Original Article

Influence of epoch length on measurement of light physical activity in the elderly: A technical analysis

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ABSTRACT

Aims: To clarify how epoch lengths of accelerometers affect measurement of physical activity in elderly people. Methods: The data was based on 70 elderly people (72.6 ± 5.4 years) living in Japan between 2017 and 2018. Furthermore, we used data obtained from triaxial accelerometers that the subjects wore for more than 10 hours every day for 7 days. We evaluated light physical activity (2.9 Mets or less) and further grouped it into sedentary behaviour (SB, 1.5 Mets or less) and Light Intensity Physical Activity (LIPA, between 1.6 and 2.9 Mets). We also compared 10-second epoch lengths (ELs) to 60-second ELs (%) by Bayesian estimation. Results: In 2017 and 2018, SB at 10-second ELs was longer than at 60-second ELs (55.5 vs. 50.4% in 2017; 55.7 vs. 48.9% in 2018); however, LIPA at 10-second ELs was shorter than at 60-second ELs (35.0 vs. 42.3% in 2017; 35.0 vs. 44.5% in 2018). The Bayesian factor varied between 3.0×10^{12} and 3.2×10^{24}. The robustness of the Bayesian factor was confirmed by the robustness check. Furthermore, effect sizes were between |1.68| and |3.00|. Conclusion: ELs of the accelerometer may affect measurement of physical activity in elderly people. Thus, SB at 10-second ELs may be longer than at 60-second ELs and may be the reverse for LIPA.
Keywords: Biomechanics; Epoch lengths; Sedentary behaviour; Bayesian estimation.

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INTRODUCTION

Accelerometers are widely used for evaluating physical activity (Masse et al., 2005; Pettee et al., 2009); however, many studies showed that the data obtained by accelerometers are influenced by various conditions (Masse et al., 2005; Trost et al., 2005) such as epoch lengths (ELs) (Gabriel et al., 2010; Dencker et al., 2012).

Accelerometers integrate filtered and digitized accelerometer signals at user-specified time intervals (e.g., 10 seconds, or 60 seconds or more), commonly called an epoch (Trost et al., 2005; Gabriel et al., 2010). Recent studies have clarified appropriate ELs for estimating physical activity (Trost et al., 2005; Gabriel et al., 2010). Some showed that shorter ELs are more appropriate in reflecting actual activity time (Michael et al., 2008; Ayabe et al., 2013), whereas others showed that, in children, the relationship between EL and actual activity time varies with age (Nilsson et al., 2001; Vale et al., 2009). However, there are few reports regarding the elderly. Therefore, we clarified how accelerometer EL affects the measurement of physical activity in the elderly.

The *p*-value has long been used to determine the strength of evidence against the null hypothesis. In particular, $p < .05$ has a major impact on whether a paper is published. Therefore, many studies have focused on statistically instead of medically significant differences. However, the *p*-value gradually decreases as the sample size increases. The American Statistical Society (ASA) has stated as follows: "a *p*-value does not provide a good measure of evidence regarding a model or hypothesis" (Ronald and Nicole, 2016). Alternatively, the ASA recommends the Bayesian estimation (a representative method of Bayesian statistics), decision-theoretic modelling, and false discovery rates, etc. (Ronald and Nicole, 2016). In particular, the Bayesian estimation (Jaynes, 1986; Hoeling et al., 1999; Wagenmakers et al., 2010) may yield more information compared with the *p*-value (John, 2013).

To our knowledge, there is no comparison of physical activity between 10- and 60-second ELs by Bayesian estimation. Therefore, in this study, we compared physical activity that was measured by two different ELs of accelerometers (Active Style Pro HJA-750C; Omron Healthcare, Japan) in elderly people.

METHODS

Subjects

This study is a second analysis from our previous study (Owari et al., 2019). The initial survey involved 86 healthy elderly people who participated at a health club of A college in Utazu, Japan between July 20 and September 15, 2017. Among these respondents, six could not be surveyed. Therefore, we used the data of 80 participants. The second phase involved a similar follow-up survey and was conducted between April 29 and May 31, 2018. We did not include the data of 10 of these respondents since they wore the accelerometer for less than 10 hours daily for 7 days. Therefore, in this study, we used data based on 70 participants (72.6 ± 5.4 years). Ethical approval for the study was obtained from the Shikoku Medical College Ethic Screening Committee, Japan (approval number: H28-9), and written informed consent to participate in the study was also obtained from each subject.

Clinical parameters and measurements

The following data regarding anthropometric and body composition parameters were assessed and re-assessed in 2017 and 2018, respectively (Owari et al., 2019): age (years), height (cm), body weight (kg), and body mass index (BMI, kg/m^2).

Physical activity

Physical activity was measured using a tri-accelerometer (Active Style Pro HJA-750C). Excluding the time during swimming and bathing, the subjects were asked to wear the accelerometer on their waist for more than 10 hours every day for 7 days including Saturday and Sunday. Physical activity was calculated using Σ [metabolic equivalent*h/week (METs*hour/week)] to determine sedentary behaviour (SB, ≤ 1.5 Mets) and light intensity physical activity (LIPA, 1.6-2.9 Mets) (minutes/day). We did not include moderate to vigorous intensity physical activity (MVPA) in the elderly aged 65 and over since the ratio of MVPA to total body activity was very low. Detailed data regarding physical activity is cited in our previous paper (Owari et al., 2019).

Statistical analyses

We divided the intensity of physical activity into two categories: those with 1.5 Mets or less (SB) and those between 1.6 and 2.9 Mets (LIPA). These values were calculated using the ratio of activity time over total wearing time. We performed Bayesian estimation using ELs of 10- and 60-seconds, which are commonly used. We assessed the Bayesian factor (Dawid, 1973; Rouder and Morey, 2011) (the ratio between the alternative and null hypothesis) in Bayesian estimation. We also performed a robustness check to confirm the robustness of the Bayesian factor (Morey et al., 2016). Next, we measured effect size, which is a statistical indicator of the magnitude of the effect. The effect size in the case of two paired groups was calculated as follows: sample mean of the difference between the two groups / standard deviation of the difference between the two groups. Furthermore, we compared the two groups by student t-test or Wilcoxon signed rank test after testing for normal distribution by Shapiro-Wilk test. All calculations were performed using SPSS version 25.

RESULTS

The clinical characteristics of the subjects are summarized in Table 1. Table 2 shows the differences in accelerometer data obtained using different ELs by Bayesian estimation. In 2017 and 2018, SB at 10-second ELs was longer than at 60-second ELs (55.5 vs. 50.4% in 2017; 55.7 vs. 48.9% in 2018); however, LIPA at 10-second ELs was shorter than at 60-second ELs (35.0 vs. 42.3% in 2017; 35.0 vs. 44.5% in 2018). All Bayesian estimations showed that the alternative hypothesis was superior to the null hypothesis (Bayesian factor, between 3.0*1012 and 3.2*1024). Furthermore, the student t-test showed that all p values were < .001. However, except for LIPA in 2017 (Shapiro-Wilk test, p = .407), the others were not of normal distribution. In this case, Wilcoxon signed rank test showed p < .001. The Bayesian factor was assessed for robustness by a robustness check. Effect sizes were between |1.68| and |3.00| (Mean). The effect sizes were between |1.22| and |2.15| in student t-test, and between |0.99| and |1.00| in Wilcoxon signed rank test (Mean) in Table 3.

Table 1. Clinical characteristics of enrolled subject.

	2017			2018		
	Mean ± SD	Minimum	Maximum	Mean ± SD	Minimum	Maximum
Number of subjects	70 (men = 21)					
Age (year)	72.6 ± 5.4	65	84			
Height (cm)	157.2 ± 9.3	138.3	178.4	157.1 ± 9.2	138.1	178.3
Body weight (kg)	55.8 ± 9.7	40.3	83	56.2 ± 9.8	40.5	86.1
BMI (kg/m^2)	22.9 ± 2.4	13.9	29.1	23.1 ± 2.6	14.9	29.2

Table 2. Results of analyses (Bayesian and Student, Wilcoxen).

2017	Mean ± SD	Bayesian factor	Median	95%CI	Bayesian Factor Robustness Check	Student t	Wilcoxon	Test of Normality Shapiro-Wilk
(SB) ≤1.5 Mets (%/day: 10sec EL) (SB) ≤1.5 Mets (%/day: 60sec EL)	55.5 ± 10.9 50.4 ± 12.7	BF10 = 3.0e+12	1.7	[1.3. 2.1]	max BF10 = 3.4e+12 at r = 1.2	$p < .001$	$p < .001$	W = 0.728 $p < .001$
(LIPA) 1.6 ≤ 2.9 Mets (%/day: 10sec EL) (LIPA) 1.6 ≤ 2.9 Mets (%/day: 60sec EL)	35.0 ± 8.2 42.3 ± 10.0	BF10 = 4.6e+22	2.3	[1.8. 2.7]	max BF10 = 7.0e+22 at r = 1.5	$p < .001$	$p < .001$	W = 0.982 $p = .407$
2018	Mean ± SD	Bayesian factor	Median	95%CI	Bayesian Factor Robustness Check	Student t	Wilcoxon	Test of Normality Shapiro-Wilk
(SB) ≤1.5 Mets (%/day: 10sec EL) (SB) ≤1.5 Mets (%/day: 60sec EL)	55.7 ± 11.0 48.9 ± 13.1	BF10 = 1.3e+18	-2.8	[-3.3. -2.3]	max BF10 = 1.8e+18 at r = 1.5	$p < .001$	$p < .001$	W = 0.937 $p < .001$
(LIPA) 1.6 ≤ 2.9 Mets (%/day: 10sec EL) (LIPA) 1.6 ≤ 2.9 Mets (%/day: 60sec EL)	35.0 ± 8.5 44.5 ± 10.6	BF10 = 3.2e+24	-3.0	[-3.4. -2.6]	max BF10 = 5.0e+24 at r = 1.5	$p < .001$	$p < .001$	W = 0.954 $p < .001$

Note. Sec EL: seconds epoch length. BF10: Bayesian Factor (the ratio of the alternative hypothesis for the null hypothesis). e+: exponent of 10. r: Cauchy prior width.

Table 3. Results of analyses (Effect Size).

	2017								
	Bayesian			t-test			Wilcoxon		
	Effect Size	95% CI		Effect Size	95% CI		Effect Size	95% CI	
	Mean	Lower	Upper	Mean	Lower	Upper	Mean	Lower	Upper
≤1.5 Mets (%/day: 10sec EL) ≤1.5 Mets (%/day: 60sec EL)	1.68	1.30	2.08	1.22	0.90	1.52	1.00	0.99	1.00
1.6 ≤ 2.9 Mets (%/day: 10sec EL) 1.6 ≤ 2.9 Mets (%/day: 60sec EL)	-2.78	-3.30	-2.28	-1.99	-2.39	-1.58	-1.00	-1.00	-1.00
	2018								
	Bayesian			t-test			Wilcoxon		
	Effect Size	95% CI		Effect Size	95% CI		Effect Size	95% CI	
	Mean	Lower	Upper	Mean	Lower	Upper	Mean	Lower	Upper
≤1.5 Mets (%/day: 10sec EL) ≤1.5 Mets (%/day: 60sec EL)	2.26	1.80	2.70	1.62	1.26	1.98	0.99	0.98	0.99
1.6 ≤ 2.9 Mets (%/day: 10sec EL) 1.6 ≤ 2.9 Mets (%/day: 60sec EL)	-3.00	-3.44	-2.56	-2.15	-2.57	-1.72	-0.99	-0.99	-0.98

Note. EL: epoch length. CI: Confidence interval.

DISCUSSION

Our study showed that the ELs of the accelerometer influenced the measurement of physical activity in elderly subjects. First, in 2017 and 2018, SB at 60-second ELs was shorter than at 10-second ELs, whereas LIPA was longer at 60-second ELs compared with that at 10-second ELs. When measuring physical activity, differences in ELs may cause discrepancies in the data. The Bayesian estimation is a more accurate statistical analysis and is not influenced by the type of data distribution. Therefore, if the difference between two distributions (10- and 60-second ELs) is small, the Bayesian estimation is better than other tests (student t-test and Wilcoxon signed rank test). However, we were not able to show that the Bayesian estimation was more effective since the difference was large in this study. We were able to obtain good results using the Wilcoxon signed rank test even if the data was not normally distributed (Table 2).

Second, the Bayesian factor is able to compare differences in quantitative degree between the null and alternative hypothesis. For example, for SB in 2017, the alternative hypothesis had a superiority of $3 * 10^{12}$ compared with the null hypothesis. Conversely, the *p*-value only showed that the null hypothesis is less than 5% ($p < .05$) in most cases.

Third, the Bayesian factors are able to check these factors for robustness. In the Bayesian factor robustness check, the Bayesian factor remained at a high value despite changes in the prior distribution from r = 1 to r = 1.5 (r, Cauchy prior width (Wagenmakers et al., 2015)) (Table 2). Thus, the Bayesian factors were robust.

Fourth, effect size is a statistical index representing the magnitude of the effect.

Effect size of the Bayesian estimation is between |1.68| and |3.00| for values greater than or equal to |0.8| (Cohen, 1988). Since this result is higher than both the student t-test and Wilcoxon signed rank test, it is more effective (Table 3).

Finally, the systematic error between the 10- and 60-second ELs was significant using Bland & Altman plots. Therefore, it was difficult to determine whether the 10- or 60-second ELs was more appropriate for evaluating SB and LIPA.

Our study had several limitations. First, the differences between the two groups for SB and LIPA were larger than expected, and we were not able to prove the superiority of the Bayesian estimation, which is able to detect small differences between parameters. To resolve this, a more complex Bayesian statistical model (Maarten et al., 2017) is required. Second, since the Bayesian model contains many parameters (Ozechowski, 2014), it is not possible to show results for all. Therefore, it is difficult to determine whether the selected parameters are appropriate or not.

CONCLUSION

The ELs of the accelerometer may affect measurements of physical activity in elderly people. Thus, SB at 10-second ELs may be longer than at 60-second ELs and may be the reverse for LIPA.

AUTHOR CONTRIBUTIONS

Y.O.: Project development, Protocol development, Data Collection, Data Analysis interpretation, and Manuscript writing (Assistance) M.: Manuscript Revision; H.S.: Supervisor.

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DISCLOSURE STATEMENT

No potential conflict of interest was reported by the authors.

REFERENCES

Ayabe, M., Kumahara, H., Morimura, K., Tanaka, H. Epoch length and the physical activity bout analysis: An accelerometry research issue. BMC Research Notes. 2013;6;20. https://doi.org/10.1186/1756-0500-6-20

Cohen, J. Statistical power analysis for the behavioral sciences (2nd ed.). Hillsdale, NJ Lawrence Erlbaum Associates. 1988.

Dawid, A.P. Posterior expectations for large observations. Biometrika. 1973;60; 664-667. https://doi.org/10.1093/biomet/60.3.664

Dencker, M., Svensson, J., El-Naaman, B., Bugge, A., Andersen, L.B. Importance of epoch length and registration time on accelerometer measurements in younger children. J Sports Med Phys Fitness. 2012;52(2);115-121.

Gabriel, K.P., McClain, J.J., Schmid, K.K., Storti, K.L., High, R.R., Underwood, D.A., Kuller, L.H., Kriska, A.M. Issues in accelerometer methodology: the role of epoch length on estimates of physical activity and relationships with health outcomes in overweight, post-menopausal women. Int J Behav Nutr Phys Act. 2010;15(7);53. https://doi.org/10.1186/1479-5868-7-53

Gelman A. Bayesian statistics then and now. Stat Sci. 2010;25;162-165.

Gelman, A., Carlin, J.B., Stern, H.S., Dunston, D.B., Vehtari, A., Rubin, D.B. Bayesian data analysis, 3rd ed. Boca Raton Chapman & Hall/CRC. 2014.

Hoeling, J.A., Madigan, D., Rafttery, A.E., Volinsky, C.T. Bayesian model averaging: A tutorial. Stat Sci. 1999;14;382-417. https://www.jstor.org/stable/2676803

Jaynes, E.T. Bayesian methods: general background. In Justice JH ed. Maximum Entry and Bayesian Methods in Applied Statistics, 1-25. Cambridge: Cambridge University Press, 1986. https://doi.org/10.1017/cbo9780511569678.003

John, K. Bayesian estimation supersedes the t test. J Exp Psychol Gen. 2013;142; 573-603.

Maarten, M., Schönbrodt, F.D., Richard, D.M., Yuling, Y., Andrew, G., Wagenmakers, E.J. A Bayesian bird's eye view of 'Replications of important results in social psychology. Royal Society Open Science. 2017. https://doi.org/10.1098/rsos.160426

Morey, R.D., Romeijn, J.W., Rouder, N. The philosophy of Bayes factors and the quantification of statistical evidence. J Math Psychol. 2016;72;6-18. https://doi.org/10.1016/j.jmp.2015.11.001

Michael, S.O., Jason, A.S., Greta, C.B., Ava, D.S., Glenn, K.K. How humans walk: bout duration, steps per bout, and rest duration. J Rehabilitation Research & Development. 2008;45;Issue 7. https://doi.org/10.1682/jrrd.2007.11.0197

Mâsse, L.C., Fuemmeler, B.F., Anderson, C.B., Matthews, C.E., Trost, S.G., Catellier, D.J., Treuth, M. Accelerometer data reduction: a comparison of four reduction algorithms on select outcome variables. Med Sci Sports Exerc, 2005;37;S44-54. https://doi.org/10.1249/01.mss.0000185674.09066.8a

Nilsson, A., Ekelund, U., Yngve, A., Sjöström, M. Assessing Physical Activity Among Children with Accelerometers using Different Time Sampling Intervals and Placements. Medicine & Science in Sports & Exercise. 2001;33(5);p5252. https://doi.org/10.1123/pes.14.1.87

Owari, Y., Miyatake, N., Suzuki, H. "Active Guide" Brochure Reduces Sedentary Behavior of Elderly People: A Randomized Controlled Trial. Acta Medica Okayama. 2019;73;427-432. https://doi.org/10.18926/AMO/57373

Ozechowski, T.J. Empirical Bayes MCMC estimation for modeling treatment processes, mechanisms of change, and clinical outcomes in small samples. J Consult Clin Psychol. 2014;82(5);854-67. https://doi.org/10.1037/a0035889

Pettee, N.K., Storti, K.L., Ainsworth, B.E., Kriska, A.M. Measurement of Physical Activity and Inactivity in Epidemiologic Studies. In Lee IM, ed. Epidemiological Methods in Physical Activity Studies. New York Oxford University Press. 2009;15-33. https://doi.org/10.1093/acprof:oso/9780195183009.003.0002

Ronald L. Wasserstein & Nicole A. Lazar (2016) The ASA Statement on p-Values: Context, Process, and Purpose, The American Statistician, 70:2, 129-133. https://doi.org/10.1080/00031305.2016.1154108

Rouder, J.N., Morey, R.D. A Bayer-factor meta analysis of Bem's ESP claim. Psychon B Rev. 2011;18(4);682-689. https://doi.org/10.3758/s13423-011-0088-7

Trost, S.G., McIver, K.L., Pate, R.R. Conducting accelerometer-based activity assessments in field-based research. Med Sci Sports Exerc. 2005;37(11 Suppl);531-543. https://doi.org/10.1249/01.mss.0000185657.86065.98

Vale, S., Santos, R., Silva, P., Soares-Miranda, L., Mota, J. Preschool children physical activity measurement: importance of epoch length choice. Pediatr Exerc Sci. 2009;21(4);413-20. https://doi.org/10.1123/pes.21.4.413

Wagenmakers, E.J., Lodewyckx, T., Kuriyal, H., Grasman, R. Bayesian hypothesis testing for psychologists: A tutorial on the savage-dickey method. Cognit Psychol. 2010; 60(3);158-189. https://doi.org/10.1016/j.cogpsych.2009.12.001

Wagenmakers, E.J., Beek, T.F., Rotteveel, M., Gierholz, A., Matzke, D., Steingroever, H., Ly, A., Verhagen, J., Selker, R., Sasiadek, A., Gronau, Q.F., Love, J., Pinto, Y. Turning the hands of time again: a purely confirmatory replication study and a Bayesian analysis. Front Psychol. 2015;6;494. https://doi.org/10.3389/fpsyg.2015.00494