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Estimating energy expenditure from accelerometer data in healthy adults and patients with type 2 diabetes

Nathan Caron[a,*], Nicolas Peyrot[b], Teddy Caderby[a], Chantal Verkindt[a], Georges Dalleau[a]

[a] Laboratoire IRISSE (EA4075), UFR Sciences de l'Homme et de l'Environnement, Université de la Réunion, Le Tampon, France
[b] Laboratoire MIP (EA4334), Faculté des Sciences et Techniques, Université du Mans, Le Mans, France

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ABSTRACT

Objective: The aim of this study was to develop specific prediction equations based on acceleration data measured at three body sites for estimating energy expenditure (EE) during static and active conditions in middle-aged and older adults with and without type 2 diabetes (T2D).

Research methods: Forty patients with T2D (age: 40–74 yr, body mass index (BMI): 21–29.4 kg·m^{-2}) and healthy participants (age: 47–79 yr, BMI: 20.2–29.8 kg·m^{-2}) completed trials in both static conditions and treadmill walking. For all trials, gas exchange was monitored using indirect calorimetry and vector magnitude was calculated from acceleration data measured using inertial measurement units placed to the participant's center of mass (CM), hip and ankle. Stepwise multiple regression analyses were conducted to select relevant variables to include in the three EE prediction equations, and three Monte Carlo cross-validation procedures were used to evaluate each separate equation.

Results: Vector magnitude ($p < 0.0001$) and personal data (gender, diabetes status and BMI; $p < 0.0001$) were used to develop three linear prediction equations to estimate EE during static conditions and walking. Cross-validation revealed similar robust coefficients of determination (R^2: 0.81 to 0.85) and small bias (mean bias: 0.008 to −0.005 kcal·min^{-1}) for all three equations. However, the equation based on CM acceleration exhibited the lowest root mean square error (0.60 kcal·min^{-1} vs. 0.65 and 0.69 kcal·min^{-1} for the hip and ankle equations, respectively; $p < 0.001$).

Conclusion: The three equations based on acceleration data and participant characteristics accurately estimated EE during sedentary conditions and walking in middle-aged and older adults, with or without diabetes.

1. Introduction

Although physical activity is an integral part of rehabilitation program, the evaluation of individual energy requirement is paramount. Aging, whether or not associated with type 2 diabetes (T2D) may result in metabolic alterations. These changes may lead to a decrease in daily physical activity level (Zhao et al., 2011) due to an elevated physiological relative effort. Indeed, it has been shown that, unlike young adults, older persons (Peterson and Martin, 2010) and T2D patients (Caron et al., 2018b; Petrovic et al., 2016) have an increased activity-related energy expenditure (EE) for a same exercise. Thus, following the exercise prescription, patients' nutrition should be adjusted to minimize the risk of dietary imbalance (i.e. malnutrition or overfeeding) or medication error (insulin therapy). In this context, the quantification of EE has gained important interest in recent years.

Actimetry represents a popular and objective alternative to other reference methods (i.e. doubly labelled water and indirect calorimetry) (Reilly et al., 2008). Inexpensive and unobtrusive, accelerometer can be integrated into different forms of wearable devises, such as a watch, waistband or chest belt. It is thus possible to measure accelerations at different body attachment sites (e.g. ankle, wrist, trunk), which offers the possibility of selecting the most appropriate placement of the sensor according to the physical activity practiced. Furthermore, this technology is able to record exhaustive data for extended periods and to

Abbreviations: BMI, body mass index; CM, center of mass; EE, energy expenditure; EE_{ankle}, estimated energy expenditure from ankle acceleration; EE_{CM}, estimated energy expenditure from center of mass acceleration; EE_{hip}, estimated energy expenditure from hip acceleration; IMU, inertial measurement unit; RMSE, Root mean square error; SEE, standard error of estimate; T2D, type 2 diabetes; VM, vector magnitude; $\dot{V}O2$, rates of oxygen consumption; $\dot{V}CO2$, rate of carbon dioxide production

* Corresponding author at: Laboratoire IRISSE (EA4075), UFR des Sciences Humaines et de l'Environnement, Université de la Réunion, 117 rue du General Ailleret, F-97430 Le Tampon, La Réunion, France.
E-mail address: nathan.caron@univ-reunion.fr (N. Caron).

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estimate precise minute-by-minute changes in estimated EE throughout a large number of activities. Algorithms estimating the EE typically use equations developed from multiple regression analysis between measured EE and accelerometer output (i.e. acceleration of each axis or vector magnitude (VM)) and basic participant characteristics such as age, gender, and body weight (Bouten et al., 1994; Chen and Sun, 1997). As the output of the accelerometer is influenced by the anatomical location of the sensor, specific equations are developed depending on the body attachment site (Kim et al., 2014).

The use of a motion sensor as EE estimation tool needs a preliminary evaluation and validation in these specific populations. To date, most published algorithms using acceleration data have been developed with small groups of healthy young adults (Bouten et al., 1994; Chen and Sun, 1997). Only a few have been tested in other populations such as middle-aged adults (Caron et al., 2018a) or patients with T2D (Caron et al., 2019). Although the Bouten's algorithm was reliable to estimate walking-related EE in both populations, it does not take into account the age and/or physical deconditioning. This results in a tendency to underestimate EE in comparison with indirect calorimetry, which may be a source of bias in the patients' daily energy requirement.

In order to go beyond these limitations, the aim of this study was to develop specific prediction equations with user-specific algorithms based on acceleration data for estimating EE during static and active conditions in middle-aged and older adults with and without T2D. Three different equations have been developed according to each accelerometer attachment site (i.e. center of mass, hip and ankle).

2. Materials & methods

2.1. Participants

Middle age to older participants, healthy or with T2D, were targeted to participate as volunteers in this study. All participants were fully informed beforehand about the test procedure, and gave their written informed consent. Exclusion criteria included peripheral neuropathy, uncontrolled fasting glycaemia (> 1.8 g·L^{-1}), history of orthopaedic lower limb surgery and any neurological or systemic disease. Moreover, participants were included if they were able to walk without assistive devices. This study was approved by the local ethics committee of the IRISSE unit research (EA 4075) and conducted in accordance with the Declaration of Helsinki.

2.2. Measurements and design

The experimental protocol was already described and previously published, for more details, see Caron et al. (2018a). Briefly, a total of forty participants volunteered in this study: 20 healthy (age: 47–79 yr) and 20 diabetics (age: 40–74 yr) middle-aged and older adults. Characteristics of the participants are presented in Table 1. Participants were asked to complete two 6-min periods in seated and standing positions and to perform five 6-min level walks at different speeds (0.5 to 1.50 m·s^{-1}) in a randomised order. Each period was separated by 5 min of rest. Throughout each period, oxygen uptake ($\dot{V}O_2$, in ml·min^{-1}) and carbon dioxide production ($\dot{V}CO_2$, in ml·min^{-1}) were collected using a breath-by-breath gas analyser (Ergostik, Geratherm Medical AG, Geschwenda, Germany). Furthermore, three inertial measurement units (IMU) (MTw™, Xsens, Enschede, Netherlands) were used to measure the three-dimensional accelerations of the center of mass (CM), right hip and ankle, with a sampling frequency at 75 Hz. Metabolic data were used to determine total energy expenditure (in kcal·min^{-1}) for the last minute of each period using the Weir formula (Weir, 1949). Acceleration data were post-processed (low-pass and high-pass Butterworth filters with a cut-off frequency at 20 Hz and 0.2 Hz, respectively) using a custom-written program in Matlab (Matlab R2015b, MathWorks, Natick, MAS, USA). Then, the mean VM integrating the three components of acceleration (a_x, a_y and a_z) was calculated from a 30s interval for each IMU position:

$$VM = \frac{1}{N}\sum_{i=0}^{N-1} \sqrt{a(i)_x^2 + a(i)_y^2 + a(i)_z^2}.$$

Table 1
Characteristics of the participants.

Parameters	T2D (n = 20)	Healthy (n = 20)	All participants (n = 40)
Female/male	12/8	12/8	24/16
Age, years	57.5 ± 8.0	57.3 ± 6.7	57.4 ± 7.4
Weight, kg	70.9 ± 12.3	68.1 ± 13.4	69.5 ± 12.8
Height, m	1.63 ± 0.1	1.65 ± 0.1	1.64 ± 0.1
BMI, kg·m^{-2}	25.8 ± 2.7	25.1 ± 2.9	25.4 ± 2.8
FBG, g·L^{-1}	1.47 ± 0.16*	0.89 ± 0.12	1.20 ± 0.30
Diabetes duration, yr	10.6 (6.1)	/	/

Values are means ± standard deviation. T2D, type 2 diabetes; BMI, body mass index; FBG, fasting blood glucose.

* Significant group difference with $P < 0.05$.

2.3. Statistical analysis

2.3.1. Selection of equation's variables

Stepwise multiple regression analyses were conducted on the entire sample to examine the relationships of VM (for each accelerometer placement) and participant's physical characteristics to indirect calorimetry across all conditions. Personal data including age (years), gender (1 = male, 0 = female), diabetes status (1 = adult with T2D, 0 = healthy adult), BMI (in kg·m^{-2}), height (in m) and weight (in kg) were examined for inclusion in equations. Variables were examined according to their influence on EE and included in the equations if they induced a significant change in the proportion of variance explained (R^2) based on overall R^2 change from nested equations.

2.3.2. Cross-validation

Following these multiple regression analyses, a Monte Carlo cross-validation procedure was used to develop EE prediction equations across the three placements (Shao, 1993). This method randomly divides the participants into two subgroups (60% in a calibration group and 40% in a validation group) with equal rates of adults with and without T2D. Multiple linear regression analysis was conducted on the calibration group (n = 24) to develop an equation for the prediction of EE that was then tested in the validation group (n = 16). This procedure (sample division, regression analysis and validation test) was repeated 500 times for each sensor placement. The final equation represents the average across the 500 replications. At each repetition, standard error of estimate (SEE), coefficients of determination (R^2), mean bias and mean relative bias between measured and predicted values, and root mean square error (RMSE) were calculated to evaluate the accuracy of predicted EE using the three equations (three sensor placements) in comparison with indirect calorimetry. One-way, repeated measures ANOVAs on RMSE and bias were used to compare the accuracy of EE obtained between the three equations (CM, hip and ankle).

All statistical analyses were performed using SPSS version 21.0 (SPSS Inc., Chicago, IL, USA). Results are presented as means (± standard deviations) and statistical significance was set at $P < 0.05$.

3. Results

All healthy participants completed the entire protocol, however one participant's mechanical data set at 1.25 m·s^{-1} was lost due to a technical failure. During the treadmill protocol, two participants with T2D did not complete the active trials at 1.25 and 1.50 m·s^{-1} due to physical

Table 2
Results of stepwise multiple regression analyses to predict EE from VM, BMI, diabetes status, gender and age for each sensor placement.

Equation	Parameter	R^2 adjusted	R^2 adjusted % of variation	SEE ($kcal \cdot min^{-1}$)	p-Value
CM	VM	0.796	79.6	0.692	$p < 0.0001$
	BMI	0.834	3.8	0.624	$p < 0.0001$
	Gender	0.854	2.0	0.568	$p < 0.0001$
	Status	0.862	0.8	0.609	$p < 0.0005$
	Age	0.863	0.01	0.568	0.22
Hip	VM	0.778	77.8	0.722	$p < 0.0001$
	BMI	0.814	3.6	0.608	$p < 0.0001$
	Gender	0.835	2.1	0.662	$p < 0.0001$
	Status	0.842	0.7	0.649	$p < 0.001$
	Age	0.845	0.1	0.603	0.20
Ankle	VM	0.771	77.1	0.733	$p < 0.0001$
	BMI	0.804	3.3	0.679	$p < 0.0001$
	Gender	0.820	1.6	0.642	$p < 0.0001$
	Status	0.825	0.5	0.671	$p < 0.008$
	Age	0.826	0.1	0.638	0.061

VM, Vector magnitude ($m \cdot s^{-2}$); BMI, Body mass index ($kg \cdot m^{-2}$).
Status, T2D = 1 and healthy = 0; Gender, M = 1 and F = 0.

deconditioning. Unpaired *t*-tests were conducted on personal characteristics and no significant difference was found between subgroups ($p > 0.05$).

3.1. Selection of equation's variables

The results of multiple linear stepwise regressions to predict EE from VM and personal data (gender, age, diabetes status and BMI) for the three attachment sites are presented in Table 2. Weight and height were excluded as potential predictors because of their collinearity with BMI. Age was also removed from the three equations because it proved insignificant with regards to EE variance (0.01 to 0.1%; $p > 0.05$). Vector magnitude of acceleration accounted for 79.6, 77.8 and 77.1% of EE variation ($p < 0.0001$) and BMI contributed to increasing the percentage of explained variance for the CM, hip and ankle equations by 3.8, 3.6, 3.3% ($p < 0.0001$), respectively. Moreover, even if both were significant ($p < 0.0001$), gender and diabetes status explained a small additional percentage of the variance (1.6 to 2.1% for gender and 0.5 to 0.8% for diabetes status).

3.2. Cross-validation

Results of the Monte Carlo cross-validation are shown in Table 3. The three predicted Eqs. (1)–(3) showed comparable mean R^2 and SEE ($R^2 = 0.86$, 0.85, 0.83 and SEE = 0.56, 0.60 and 0.63 $kcal \cdot min^{-1}$ for the CM, hip and ankle equations, respectively).

$$EE_{CM} = -0.818 + 0.53 \times VM + 0.066 \times BMI + 0.299 \times Status + 0.455 \times Gender \quad (1)$$

$$EE_{hip} = -0.763 + 0.491 \times VM + 0.063 \times BMI + 0.282 \times Status + 0.47 \times Gender \quad (2)$$

$$EE_{ankle} = -0.683 + 0.216 \times VM + 0.063 \times BMI + 0.232 \times Status + 0.42 \times Gender \quad (3)$$

where, *VM* ($m \cdot s^{-2}$) represents the mean vector magnitude calculated from a 30s interval, *BMI* ($kg \cdot m^{-2}$) the body mass index, *Status* the diabetic condition with 1 for patients T2D and 0 for healthy person and *Gender* is 1 for man and 0 for woman.

During cross-validation, the three equations presented strong coefficients of determination ($R^2 = 0.85$ for CM equation, 0.83 for hip equation and 0.81 for ankle equation). Results showed that the CM equation slightly overestimated EE in comparison with indirect calorimetry (mean bias = 0.008 $kcal \cdot min^{-1}$; 4.3%), while the hip and ankle equations tended to underestimate it (mean bias = −0.005 $kcal \cdot min^{-1}$; −4% for the hip equation and −0.009 $kcal \cdot min^{-1}$; −4.1% for the ankle equation). RMSE were 0.60, 0.65 and 0.69 $kcal \cdot min^{-1}$ for the CM, hip and ankle equations, respectively.

When comparing all three equations, ANOVA presented no significant effect on mean difference ($p = 0.16$), but did show significant differences in RMSE ($p < 0.001$). The CM equation presented a RMSE significantly lower than hip (mean difference = −0.05 $kcal \cdot min^{-1}$ (95%CI: −0.06 to −0.04 $kcal \cdot min^{-1}$)) and ankle equations (mean difference = −0.085 $kcal \cdot min^{-1}$ (95%CI: −0.09 to −0.07 $kcal \cdot min^{-1}$)). RMSE obtained with hip and ankle equations were significantly different with a mean difference of −0.037 $kcal \cdot min^{-1}$ (95%CI: −0.05 to −0.03 $kcal \cdot min^{-1}$).

Table 3
Regression coefficients for estimating EE with each sensor placement.

Parameter	CM Equation		Hip Equation		Ankle Equation	
	Coefficients (95% CI)	SEE	Coefficients (95% CI)	SEE	Coefficients (95% CI)	SEE
Intercept	−0.818 (−1.61 to −0.02)	0.437	−0.763 (−1.61 to 0.08)	0.337	−0.683 (−1.58 to 0.22)	0.126
VM	0.530 (0.50 to 0.56)	0.014	0.491 (0.46 to 0.53)	0.014	0.216 (0.20 to 0.23)	0.005
BMI	0.066 (0.03 to 0.10)	0.013	0.063 (0.03 to 0.10)	0.014	0.063 (0.03 to 0.10)	0.005
Status	0.299 (0.11 to 0.49)	0.075	0.282 (0.08 to 0.48)	0.080	0.232 (0.02 to 0.44)	0.030
Gender	0.455 (0.26 to 0.65)	0.076	0.470 (0.26 to 0.68)	0.082	0.420 (0.20 to 0.64)	0.030

VM, Vector magnitude ($m \cdot s^{-2}$); BMI, Body mass index ($kg \cdot m^{-2}$); Status, T2D = 1 and Healthy = 0; Gender, M = 1 and F = 0.

4. Discussion

Regular physical exercise is positively associated with health benefits in middle-aged adults, regardless of health status (Nordstoga et al., 2019; Emerenziani et al., 2015). Motion sensor (i.e. accelerometer) may be an objective tool allowing patients to accurately quantify and estimate their daily physical activity in terms of EE, and to promote a healthy lifestyle. The aim of this study was to develop equations from accelerometer data and personal characteristics to estimate EE during static conditions and walking specifically in middle-aged and older adults with and without type 2 diabetes.

Results of the regression calculation support the association between body acceleration and energy expenditure (Bouten et al., 1994; Brandes et al., 2012; Chen and Sun, 1997), with VM of acceleration explaining a major proportion of EE variance (77.1 to 79.6% vs. $\approx$3.5, 2 and 1% for BMI, gender and status, respectively). Our results are consistent with past literature concerning a positive impact of BMI on the walking related EE (Browning et al., 2006; Peyrot et al., 2012), with a 3.5% of explained variance of EE. Gender was also added as an independent variable in multiple regression equations despite no consensus in past literature regarding differences in walking activity EE between gender (Abadi et al., 2010). While there would not appear to be a difference in walking EE among women and men at self-selected speeds, women have a greater walking EE than men at a fixed speed, presumably because of higher step frequency (Wu, 2007). In contrast, our results demonstrated a greater EE in men than in women as observed in Waters and Mulroy (1999). However, gender slightly influenced explained variance ($\approx$2%) and predictive precision (≈ -0.01 kcal·min^{-1} on SEE) (Table 2). Regarding the effect of age on EE, results also differ between studies (Abadi et al., 2010). In the current study, age was not a significant factor in EE variance and it was therefore removed from equations. The specific age group used (middle-aged and older) in the study, which is not broad enough to induce age-related differences in EE may explain this result. Finally, our results were consistent with studies showing a higher metabolic cost for walking in patients with T2D as compared with healthy people (Caron et al., 2018b; Petrovic et al., 2016). Indeed, even if minimal, diabetes status was a significant factor explaining the variation in EE in all three equations (Table 2).

Some previous studies relied on other activity monitors than those used in the current study to predict EE or activity-related EE. Previous studies conducted in our laboratory focused on the validity of Bouten's algorithm in these particular populations to estimate activity EE during walking. Despite a slight underestimation (bias ranging from -0.08 to -0.28 kcal·min^{-1} in healthy middle-aged adults and patients with T2D), no significant difference was found between activity EE estimated by Bouten's algorithm and activity EE measured using indirect calorimetry during walking (Caron et al., 2018a; Caron et al., 2019). In the current study, EE was underestimated only in the hip and ankle equations even though observed mean bias was negligible (-0.005 and -0.009 kcal·min^{-1} for the hip and ankle equations, respectively). Finally, the study conducted by Machac et al. (2013) was interested in comparing EE assessed using SenseWear™ Armband Pro3 and Omron in patients with T2D. These findings revealed that during level walking these two sensors have a tendency to overestimate EE ($>$ 70%). Comparatively, relative bias observed in the current study ranged from -4.1 to 4.3% for level walking.

Our results present clinical relevance for exercise prescription or rehabilitation program. Currently, general guidelines recommend accumulating 30 min of physical activity at moderate intensity, five days per week (Pate et al., 1995). However, energy requirement cannot be adjusted based on these standardized exercise recommendations because the related EE may be different between two patients. However, a more widespread use of the EE as a prescription criterion for physical activity could allow practitioners to optimise beneficial effect of exercise by precisely regulating the patients' daily energy balance. In this purpose, we developed specific prediction equations for estimating EE in middle-aged healthy adults and patients with T2D. These equations can be used mainly for walking which remains one of the most recommended physical activity in both populations.

In the current study, our population was characterised by a wider, more specific age range (representative of middle-aged to older people, i.e. 40–79 yr) and included both normal-weight and overweight participants (BMI, 20.2–29.8 kg·m^{-2}). The large diversity of personal characteristics contributed to improving the accuracy of equations in this age-BMI group but presents limitations for use with younger persons with a better physical condition. The three equations being developed from data obtained during standardized activities (that may differ from free-living conditions), its use is limited to similar activities; e.g. to estimate the EE during an aerobic exercise on treadmill. Nevertheless, because these equations can be implemented in any device measuring acceleration using the International System of Units, they offer an attractive method for EE estimation in both healthy middle-aged individuals as well as those with T2D.

Three regression equations based on accelerometer data (according to three sensor body-placements) and personal data were derived to predict EE during static conditions and walking in a heterogeneous sample of healthy and diabetic middle-aged and older adults. All three equations showed comparable strong correlation and great agreement between estimated and measured EE. Nonetheless, for free-living activities, further studies are needed to validate these equations using a reference method as doubly labelled water to measure related EE.

CRediT authorship contribution statement

Nathan Caron: Methodology, Formal analysis, Investigation, Writing - original draft. **Nicolas Peyrot:** Conceptualization, Methodology, Writing - review & editing, Supervision. **Teddy Caderby:** Methodology, Software, Writing - review & editing. **Chantal Verkindt:** Conceptualization, Investigation, Writing - review & editing. **Georges Dalleau:** Conceptualization, Methodology, Writing - review & editing, Supervision.

Declaration of competing interest

The authors declare that they have no competing interests.

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