

UK Biobank

Physical activity monitor (accelerometer)

Version 1.0

<http://www.ukbiobank.ac.uk/>

27 Jan 2016



This document details the procedure for processing of the accelerometer data and the creation of derived summary variables performed by the Physical Activity Expert Working Group for UK Biobank.

Contents

1. Introduction	1
2. Accelerometer device.....	2
3. Data collection	2
4. Data Processing and summary fields	3
5. Data available in Showcase	5
6. References	5
7. Physical Activity Expert Working Group	6

1. Introduction

1.1: Interpreted levels of accelerometer measured physical activity can vary, as many data processing approaches can be taken to extract summary information from raw device data. This document describes the process used to generate derived data-fields of accelerometer measured physical activity. This has been developed by the UK Biobank Physical Activity Expert Working Group, the members of which are listed at the end of this document.

The overall approach to processing the data is summarised in Fig 1. This analysis is freely available and hosted as an open source software project¹.

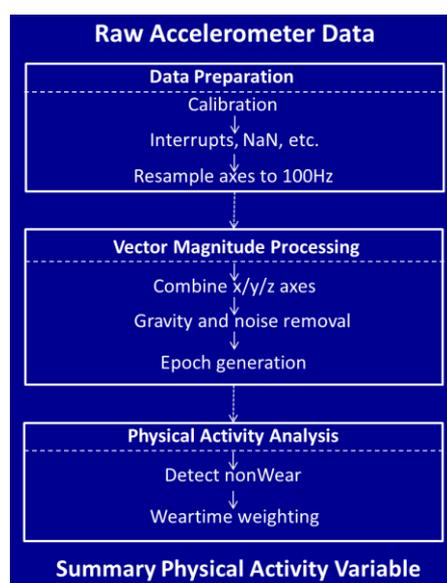


Fig 1. Overall approach for the processing of the accelerometer data

¹ <https://github.com/computationalEpidemiology/biobankAccelerometerAnalysis>

2. Accelerometer device

2.1: For objective assessment of physical activity, UK Biobank has used the Axivity AX3 wrist-worn triaxial accelerometer, a commercial version of the Open Movement AX3 open source sensor designed by Open Lab, Newcastle University². The Axivity device facilitates transparent data processing analysis due to its open-source firmware platform and unforced sampling of raw measurement data. It is easily deployed (and returned) by post. The device demonstrates equivalent output on multi-axis shaking tests (Ladha et al. 2013) to the GENEActiv accelerometer used in other large-scale population cohorts (Sabia et al. 2013, da Silva et al., 2014, van Hees et al. 2014).

2.2: The Axivity device was set up to capture tri-axial acceleration data over a seven day period at 100Hz with a dynamic range of +-8g.

3. Data collection

3.1: Participants were emailed to invite them to wear an accelerometer in order to capture data on physical activity for a 7-day period.

3.2: Participants were informed in the invitation email and device mail-out letter that the accelerometer should be worn continuously and to carry on with their normal activities.

3.3: Once the participants had received the device in the mail, they were asked to start wearing the accelerometer immediately on the wrist of the hand that they usually write with.

3.4: Participants were informed that the device is configured to turn itself on and off automatically at pre-determined times.

3.5: At the end of the 7-day period, participants were asked to mail the device back to the co-ordinating centre in the pre-paid envelope provided.

3.6: On receipt at the co-ordinating centre, the data was downloaded and the devices cleaned and recharged ready to be dispatched to the next participant.

² <https://github.com/digitalinteraction/openmovement>

3.7: Accelerometer data from 103,720 participants were collected from May 2013 until Dec 2015. Overall, 240,000 invitations were sent, with a response rate of 44%. Devices were dispatched for 106,053 participants and, of these, data were received from 103,720 - with data on activity on 3 days or more from 93% of devices. The median return rate was 17 days, and the loss rate of devices was very low (1.2%).

4. Data Processing and summary fields

4.1: Data Preparation

4.1.1: Calibration: To ensure different devices provided a similar output under similar conditions we calibrated the acceleration signals to local gravity using the procedure described by van Hees and colleagues¹⁴. Briefly, we identified stationary periods in ten second windows where all three axes had a standard deviation of less than 13.0 mg. These stationary periods were then used to optimise the gain and offset for each axis (6 parameters) to fit a unit gravity sphere using ordinary least squares linear regression. If insufficient data were available to conduct calibration for a given participant (where any of the three sensor axes did not have values outside a ± 300 mg range), we used the calibration coefficients from the previous (or if unavailable, the next) accelerometer record from the same device worn on a different participant.

4.1.3: Highlight interrupts, and invalid values: Clipped values, which occur when the sensor's dynamic range of $\pm 8g$ is exceeded, were flagged before and after calibration. Recording errors and 'interrupts', which could have occurred for example if participants tried to plug their accelerometer device into a computer, were also logged.

4.1.2: Resampling: While the accelerometer is setup to record data at 100Hz, the actual sample rate can fluctuate between 94-104Hz. Thus, valid data was then resampled to 100 Hz using linear interpolation, except for interrupts lasting longer than 1 second which were set to missing.

4.2: Vector Magnitude Processing

4.2.1: Combine x/y/z axes: We calculated the sample level Euclidean norm of the acceleration in x/y/z axes (Sabia et al., 2014).

4.2.2: Gravity and noise removal: Machine noise was removed using a fourth order Butterworth low pass filter with a cut-off frequency of 20Hz. This filter is applied to the vector magnitude scores, rather than the individual axes, due to more precisely capturing arm rotations. In order to separate out the activity-related component of the acceleration signal, we removed one gravitational unit from the vector magnitude, with remaining negative values truncated to zero (Sabia et al., 2014; Van Hees et al. 2011; da Silva et al., 2014).

4.3.3: Epoch generation: To describe the overall level and distribution of physical activity intensity, we combined the sample level data into five second epochs for summary data analysis, maintaining the average vector magnitude value over the epoch. To represent the distribution of time spent by an individual in different levels of physical activity intensity, we generated an empirical cumulative distribution function from all available five second epochs (Hammerla et al., 2013).

4.3: Physical activity analysis

4.3.1: Detect non-wear: We removed non-wear time, defined as consecutive stationary episodes lasting for at least 60 minutes. The same standard deviation threshold criteria were applied as described in the calibration procedure to identify stationary episodes from the selected epochs.

4.3.2: Wear-time weighting: We imputed non-wear data segments using the average of similar time-of-day vector magnitude and intensity distribution data points with one minute granularity on different days of the measurements. This imputation accounts for potential wear time diurnal bias where, for example, if the device was systematically not worn during sleep in an individual, the crude average vector magnitude during wear time would be a biased overestimate of the true average (Van Hees et al., 2011).

4.4: Summary Physical Activity Variable: A physical activity outcome variable was generated by averaging all worn and imputed values. The expert working group decided that it may be prudent to remove individuals who had less than three days (72 hours) of data or who did not have data in each one-hour period of the 24-hour cycle. They defined these minimum wear-time guidelines by performing missing data simulations on 29,765 participants. Using intraclass correlation coefficients, at least 72 hours (3 days) of wear were needed to be within 10% of the true stable seven day measure.

4.5: Time series file: A .csv time series file is generated for each participant. This will provide researchers with a simple way to interrogate the five second by five second interpreted physical activity variable, without the need for expertise in processing large complex raw data files.

5. Data available in Showcase

5.1: Data-fields are available that describe:

- Raw acceleration data
- Average acceleration by day and by hour
- Acceleration intensity distribution
- Wear time/non-wear time and duration by day and by hour
- Accelerometer calibration and quality metrics

6. References

Da Silva IC, Hees VT van, Ramires V V, et al. Physical activity levels in three Brazilian birth cohorts as assessed with raw triaxial wrist accelerometry. *Int J Epidemiol.* 2014 Dec 1;**43**(6):1959–68.

Esliger DW, Rowlands A V, Hurst TL, Catt M, Murray P, Eston RG. Validation of the GENE Accelerometer. *Med Sci Sport Exerc.* 2011 Jun;**43**(6):1085–1093.

Hees VT van, Fang Z, Langford J, et al. Autocalibration of accelerometer data for free-living physical activity assessment using local gravity and temperature: an evaluation on four continents. *J Appl Physiol*. 2014 Oct 1;**117**(7):738–44.

Hammerla NY, Kirkham R, Andras P, Ploetz T. On preserving statistical characteristics of accelerometry data using their empirical cumulative distribution. *Proc 17th Annu Int Symp Int Symp wearable Comput - ISWC '13*. New York, New York, USA: ACM Press; 2013. p. 65

Ladha C, Ladha K, Jackson D, Olivier P. Shaker Table Validation Of Openmovement Ax3 Accelerometer. *3rd Int Conf Ambul Monit Phys Act Mov*. Amherst, MA, USA; 2013. p. 69–70.

Mannini A, Intille SS, Rosenberger M, Sabatini AM, Haskell W. Activity recognition using a single accelerometer placed at the wrist or ankle. *Med Sci Sports Exerc*. 2013 Nov 1;**45**(11):2193–203.

Sabia S, Hees VT van, Shipley MJ, et al. Association Between Questionnaire- and Accelerometer-Assessed Physical Activity: The Role of Sociodemographic Factors. *Am J Epidemiol*. 2014 Feb 4;**179**(6):781–790.

Van Hees VT, Renström F, Wright A, et al. Estimation of daily energy expenditure in pregnant and non-pregnant women using a wrist-worn tri-axial accelerometer. *PLoS One*. 2011 Jan;**6**(7):e22922.

Van Hees VT, Fang Z, Langford J, et al. Autocalibration of accelerometer data for free-living physical activity assessment using local gravity and temperature: an evaluation on four continents. *J Appl Physiol*. 2014 Oct 1;**117**(7):738–44.

7. Physical Activity Expert Working Group

Listed in alphabetical order:

- Soren Brage, University of Cambridge
- Aiden Doherty, University of Oxford
- Nils Hammerla, Newcastle University
- Vincent van Hees, Newcastle University

- Malcolm Granat, University of Salford
- Dan Jackson, University of Newcastle & Axivity
- Patrick Olivier, Newcastle University
- Chris Owen, St. Georges, University of London
- Thomas Plöetz, Newcastle University
- Steve Preece, University of Salford
- Mike Trenell, Newcastle University
- Nick Wareham, University of Cambridge (Chair)