Data collection and analysis of activity patterns with W2 Activity Tracker

Balazs Borbely[1], Attila Safar[1] and Jozsef Halasz[1,2]
1. Obuda University, AMK, Szekesfehervar, Hungary
2. Vadaskert Child Psychiatry Hospital, Budapest, Hungary

balazs.borb@gmail.com
safar.attila@amk.uni-obuda.hu
halasz.jozsef@amk.uni-obuda.hu

Abstract— **Data collection of different biological signals became easily accessible with commercially available smart instruments. Still, the interpretation and validation of the acquired data create a major debate in the usage of smart instruments in scientific data collection. The aim of the present study was to perform a reliability analysis of the W2 Activity Tracker, and to establish differences according to different locations, like location of the devices at arm and hip. In the first set of experiments, data from the W2 Activity Tracker was compared with data acquired from the Xiaomi Mi Band, and with data from a GPS device. In the second set of experiments, diurnal data collection was performed with W2 Activity Trackers in identical locations. In the third set of experiments, the arm and hip movement was compared during sport classes, data were collected from ten male university students.**
Our results indicate that the examined device has a high level of reliability (in identical locations). Additionally, there was a significant difference in the activity counts according to the origin of data (arm or hip). This major effect has to be considered in the interpretation of activity data collected by different instruments.

Keywords: Activity tracker, Data collection, Laterality, Locomotion pattern, Reliability.

I. INTRODUCTION

A. Activity trackers and their application

Several applications involving the e-health sector became available recently, targeting and continuously monitoring biological signals as heart rate, body temperature, skin conductance, blood pressure, and even daily activity patterns [1]. The interpretation of these biological signals is related to big data analysis, and the optimal strategies for data collection with widely available instruments was not verified. One major problem of these equipment is not only the lack of guidelines for scientific data collection strategies, but the scientific validation of the collected data.

3-D accelerometers were widely used to establish different human locomotion patterns, and the signal acquisition and transformation seems verified [2, 3]. Human locomotion patterns have high importance in establishing daily physical activity, and physical locomotion activity per se. Movement disorders have a major impact on locomotor abilities, but different cardiovascular and chronic conditions might alter locomotion patterns. E.g., the prognosis and cross-sectional condition could be monitored with daily physical activities in patients with Parkinson's disease, patients with heart failure and patients with renal failure [4-6]. Physical activity in itself might be able to help in the recovery in certain chronic conditions [7]. In this respect, these instruments might also be used for motivational purposes both in different populations with certain chronical conditions and healthy individuals [4, 8].

Theoretically, the application of accelerometers might have major importance in conditions where the daily activity patterns are crucial (and not just indicator) symptoms. According to the data of two major meta-analyses, attention deficit/hyperactivity disorder (ADHD) is the most common neurodevelopmental disorder, with a worldwide prevalence rate of 5-7 percent [9, 10]. The core symptoms of the disorder are inattention, hyperactivity and impulsivity [11, 12]. The diagnosis of the above condition is based on clinical symptoms, so far no systematic measure was applied to characterize the physical extent of hyperactivity (the exact locomotion pattern). Additionally to the basic symptoms, children and adolescents with ADHD might have multiple comorbid psychiatric conditions including externalizing and internalizing disorders [13], and even certain aspects of social dysfunction in patients with ADHD emerged. Data also suggest that impaired social skills and behavioral problems in children and adolescents with ADHD are also present [14, 15]. Thus, ADHD symptom severity does not end with hyperactivity per se, but is related with serious consequences. Monitoring the precise nature of locomotion patterns might help to characterize other type of difficulties in affected individuals.

Earlier papers used different validation/reliability strategies. E.g., Holowachuk validated Tritac with both a similar instrument and a questionnaire [16]. In the above paper a rather large (day-based) time frame was chosen, as an activity questionnaire could not be established for rather short time frame (hours or even minutes). Later studies focused on smart-instrument activity data collection in different populations [17, 18], and the description of validation strategies between instruments from different providers was also documented [19, 20]. Still, certain elements were not targeted so far.

To our best knowledge, earlier validation strategies did not apply identical instruments in different locations (like arm and hip), and reliability analysis (instruments with same locations, at different time points) was not performed. Additionally, the above papers used instruments that were capable of collecting data with a relatively large time frame (like hours, days, or weeks), and this time frame can not be used for a relative smooth discrimination in problems like ADHD, were parallel neuropsychological measures might have crucial importance. Thus, our major intention was to use an instrument what could be used for a relatively smooth (minute resolution) data collection.

B. Aims

The aims of the present experiments were to perform a validation and reliability analysis of the W2 Activity Tracker, what later can be used in real life experimental design in children and adolescents with ADHD and externalization problems. The experiments were used as preliminary experiments for the Grant "Dimensional approach in externalization disorders".

II. METHODS

The W2 Activity tracker was chosen for (i) capability for a rather smooth data collection (2-min intervals) and (ii) the relatively easy accessibility of the output file for scientific data analysis (Fig. 1). The majority of commercially available instruments use internal statistical procedures, what is not sufficient for deeper interpretation of the data.

Fig. 1. The devices used during the measures. From left to right, Xiaomi Mi Band, and W2 devices. The W2 devices were labeled with a special string, and that was used as color code of a given device.

With the built-in high sensitivity 3D acceleration sensor, the device can capture every tiny movement of the pedometer, which provides more accurate functioning. The smartband can track the burned calories, exercise steps, moved distance, and also can set the query of the movement goal completion. The strap can be set by the built in USB2.0 interface, which is fully plug and play. It has a built in large capacity storage space (up to 16GB), which can be used as mobile hard disk, and the strap has motion data memory function. The watch can be charged by USB interface, and replenish the built-in rechargeable (95mAh) battery.

Three sets of experiments were performed. For easier discrimination, 'color codes' were used. Altogether, the codes green, orange, blue, black represent individual W2 Activity Trackers.

In the first set of experiments (Experiment1), data collection was performed with W2 devices in different arm and hip locations, while a Xiaomi Mi Band activity tracker was also used. During the experiment, the data collector was walking a circumscribed distance of 110 meters. The procedure was repeated 20 times, while a GPS tracker was also used (Fig. 2). The Xiaomi Mi Band was located at the dominant arm, while one of the W2 Activity Trackers at the dominant arm, and an additional W2 Activity Tracker at the hip. During Experiment1, green code was used for the subdominant arm, and orange code was used for the hip. The major aim in Experiment1 was to establish correlation patterns between different devices and locations. The highest correlation was suggested between identical localizations, in spite of the differences of the providers.

In the second set of experiments (Experiment2), spontaneous diurnal data collection was performed with different W2 devices. In a subset of the experiment, a data collector (B. B.) was continuously wearing W2 activity trackers, but for constant data collection, the capacity of the setup could not bear over 14 hours in preliminary experiments. Thus, a single device was used for 12 hours (from 7a.m. to 7 p.m.), than an additional W2 Activity tracker was used (from 7 p.m. to 7 a.m.). In the other subset of Experiment2, three parallel devices were used for a week from 7 a.m. to 7 p.m., at the dominant arm (green), directly near the green in proximal position (blue), and at the subdominal arm (black, Fig. 2). This experiment had a major importance in the validation strategy for spontaneous daily activities, comparing data between dominant and subdominant locations, with internal control (setup at proximal dominant position).

In the third set of experiments (Experiment3), a 30-min controlled sport activity was used for data collection, with two W2 Activity Trackers at arm (green/black) and at hip (orange/blue) location, after informed consent in 10 male university students (ages between 18-24 years, average: 21.1 years). The heights and weights were also registered. The students were free to discontinue the experiment, but none of them dropped from the data collection. The data collection was approved by Obuda University, Alba Regia Technical Faculty. Part of the data collection was also used as diploma work one of the Authors [1], and as we stated earlier, data collection was used as preliminary experiment for the Grant "Dimensional approach in externalization disorders".

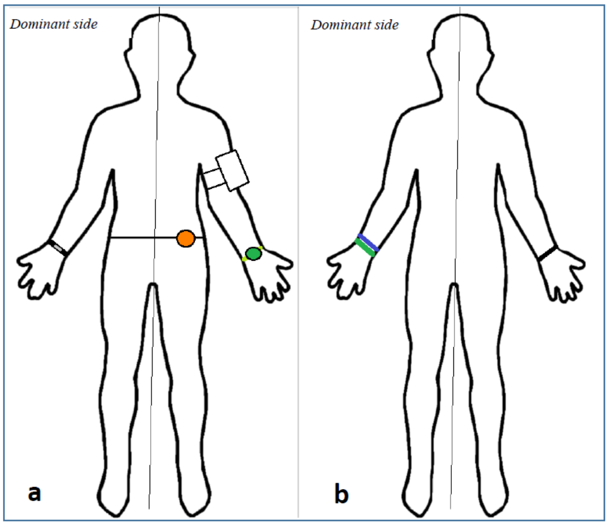

Fig. 2. The localization of the devices during Experiment 1 (a) and during Experiment2 (b). In Experiment1, a Xiaomi Mi Band was located at the dominant arm, while 2 W2 devices were located at the hip (orange) and at the subdominant arm (green). In Experiment2, 2 W2 devices were located at the dominant arm, while an additional w2 was located at the subdominant arm.

Statistical analysis. Statistica 7.0 was used to analyze datasets. In Experiment1, Spearman correlation was performed between different devices in different locations. Additionally, a General Linear Model (GLM) was also used. In Experiment2, diurnal sets from different W2 devices were analyzed in a GLM-based testing. Two factors were used: a time (hours) and a location factor. In Experiment3, a repeated measure design was applied, basically in 2-min datasets, but also in 10-min and 30-min intervals. The level of significance was set at p=0.05.

III. RESULTS

In Experiment1, Spearman correlation was significant between activity counts from Xiaomi Mi Band and the green W2 Activity Tracker (Spearman R=0.602, p<0.005), while no significant correlation occurred between other locations. Activity counts in identical locations did not show significant differences ($F_{(1,38)}$=3,60; p=NS; Xiaomi Mi Band and green W2 Activity Tracker).

Table 1. Data from Experiment1, Spearman correlations.

	Valid N	Spearman R	p-level
W2Gr & W2Or	20	0,383	0,096
W2Gr & Xiaomi	20	0,602	0,005
W2Gr & GPS (m)	20	0,298	0,202
W2Or & Xiaomi	20	0,012	0,958
W2Or & GPS (m)	20	0,215	0,364
Xiaomi & GPS (m)	20	0,326	0,165

Spearman correlation data from Experiment1. In Experiment1, the devices were used on a fixed distance of 100 meters in a repeated order. A GPS tracker was located at the subdominant arm, Xiaomi Mi Band was located at the dominant arm, W2Gr (W2, green string) was located at the subdominant arm, while W2Or (W2, orange string) was located at the hip. Strong correlation occurred only between devices from different origin but with identical (mirror) location (W2Gr and Xiaomi).

In Experiment2, significant differences could be observed in diurnal variations ($F_{(11,72)}$=9.01; p<0.00001). During the day, two major activity peaks could be observed (Fig. 3). Day and night activities were clearly visible during data collection. When data collection was repeated on a daily basis with 3 W2 Activity Trackers, a similar pattern in the diurnal variation emerged (data not shown), but no significant differences occurred between different setups (F=0.066; p=NS; Fig. 4).

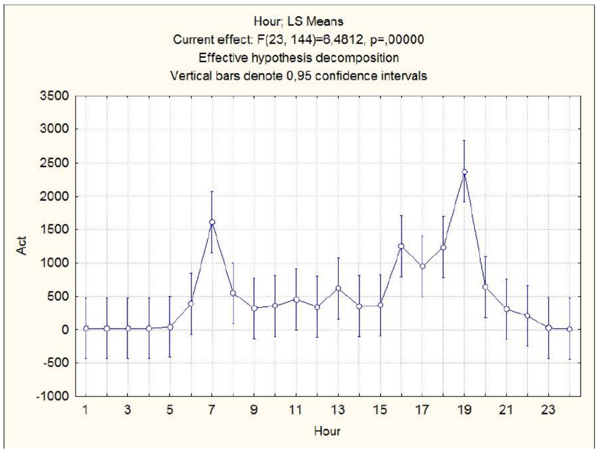

Fig. 3. Summary of the data (from Statistica 7.0, hour averages and 95% confidence intervals) from Experiment2. Two daily activity peaks could be clarified.

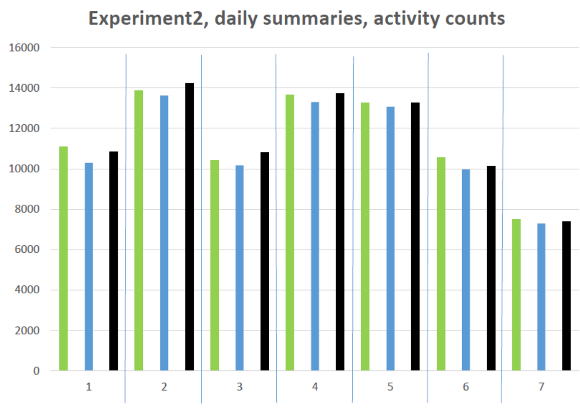

Fig. 4. Daily activity count summary data (for seven days) during Experiment2, with 3 W2 devices. Green, distal dominant arm, Blue, proximal dominant arm, Black, subdominant arm. No statistical difference occurred between the W2 devices labeled with different strings during Experiment2.

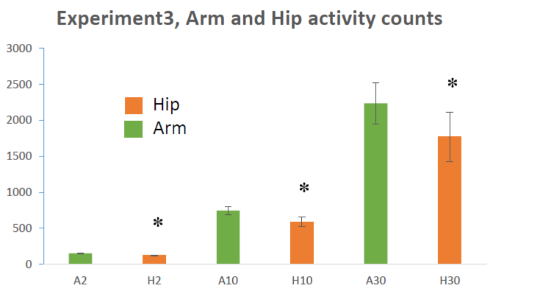

*Fig. 5. Activity count averages and SEM values during Experiment3, with 2 different W2 devices. Green, subdominant arm, Orange, hip. Distributions for 2, 10 and 30 minutes were presented. *, significantly different (p<0.05) from subdominant arm activity count values.*

In Experiment3, major differences occurred between different locations, irrespective of the time frame (2-min, $F=89.349$; $p<0.0000001$; 10-min, $F=38.779$; $p<0.00001$; 30-min, $F=15.905$; $p<0.004$). The most sensitive was the smooth data collection, and the average difference between hip and arm activity was 26% (Fig. 5).

IV. Discussion

The main results of the present study were the followings. First, the correlation patterns between activity counts were strongest in identical locations, irrespective to the origin/provider of the setup. Second, stable daily activity patterns could be observed, and no differences occurred between the activity counts data from subdominant and dominant arms. Third, major differences could be observed in activity counts during a limited (30-min long) sport activity, when W2 Activity Trackers could be localized at arm or at hip.

The activity count patterns between identical setups in different locations (Experiment1, green vs. orange, Table 1) was shown significantly weaker correlation patterns than activity count patterns measured with different setups and identical locations (Xiaomi Mi Band and (green) W2 Activity Tracker). This information was underlined in Experiment2, where the activity differences from 3 identical setups (dominant arm, proximal position, dominant arm, distant position and subdominant arm) shown differences of 0.05% during a week of data collection. Thus, identical locations (even if the dominant and subdominant arm movement theoretically could not be considered completely identical) resulted in very small alterations. Surprisingly, activity patterns (W2 Activity Tracker) were highly different during a 30-min sport activity in male university students, having 26% more activity counts registered at arm compared to the activity counts registered at hip. Identical locations (hip) were also tested by Noah et al, where highly reliable data were emerged from different providers [20].

Earlier validation and reliability analyses focused mainly on the comparison of two different systems [16, 17, 20]. E.g., Sasaki et al compared the estimated energy expenditure used by the Fitbit Activity Tracker and the Oxycon Mobile portable system [17]. Importantly, the hip-based registration (no other registration point was tested) significantly underestimated energy expenditure compared to the Oxycon system in the majority of the tested conditions. Thus, the localization should be weighted in the algorithms used for calculation.

These data were crucial in order to plan later data collection strategies in children and adolescents with ADHD, where a core symptom of the condition is hyperactivity [11, 12]. Localization of the activity tracker was crucial in our experiments, and should be considered during experiments planned in the future. In Experiment3, where different sport activities could be observed, data indicate that intensive running and leg-activities might change the differences between hip and arm data. Interestingly, when the data analysis was performed without the data of a professional runner, the difference between arm and hip activities was further increased, thus this effect also should be considered.

The limitations of the study were the followings. During Experiment1 and Experiment2, a repeated measure design was applied, and the data collector was repeatedly the same person, one of the Authors of the present manuscript (B.B.). Albeit this design was inevitable during the validation procedure, the present measures could have been repeated with more people. In Experiment3, the sport experiment was freely chosen for the individuals, and the nature of sport activity was not unified. As we stated above, running, free activity and badminton were also among the sport activities. Thus, our design could be considered as soft in this respect, but still major significant differences occurred. It is assumed that data collection in case of targeted activities (like systematically comparing running, badminton) might significantly increase our knowledge on terms of activity counts on different body parts, but this was not a direct target of our present study. In future studies, these issues also should be addressed.

V. Summary

In the present paper, the validation and reliability analysis of the W2 Activity Tracker was performed. According to our data, W2 Activity tracker was highly reliable in identical locations, but differences in data collection locations (like arm or hip) was accompanied by major differences in activity counts. This effect should be considered during later data collections, and also has to be considered in the planned data collection in children with ADHD and externalization problems.

VI. Acknowledgment

The authors declare no conflict of interest. The work was supported by OTKA Grant No. 108336. The authors would like to express their gratitude to those university students who participated in the project.

References

[1] B. Borbely, "Parametric data configuration of an activity tracker", diploma work, Obuda University, 2016.

[2] F. Foerster and J. Fahrenberg, "Motion pattern and posture: correctly assessed by calibrated accelerometers", *Behav. Res. Methods Instrum. Comput.*, vol. 32, pp. 450–457, 2000.

[3] N. Ravi, N. Dandekar, P. Mysore and M.L. Littman, "Activity recognition from accelerometer data", *I.A.A.I.*, pp. 1541–1546, 2005.

[4] M. van Nimwegen, A.D. Speelman, S. Overeem, B.P. van de Warrenburg, K. Smulders, M.L. Dontje, G.F. Borm, F.J.G. Backx, B.R. Bloem and M. Munneke, "Promotion of physical activity and fitness in sedentary patients with Parkinson's disease: randomized controlled trial", *B.M..J.*, vol. 346, doi: 10.1136, 2013.

[5] M.L. Dontje, M.H.L. van der Wal, R.P. Stolk, J. Brügemann, T. Jaarsma, P.E.P.J. Wijtfliet, C.P. van der Schans and M.H.G. de Greef, "Daily physical activity in stable heart failure patients", *SJ. Cardiovasc. Nurs.*, vol. 29, pp. 218–226, 2014.

[6] K.L. Johansen, G.M. Chertow, A.V. Ng, K. Mulligan, S. Carey, P.Y. Schoenfeld and J.A. Kent-Braun, "Physical activity levels in patients on hemodialysis and healthy sedentary controls", *Kidney Int.,* vol. 57, pp. 2564–2570, 2000.

[7] G. Hu, N.C. Barengo, J. Tuomilehto, T.A. Lakka, A. Nissinen and P. Jousilahti, "Relationship of physical activity and body mass index to the risk of hypertension: a prospective study in Finland", *Hypertension,* vol. 67, pp. 693–700, 2016.

[8] M. Iwane, M. Arita, S. Tomimoto, O. Satani, M. Matsumoto, K. Miyashita and I. Nishio, "Walking 10000 steps/day or more reduces blood pressure and sympathetic nerve activity in mild essential hypertension", *Hypertens. Res.,* vol. 23, pp. 573–580, 2006.

[9] G. Polanczyk, M.S. de Lima, B.L. Horta, J. Biederman and L.A. Rohde, "The worldwide prevalence of ADHD: a systematic review and metaregression analysis", *Am. J. Psychiatry,* vol. 164, pp. 942–948, 2007.

[10] E.G. Willcutt, "The prevalence of DSM-IV attention-deficit/hyperactivity disorder: a meta-analytic review", *Neurotherapeutics,* vol. 9, pp. 490–499, 2012.

[11] American Psychiatric Association, "Diagnostic and Statistic Manual of Mental Disorders, DSM-5", New York, American Psychiatric Publishing, 2013.

[12] National Institute for Health and Care Excellence, "Attention deficit hyperactivity disorder. Diagnosis and management of ADHD in children, young people and adults", British Psychological Society and The Royal College of Psychiatrists, *National Clinical Guideline Number 72,* pp. 1–664, 2016.

[13] E.J. Costello, S. Mustillo, A. Erkanli, G. Keeler and A. Angold, "Prevalence and development of psychiatric disorders in childhood and adolescence", *Arch. Gen. Psychiatry,* vol. 60, pp. 837–844, 2003.

[14] J. Uekermann. M. Kraemer, M. Abdel-Hamid, B.G. Schimmelmann, J. Hebebrand, I. Daum, J. Wiltfang and B. Kis, "Social cognition in attention-deficit hyperactivity disorder (ADHD)", *Neurosci. Biobehav. Rev.,* vol. 34, pp. 734–743, 2010.

[15] J.S. Nijmeijer, R.B. Minderaa, J.K. Buitelaar, A. Mulligan, C.A. Hartman and P.J. Hoekstra, "Attention-deficit/hyperactivity disorder and social dysfunctioning", *Clin. Psychol. Rev., vol. 28,* pp. 692–708, 2008.

[16] D.R. Holowachuk, "Field validation of the Tritac-3D Activity Monitor for the assessment of physical activity in older children", diploma work, University of Saskatchewan, 1998.

[17] J.E. Sasaki, A. Hickey, M. Mavilia, J. Tedesco, D. John, S.K. Keadle and P.S. Freedson, "Validation of the Fitbit wireless activity tracker for prediction of energy expenditure", *J. Physical Act. Health,* vol. 12, pp. 149–154, 2014.

[18] S.S. Paul, A. Tiedemann, L.M. Hassett, E. Ramsay, C. Kirkham, S. Chagpar and C. Sherrington, "Validity of the Fitbit activity tracker for measuring steps in a community-dwelling older adults", *B.M.J. Open, Sport, Exercise and Medicine,* doi: 10.1136, 2015.

[19] A. Giannini, "Comparison of the Fitbit Zip to the Actical accelerometer in children and adults", diploma work, University of Delaware, 2013.

[20] J.A. Noah, D.K. Spierer, J. Gu and S. Bronner, "Comparison of steps and energy expenditure assessment in adults of Fitbit Tracker and Ultra to the Actual and indirect calorimetry", *J. Med. Eng Technol.,* doi: 10.3109, 2013.