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## Using accelerations of single inertial measurement units to determine the intensity level of light-moderate-vigorous physical activities: Technical and mathematical considerations

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1 **Title :** Using accelerations of single inertial measurement units to  
2 determine the intensity level of light-moderate-vigorous physical  
3 activities: technical and mathematical considerations

4

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13 Abstract (181 words)

14 Quantifying physical activity and estimating the metabolic equivalent of tasks based on inertial  
15 measurement units has led to the emergence of multiple methods and data reduction approaches  
16 known as physical activity metrics. The present study aims to compare those metrics and reduction  
17 approaches based on descriptive and high order statistics. Data were obtained from 147 young  
18 healthy subjects wearing inertial measurement units at their wrist or ankle during standing, walking  
19 and running, labeled as light, medium or vigorous activities. The research question was, first, if those  
20 metrics allowed differentiating between light, moderate, and vigorous physical activities, and,  
21 secondly, what was the relationship with the metabolic equivalent of the task performed. The results  
22 showed that each metric differentiated the level of activity and presented a high correlation with the  
23 metabolic equivalent of the task. However, each metric and data reduction approach demonstrated  
24 its specific statistical characteristics related to the localization of the sensors. Our findings also  
25 confirm the absolute necessity to detail explicitly all calculus and post processing of metrics in order  
26 to quantify the level of activity by inertial measurement units.

27 Key words : Physical activity; gait; run; IMU; Wearable inertial sensor; motion capture;  
28 biomechanics;

29 **Main text** (3498 words)

### 30 **Introduction**

31 Physical activity improves the general well-being (Kubota et al. 2017). However, for an efficient  
32 physical activity program, the optimal physical activity intensity has to be determined. Planning  
33 adequate physical activity and then prescribing an optimal intensity for those is a challenge for health  
34 care policies (WHO, 2010). The relevance of on-body sensors to monitor physical activity is well-  
35 established (Marschollek et al. 2016) and inertial measurement units (IMUs) have become a popular  
36 technical solution (Rault et al. 2017) within their constraints (Kerr et al. 2017).

37 Although multiple studies have dealt with physical activity monitoring (Marin et al. 2016), there has  
38 been little investigation of the mathematical and technical rationale regarding the methodology used  
39 to establish the correspondence between the inertial sensors signal (commonly acceleration) and the  
40 physical activity measure itself. The technical rationale or the mathematical background are most of  
41 the time superficial, not demonstrated and, in most cases, only a final output without any technical  
42 background is provided. In addition, as far as the technical implementation is concerned, there is no  
43 consensus as to sensor placement or input data prerequisites (Nez et al. 2018). Often various  
44 positions are suggested for the use of the sensor (Storm et al. 2015) even though the hip is already  
45 recognized as providing better results than the wrist (Cleland et al. 2013). Hardware heterogeneity  
46 (Storm 2015) is another well-known issue, potentially causing different results (Nez et al. 2016). An  
47 example is the varying sampling rate according to the hardware of the sensor (Yang 2010) and the  
48 difference between continuous and intermittent data collection. Some recent studies have  
49 demonstrated the influence of sampling frequency on PA estimation (Brønd et Arvidsson, 2016).

50 Regarding the mathematical background, the most common outputs are “activity count”, identified  
51 over a specific period of time (Yang et al. 2010). However, the exact calculation of such parameters is  
52 often missing, and leaves room for speculation. Most of the time, this activity count derives from  
53 acceleration measurements of the IMU and analytical approaches have been proposed (Chen et al.  
54 2005). The acceleration signal is rectified and integrated by a user-defined epoch. An “activity” is  
55 counted once the resulting signal exceeds a certain threshold. However, this threshold is often  
56 undocumented.

57 To quantify movement performance various metrics based on IMU have been proposed in the  
58 literature (Lepetit et al. 2019). Some are easy to determine, such as the vector magnitude minus one

59 (Van Hees 2013 ), others, however, require numerous calculi (Fradet et al. 2016). After this metric  
60 computation, regression equations are proposed to estimate energy expenditure (Rothney et al.  
61 2010) or cut-points are proposed for sedentary time and physical activity intensity classification  
62 (Migueles et al. 2017). The level of activity as “light”, “moderate” or “vigorous” is based on Metabolic  
63 Equivalent of Task (MET) (Ainsworth 2011) even though the relationship between IMU based metrics  
64 and MET is questionable (Yang et al. 2010).

65 Previous elements showed that the use of a single IMU to qualify and classify the intensity of physical  
66 activity did not find consensus in terms of set up and mathematical rationale for IMU deduced  
67 metrics. Consequently, IMU’s users are faced with multiple options to place the IMU on the body as  
68 well as with various calculations to score the level of activity. In addition, in some propriety systems,  
69 this calculation is hidden. In this context, the aim of this paper is (i) to provide direct comparison of  
70 the efficiency of various IMU deduced metrics according to IMU localization to quantify and  
71 differentiate light-moderate-vigorous physical activities, and (ii) to assess the relationship between  
72 those metrics and the MET.

### 73 **Material and Methods**

74 147 participants (108 females and 39 males; age: 21.0 years (SD 2.0 y.), body mass index: 21.7 kgm<sup>-2</sup>  
75 (SD 2.6 kgm<sup>-2</sup>) voluntarily participated in the experiment after signing a statement of informed  
76 consent pertaining to the experimental procedure as required by the Helsinki declaration. Data were  
77 collected (figure 1) in two sessions: one when the IMU (Opal, APDM) was located at the wrist and the  
78 second one when the IMU was located at the ankle. All sensors were calibrated before each session  
79 to avoid sensor drift or offsets according to the manufacturer’s procedure. The sample rate was 128  
80 Hz. Participants were asked to maintain a standing posture for 2 minutes, followed by self-pace  
81 walking (466 m), followed by another 2 minutes standing, followed by a self-pace run over (700 m).  
82 The session ended in a quiet standing position.

83 According to the physical activity classification (WHO 2010), the standing position was defined as  
84 light physical activity (L), walking as moderate physical activity (M) and running as a vigorous one (V).  
85 In order to individually quantify the level of the physical activity, the corrected MET was computed  
86 according to the physical activity, age, gender, height, weight and the locomotion speed (Ainsworth  
87 et al. 2011).

88 The post processing of the IMU’s measurements was computed in five steps and this study focuses  
89 specifically on the accelerometer data (Figure 2):

90 *a) Accelerations deduced from IMU’s measurements*

91 According to the hardware of the sensors, IMU measurements are finite data with a frequency of  $f$   
 92 herz . Consequently, if the session time is  $T$  in seconds, we obtained data with  $n$  measurements (eq.  
 93 1).

$$n = T \cdot f \quad (\text{eq. 1})$$

94 In a second step, three different accelerations were computed: raw accelerations, IMU accelerations  
 95 and body accelerations.

96 The raw sensor acceleration data is expressed in the reference frame of the sensor, named  $\overrightarrow{a_{raw}}$  at  
 97 each measure  $i \in [1, n]$  , it corresponds to a vector in  $\mathbb{R}^3$  according to the values on the 3 axis of the  
 98 sensors in the case of 3D accelerometers (eq. 2).

$$\overrightarrow{a_{raw}(i)} = [ax_{raw}(i) \quad ay_{raw}(i) \quad az_{raw}(i)] \quad (\text{eq. 2})$$

99 As the sensor is an inertial measurement unit including a 3D gyroscopes and a 3D magnetometers it  
 100 is possible to determine the orientation matrix  $\mathbf{R}_{Lab}^{Sensor}(i)$  For each measure  $i$  describing the  
 101 orientation of the IMU relative to the laboratory frame using data fusion algorithms (Nez et al 2018).  
 102 The accelerations were then expressed in the laboratory reference frame  $\overrightarrow{a_{IMU}}$  (eq. 3). Classically, the  
 103 x axis and y axis of the laboratory are in the horizontal plane and the z axis is vertical (eq. 4).

$$\overrightarrow{a_{IMU}(i)} = \mathbf{R}_{Lab}^{IMU}(i) \overrightarrow{a_{raw}(i)} \quad (\text{eq. 3})$$

$$\overrightarrow{a_{IMU}(i)} = [ax_{IMU}(i) \quad ay_{IMU}(i) \quad az_{IMU}(i)] \quad (\text{eq. 4})$$

104

105 Due to the microelectromechanical components, the measure of the acceleration includes the  
 106 acceleration of the rigid body (i.e. the IMU) and the gravity (Tamura 2014). Accordingly the z axis of  
 107 the laboratory reference frame is vertical such as the gravitational component  $g$  ( $1 g = 9.806 \text{ ms}^{-2}$ )  
 108 can be subtracted ( eq. 5 ). We deduced then the acceleration of the rigid body in the laboratory  
 109 reference frame, named  $\overrightarrow{a_{body}}$  ( eq. 6 )

$$\begin{aligned} \overrightarrow{a_{body}(i)} &= \overrightarrow{a_{IMU}(i)} - g\vec{z} \\ &= [ax_{IMU}(i) \quad ay_{IMU}(i) \quad az_{IMU}(i) - g] \quad (\text{eq. 5}) \end{aligned}$$

$$\overrightarrow{a_{body}(i)} = [ax_{body}(i) \quad ay_{body}(i) \quad az_{body}(i)] \quad (\text{eq. 6})$$

110

111 *b) Physical activities metrics calculation*

112 To quantify the intensity of physical activities at each  $i$ -th measurement, various parameters deduced  
 113 from the accelerations previously obtained are proposed in the literature.

114 Van Hees (2013) and Hildebrand (2014) proposed the "vector magnitude minus one" named  
 115  $ENMO(i)$  (eq. 7).

$$ENMO(i) = \sqrt{ax_{raw}(i)^2 + ay_{raw}(i)^2 + az_{raw}(i)^2} - g \quad (eq. 7)$$

116

117 Vähä-Ypyä (2015) proposed to compute the "amplitude deviation" named  $AD(i)$  (eq 8).

$$AD(i) = \left| \sqrt{ax_{raw}(i)^2 + ay_{raw}(i)^2 + az_{raw}(i)^2} - \frac{1}{n} \sum_{j=1}^n \sqrt{ax_{raw}(j)^2 + ay_{raw}(j)^2 + az_{raw}(j)^2} \right| \quad (eq. 8)$$

118 Based on  $\overrightarrow{a_{body}(i)}$ , Taruma (2014) suggested the use of the "vertical acceleration", named  $VA(i)$   
 119 (eq. 9).

$$VA(i) = az_{body}(i) \quad (eq. 9)$$

120 VanHees (2011) identified the "vector magnitude" of the acceleration named  $VM(i)$  (eq.10) as an  
 121 indicator of the intensity of the physical activity.

$$VM(i) = \sqrt{ax_{Body}(i)^2 + ay_{Body}(i)^2 + az_{Body}(i)^2} \quad (eq.10)$$

122

123 Chen (1997) suggested a direct estimation of the energy expenditure named  $EEact(i)$  (eq. 11) based  
 124 on the magnitude of the horizontal acceleration and vertical acceleration.

$$EEact(i) = a_N \left( \sqrt{ax_{Body}(i)^2 + ay_{Body}(i)^2} \right)^{p1} + b_N \left( az_{Body}(i) \right)^{p2}$$

with,

$$p1 = \frac{2.66M_{subject} + 146.72}{1000}$$

$$p2 = \frac{-3.85M_{subject} + 968.28}{1000}$$

$$a_N = \frac{12.81M_{subject} + 843.22}{1000}$$

, for female subjects

$$b_N = \frac{38.90M_{subject} - 672.38}{1000}$$

, and for male subjects

$$b_N = \frac{38.90M_{subject} - 10.06}{1000}$$

(eq. 11)

125

126 ( $M_{subject}$  is the mass of the subject in kg)

127 At this stage, five PA metrics are available; ENMO, AD, VA, VM and EEact which are  $\mathbb{R}^n$  vectors were  
 128 defined as indicators of the level of physical activity based on accelerations measured or deduced by  
 129 IMU. The metric  $M_{PA}$  is one of the five PA metrics:  $M_{PA} \in \{ ENMO, AD, VA, VM, EEact \}$

130 For each subject (S), and for the wrist (W) and ankle session (A), sensor data were segmented to  
 131 extract the metric  $M_{PA}$  from L, M and V physical activity (Fradet et al 2016). At this stage,  $M_{PA}$  is a  $\mathbb{R}^n$   
 132 vectors. In addition,  $n$  is subject dependent because duration walking and running sessions were self-  
 133 paced.

134 Hammerla (2013) suggest analyzing the quantile function of the metric  $M_{PA}$ . The quantile function  
 135  $f_Q(c)$  is defined as the inverse of the empirical cumulative distribution.  $f_Q(c)$  is a strict  
 136 monotonically increasing function which associates a cumulative probability  $c$  from zero to one with  
 137 the level of the value of the metric  $M_{PA}$  ( Gilchrist 2000 ). Consequently,  $c = 0$  would be associated  
 138 with  $min(M_{PA})$  , and  $c = 1$  with  $max(M_{PA})$  (figure 4). Then,  $f_Q(c)$  was linearly interpolated (0 to 1  
 139 with a step of 0.1). We obtained discrete quantile function  $Q_{M_{PA}}$  as  $\mathbb{R}^{101}$  vector for a metrics  $M_{PA}$   
 140 associated at a subject, a sensor localization and session.

#### 141 *c) Data reductions*

142 Data reduction consist in reducing data dimension. It consisted in reducing  $M_{PA}$  which is  $\mathbb{R}^n$  vectors  
 143 to  $\mathbb{R}^m$  vector with  $m < n$ .

144 Usually in literature, data reduction of a metric  $M_{PA} \in \mathbb{R}^n$  to a single value in  $\mathbb{R}$  is concerned,  
 145 authors suggest to determine the mean value (MEAN) (Vähä-Ypyä 2015) and the root mean square  
 146 (RMS) value (Taruma 2014).

147 For the data reduction of a quantile function, L-moments method as higher order descriptive  
 148 statistical tool is used (Karvanen 2005) and computed as follows: First,  $\lambda$ -coefficients and L-moments  
 149 are computed with numerical integration performed by rectangle rule.

$$\lambda_1 = \int_0^1 f_Q(c) dc \approx \sum_{j=1}^{101} Q_{M_{PA}} \quad (eq. 14)$$

$$\lambda_2 = \int_0^1 (2c - 1)f_Q(c) dc \approx \sum_{j=1}^{101} \left(2 \left(\frac{j-1}{101}\right) - 1\right) Q_{M_{PA}} \quad (eq. 15)$$

$$\lambda_3 = \int_0^1 (6c^2 - 6c + 1)f_Q(c) dc \approx \sum_{j=1}^{101} \left(6 \left(\frac{j-1}{101}\right)^2 - 6 \left(\frac{j-1}{101}\right) + 1\right) Q_{M_{PA}} \quad (eq. 16)$$

$$\begin{aligned} \lambda_4 &= \int_0^1 (30c^3 - 30c^2 + 12c - 1)f_Q(c) dc \\ &\approx \sum_{j=1}^{101} \left(30 \left(\frac{j-1}{101}\right)^3 - 30 \left(\frac{j-1}{101}\right)^2 + 12 \left(\frac{j-1}{101}\right) - 1\right) Q_{M_{PA}} \end{aligned} \quad (eq. 17)$$

150

151 L-moments analogous to the coefficient of variation (CV), the skewness of the distribution and the  
152 coefficient of kurtosis could be deduced (Karvanen 2005):

$$L_{CV} = \frac{\lambda_2}{\lambda_1} \quad (eq. 18)$$

$$L_{skewness} = \frac{\lambda_3}{\lambda_2} \quad (eq. 19)$$

$$L_{kurtosis} = \frac{\lambda_4}{\lambda_2} \quad (eq. 20)$$

153

154 *d) Statistics analysis*

155 First, the Kolmogorov-Smirnov tests were performed on all data reductions. All null hypotheses of a  
156 standard normal distribution at the 5% significance level were rejected. It motivated to do the  
157 Kruskal-Wallis test, a non-parametric version of the classical one-way ANOVA to compare data  
158 between each other.

159 Then, a Kruskal-Wallis test between the data reductions (MEAN, RMS, L-CV, L-Skewness and L-  
160 Kurtosis) of the metric  $M_{PA}$  of a single localization (wrist or ankle) was performed to compare the  
161 significant difference between the level of activity. A  $p$ -values of less than 0.001 were rejected as the  
162 null hypothesis. The null hypothesis is defined when median values of the data reduction of the  
163 metric  $M_{PA}$  for L and M levels, or, for M and V levels of physical activity are equal.

164 To quantify the similarity of the inter-subject of the quantile curves, the coefficient of multi  
165 correlation (CMC) on the quantile functions  $Q_{M_{PA}}$  of all parameters for all subjects and for each  
166 physical activity and sensor's positions was computed in order to analyze the inter-subject reliability  
167 of this analysis (Kabada 1989). CMC scores the similarity between curves by a value between 0 (very  
168 different) to 1 (very similar) (Kabada 1989).

169 Finally, the relationship between data reductions MEAN and RMS and MET values of the subject was  
170 investigated by a linear regression model with a robust linear least mean square method. The  
171 relevance of the linear regression model by the coefficient of determination  $R^2$  was reported (Draper  
172 1998). All computation and statistics analyses were performed in Matlab (R2016a, The Mathworks  
173 Inc, Natick, MA).

## 174 **Results**

175 Based on the Kruskal-Wallis test, we noticed no significant difference between the wrist and ankle  
176 sensor for the mean values of the ENMO, the RMS values of the ENMO and AD metrics for only for  
177 the light physical activities (Figures 3). Consequently, for all other parameters, we noticed a  
178 significant difference according to the localization of the sensor and the level of the physical activities  
179 (Figure 3). When the sensor is located on the wrist, we noticed that the box plots for all data  
180 reductions during light and moderate activities were close, which means that ranges of data  
181 reductions for light activity were close to that during a moderate one. These observations presented  
182 a lower differentiation ability. On the contrary, box plots for data reductions during vigorous activity  
183 were more clearly separated from those occurring during light and moderate ones, which suggests  
184 that vigorous level of physical activity could easily be differentiated.

185 For the quantile function of all metrics (Figure 4), we found a CMC value from 0.74 to 0.98 which  
186 demonstrated as a good to very good inter-subject reliability (Rezgui et al 2013). The values of less  
187 than 0.80 were obtained for a light level of physical activity at the wrist localization for the AD, VM  
188 and EEact metrics and at the ankle localization for the VA and EEact metrics. High level of CMC ( $>$   
189 0.9) for the three levels of activity were obtained for the quantile function of the metrics ENMO  
190 when the sensor is located at the wrist or ankle, and only for the ankle localization for the quantile  
191 function of metrics AD, VA and VM at moderate and vigorous physical activities.

192 Figure 5 showed results for L-CV, L-Skewness and L-Kurtosis of the quantile function of all metrics.  
193 We noticed no significant difference between the wrist and ankle sensor for the L-CV of VA and EEact  
194 at light activity, and for L-Skewness of VM and L-Kurtosis of ENMO and EEact at vigorous activity .  
195 We also found no significant difference between the light and the moderate activities for the L-CV of

206 ENMO at the ankle, and between the moderate and vigorous activities for the L-CV of AD and VM at  
207 the wrist, for the L-CV of AD at the ankle, and for the L-Skewness of AD and EEact of the ankle. We  
208 also noticed the box plots for L-Skewness and L-Kurtosis of light level are more clearly separated  
209 from moderate and vigorous ones, which suggests that light level of physical activity could easily be  
210 differentiated from the moderate and vigorous ones using these metrics.

211 Good to very good linear relationship between the MEAN and RMS of all parameters with the MET  
212 values has been shown with values of the coefficient of determination  $R^2$  from 0.78 to 0.97 (Figure  
213 6). Indeed, based on the wrist sensor data, 97% of the linear relationships between the mean values  
214 and AUC of the AD and VM with the MET values has been accounted for. For the ankle sensor data,  
215 97% of the linear relationships between the mean values of the ENMO with the MET. We also  
216 noticed visible difference on the slope obtained for wrist and ankle based data for MEAN-Met linear  
217 function of the metrics ENMO and VM (figure 6).

## 218 **Discussion**

219 The purpose of this study was to highlight the influence of IMU deduced metrics to quantify three  
220 levels of physical activity intensity and to compare between sensor locations. Our findings  
221 demonstrate that the five data reductions (MEAN, RMS, L-CV, L-Skewness and L-Kurtosis) of five  
222 metrics (ENMO, AD, VA VM ,EEact) at the two localizations (wrist and ankle) could mainly  
223 differentiate between three levels of physical activity (light, moderate or vigorous). The second  
224 purpose was to test the relationship between those metrics and the MET, for which we found strong  
225 correlations and high coefficients of determination.

226 Research on post-processing methods of IMU based accelerometer data to quantify and classify  
227 physical activity is abundant (Fradet et al. 2016) , but no standard procedure or reference data are  
228 available to test the reliability and the robustness of these methods. While some metrics like ENMO  
229 (eq. 7) and AD (eq. 8) are easy to compute (only based on 3D accelerations), obtaining metrics for VA  
230 (eq. 9) and VM (eq. 10) require additional sensors (e.g. gyroscope / magnetometer) and an additional  
231 sensor fusion algorithm (Nez 2018). Concerning the MET modeling, the metric EEACT (eq. 11) links  
232 the IMU measures and the metabolic energy using nonlinear equations. Non-linear equations  
233 present a computational cost and their generalizability to the whole population remains  
234 questionable.

235 Our results show a strong relationship between the MET estimation and the computed metrics  
236 ( $R^2 > 0.8$ ) and are consistent with previous research (Hamilton et al. 2015). This emphasizes the  
237 relevance of acceleration based metrics when estimating the level of activity (Crouter et al. 2006)

228 even though reliability might be low (Hargen et al. 2017). The low reliability is due to the counts.min<sup>-1</sup>  
229 (cpm) is a common metric to quantify physical activity based on the acceleration (Aspvik et al. 2016).  
230 Cpm values represent the number of how many times the magnitude of acceleration reaches a  
231 defined threshold (Migueles et al. 2017) and consequently does not allow to quantify the level of  
232 acceleration. This metric is often a proprietary format by the IMU manufacturers and exact  
233 calculation and processing is unknown (Paul et al 2007) leading to a heterogeneity of the cpm values  
234 (Alhassan et al. 2012). This emphasizes the importance of metric based computations that include  
235 the magnitude of the acceleration to quantify the intensity of physical activity (van Hees 2011). We  
236 also noticed a higher correlation with the metrics based on the wrist sensor, which could be linked to  
237 the relation between the swinging of the arms and the energy efficiency of the locomotion (Arellano  
238 et al. 2011)

239 We focused our investigation on the IMU located on the wrist and ankle. The rationale of this choice is  
240 the “wearability” (Gemperle et al 1998) of the wrist and ankle, which are convenient for the subject  
241 and easy to fix an IMU with adjustable belt. Concerning the sensor location, the computed metrics  
242 showed different values and emphasized the importance of the sensor location (Yang et al. 2010)  
243 depending on the type of physical activity investigated (Altini et al. 2015). The current study excluded  
244 the waist localization due to the risk of wobbling mass i.e. soft tissue artifacts (Camomilla et al. 2017)  
245 affecting the acceleration measurement.

246 The data reduction techniques in this study ranged from rather descriptive parameters (MEAN, RMS)  
247 to quantile function. The quantile function presents the advantage to preserve the whole distribution  
248 of the accelerations, which is valuable for physical activity recognition (Hammerla et al. 2013). In  
249 order to describe this distribution, we used the L-moment formalism (Hosking, 1990) which is known  
250 for its robustness. L-moments such as skewness and kurtosis are part of the high-order statistics  
251 (HOS) parameters (Karvanen 2006) and allow for the description of the statistical shape distribution  
252 (Boudaoud et al. 2009). In addition, they could be used as parameters in a classification procedure  
253 (Jones et al. 2019). We refrained from computing as data reduction the integral per unit time  
254 (Bouten 1994, Tsurumi 2002, Sandroff 2014) or the quadratic integral per unit time (Lu 2013) as the  
255 numerical integration by rectangle rule is associated at a summation meaning that the integral per  
256 unit time is homogenous to the mean value and the quadratic integral to the RMS. Our result  
257 suggested that, on the one hand MEAN and RMS data reductions of all metrics present a better  
258 ability to largely discriminate between vigorous level of physical activity as opposed to low and  
259 moderate ones, on the other hand, L-skewness and L-kurtosis are more efficient to differentiate  
260 between low-level against moderate and vigorous activity. The combination of these observations

261 could be a perspective to better segment low, moderate and vigorous levels during a continuous  
262 physical activity.

263

264 Our study also presented limitations. The reliability of the measurement of accelerations is a  
265 limitation as the calibration and sensor shift can have a dramatic effect on the accuracy (Ricci et al.  
266 2016, Nez et al. 2017). However as the duration of the measurements was relatively short (less than  
267 20min), we expected that the effect of such phenomena are limited and longer measurements will  
268 require drift correction (Nez et al. 2017). The investigation of walking and running as moderate and  
269 vigorous physical activities could be questionable, especially as numerous other moderate and  
270 vigorous physical activities do exist. However, walking and running are the most common and  
271 accessible physical activities for a large part of the population (WHO 2010) and way of monitoring  
272 physical activity is still controversial (Aadland et al. 2020). In addition, our population is  
273 homogeneous in terms of age and health status, which cannot reflect all variations in walking and  
274 running matters. Our study reflected an “ideal situation” and could be seen as a baseline for further  
275 specific investigation of a more heterogeneous population, including children and senior citizens, as  
276 well as a pathological population.

## 277 **Conclusion**

278 When it comes to quantifying a physical activity, there is currently a lot of heterogeneity in terms of  
279 computation cost and output, namely as far as metrics and data reduction approaches are  
280 concerned. Our findings suggest a good method for differentiation applied to standing, walking, and  
281 running, all three popular physical activities of a larger population. According to the various metrics  
282 available to quantify and analyze physical activity and differences between them, our recommended  
283 “best practice” would be to fully document methods of calculation and set-up. Our results also  
284 suggest that MEAN and RMS data reductions are more suitable to discriminate between a vigorous  
285 level of physical activity as opposed to low and moderate ones. On the other hand, L-skewness and L-  
286 kurtosis are better at differentiating between low-level versus moderate or vigorous activities. These  
287 findings can be implemented in classification algorithms.

288 To conclude, wearable devices as a preview of “mobile monitoring of neuro-musculoskeletal  
289 performance” confirm a high ability for monitoring biomechanical behaviours of healthy subjects  
290 during their daily activities, but need rigorous methods and practice to develop fully their potential.

291 Conflict of interest statement

292 The authors have no conflicts of interest to report related to this study.

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434

## Figures captions

Figure 1 : Experimental sessions description

Figure 2 : Post-processing procedure included: a) acceleration calculations deduced from IMU's measurement detailed in the equations 2 to 6 in the text ; b) computation of physical activity metrics detailed in the equations 7 to 11 in the text, and ; c) determination of the associated quantile function of previous metrics; d) data reduction of the metrics and their associated quantile function by MEAN and RMS values and L-Moments ; e) statistical analyses performed on MEAN and RMS values and L-Moments

Figure 3 : Descriptive statistics of the MEAN and RMS values of all metrics. The sign " $\neq$ " refers to no significant difference between the pointed values. On the contrary, if there is no sign, this refers to the fact that there is a significant difference between levels or sensors localization of PA metrics

Figure 4 : Quantiles functions of all metrics.

Figure 5 : Descriptive statistics of the L-CV, L-Skewness and L-Kurtosis values of all metrics. The sign " $\neq$ " refers to no significant difference between the pointed values.

Figure 6 : Graph of the relationship between the MEAN and RMS values of all metrics with the MET evaluation of the standing, walking and running activities.

Moderate

Light

Vigorous

2 min

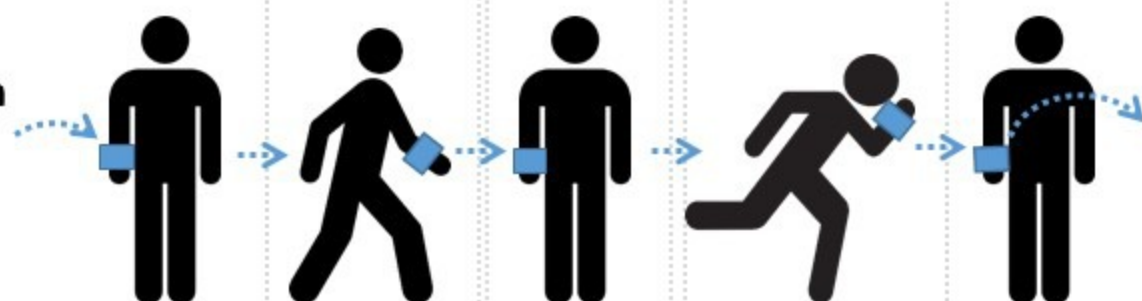
466 m

2 min

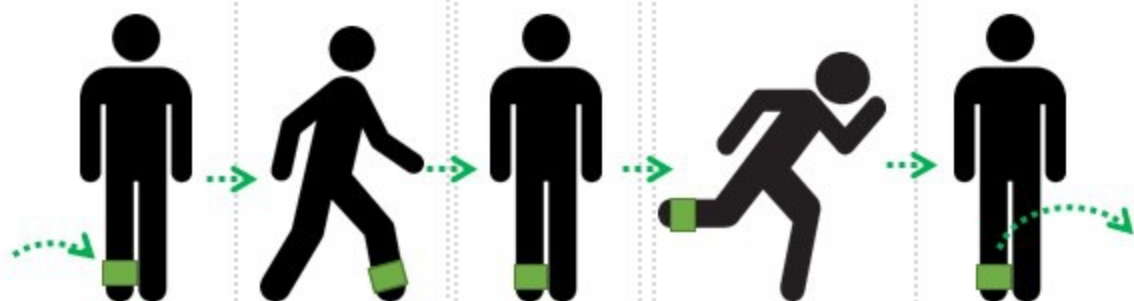
700 m

2 min

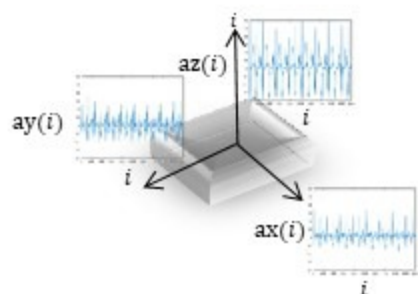
session  
Wrist



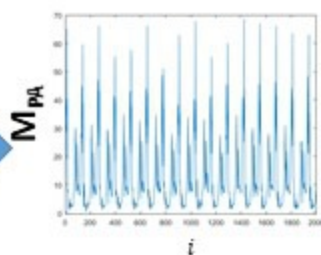
session  
Ankle



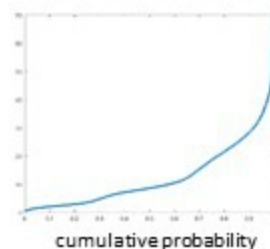
**a) Data's IMU postprocessing**



**b) PA metric  $M_{PA}$  calculation**



**c) Quantile analyse  $Q_{M_{PA}}$**



**d) Data reduction**

MEAN  
RMS

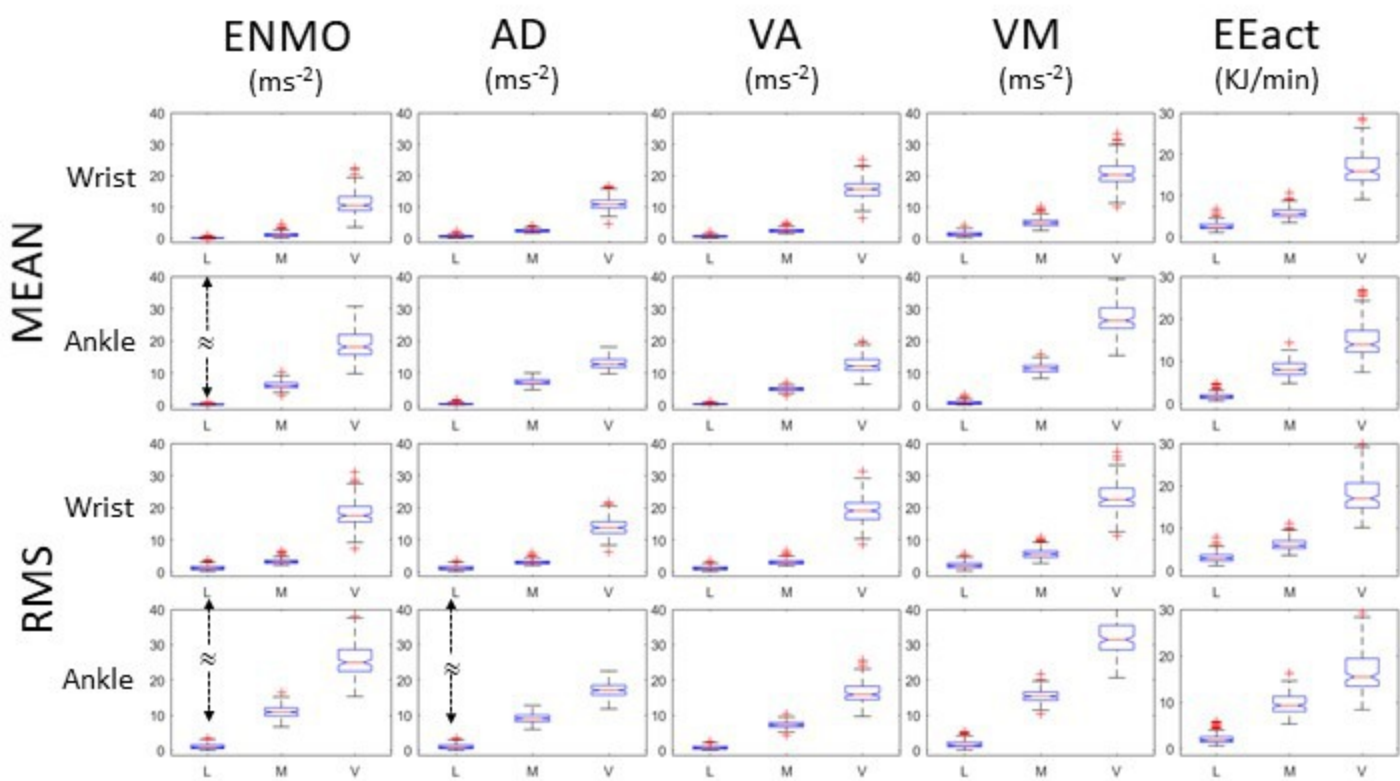
L-CV  
L-skewness  
L-Kurtosis

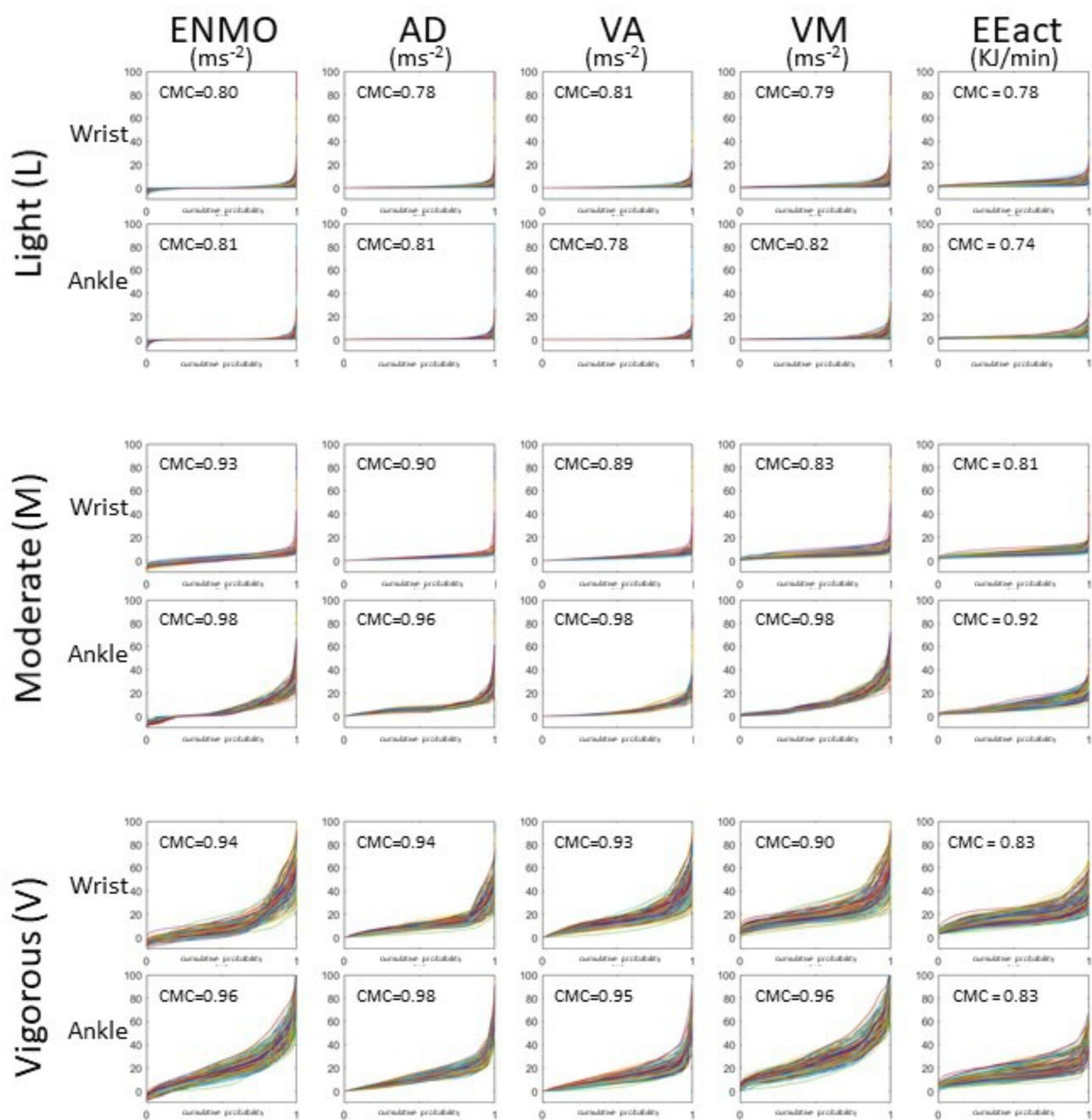
**e) Statistics**

Kruskal-Wallis test on Inter- IMU localization

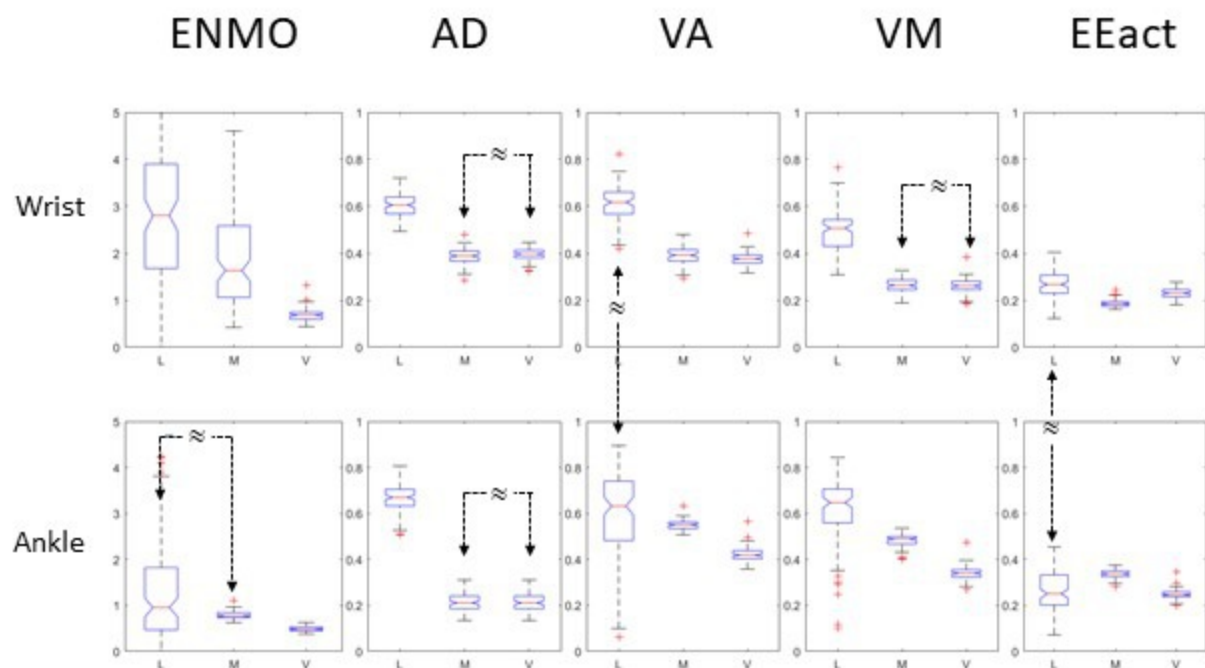
Kruskal-Wallis test on Inter- Physical Activity level

Linear fitting and  $R^2$  with MET

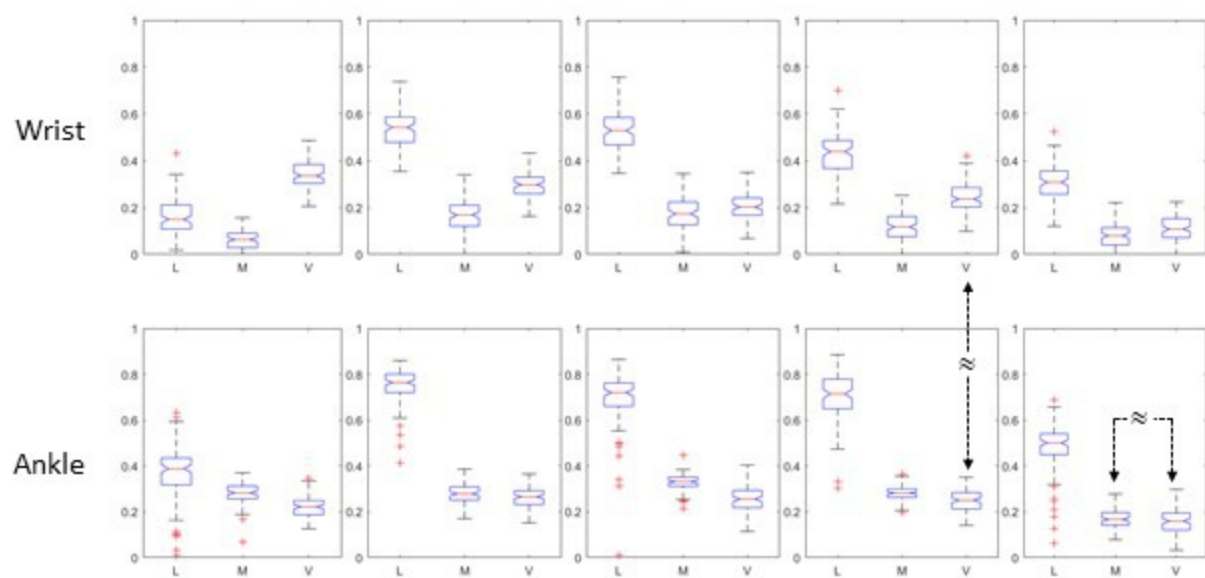




# L-CV



# L-Skewness



# L-Kurtosis

