibration approaches, larger sample studies may not be prohibitive. The following research recommendations are offered to further advance the field of combination monitoring:

- The reliability and validity of new combination monitoring devices that enter the field need to be carefully examined. Research designs could borrow from the accelerometry field and employ methodologically rigorous designs.
- Further modeling technique development and evaluation are warranted. The primary outcome from PA instruments is ultimately PAEE per unit of time, and standardizing for body size is necessary. Knowledge of relationships with PAEE in different conditions for each of the employed sources of data in combined monitors may help inspire new modeling techniques.
- Study designs examining the validity of combined sensing in the laboratory and during free-living scenarios across the full-intensity spectrum are warranted. With the memory capacity of current devices, frequency and duration domains are easily obtained from such valid intensity measures with high time resolution.
- There is a need to assess combination approaches and modeling techniques in varied populations, for instance, older adults, patient populations, children, and more heterogeneous samples.
- Combination monitoring approaches to increase precision in PAEE assessment will require data management strategies that simplify results and data output.
- There is a need to develop different levels of calibration and to examine the accuracy of these calibration levels when assessing PAEE by combined sensing.

The authors thank Ann M. Swartz, from the Department of Human Movement Sciences, University of Wisconsin-Milwaukee; Nick Wareham and Jian'an Luan from the MRC Epidemiology Unit, Cambridge, UK; and Niels Brage from the Institute of Sports Science & Clinical Biomechanics, University of Southern Denmark, Odense for useful comments during preparation of this manuscript.

The results of the present study do not constitute endorsement by the authors or ACSM of the products described in this paper.

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