TITLE: Validation of the use of Actigraph GT3X accelerometers to estimate energy expenditure in full time manual wheel chair users with Spinal Cord Injury.

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Validation of the use of Actigraph GT3X accelerometers to estimate energy expenditure in full time manual wheelchair users with Spinal Cord Injury.

ABSTRACT

Study Design: cross-sectional validation study.

Objectives: The main goal of this study was to validate the use of accelerometers by means of multiple linear models to estimate the O\textsubscript{2} consumption (VO\textsubscript{2}) in paraplegic persons and, secondary, to determine the best placement for accelerometers on the human body.

Setting: Non hospitalized paraplegics’ community.

Methods: A volunteer sample of participants (n=20, mean age = 40.03 years, mean weight = 75.8 kg and mean height = 1.76 m) completed a series of sedentary, propulsion and housework activities for 10 min each. A portable gas analyzer was used to record breath-by-breath VO\textsubscript{2}. Additionally, four accelerometers (placed on the non-dominant chest, non-dominant waist and both wrists) were used to collect second-by-second acceleration signals. Minute-by-minute VO\textsubscript{2} (ml·kg\textsuperscript{-1}·min\textsuperscript{-1}) collected from minute 4 to minute 7 was used as the dependent variable. A total of 36 features extracted from the acceleration signals were used as independent variables. These variables were, for each axis including the resultant vector, the percentiles 10\textsuperscript{th}, 25\textsuperscript{th}, 50\textsuperscript{th}, 75\textsuperscript{th} and 90\textsuperscript{th}; the autocorrelation with lag of 1
second and three variables extracted from wavelet analysis. The independent variables that were determined to be statistically significant using the forward stepwise method were subsequently analyzed using multiple linear models.

**Results:** The model obtained for the non-dominant wrist accelerations was the most accurate

\[ VO_2 = 4.0558 - 0.0318Y_{25} + 0.0107Y_{90} + 0.0051Y_{ND2} - 0.0061Z_{ND2} + 0.0357VR_{50} \]

with a correlation coefficient of 0.86 and a root mean square error of 2.23 ml·kg⁻¹·min⁻¹.

**Conclusions:** The use of multiple linear models is appropriate to estimate oxygen consumption by accelerometer data in paraplegic persons. The model obtained to the non-dominant wrist accelerometer data improves the previous published models for this population. In addition, the results show that the best placement for the accelerometer is on the wrists.

**Keywords**

Paraplegia, physical activity, signal processing, accelerometer, evaluation methodology
People with spinal cord injury (SCI) adopt sedentary habits as a consequence of their disability. Sedentary habits worsen fitness in persons with SCI compared with their able-bodied peers and, in some cases, these individuals present a higher risk of suffering long-term disorders or malfunctions of their organs and systems.

Physical Activity (PA) protects against such malfunctions or pathologies and is inversely correlated with all-cause mortality. While most of the studies in the literature that have analyzed the relationship between PA and disease prevention have been conducted with able-bodied persons, there are a few epidemiological studies performed in persons with SCI that have shown similar results. For this reason, it is very important to know if persons with SCI who perform a minimum level of PA can avoid disorders associated with a sedentary lifestyle.

To date, most of the studies using able-bodied persons have employed questionnaires to assess PA. This method is inexpensive and easy to administer. Nevertheless, questionnaires present greater subjectivity, and the results depend on the accuracy of the subjects’ memories.

Other methods employed to estimate PA level based on energy expenditure are indirect calorimetry and heart rate monitors. Due to the high price and the difficulty of employing indirect calorimetry measures in a daily scenario
and the low accuracy of heart rate monitoring (during group calibration),
neither option is optimal for PA assessment. Another technology used to assess energy expenditure is accelerometry, which is inexpensive, accurate and could be employed in daily activity. In fact, this technique has been one of the most widely accepted method for assessing PA in recent decades and has been validated in numerous recent studies. Gracias a estos estudios de validación ya han sido publicados algunos trabajos en los que se ha valorado la actividad física en free-living condition mediante acelerómetros in able-body people. In persons with SCI, only a few studies have focused on the relationship between the accelerations and the energy expenditure values. Broadly, these studies present some restrictions. For example, the equations were obtained for a restricted number of daily activities, and consequently, the estimation of the energy expenditure in a real scenario could be biased. Likewise, in most of these previous studies, the authors chose integration epochs of 1 minute, which implies having only one feature for the estimation of minute-to-minute energy expenditure.

On the other hand, the placement location is a critical point to estimate energy expenditure from accelerometer. There are studies in persons with disabilities (e.g., multiple sclerosis or chronic obstructive pulmonary disease) that investigate the best placement location. This topic should...
be investigated in spinal cord injured people due to their restricted patterns of movements.

Therefore, the main goal of this study is to validate the use of accelerometers by means of multiple linear models (MLM) to estimate the $O_2$ consumption ($VO_2$) in paraplegic persons. Furthermore, this study also aims to determine the best placement of the accelerometer on the human body to obtain the best possible estimation.

MATERIALS AND METHODS

Participants

A consecutive non-randomized sample of twenty subjects whose age, weight and height, in mean (SD), were 40.03 (10.57) years, 75.8 (17.54) kg and 1.76 (0.09) m, respectively, participated in the study. The participants were recruited from the Hospital la Fe of Valencia and from the Asociación Provincial de Lesionados Medulares y Grandes Discapacitados (ASPAYM). These subjects were selected using the following inclusion criteria: i. spinal injury between T2 and L5 and diagnosed one year before beginning study participation, ii. full time wheelchair users and iii. completely lost motor ability in their lower extremities (50/100 in ASIA impairment scale). The cause of the injury was traumatic in fifteen of the participants, tumoral in two subjects, iatrogenic in one case, and due to multiple sclerosis and congenital sclerosis in two more cases.
Subjects were excluded if they presented depressive or cognitive disorders; suffered from posttraumatic cervical myelopathy, motor or sensory impairment of the upper extremities, ischemic heart disorder, or recent osteoporotic fractures; had been tracheotomized; or presented sacrotuberous ulcers or hypertension. All subjects gave written consent to participate in the study (approved by the ethical committee of the University of Valencia). We certify that all applicable institutional and governmental regulations concerning the ethical use of human volunteers were followed during the course of this research.

Data collection

All subjects completed a routine of ten activities: lying down, body transfers, moving items, mopping, working on a computer, watching TV, arm-ergometer exercise, passive propulsion, slow propulsion and fast propulsion. These activities of daily living were selected with the objective of having a wide range of intensities of PA and being typical for manual wheelchair users (Table 1). The subjects carried out each activity for 10 minutes with 1-2 minutes of rest between activities. There was only one exception corresponding to the activity of body transfers. In this case, the subjects carried out the activity for one minute and rested for another minute for a total of ten minutes. The transfer task was configured in this way to avoid an overload of the musculoskeletal system in the shoulders.
During each activity, VO$_2$ was monitored with Cosmed K4b$^2$ portable (Cosmed, Rome, Italy) gas analysis system. The calibration and placement of the device took into account instructions provided by the manufacturer. This device has been broadly employed as criterion to validate accelerometers. Macfarlane$^{22}$ published a manuscript about the validity and reliability of different systems to measure the VO$_2$ where the readers can check this data for the Cosmed K4b$^2$. The subjects wore four accelerometers (Actigraph model GT3X, Actigraph, Pensacola, FL, USA): one on each wrist, one on the waist (above the non-dominant anterior superior iliac crest) and the last in the chest (below the non-dominant armpit at the height of the xiphoid apophysis) (Figure 1). The Actigraph was initialized using 1-second epochs, and the time was synchronized with a digital clock so the start time could be synchronized with the gas analyzer.

**Signal processing**

The Matlab R2010a (Mathworks Inc, Natick, USA) program was used to the preprocessing, segmentation and feature extraction from the signals. The VO$_2$ signal was preprocessed using averaged blocks of thirty seconds. The time interval between the start of minute 4 and the end of minute 7 was selected. The VO$_2$ expressed in ml·kg$^{-1}$·min$^{-1}$ was calculated for each of these minutes. The segmentation of the signals was similar to previous works and confirmed that steady-state VO$_2$ was reached $^{23}$. The VO$_2$ for
each of the selected minutes was used as the dependent or output variable in
the designed models.

The outputs from accelerometers (counts·s$^{-1}$) were used to obtain predicting
variables. Counts are a unit of acceleration used broadly in this topic that
represents the amount of acceleration between two consecutive levels of
quantization during the analogical-to-digital conversion. We obtained nine
total variables for each axis (i.e. X, Y, Z and resultant vector) in minutes
number four, five, six and seven of each activity. These variables
correspond to features that have been extracted from the time domain and
from the Discrete Wavelet Transform (DTW) of the signal. In the time
domain, the 10$^{th}$, 25$^{th}$, 50$^{th}$, 75$^{th}$ and 90$^{th}$ percentiles were calculated.
Furthermore, as a measurement of the temporal dynamics, the lag-one
correlation of each minute was calculated.$^{23}$

Finally, three variables were included as a result of the DWT. To present the
experimental information in a compressed and arranged format, we have
analyzed the signal with multiresolution analysis based on wavelet
transform.$^{24,25}$ The signal was sampled up to two levels of decomposition
using the Daubechies 2 mother wavelet. We calculated the Euclidean norm
of the three vectors corresponding to the detail coefficients of the first and
second levels of resolution and the approximation coefficients of the second
level (i.e. ND$_1$, ND$_2$, NA$_2$). These variables were also included in our
analysis (all the descriptive parameters can be seen in the supplementary file).

Mathematical models

We obtained a MLM for each of placement location. We only used statistically significant features determined by the forward stepwise method.

The dependent variable was the consumption of VO$_2$ in every minute (i.e., 800 values in total). The validation of the model was determined by 20-fold cross-validation. For every model, we computed the following statistical parameters: mean square error (MSE), mean absolute error (MAE), root mean square error (RMSE) and the coefficient of correlation ($r$). Moreover we calculate the mean error and the percentage error between the estimation and the VO$_2$ measured by K4b$^2$ for the validation data. Moreover, t-student test for related samples were performed to establish significant differences between criterion and estimate VO$_2$ values. The level of significance was set at $p=0.05$. 
From the analysis of our data, we obtained four linear models with multiple independent variables, one model for each placement location. The models for the waist and the chest have 18 and 11 independent variables, respectively. Due to the large number of independent variables and poor performance of the waist and chest models compared to those corresponding to each wrist, these equations have been included in a supplementary file.

Model 1 (equation 1) corresponds to the data obtained from the dominant wrist, while model 2 (equation 2) corresponds to the data obtained from the non-dominant wrist.

\[
\begin{align*}
VO_2 &= 4.1355 + 0.0376X_{50} - 0.0155X_{90} - 0.0047X_{NA_1} \\
&+ 0.0062X_{ND_1} + 0.02Z_{75} - 0.0363Z_{90} + 0.0161VR_{75} + 0.253VR_{90} \\
\end{align*}
\]

Eq. 1

\[
\begin{align*}
VO_2 &= 4.0558 - 0.0318Y_{25} + 0.0107Y_{90} \\
&+ 0.0051Y_{ND_2} - 0.0061Z_{ND_2} + 0.0357VR_{50} \\
\end{align*}
\]

Eq. 2

In these equations, capital letters X, Y and Z represent axes, the sub-indexes represent variables, and VR is the resultant vector. The sub-indexes 25, 50, 75 and 90 are percentiles, and for the variable J, the symbol \( J_i \) for \( i = 25, 50, 75, 90 \) denotes the value of the \( i \)-th percentile of the variable J. The norm of the vector of the approximation coefficients in the first level in DWT is denoted by \( NA_1 \), the norm of the vector of the detail coefficients in the first
level by ND_{1}, and the norm of the vector of the detail coefficients in the
second level by ND_{2}. It can be noted that equation 2 has five independent
variables, while equation 1 has eight.

The models corresponding to both wrists provide a good estimate of VO_{2}.
The predictions obtained using the accelerometers corresponding to the
chest and waist were not very accurate (table 2).

In Figure 2, we show dispersion and Bland-Altman plots for each of the
models established. In each case analyzed, no systematic error is observed,
but the residuals obtained in the models for the waist and the chest are large
(i.e., wider range between ±2 standard deviations).

Additionally, in each of the Bland-Altman plots, there is a tendency to
underestimate VO_{2} for values larger than 20 ml·kg^{-1}·min^{-1}. This tendency is
less pronounced for the model corresponding to the non-dominant wrist.
Moreover, when we analyzed the activity error expressed as a percent, the
relative values obtained were all lower than 20% for the model of the
dominant and non-dominant wrist (table 3).

**DISCUSSION**

The fitting models obtained in the present study improve on the data
previously published related to the assessment of PA in paraplegic subjects
by means of accelerometry. This improvement can be seen in both the
achievement of a stronger correlation between the estimation of VO_{2} and
the measured value and a lower prediction error for the activities evaluated.

We interpret these data to be the result of our use of 1-second epochs for the acquisition of acceleration data.

To the best of our knowledge, there are few studies that have estimated the energy expenditure in persons with paraplegia by means of movement sensors, and most of these studies have used 1-minute epochs of accelerometry data. The current study aimed to improve this aspect by including statistical parameters about count distribution during each minute through the acquisition of 1-second epochs. Due to this amount of data (60 per minute), we can perform a feature extraction process and, as a consequence, obtain several variables with relevant information for the estimation of the energetic expenditure.

Moreover, performing 10 different tasks that are representative of daily living provides a wide variety of motion patterns. This variety gives greater consistency to the estimation method obtained. Previous studies only performed sedentary tasks, propulsion by wheelchair and arm-ergometer exercise. Therefore, the estimation methods employed could be insufficient for the assessing of different motion patterns (e.g., transfers, mopping).

Of the models generated in our study those of the wrists were more accurate as are expressed by their MAE, MSE, RMES and Pearson coefficients. Moreover the percentage error for each activity was lower for wrists models than for chest and waist equations. This can be due to the reduced mobility
of the chest and waist of people with SCI. This fact could uncorrelated the accelerations of these locations with the intensity of the activity.

Regarding the VO$_2$ values obtained with the gas analyzer from the participants performing the tasks, the data were confirmed to be similar to those provided in previous studies. In the slow propulsion task the consumption measured in our work (i.e., 7.42 ml·kg$^{-1}$·min$^{-1}$) was almost identical to previous values reported (i.e., 7.35-7.4) when the task was executed at a rate of 4.8-4.9 km·h$^{-1}$.

Similar results were also observed in previous studies for other tasks, such as working on a computer, watching TV and moving items.

Regarding arm-ergometer exercise, we obtained a value of 14.83 ml·kg$^{-1}$·min$^{-1}$, and we have found values from 7.66 to 20.55 ml·kg$^{-1}$·min$^{-1}$ in the previous literature, depending on the power developed and the level of the SCI.

The first paper that tried to establish regression equations to estimate the VO$_2$ in persons with SCI through accelerometry was written by Washburn and Copay in 1999. They obtained a simple linear equation using the accelerations of the non-dominant wrist with an SEE of 4.99 ml·kg$^{-1}$·min$^{-1}$.

Furthermore, they could explain 44% of the variability of the VO$_2$ using the counts·min$^{-1}$. Comparing these results with those obtained with the general linear model employed in our study, we can observe some improvements. It is important to note that the estimation errors and r-value depend on the
number and type of activities performed to acquire the data use in the validation. Nevertheless to compare between estimators we only have this parameters since are commonly reported in the validation studies. The RMSE in our work is $2.23 \text{ ml kg}^{-1} \text{ min}^{-1}$, and the determination coefficient has a value of 0.74. In view of these results work, we found that the use of methodologies that maximize the data available for the estimation of VO$_2$ can provide general linear models that have better accuracy.

Recently, Hiremath and Ding$^{17}$ developed a new equation based on a MLM that was designed using 19 individuals and tested on another 4 for validation. Acceleration data were obtained from the left arm, and indirect calorimetry was employed as a reference measurement during the performance of a limited routine of activities. With the data used to develop the equation (the fitting data set), the authors found an SEE of 1.02 kcal·min$^{-1}$ ($2.55 \text{ ml kg}^{-1} \text{ min}^{-1}$ approximately) and a $r^2$ of 0.7. Although these authors improved on preexisting models, the estimation was not as accurate as those models for persons without disabilities. This discrepancy was due to the considerable percentage of error observed for the validation data; this error ranged from 14.12% for arm-ergometer exercise (at 40 W and 90 rpm) up to 113.68% for the resting task.

The MLM of the non-dominant wrist designed in our study have shown values of RMSE and $r^2$ similar to those obtained in previous studies. However, the percentage of error in each of the activities is lower, and there
is less dispersion between activities. Moreover, the minimum and maximum
error obtained were 0.67% and 18.68%, respectively. For this reason, the
MLM applied in this study provides a methodological improvement for the
description of the VO$_2$ in persons with SCI. In our case, the model for
persons with paraplegia showed similar estimation errors than the models
corresponding to persons without disabilities such as the 2-regression model
$2^8$ or ANN based models $^{23}$ (although these models were designed with more
activities than our model).

The present study does have some limitations. First, although the
participants performed a wide range of activities, there are additional
activities that should be assessed in future studies (e.g., sports activities as
basketball or household activities as washing dishes). Due to the difficulty
in recruiting individuals with SCI and the significant administrative burden
in the application of all of the protocols, it was not possible to extend the
number of tasks executed. In this sense could be interesting to increase also
the number of subjects for account with more inter-subjects variability and
therefore improve the robustness of the estimator. Acceleration data have
been recorded in counts·s$^{-1}$; raw acceleration data in m·s$^{-2}$ would provide
more information and therefore a more accurate estimation. Nevertheless we
chose 1sec epochs for the memory limitation of the GT3X.

In conclusion, MLM that employ feature extraction from accelerometer
signals measured in counts·s$^{-1}$ can be used to obtain accurate estimations of
the VO$_2$ in paraplegic persons. Furthermore, it has been demonstrated that in this population, it is possible to record data from either wrist, although there are some benefits of using the non-dominant wrist (i.e., fewer predictive variables and slightly better parameters of performance).

The results of our study could be used to understand PA level in SCI and guide future descriptive studies in this population. The results presented in this work can contribute to identifying patients who are at risk of suffering problems related to a sedentary lifestyle.
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CONFLICT OF INTEREST.

The authors declare no conflict of interest.
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### Table 1. Activity routine

<table>
<thead>
<tr>
<th>Order</th>
<th>Activity</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Lying down</td>
<td>Lying in the lateral decubitus position</td>
</tr>
<tr>
<td>2</td>
<td>Body transfers</td>
<td>Self-shifting the bodyweight from one side to the other using a stretcher (simulating body transfers)</td>
</tr>
<tr>
<td>3</td>
<td>Moving items</td>
<td>Loading and transferring boxes with different weights between shelves placed on opposite sides of the laboratory</td>
</tr>
<tr>
<td>4</td>
<td>Mopping</td>
<td>Simulation of mopping housework throughout the laboratory</td>
</tr>
<tr>
<td>5</td>
<td>Watching TV</td>
<td>Viewing of different television programs</td>
</tr>
<tr>
<td>6</td>
<td>Working on computer</td>
<td>Simulation of personal computer work using a word processing program and the internet</td>
</tr>
<tr>
<td>7</td>
<td>Arm-ergometry exercise</td>
<td>Performance of an ergometer work sequence with an intensity corresponding to a perception of 8 points based on the OMNI-Res perception scale</td>
</tr>
<tr>
<td>8</td>
<td>Passive propulsion</td>
<td>Propulsion of the individual by the researcher</td>
</tr>
<tr>
<td>9</td>
<td>Slow propulsion</td>
<td>Self-propulsion of the wheelchair over the floor at a moderate speed</td>
</tr>
<tr>
<td>10</td>
<td>Fast propulsion</td>
<td>Fast self-propulsion of the wheelchair over the floor</td>
</tr>
</tbody>
</table>
Table 2. General linear model efficiency of the four accelerometers.

<table>
<thead>
<tr>
<th>Location</th>
<th>Data</th>
<th>$r$</th>
<th>MSE</th>
<th>MAE</th>
<th>RMSE</th>
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</thead>
<tbody>
<tr>
<td>Waist</td>
<td>Fit</td>
<td>0.64</td>
<td>11.33</td>
<td>2.47</td>
<td>3.32</td>
</tr>
<tr>
<td></td>
<td>Validation</td>
<td>0.67</td>
<td>10.61</td>
<td>2.39</td>
<td>3.26</td>
</tr>
<tr>
<td></td>
<td>All</td>
<td>0.67</td>
<td>10.65</td>
<td>2.39</td>
<td>3.26</td>
</tr>
<tr>
<td></td>
<td>Fit</td>
<td>0.66</td>
<td>10.80</td>
<td>2.45</td>
<td>3.26</td>
</tr>
<tr>
<td>Pan</td>
<td>Validation</td>
<td>0.68</td>
<td>10.41</td>
<td>2.41</td>
<td>3.23</td>
</tr>
<tr>
<td></td>
<td>All</td>
<td>0.68</td>
<td>10.43</td>
<td>2.41</td>
<td>3.23</td>
</tr>
<tr>
<td></td>
<td>Fit</td>
<td>0.85</td>
<td>5.32</td>
<td>1.69</td>
<td>2.28</td>
</tr>
<tr>
<td>Dominant wrist</td>
<td>Validation</td>
<td>0.86</td>
<td>5.16</td>
<td>1.67</td>
<td>2.27</td>
</tr>
<tr>
<td></td>
<td>All</td>
<td>0.86</td>
<td>5.16</td>
<td>1.67</td>
<td>2.27</td>
</tr>
<tr>
<td></td>
<td>Fit</td>
<td>0.86</td>
<td>5.08</td>
<td>1.66</td>
<td>2.23</td>
</tr>
<tr>
<td>Non-dominant wrist</td>
<td>Validation</td>
<td>0.86</td>
<td>4.98</td>
<td>1.65</td>
<td>2.23</td>
</tr>
<tr>
<td></td>
<td>All</td>
<td>0.86</td>
<td>4.98</td>
<td>1.65</td>
<td>2.23</td>
</tr>
</tbody>
</table>

$r=\text{coefficient of correlation}, \text{ MSE}=\text{mean square error}, \text{ MAE}=\text{mean absolute error}, \text{ RMSE}=\text{root mean square error}. \text{ Fit corresponds with the data set used to adjust the model. Validation corresponds with the data set used to validate the model. All corresponds with fit and validation data sets together.}$