Impact of Reduced Sampling Rate on Accelerometer-based Physical Activity Monitoring and Machine Learning Activity Classification

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Abstract

Purpose: Lowering the sampling rate of accelerometer devices can dramatically increase study monitoring periods through longer battery life, however the validity of its output is poorly documented. We therefore aimed to assess the effect of reduced sampling rate on measuring physical activity both overall and by specific behaviour types.

Methods: Healthy adults wore sets of two Axivity AX3 accelerometers on the dominant wrist and hip for 24 hours. At each location one accelerometer recorded at 25Hz and the other at 100Hz. Overall acceleration magnitude, time in moderate-to-vigorous activity, and behavioural activities were calculated, processed using both linear and nearest-neighbour resampling. Correlation between acceleration magnitude and activity classifications at both sampling rates was calculated and linear regression was performed.

Results: Of the 54 total participants, 45 contributed >20 hours of hip wear time and 51 contributed >20 hours of wrist wear time. Strong correlation was observed between 25Hz and 100Hz sampling rates in overall activity measurement ($r = 0.97$ to 0.99), yet consistently lower activity was observed in data collected at 25Hz (3.1% to 13.9%). Reduced sleep and light activity, and increased sedentary was classified in 25Hz data by machine learning models. Discrepancies were increased when linear interpolation resampling was used in post-processing.

Conclusions: 25Hz and 100Hz accelerometer data are highly correlated with predictable differences which can be accounted for in inter-study comparisons. Sampling rate and resampling methods should be consistently reported in physical activity studies, carefully considered in study design, and tailored to the outcome of interest.

Key Words: Self-Reported, Ambulatory Monitoring, Sampling Frequency, Activities of Daily Living, Accelerometry

Introduction

Accelerometers are increasingly used to obtain exposure measures in large observational physical activity healthcare studies (Doherty et al., 2017; Ekelund et al., 2019; Troiano et al., 2008) and to obtain outcome measures in randomised controlled trials (Redfield et al., 2015). Seven days of physical activity measurement is a common measurement window across a variety of accelerometer studies (Da Silva et al., 2018; Ricardo et al., 2019; Taraldsen et al., 2014; Wolff-Hughes et al., 2016); however, in the case of activity monitoring in clinical populations recovering from trauma or a surgical intervention, extended monitoring well beyond a standard seven day protocol may be desired (Armitage et al., 2020). Extended longitudinal protocols incorporating measurement windows beyond a few weeks requires frequent participant interaction for battery charging, which is burdensome and undesirable (Small et al., 2019). In these cases, a reduction of sampling rate would offer the potential for longer continuous physical activity measurement, while reducing patient and caregiver interactions with the monitoring device.

Currently, Brønd and Arvidsson offer the only side-by-side comparison of accelerometers recording at different sampling rates, recording laboratory-based activities with hip-mounted Actigraph GTX3+ devices (Brønd & Arvidsson, 2016). Other studies generate downsampled data from a single accelerometer to assess the effects of varying sampling rates, while relying on the untested assumption that this postprocessing accurately reproduces the recording behaviour of the underlying hardware (Clevenger et al., 2019; Zhang, Murray, et al., 2012). In addition, studies of this nature have been limited to the ActiGraph GTX3+ and GENEA triaxial accelerometers (Brønd & Arvidsson, 2016; Clevenger et al., 2019; Karas et al., 2018; Zhang, Murray, et al., 2012), and not the Axivity AX3, which has been used in the UK Biobank study of 100,000 participants (Doherty et al., 2017). This dataset is a valuable resource and can serve as a reference for physical activity within a wide range of populations. Therefore, the ability to compare physical activity data between studies integrating non-standard sampling rates remains unverified.

The aim of this study was to validate data collected at a reduced sampling rate (25 Hz) in comparison to that collected at the commonly used rate of 100 Hz within the AX3 accelerometer. The objectives were to: 1) identify any effect of sampling rate on device-measured activity for both overall and in specific free-living activities; 2) characterise the effect of reduced sampling rate on machine learning activity classification; 3) develop a transformation so that data collected at standard and reduced sampling rates can be directly compared.

Methods

Study design

Ethical approval for participant recruitment was obtained from the Central University Research Ethics Committee of the University of Oxford (Ref: R63137/RE001). Written informed consent was obtained from adult volunteers (aged 18 and above) with no lower limb injury within the previous 6 months and who were able to walk without an assistive device. Participants were recruited through advertising within Oxford University, the local community and in senior citizen groups.

Participants were instructed to wear four triaxial accelerometers (AX3, Axivity, Newcastle, UK) for 24 hours, except during bathing or swimming activities. Participants could remove sensors at night if they disrupted sleep. Two accelerometers were placed side-by-side on the dominant wrist using a wristband, and two on the dominant-side hip, waist level at the anterior-posterior midline via a belt clip (Figure 1).

Accelerometers were synchronised and programmed via the Open Movement software (v1.0.0.42) (https://openmovement.dev). At each body location, one sensor was programmed to collect data at a sampling rate of 25 Hz while the other collected data at 100 Hz, both with a dynamic range of ±8 *g*. The same four unique sensors were used in all participants. Accelerometer orientation and axis alignment within the hip and wrist straps were consistent with manufacturer guidance and verified prior to the start of each recording session. The assignment of hip or wrist body location and sampling

rate of each specific accelerometer was randomized by serial number so that the four accelerometers contributed to measurements at both body locations and sampling rates (Supplemental Table 1). Participants additionally filled out an activity diary (Supplement Note 1) to log the times during which they slept, cycled, walked more than 100 meters, ate a meal, participated in self-defined exercise, or removed the accelerometer.

Activity Metrics – Primary Analysis with the Biobank Accelerometer Analysis Tool

A schematic of the primary study analysis is presented in Figure 2a. Following the monitoring period, triaxial acceleration data was processed using the open source Biobank Accelerometer Analysis Tool (https://github.com/activityMonitoring/biobankAccelerometerAnalysis) (v3.1, commit 704ea71) (Doherty et al., 2017). Acceleration data was automatically calibrated by identifying stationary points within the data to reduce sensor-based measurement bias and offset error (Doherty et al., 2017; van Hees et al., 2014). Overall wear time was calculated and stationary non-wear episodes of 60 minutes or greater wherein all three axes had a standard deviation of less than 13 m*g* were automatically removed from analysis (Doherty et al., 2017). Data nominally collected at 25 Hz and 100 Hz were resampled using linear interpolation to eliminate device sampling errors and generate datasets with precisely 25 and 100 samples per second. A duplicate dataset from the 100 Hz recording was downsampled to 25 Hz for an additional comparison, as implemented in previous studies (Clevenger et al., 2019; Karas et al., 2018). Overall acceleration was calculated as the Euclidean norm of the three accelerometer axes with 1 *g* subtracted to account for gravity and negative values truncated to zero (ENMO). A fourth-order Butterworth lowpass filter (20 Hz cutoff) was applied to the 100 Hz data to eliminate machine noise. Acceleration metrics were collected into 30 second epochs for analysis and overall 24-hour activity was calculated with data reported in milli gravitational units (m*g*) following the same processing methodology as was used in the UK Biobank physical activity cohort (Doherty et al., 2017).

ENMO was also calculated for all diary-logged bouts of extended walking, cycling, sleeping, exercising, and eating. Time and duration of these activities were extracted from participant activity diaries. Beginning and ending times for diary labels were manually verified by inspecting and cross-referencing raw accelerometer data. If no end time was given for eating activities, a conservative estimate of 15 minutes was designated per meal. Overall moderate-to-vigorous physical activity (MVPA) was additionally quantified, defined as time spent at ENMO ≥ 100 m*g* at the wrist and ≥ 70 m*g* at the hip (Hildebrand et al., 2014).

Analysis of Resampling Methodology

In the primary analysis, nearest neighbour interpolation was used during resampling to minimize any potential down-smoothing of the raw accelerometer data. However, linear interpolation during resampling of raw accelerometer data is common practice in physical activity data analysis as the methodology in both the UK Biobank physical activity cohort and in the popular GGIR R Package (https://cran.r-project.org/web/packages/GGIR/vignettes/GGIR.html). Additional data analysis was performed using linear interpolation while resampling datasets to assess the effect of interpolation method on activity metric comparability between sampling rates.

Activity Metrics – Secondary Analysis with the GGIR R Package

A secondary analysis was performed to assess the effect of reduced sampling rate on shorter epoch lengths and in other commonly used activity metrics. In this analysis, the GGIR (v.2.3-0) R Package (Migueles et al., 2019) was used to resample and calibrate data, followed by 5 s epoch calculations of ENMO, Lowpass Filtered Euclidean Norm (LFENMO), Highpass Filtered Euclidean Norm (HFEN) and Mean Amplitude Deviation (MAD). Signal filtering utilised a 4^{th}-order Butterworth filter, with a 0.2 Hz cutoff for HFEN and 20 Hz cutoff for LFENMO. Within this manuscript, all data calculated through the Biobank Accelerometer Analysis tool is referred to as ENMO, and all data calculated through GGIR is designated by either ENMO [GGIR], LFENMO, HFEN, or MAD. It should be noted that LFENMO and

ENMO generate very similar metrics and are analogous to the lowpass filtered ENMO as calculated within the Biobank Accelerometer Analysis tool.

Activity Classification

Machine learning methods for activity classification of wrist-worn accelerometer data were performed using a two-stage machine learning model of balanced random forests and hidden Markov models (Willetts et al., 2018). The classification model used in the current study are open-source models implemented within the Biobank Accelerometer Analysis tool, having been previously developed and validated for activity classification of the UK Biobank physical activity cohort (Walmsley et al., 2020; Willetts et al., 2018). The models were trained using data from Axivity AX3 accelerometer recording at 100 Hz (±8 g) on the dominant wrist, with concurrent ground truth images recorded every 20 seconds for a total of 160,000 minutes in 134 participants. Linear resampling during feature extraction is performed in both models and was retained in processing in the current study. Activities were classified in 30 s epochs as time spent cycling, mixed activity, sit/stand, sleep, vehicle, and walking within the Willetts model, and in time spent in sleep, sedentary, light, and moderate-to-vigorous activity fusing rotation-invariant features in the Walmsley model (Clark et al., 2018; Ellis et al., 2016; Mannini et al., 2013; Vähä-Ypyä et al., 2015; Zhang, Rowlands, et al., 2012).

Statistical Analysis

A minimum sample size of 30 participants was calculated to detect a conservative correlation coefficient estimate of 0.6 between sampling rate and body location measurements with 80% power and alpha set at 0.05. This minimum sample size allowed for 30% data loss for dropout, protocol non-compliance, or poor data quality. Participants with less than 20 hours of wear were excluded from analysis. Summary and descriptive statistics were calculated for participant demographics, overall activity levels, and activity levels performed during self-reported activity designations. Mean ENMO was plotted in 1-hour increments over a 24-hour day to visualise differences in activity patterns recorded at either sampling rate. Two-sided Spearman's rank correlation was calculated to compare

activity levels, time in MVPA, and time in classified activities between accelerometer sampling rates and body locations. Mean difference and relative percentage difference in activity level between sampling rates was calculated with reference to 100 Hz measurements. Bland-Altman plots were used to assess fixed or proportional bias and limits of agreement between sampling rates across the full range of participant activity metrics and between resampling interpolation methods. Linear and 3rd order polynomial regression was used to determine the association between sampling rates and to estimate a conversion factor between acceleration metrics and activity classification recorded at the two sampling rates, with 25 Hz measurements modelled as the predictor and 100 Hz measurements as the regression outcome. Leave-one-subject-out cross validation (*n*-1) was repeated *n* times across each dataset to assess linear model generalisability, with the corresponding root mean square error (RMSE) and R^2 reported. Statistical analysis was performed in R (v.4.0.3) and RStudio (v1.4.1103).

Results

Participant Demographics

Fifty-four healthy adults (33 female, 21 male) with a mean age of 43.4 years (SD 17.6; range 19.5 - 81.2 years) participated in free-living physical activity analysis (Table 1). Acceleration measurement error following self-calibration was <2.6 m*g* across all recordings in the Biobank Accelerometer Analysis tool and <4.1 m*g* in GGIR processing, with no instances of calibration failure or device malfunction. Median hip and wrist accelerometer wear time was 23.7 hours (IQR 0.6) and 24.0 hours (IQR 0.5), respectively. Three sets of wrist-worn and nine sets of hip-worn sensors were removed from analysis as they were worn for less than 20 hours. Participants self-reported an overall mean of 7.4 hours of sleep (SD 1.0), 46.8 minutes of eating (SD 37.8), 28.4 minutes of general exercise (SD 56.7), 58.2 minutes of extended walking (SD 64.0), and 34.1 minutes of cycling (SD 27.8) over the 24-hour assessment period as calculated in participants who logged non-zero time in those activities.

24-Hour Physical Activity Assessment

Mean physical activity across all valid measurements according to time of day is presented in Figure 3 and 30 s epoch ENMO for wrist and hip accelerometers are presented in Table 2. Data calculated using linear interpolation resampling is reported in supplemental Table S1. Strong correlation was observed between 25 Hz and 100 Hz recorded data in overall ENMO and time spent in MVPA at both the hip (r = 0.99 to 1.00) and the wrist (r = 0.98 to 0.99). At the hip, ENMO collected at 25 Hz resulted in consistently lower overall activity compared to the 100 Hz data, with an absolute mean difference in ENMO (SD) of 0.5 (1.4) m*g* and 4.9 (10.0) minutes of MVPA per 24 hours. This represents a -3.1% relative difference in 24-hour activity and -5.9% difference in MVPA time when 25 Hz measurements when compared to 100 Hz measurements at the hip. At the wrist, 25 Hz data collection also resulted in consistently lower overall activity compared to the 100 Hz data, with an absolute mean difference (SD) of 1.9 (2.4) m*g* in ENMO and 13.1 (10.5) minutes of MVPA, a -5.7% and -11.5% relative difference in 25 Hz measurements at the wrist, respectively. Bland-Altman plots exhibiting the difference between 25 Hz and 100 Hz 24-hour ENMO are presented in Figure 4. A secondary analysis of ENMO [GGIR], LFENMO, HFEN, and MAD calculated in 5 s epochs in GGIR are presented in Table 3. Differences between these 25 Hz and 100 Hz activity metrics calculated with linear interpolation resampling at 5 s epochs with the GGIR package are more pronounced than in the primary analysis. In this secondary analysis, 25 Hz data capture resulted in 24-hour relative differences of -13.9% in ENMO [GGIR], 10.6% in LFENMO, -9.6% in HFEN, and -13.3% in MAD metrics.

At both hip and wrist locations, effectively perfect correlation (r = 1.000) was observed for overall ENMO between the recorded 100 Hz and the downsampled measurements from the same sensor (Table S3). Comparison of sampling rate via the downsampling of 100 Hz data to 25 Hz in the same sensor resulted in less than 0.1% difference in overall activity and MVPA across both the hip and wrist (Table S3, Figure S1).

Intensity of Self-Reported Activities

Correlation between acceleration ENMO measured at 25 Hz and 100 Hz sampling rates was high during all self-reported non-sleeping activities at the wrist (r = 0.97 to 1.00) and hip (r = 0.94 to 0.99) (Table 2). With nearest neighbour resampling, the 25 Hz sampling rate at the hip resulted in a mean relative difference in ENMO of -4.7% to -8.9% when compared to the 100 Hz sampling rate across all non-sleeping activities. The greatest difference in 25 Hz and 100 Hz data at the wrist was observed during cycling activity, where the 25 Hz accelerometer recorded relative difference of -27.6% when compared to the 100 Hz recording. Other non-sleeping activities resulted in a -1.6% to -6.9% relative difference when recorded at 25 Hz at the wrist. ENMO during sleep was predictably low, with lower correlation between sampling rates when compared to other activities (r = 0.55 to 0.95). Actual differences are small due to the very activity measured during sleep intervals.

Machine Learning Activity Classification

Results of the machine learning activity classification are presented in Table 4a/b. In Willetts classifications (Table 4a), periods of walking, sleep, sit/stand activities, and mixed activities were identified in all participants, whereas periods of cycling and vehicle activities were identified in 13 and 41 participants, respectively. In all participants who had cycling or vehicle activities classified within the 100 Hz 24-hour recording, that activity was also identified within the 25 Hz data. Notably, reduced sampling rate resulted in a 7.2% increase in estimated sit/stand time and a 10.1% decrease in estimated vehicle time. Within the more robust, rotation-invariant Walmsley model (Table 4b), 25 Hz data collection resulted in increased classification of sedentary activity at the expense of time classified in both sleep and light activities. A 18.2% increase in sedentary time classification in 25 Hz data was countered by a 12.0% reduction in classified sleep and a 14.8% reduction in classified time in light activities. Classification of MVPA was consistent between the two sampling rates.

A comparison of rotation-invariant machine learning features as calculated from 25 Hz and 100 Hz wrist data is presented in Table 5. Mean values across all participants and epochs demonstrate 19.8%

lower maximum vector magnitude, 34.8% lower skewness, 0.2% to 3.5% lower Fourier transform coefficients corresponding to 1-11 Hz and 4.7% to 6.5% lower values in the first twelve Fourier coefficients in 25 Hz collected data. Epoch minimum and mean power deviation values were calculated 34.3% and 80.9% higher in the 25 Hz compared to 100 Hz collected data.

Linear and Nearest Neighbour Resampling Methods

Bland-Altman plots comparing sampling rate interpolation methods are presented in Figures 5 and 6. Figure 5 demonstrates the mean bias when calculating ENMO of 25 Hz data using nearest neighbour interpolation in comparison to 100 Hz linearly interpolated data. In this instance the nearest neighbour interpolation of the 25 Hz data reduces the mean bias between sampling rates to -1.84 m*g* at the wrist and -0.53 m*g* at hip, similar to comparisons between sampling rates when both datasets are resampled using nearest neighbour interpolation. Conversely, a comparison of linearly interpolated 25 Hz and 100 Hz data is presented in Figure 6, with a mean bias of -4.39 m*g* and -2.04 m*g* between sampling rates at the wrist and hip, respectively.

Converting data collected at lower sample rates to enable comparison with other studies

Results from the linear regression and cross-validation relating sampling rates based on overall 24-hour activity metrics and activity classification models are presented in Table 6a/b. Coefficients beyond the 1st order in all activity metric polynomial regression models were statistically insignificant (<0.05), thus only linear transformations are reported. At the hip and wrist, the linear model of sampling rate accounted for between 97% and 99% of the adjusted variability in the linearly interpolated ENMO as described by R^2. N-1 cross-validation resulted in RSME values of 6.5% and 4.7% of the mean wrist and hip ENMO, respectively. Transformations for ENMO and combinations of nearest neighbour and linear interpolation, as well as for alternate metrics in 5 s epochs as calculated in GGIR are additionally reported with high cross-validated R^2. An example of activity metric transformation between 25 Hz collected data and a 100 Hz reference dataset is presented in Box 1.

Transformations from 25 Hz to 100 Hz data were generated for classifications in both Willetts and Walmsley models. In wrist-based activity classification, 69% to 97% of the variability between sampling rates was accounted for in the Willetts model, with cross-validation RMSE representing 7.5% of the mean time in the sit/stand classification and up to 29.9% the mean vehicle time. Within the Walmsley model incorporating rotation-invariant features, 70.7% to 92.4% of variability was accounted for, with RMSE representing 7.0%, 8.8%, 12.2%, and 10.7% of mean sleep, sedentary, light, and MVPA time.

Discussion

Outcome measures based on acceleration magnitude, cutpoint thresholds, and activity classification are commonly used in clinical and population studies of physical activity (Doherty et al., 2017; Migueles et al., 2017; Small et al., 2019). To validate the use of reduced sampling rate during physical activity measurement, acceleration metrics and activity classification were assessed across body location and self-reported activity types. Reduction in recorded sampling rate from 100 Hz to 25 Hz resulted in consistently lower measured overall activity at both hip and wrist body locations across all generated activity metrics in both the Biobank Accelerometer Analysis and GGIR processing tools. Linear interpolation produced a larger discrepancy between sampling rates, particularly when applied to the 25 Hz collected data. Reduced sampling rate resulted in large increases in several rotation-invariant signal features used for machine learning activity classification, and subsequently resulted in increased pooling of data into sedentary activity classification at the expense of sleep and light activity classifications. While both acceleration magnitude and activity classification are highly correlated between sampling rates, subtle, yet real differences in outcome measures were observed. Transformation of 25 Hz data can enable extended activity monitoring protocols while retaining comparability to data collected at 100 Hz.

In the current study of healthy adults in the free-living environment, we found a repeatable difference in activity metrics and MVPA in a side-by-side comparison of data collection at 25 Hz and 100 Hz. When

using a reduced sampling rate, a 3.1% to 13.9% lower 24-hour activity was observed when compared to 100 Hz data collection at the hip or wrist. Consistently lower ENMO was also observed in the 25 Hz recording across diary-logged free-living activities. Similar to the current study, Brønd and Arvidsson (Brønd & Arvidsson, 2016) found ActiGraph GT3x counts demonstrated small differences between sampling rates (30 Hz, 40 Hz, and 100 Hz) during walking, yet large differences between sampling rates during running, with up to 3000 counts per minute greater intensity recorded in the faster sampling rates. Two other prior investigations of accelerometer sampling rate relied on downsampling accelerometer data from a single sensor, with mixed results and frequently little difference between sampling rates when using raw acceleration-based metrics(Clevenger et al., 2019; Karas et al., 2018). In this study we conducted a secondary analysis by downsampling data initially collected at 100 Hz, which also resulted in no difference in 24-hour activity and MVPA at a lower sampling rate, even while raw data collection at 25 Hz demonstrated a reduction in the activity intensity captured during acceleration analysis. Subsequently, basic downsampling of data from a single accelerometer is probably insufficient to determine the full effect of different sampling rates. As a measurement device, the AX3 stores the output of the underlying ADXL345 accelerometer with no material difference in how the device behaves at a lower sampling rate. We hypothesize that a contributor to the observed differences in data collected at different sampling rates may be the result of the internal ADXL345 single-pole IIR digital filter or otherwise related to the data capture of the MEMs accelerometer. Subsequently, a similar effect would be observed in the GENEActiv activity monitor, which uses the same underlying hardware.

The resampling of raw accelerometer data is a common processing step in order to eliminate inconsistent data timing in raw datasets. Both GGIR and the Biobank Accelerometer Analysis utilise linear interpolation methods by default. In the current study, we demonstrate an increased sensitivity to interpolation method in the lower sampling rate, with little difference between methods in the 100 Hz data. Because published bulk data has likely been processed via linear interpolation resampling (eg. 100 Hz activity data from the UK Biobank Physical Activity Cohort), we have generated transformations

to enable direct data comparison between combinations of nearest neighbour and linear interpolations at 25 Hz and 100 Hz sampling rates. We recommend the use of nearest neighbour resampling going forward, particularly in the instance of reduced sampling rate, in order to avoid unintended smoothing of the slower sampled data.

When using machine learning models of activity classification, we found high correlation between different sampling rates across classified activities. Transformations are provided for activity classifications of time spent in sit/stand, sleep, vehicle, sedentary, and light activity captured at a 25 Hz sampling rate when comparing to a 100 Hz dataset. Due to the small difference in classification of mixed activity, cycling, and MVPA, transformation for these activities is not recommended. Most notably, a reduced sampling rate resulted in increased classification of sedentary activity with decreased contributions of sleep and light activity within the Walmsley classification model. The 15% reduction in classified light activity is likely due in part to the general underestimation of ENMO throughout the 25 Hz timeseries. This finding is contrary to a study published by Zhang et al. (Zhang, Murray, et al., 2012) which reported no significant reduction in activity classification accuracy when comparing downsampled data to the original 80 Hz sequence. It is likely the use of downsampling versus a side-by-side comparison has contributed to the opposing findings.

Most recent physical activity studies include protocols where acceleration data is collected at a sampling frequency between 20 and 100 Hz (Farrahi et al., 2018; Migueles et al., 2017; Small et al., 2019). It is important to note that reporting of sampling rate used in testing protocols remains a problem in the field of physical activity, with recent reviews finding that 16% to 73% studies failed to report the sampling rate used in their data collection protocol (Migueles et al., 2017; Small et al., 2019). In an assessment of benchmark datasets, Khan et al (Khan et al., 2016) have argued that typical accelerometer sampling rates in many human motion studies are up to 57% higher than necessary for adequate data analysis, with optimal sampling rates between 12 and 63Hz depending on body location and model of accelerometer. Migueles et al(Migueles et al., 2017), however, argue that future data

processing needs are unknown, and thus the highest possible sampling frequency should be used. The world's largest objectively-measured physical activity database contains accelerometer data from 100 Hz data collection using the AX3 device (Doherty et al., 2017). Based on the results of the current study, if a reduced sampling rate of 25 Hz is selected in a measurement protocol, acceleration magnitude can be adjusted for comparison to a more standard 100 Hz dataset.

Strengths and limitations

A major strength of our study is that it includes a side-by-side comparison of standard and reduced accelerometer sampling rates at multiple body locations, without dependency on downsampling. This methodology includes the comprehensive use of acceleration-based activity metrics, cut-point, and machine learning variables to facilitate direct comparison of data collected at 25 Hz with existing large physical activity cohorts that have collected data at 100 Hz. However, data was collected in a healthy convenience sample, and there may be unquantified effects of measurement in disease populations. While individual devices were randomised to body location (hip/wrist), a potential limitation is that the exact position of devices at each location was not randomised by design. For example, when sensors were placed side-by-side on participants' wrists, it could be possible that the 100 Hz sensor was more frequently placed nearer to the wrist and thus experience slightly higher accelerations. However, we feel this alternative explanation is unlikely to account for the differences we and others have found (Brønd & Arvidsson, 2016). The analysis of additional intermediate sample rates was not conducted in this study but could further shape the understanding of the relationship between sampling rates and activity metrics. Additionally, the given linear transformations may not be well suited for activity transformation during extended near-zero acceleration activity levels. Epoch-based comparisons can have sensitivity to exact epoch boundaries, as all individual sensor clocks drift slightly over time. Comparing two epochs between devices that report the same boundaries may be comparing two slightly different periods.

Conclusion

Reducing accelerometer sampling rate from 100 Hz to 25 Hz can dramatically extend study monitoring periods while still providing valid data, after appropriate transformations. In order to facilitate comparisons between studies, researchers should consider and discuss the effect of both sampling rate and resampling interpolation method on data analysis, and fully report all accelerometer parameters in the study methodology.

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Box 1: Example of converting data collected at 25 Hz so that it can be compared to data collected at 100 Hz

A 68-year-old female participant has 7-day mean overall acceleration magnitude, ENMO, of 24.8 m*g* as recorded at 25 Hz on the dominant wrist with an AX3 accelerometer (Acc_{25}). Researchers wish to compare this individual to the baseline 65-74 year-old female in the UK Biobank database 26.6 (SD 7.1) m*g*, recorded at 100 Hz with an AX3 accelerometer (Acc_{100}) (Doherty et al., 2017). Without sampling rate conversion, a 24.8 m*g* activity level is below average for her age group, and places this patient in the 40th percentile of activity in the 65-74 year-old female cohort. With 25 Hz to 100 Hz conversion following the wrist-based regression model with default linear interpolation resampling, $Acc_{100} = 1.038*Acc_{25} + 3.310$, the participant's comparable acceleration magnitude is 29.1 m*g*, placing her in the 64th percentile of the appropriate demographic cohort. Conversely, if 25 Hz data is resampled using nearest neighbour interpolation (Acc_{25nn}), the appropriate conversion for comparison to the linearly resampled 100 Hz reference database would be $Acc_{100} = 0.989*Acc_{25nn} + 2.179$.

Table 1: Participant demographics

	Mean	SD
Age (years)	43.4	17.6
Height (cm)	170.5	10.8
Weight (kg)	70.5	13.3
BMI (kg/m^2)	24.2	3.6
	n	%
Sex		
Female	33	61%
Male	21	39%
Handedness		
Left	8	15%
Right	46	85%

Table 2: Accelerometer measured physical activity for both overall and diary-reported activities in a convenience sample of 51 adults over a single 24hr period (30 second epoch)

	ENMO mg	Time in MVPA* mins	Cycling m*g*	Eating m*g*	Exercising m*g*	Sleeping m*g*	Walking m*g*
Wrist	*n = 51*	*n = 51*	*n = 13*	*n = 44*	*n = 16*	*n = 51*	*n = 44*
25 Hz mean [SD]	31.3 [12.0]	100.9 [52.1]	91.9 [28.3]	29.6 [13.5]	317.9 [321.7]	3.7 [0.8]	134.1 [55.4]
100 Hz mean [SD]	33.2 [12.1]	114.0 [54.3]	126.9 [58.0]	31.8 [13.9]	331.2 [327.5]	3.2 [0.8]	136.3 [58.7]
25 Hz -100 Hz mean difference [SD]	-1.9 [2.4]	-13.1 [10.5]	-35.0 [17.9]	-2.2 [2.9]	-13.3 [114.8]	0.5 [0.2]	-2.2 [12.2]
Spearman's correlation	0.98	0.98	0.98	0.97	1.00	0.92	0.98
ICC	0.99	0.98	0.74	0.99	1.00	0.95	0.98
Hip	*n = 45*	*n = 45*	*n = 11*	*n = 40*	*n = 14*	*n = 45*	*n = 39*
25 Hz mean [SD]	15.6 [6.8]	77.6 [47.1]	57.4 [18.7]	10.2 [7.0]	109.0 [115.6]	2.8 [0.4]	114.0 [48.0]
100 Hz mean [SD]	16.1 [7.2]	82.5 [47.7]	60.6 [18.8]	10.7 [7.6]	119.6 [128.9]	2.3 [0.3]	121.7 [51.3]
25 Hz -100 Hz mean difference [SD]	-0.5 [1.4]	-4.9 [10.0]	-3.2 [7.4]	-0.5 [1.6]	-10.6 [43.3]	0.1 [0.1]	-7.7 [10.6]
Spearman's correlation	0.99	0.99	0.99	0.98	0.99	0.55	0.99
ICC	0.99	1.00	0.99	0.99	0.99	0.61	1.00

*MVPA reported in minutes calculated by 30s epochs with ENMO ≥ 100 m*g* at the wrist and ≥ 70 m*g* at the hip

Table 3: Secondary analysis of alternative physical activity metrics as calculated in wrist sensors over 5 second epochs in GGIR

	ENMO [GGIR] m*g*	LFENMO m*g*	HFEN m*g*	MAD m*g*
25 Hz mean [SD]	28.6 [12.2]	28.7 [12.2]	90.7 [24.4]	41.6 [13.0]
100 Hz mean [SD]	33.2 [12.7]	32.1 [12.6]	100.4 [25.8]	48.0 [14.4]
25 Hz -100 Hz mean difference [SD]	-4.6 [2.7]	-3.4 [2.7]	-9.7 [5.5]	-6.4 [3.0]
Spearman's correlation	0.97	0.97	0.98	0.98
ICC	0.96	0.97	0.95	0.94

Table 4a: Machine learned activity classification for wrist accelerometers in a convenience sample of 51 adults over a single 24hr period (Willetts model).

	Cycling min	**Mixed Activity min**	**Sit/Stand min**	**Sleep min**	**Vehicle min**	**Walking min**
Participants with the identified activity	*n = 13*	*n = 51*	*n = 51*	*n = 51*	*n = 41*	*n = 51*
25 Hz classified mean time [SD]	28.6 [19.1]	161.9 [121.3]	595.7 [142.2]	452.8 [64.4]	70.4 [56.2]	161.5 [87.1]
100 Hz classified mean time [SD]	28.5 [19.3]	164.1 [127.9]	555.2 [148.5]	475.9 [73.9]	78.3 [55.9]	170.4 [86.7]
25-100 Hz mean difference in classified time [SD]	0.1 [7.5]	-2.2 [24.7]	40.5 [28.8]	-23.1 [13.7]	-7.9 [12.4]	-8.9 [17.2]
Spearman's correlation	0.99	0.91	0.93	0.86	0.92	0.89
ICC	0.99	0.96	0.96	0.84	0.92	0.92

Table 4b: Machine learned activity classification for wrist accelerometers in a convenience sample of 51 adults over a single 24hr period (Walmsley model).

	Sleep min	**Sedentary min**	**Light Activity min**	**MVPA min**
Participants with the identified activity	*n = 51*	*n = 51*	*n = 51*	*n = 48*
25 Hz classified mean time [SD]	415.1 [63.0]	683.4 [129.6]	280.8 [133.1]	60.8 [41.5]
100 Hz classified mean time [SD]	471.6 [61.5]	578.2 [143.9]	329.7 [147.3]	60.5 [42.4]
25-100 Hz mean difference in classified time [SD]	-56.5 [12.3]	105.2 [27.1]	-48.9 [27.8]	0.3 [8.6]
Spearman's correlation	0.82	0.94	0.96	0.98
ICC	0.85	0.93	0.96	0.99

Table 5: Comparison of Rotation-Invariant Machine Learning Features Between 100 Hz and 25 Hz Data Collection

Feature	100 Hz Mean (SD)	25 Hz Mean (SD)	% Difference (25 Hz-100 Hz) (SD)
ENMO (Truncated)	0.032 (0.075)	0.030 (0.073)	-4.6% (1.4%)
Mean	0.243 (0.275)	0.239 (0.271)	-1.7% (5.2%)
Standard deviation	0.133 (0.142)	0.128 (0.136)	-3.5% (2.7%)
Coefficient of variation	0.696 (0.462)	0.670 (0.411)	-3.7% (8.4%)
Median	0.207 (0.250)	0.204 (0.247)	-1.4% (4.8%)
Minimum	0.033 (0.054)	0.044 (0.064)	34.3% (1.1%)
Maximum	1.085 (1.397)	0.870 (0.999)	-19.8% (23.4%)
25^{th} percentile	0.157 (0.192)	0.155 (0.191)	-1.1% (3.7%)
75^{th} percentile	0.295 (0.344)	0.290 (0.338)	-1.7% (6.6%)
1 second autocorrelation	0.285 (0.278)	0.287 (0.282)	0.8% (5.4%)
Dominant frequency	1.141 (3.015)	1.116 (2.462)	-2.2% (53.0%)
Power of dominant frequency	-10.405 (4.533)	-10.442 (4.517)	0.4% (87.1%)
Dominant frequency (0.3 to 5 Hz)	0.787 (0.625)	0.869 (0.717)	10.5% (12.9%)
Power of dominant frequency (0.3 to 5 Hz)	-12.261 (3.971)	-12.182 (3.805)	-0.6% (74.8%)
Spectral entropy	0.562 (0.214)	0.604 (0.195)	7.5% (3.9%)
Fourier transform coefficient (1 Hz)	-3.378 (1.983)	-3.373 (1.907)	-0.2% (37.4%)
Fourier transform coefficient (2 Hz)	-4.037 (1.980)	-3.987 (1.898)	-1.3% (37.3%)
Fourier transform coefficient (3 Hz)	-6.054 (1.925)	-5.843 (1.717)	-3.5% (35.1%)
Fourier transform coefficient (4 Hz)	-6.249 (1.815)	-6.068 (1.597)	-2.9% (32.9%)
Fourier transform coefficient (5 Hz)	-6.337 (1.697)	-6.202 (1.514)	-2.1% (30.9%)
Fourier transform coefficient (6 Hz)	-6.428 (1.611)	-6.313 (1.442)	-1.8% (29.4%)
Fourier transform coefficient (7 Hz)	-6.557 (1.596)	-6.408 (1.386)	-2.3% (28.8%)
Fourier transform coefficient (8 Hz)	-6.653 (1.572)	-6.487 (1.340)	-2.5% (28.1%)
Fourier transform coefficient (9 Hz)	-6.711 (1.541)	-6.549 (1.307)	-2.4% (27.5%)
Fourier transform coefficient (10 Hz)	-6.768 (1.505)	-6.602 (1.279)	-2.4% (26.9%)
Fourier transform coefficient (11 Hz)	-6.839 (1.465)	-6.652 (1.251)	-2.7% (26.2%)
Mean absolute deviation	0.049 (0.086)	0.046 (0.082)	-5.8% (1.6%)
Mean power deviation	0.000 (0.002)	0.001 (0.003)	80.9% (0.0%)
Skewness	1.393 (3.214)	0.908 (2.712)	-34.8% (57.2%)
Kurtosis	-2.992 (0.029)	-2.981 (0.059)	-0.4% (0.9%)
Dominant frequency (0.3 to 15 Hz)	3.128 (3.095)	3.006 (2.895)	-3.9% (57.7%)
Power of dominant frequency (0.3 to 15 Hz)	-13.750 (3.735)	-13.645 (3.551)	-0.8% (70.1%)
Second dominant frequency (0.3 to 5 Hz)	3.324 (3.168)	3.166 (2.959)	-4.8% (59.0%)
Dominant frequency (0.6 to 2.5 Hz)	1.465 (0.552)	1.482 (0.558)	1.2% (10.7%)
Power of dominant frequency (0.6 to 2.5 Hz)	-13.998 (3.769)	-13.856 (3.573)	-1.0% (70.7%)
Total power	-10.463 (3.913)	-10.236 (3.565)	-2.2% (72.0%)
First Fourier coefficient	0.008 (0.019)	0.008 (0.019)	-4.7% (0.4%)
Second Fourier coefficient	0.004 (0.010)	0.004 (0.010)	-4.9% (0.2%)
Third Fourier coefficient	0.002 (0.004)	0.001 (0.003)	-6.5% (0.1%)
Fourth Fourier coefficient	0.001 (0.003)	0.001 (0.003)	-6.3% (0.1%)
Fifth Fourier coefficient	0.001 (0.002)	0.001 (0.002)	-6.1% (0.0%)
Sixth Fourier coefficient	0.001 (0.002)	0.001 (0.002)	-6.0% (0.0%)
Seventh Fourier coefficient	0.001 (0.002)	0.001 (0.002)	-5.8% (0.0%)
Eighth Fourier coefficient	0.001 (0.002)	0.001 (0.002)	-5.4% (0.0%)
Ninth Fourier coefficient	0.001 (0.002)	0.001 (0.002)	-5.2% (0.0%)
Tenth Fourier coefficient	0.001 (0.002)	0.001 (0.002)	-5.1% (0.0%)
Eleventh Fourier coefficient	0.001 (0.002)	0.001 (0.002)	-5.0% (0.0%)
Twelfth Fourier coefficient	0.001 (0.002)	0.001 (0.001)	-4.5% (0.0%)

Italicized features are calculated using a lowpass filtered 3-axis acceleration vector magnitude, $\sqrt{x^2 + y^2 + z^2}$, as described by Ellis et al. (Ellis et al., 2016). Code used for feature generation can be found at: https://github.com/activityMonitoring/biobankAccelerometerAnalysis/blob/master/java/Features.java

Table 6a: Linear regression to 24-hour convert accelerometer metrics collected at 25 Hz so that it can be compared to data collected at 100 Hz. R^2 and RMSE values are reported from leave-one-subject-out cross-validation.

	Coefficient [SE]	95% CI	Intercept [SE]	95% CI	R^2	RMSE
ENMO (BiobankAA) [30 s epoch] (m*g*) 25 Hz Linear Interpolation to 100 Hz Linear Interpolation Resampling						
Wrist	1.038 [0.026]	(0.986, 1.090)	3.310 [0.798]	(1.706, 4.914)	0.967	2.155
Hip	1.158 [0.019]	(1.120, 1.195)	-0.180 [0.283]	(-0.751, 0.391)	0.988	0.757
ENMO (BiobankAA) [30 s epoch] (m*g*) 25 Hz Nearest Neighbour Interpolation to 100 Hz Linear Interpolation Resampling						
Wrist	0.989 [0.021]	(0.947, 1.031)	2.179 [0.699]	(0.775, 3.584)	0.976	1.832
Hip	1.042 [0.014]	(1.013, 1.071)	-0.121 [0.245]	(-0.615, 0.372)	0.991	0.659
ENMO (BiobankAA) [30 s epoch] (m*g*) 25 Hz Nearest Neighbour Interpolation to 100 Hz Nearest Neighbour Interpolation Resampling						
Wrist	0.997 [0.021]	(0.956, 1.039)	2.000 [0.693]	(0.608, 3.392)	0.977	1.824
Hip	1.062 [0.014]	(1.034, 1.090)	-0.415 [0.237]	(-0.892, 0.063)	0.992	0.637
ENMO (GGIR) [5 s epoch] - 25 Hz to 100 Hz (m*g*)						
Wrist	1.025 [0.032]	(0.961, 1.089)	3.684 [0.988]	(1.685, 5.683)	0.960	2.536
LFENMO (GGIR) [5 s epoch] - 25 Hz to 100 Hz (m*g*)						
Wrist	1.014 [0.030]	(0.954, 1.074)	2.988 [0.927]	(1.113, 4.862)	0.964	2.368
HFEN (GGIR) [5 s epoch] - 25 Hz to 100 Hz (m*g*)						
Wrist	1.042 [0.031]	(0.980, 1.104)	5.862 [2.873]	(0.051, 11.673)	0.964	4.851
MAD (GGIR) [5 s epoch] - 25 Hz to 100 Hz (m*g*)						
Wrist	1.096 [0.025]	(1.036, 1.156)	2.365 [1.292]	(-0.274, 4.978)	0.969	2.488

BiobankAA – Biobank Accelerometer Analysis tool

Table 6b: Linear regression to convert machine learning activity classification collected at 25 Hz so that it can be compared to data collected at 100 Hz. R^2 and RMSE values are reported from leave-one-subject-out cross-validation. Linear interpolation resampling was used in both 25 Hz and 100 Hz datasets.

Willetts Model Activity Classification at Wrist (min) 25 Hz to 100 Hz	Coefficient [SE]	95% CI	Intercept [SE]	95% CI	R^2	RMSE
Cycling	0.996 [0.023]	(0.950, 1.042)	-0.26 [0.51]	(-1.28, 0.76)	0.972	3.14
Mixed Activity	1.013 [0.042]	(0.929, 1.097)	0.12 [8.42]	(-16.79, 17.03)	0.919	36.05
Sit/Stand	1.005 [0.040]	(0.927, 1.095)	-43.41 [24.75]	(-99.88, 2.45)	0.920	41.5
Sleep	0.974 [0.087]	(0.840, 1.250)	34.82 [39.63]	(-73.65, 100.33)	0.687	40.3
Vehicle	0.914 [0.063]	(0.769, 1.049)	13.87 [5.66]	(5.09, 29.34)	0.822	23.4
Walking	0.916 [0.056]	(0.804, 1.028)	22.4 [10.18]	(1.94, 42.86)	0.831	35.3
Walmsley Model Activity Classification at Wrist (min) 25 Hz to 100 Hz						
Sleep	0.835 [0.073]	(0.629, 0.962)	124.94 [30.45]	(72.3, 210.8)	0.707	33.0
Sedentary	1.043 [0.054]	(0.952, 1.161)	-134.4 [37.79]	(-216.5, -70.1)	0.873	50.7
Light	1.066 [0.042]	(1.005, 1.138)	30.35 [13.07]	(12.40, 50.17)	0.924	40.1
MVPA	1.011 [0.022]	(0.967, 1.055)	-0.923 [1.61]	(-4.16, 2.32)	0.976	6.5

Figure Legend

Figure 1: Diagram of accelerometer placement with flow chart of participants with valid wear time at each body location. (Created with BioRender)

Figure 2a: Schematic of primary data analysis to inform conversion of accelerometer data collected at 25 Hz to enable comparison with studies collected at 100 Hz within the Biobank Accelerometer Analysis Tool with linear and nearest neighbour resampling interpolation methods.

Figure 2b: Schematic of secondary activity metric data analysis with the GGIR R package to enable comparison of 25 Hz and 100 Hz collected data in 5 s epochs and in alternate activity metrics.

Figure 3: Plot of mean (95%CI) 24-hour activity in 1-hour epochs as measured by ENMO [GGIR] with linear interpolation resampling across a convenience sample of 51 participants at each of the four sensor location/rate combinations.

Figure 4: Bland-Altman plots comparing the mean 24-hour ENMO and differences between the 25 Hz and 100 Hz sensors at the wrist and hip in a convenience sample of 51 adults. Dashed lines indicated mean bias and 95% limits of agreement. Negative bias on the y-axis indicates lower values in the 25 Hz sensor. Both 25 Hz and 100 Hz data calculated using nearest neighbour interpolation resampling.

Figure 5: Bland-Altman plots comparing the mean 24-hour ENMO and differences between the 25 Hz and 100 Hz sensors at the wrist and hip in a convenience sample of 51 adults. Dashed lines indicated mean bias and 95% limits of agreement. Negative bias on the y-axis indicates lower values in the 25 Hz sensor. 25 Hz data calculated using nearest neighbour interpolation resampling, 100 Hz data calculated using linear interpolation resampling, as would be the case when comparing to a reference 100 Hz dataset.

Figure 6: Bland-Altman plots comparing the mean 24-hour ENMO and differences between the 25 Hz and 100 Hz sensors at the wrist and hip in a convenience sample of 51 adults. Dashed lines indicated mean bias and 95% limits of agreement. Negative bias on the y-axis indicates lower values in the 25 Hz sensor. All data calculated using linear interpolation resampling.

Supplemental Figure 1: Bland-Altman plots comparing the mean 24-hour ENMO and differences between the downsampled 25 Hz acceleration and 100 Hz raw acceleration from sensors recording at 100 Hz at the wrist and hip. Dashed lines indicated mean bias and 95% limits of agreement. Negative bias on the y-axis indicates lower values in the downsampled 25 Hz data.

Supplemental Table 1: Accelerometer measured physical activity for both overall and diary-reported activities in a convenience sample of 51 adults over a single 24hr period (30 second epoch) using linear interpolation resampling.

	ENMO mg	Time in MVPA* mins	Cycling m*g*	Eating m*g*	Exercising m*g*	Sleeping m*g*	Walking m*g*
Wrist	*n = 51*	*n = 51*	*n = 13*	*n = 44*	*n = 16*	*n = 51*	*n = 44*
LR: 25 Hz mean [SD]	28.7 [11.4]	86.2 [47.9]	73.4 [21.1]	26.9 [12.4]	301.7 [307.7]	3.2 [0.7]	126.2 [56.0]
LR: 100 Hz mean [SD]	33.1 [12.0]	112.1 [53.7]	119.5 [46.5]	31.7 [13.8]	329.5 [326.3]	3.4 [0.8]	136.3 [58.8]
LR: 25 Hz -100 Hz mean difference [SD]	-4.4 [2.3]	-25.9 [10.1]	-46.1 [14.2]	-4.8 [2.8]	-27.8 [112.1]	-0.2 [0.1]	-10.1 [12.2]
Spearman's correlation	0.97	0.96	0.96	0.96	1.00	0.90	0.96
ICC	0.98	0.95	0.71	0.98	1.00	0.92	0.98
Hip	*n = 45*	*n = 45*	*n = 11*	*n = 40*	*n = 14*	*n = 45*	*n = 39*
LR: 25 Hz mean [SD]	14.1 [6.1]	72.0 [46.0]	51.7 [16.9]	9.2 [6.4]	97.5 [102.0]	2.5 [0.3]	102.2 [44.6]
LR: 100 Hz mean [SD]	16.1 [7.1]	81.7 [47.6]	60.2 [18.7]	10.8 [7.5]	117.2 [125.5]	2.6 [0.3]	117.3 [52.0]
LR: 25 Hz -100 Hz mean difference [SD]	-2.0 [1.4]	-9.7 [9.9]	-8.5 [7.6]	-1.6 [1.6]	-19.6 [43.2]	-0.1 [0.1]	-15.1 [11.0]
Spearman's correlation	0.99	0.99	1.00	0.98	1.00	0.48	0.99
ICC	0.98	0.99	0.99	0.98	0.98	0.57	0.99

*MVPA reported in minutes calculated by 30s epochs with acceleration magnitude ≥ 100 m*g* at the wrist and ≥ 70 m*g* at the hip

LR: Linear interpolation resampling

Supplemental Table 2: Accelerometer Body Position Randomised Distribution

AX3 45416	AX3 46810	AX3 46833	AX3 46957
Hip - 100 Hz	Wrist - 100 Hz	Hip - 25 Hz	Wrist - 25 Hz
Wrist - 25 Hz	Hip - 100 Hz	Hip - 25 Hz	Wrist - 100 Hz
Wrist - 100 Hz	Wrist - 25 Hz	Hip - 100 Hz	Hip - 25 Hz
Hip - 25 Hz	Hip - 100 Hz	Wrist - 100 Hz	Wrist - 25 Hz
Hip - 100 Hz	Wrist - 100 Hz	Hip - 25 Hz	Wrist - 25 Hz
Wrist - 100 Hz	Hip - 100 Hz	Hip - 25 Hz	Wrist - 25 Hz
Wrist - 25 Hz	Wrist - 100 Hz	Hip - 100 Hz	Hip - 25 Hz
Hip - 25 Hz	Wrist - 25 Hz	Hip - 100 Hz	Wrist - 100 Hz
Wrist - 25 Hz	Hip - 100 Hz	Hip - 25 Hz	Wrist - 100 Hz
Hip - 100 Hz	Hip - 25 Hz	Wrist - 25 Hz	Wrist - 100 Hz
Hip - 100 Hz	Wrist - 100 Hz	Hip - 25 Hz	Wrist - 25 Hz
Hip - 25 Hz	Wrist - 25 Hz	Hip - 100 Hz	Wrist - 100 Hz
Hip - 100 Hz	Wrist - 100 Hz	Wrist - 25 Hz	Hip - 25 Hz
Hip - 25 Hz	Wrist - 25 Hz	Hip - 100 Hz	Wrist - 100 Hz
Hip - 100 Hz	Wrist - 100 Hz	Hip - 25 Hz	Wrist - 25 Hz
Wrist - 25 Hz	Hip - 25 Hz	Hip - 100 Hz	Wrist - 100 Hz
Hip - 25 Hz	Hip - 100 Hz	Wrist - 25 Hz	Wrist - 100 Hz
Hip - 100 Hz	Wrist - 100 Hz	Hip - 25 Hz	Wrist - 25 Hz
Wrist - 25 Hz	Hip - 25 Hz	Hip - 100 Hz	Wrist - 100 Hz
Wrist - 25 Hz	Hip - 100 Hz	Hip - 25 Hz	Wrist - 100 Hz
Wrist - 100 Hz	Hip - 25 Hz	Wrist - 25 Hz	Hip - 100 Hz
Wrist - 25 Hz	Wrist - 100 Hz	Hip - 25 Hz	Hip - 100 Hz
Hip - 25 Hz	Wrist - 25 Hz	Hip - 100 Hz	Wrist - 100 Hz
Wrist - 25 Hz	Wrist - 100 Hz	Hip - 25 Hz	Hip - 100 Hz
Wrist - 100 Hz	Hip - 100 Hz	Hip - 25 Hz	Wrist - 25 Hz
Wrist - 25 Hz	Wrist - 100 Hz	Hip - 100 Hz	Hip - 25 Hz
Hip - 100 Hz	Wrist - 100 Hz	Hip - 25 Hz	Wrist - 25 Hz
Hip - 100 Hz	Wrist - 25 Hz	Hip - 25 Hz	Wrist - 100 Hz
Wrist - 100 Hz	Hip - 25 Hz	Wrist - 25 Hz	Hip - 100 Hz
Hip - 100 Hz	Wrist - 100 Hz	Hip - 25 Hz	Wrist - 25 Hz
Wrist - 25 Hz	Wrist - 100 Hz	Hip - 25 Hz	Hip - 100 Hz
Wrist - 25 Hz	Hip - 100 Hz	Hip - 25 Hz	Hip - 25 Hz
Wrist - 100 Hz	Wrist - 25 Hz	Wrist - 100 Hz	Wrist - 25 Hz
Wrist - 100 Hz	Hip - 100 Hz	Wrist - 25 Hz	Hip - 25 Hz
Wrist - 100 Hz	Hip - 100 Hz	Wrist - 25 Hz	Hip - 25 Hz
Wrist - 25 Hz	Wrist - 100 Hz	Hip - 100 Hz	Hip - 25 Hz
Wrist - 100 Hz	Wrist - 25 Hz	Hip - 100 Hz	Hip - 25 Hz
Hip - 25 Hz	Wrist - 25 Hz	Hip - 100 Hz	Wrist - 100 Hz
Wrist - 25 Hz	Hip - 25 Hz	Hip - 100 Hz	Wrist - 100 Hz
Hip - 100 Hz	Wrist - 100 Hz	Hip - 25 Hz	Wrist - 25 Hz
Wrist - 25 Hz	Wrist - 100 Hz	Hip - 100 Hz	Hip - 25 Hz
Wrist - 100 Hz	Hip - 25 Hz	Hip - 100 Hz	Wrist - 25 Hz
Hip - 25 Hz	Hip - 100 Hz	Wrist - 25 Hz	Wrist - 100 Hz
Wrist - 100 Hz	Wrist - 25 Hz	Hip - 25 Hz	Hip - 100 Hz
Wrist - 100 Hz	Hip - 100 Hz	Wrist - 25 Hz	Hip - 25 Hz
Hip - 100 Hz	Wrist - 100 Hz	Wrist - 25 Hz	Hip - 25 Hz
Hip - 25 Hz	Wrist - 25 Hz	Wrist - 100 Hz	Hip - 100 Hz
Hip - 100 Hz	Hip - 25 Hz	Wrist - 25 Hz	Wrist - 100 Hz
Wrist - 100 Hz	Wrist - 25 Hz	Hip - 100 Hz	Hip - 25 Hz
Wrist - 25 Hz	Wrist - 100 Hz	Hip - 25 Hz	Hip - 100 Hz
Hip - 25 Hz	Wrist - 25 Hz	Hip - 100 Hz	Wrist - 100 Hz
Hip - 25 Hz	Wrist - 25 Hz	Wrist - 100 Hz	Hip - 100 Hz
Hip - 25 Hz	Hip - 100 Hz	Wrist - 25 Hz	Wrist - 100 Hz
Wrist - 25 Hz	Wrist - 100 Hz	Hip - 100 Hz	Hip - 25 Hz

Supplemental Table 3: Overall and Diary-Associated ENMO and MVPA (30s epoch) - Comparison Between 100 Hz and 25 Hz-Downsampled Data

	24 Hour ENMO m*g*	Time in MVPA** mins	Cycling m*g*	Eating m*g*	Exercising m*g*	Sleeping m*g*	Walking m*g*
Wrist	*n = 51*	*n = 51*	*n = 13*	*n = 44*	*n = 16*	*n = 51*	*n = 44*
100 Hz mean [SD]	33.1 [12.0]	112.1 [53.7]	119.5 [46.5]	31.7 [13.8]	329.5 [326.3]	3.4 [0.8]	136.3 [58.8]
25 Hz DS* [SD]	33.1 [12.0]	112.1 [53.6]	119.3 [45.9]	31.7 [13.8]	329.5 [326.2]	3.4 [0.9]	136.3 [58.7]
25 DS*-100 mean absolute difference [SD]	0.0 [0.1]	-0.0 [1.0]	-0.2 [1.1]	0.0 [0.1]	0.0 [0.2]	0.0 [0.0]	0.0 [0.1]
Spearman's correlation coef	1.00	1.00	1.00	1.00	1.00	1.00	1.00
ICC	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Hip	*n = 45*	*n = 45*	*n = 11*	*n = 40*	*n = 14*	*n = 45*	*n = 39*
100 Hz mean [SD]	16.1 [7.1]	81.7 [47.6]	60.2 [18.7]	10.8 [7.5]	117.2 [125.5]	2.6 [0.3]	117.3 [52.0]
25 DS*Hz [SD]	16.1 [7.1]	81.8 [47.6]	60.2 [18.7]	10.8 [7.5]	117.2 [125.7]	2.6 [0.3]	117.3 [52.0]
25 DS*-100 mean absolute difference [SD]	0.0 [0.0]	0.0 [0.6]	0.0 [0.1]	0.0 [0.0]	0.1 [0.2]	0.0 [0.0]	0.0 [0.2]
Spearman's correlation coef	1.00	1.00	1.00	1.00	1.00	1.00	1.00
ICC	1.00	1.00	1.00	1.00	1.00	1.00	1.00

*DS – Recorded at 100 Hz and downsampled to 25 Hz

**MVPA reported in minutes calculated by 30s epochs with ENMO >100 m*g* at the wrist and >70 m*g* at the hip

Supplement Note 1:

Activity and Sleep Diary

Instructions: Please complete the diary to record physical activity that you complete, while wearing your activity monitors, during your 24-hour activity monitoring session. Please note the beginning and ending time of each activity to the nearest 5 minutes, if possible.

	STUDY DAY 1	STUDY DAY 2
What time did you go to bed?		
What time did you wake up?		
At what times, if any, did you ride a bicycle?		
At what times, if any, did you take a walk (more than 100 meters)?		
At what times did you do any other exercise (please note specific activity)?		
What times did you eat meals?		
At what times, if any, did you remove the monitors?		

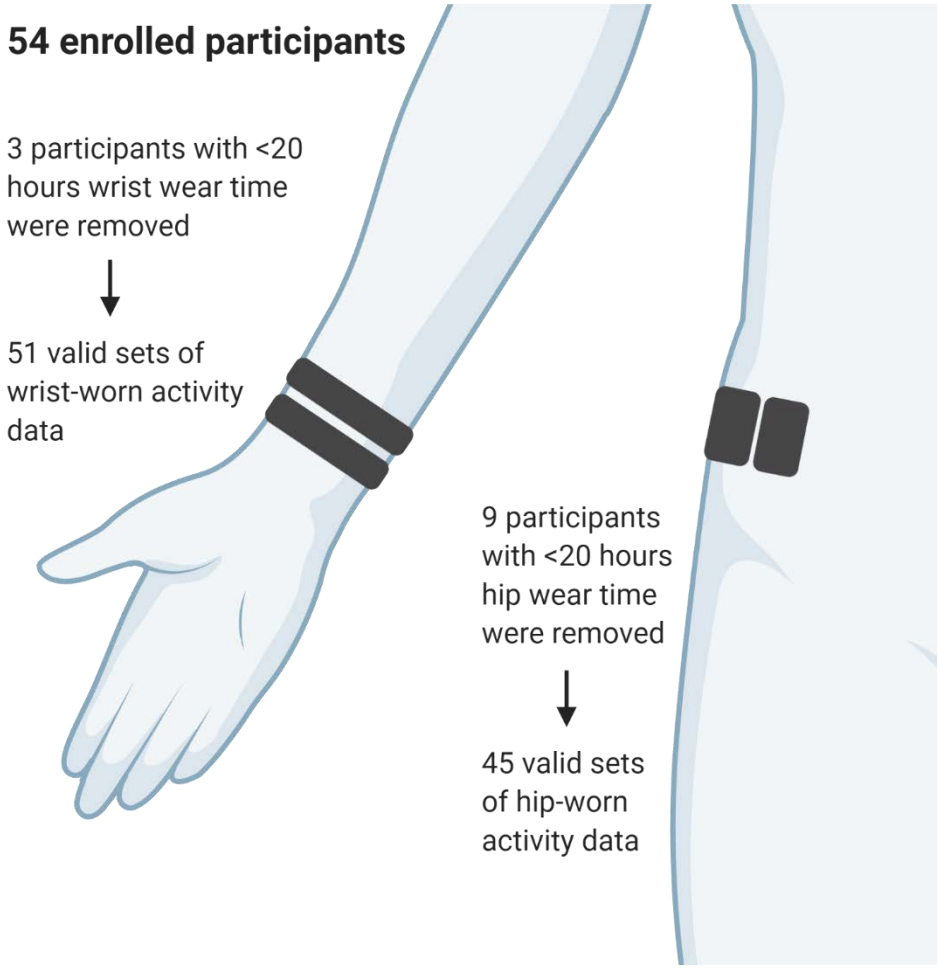
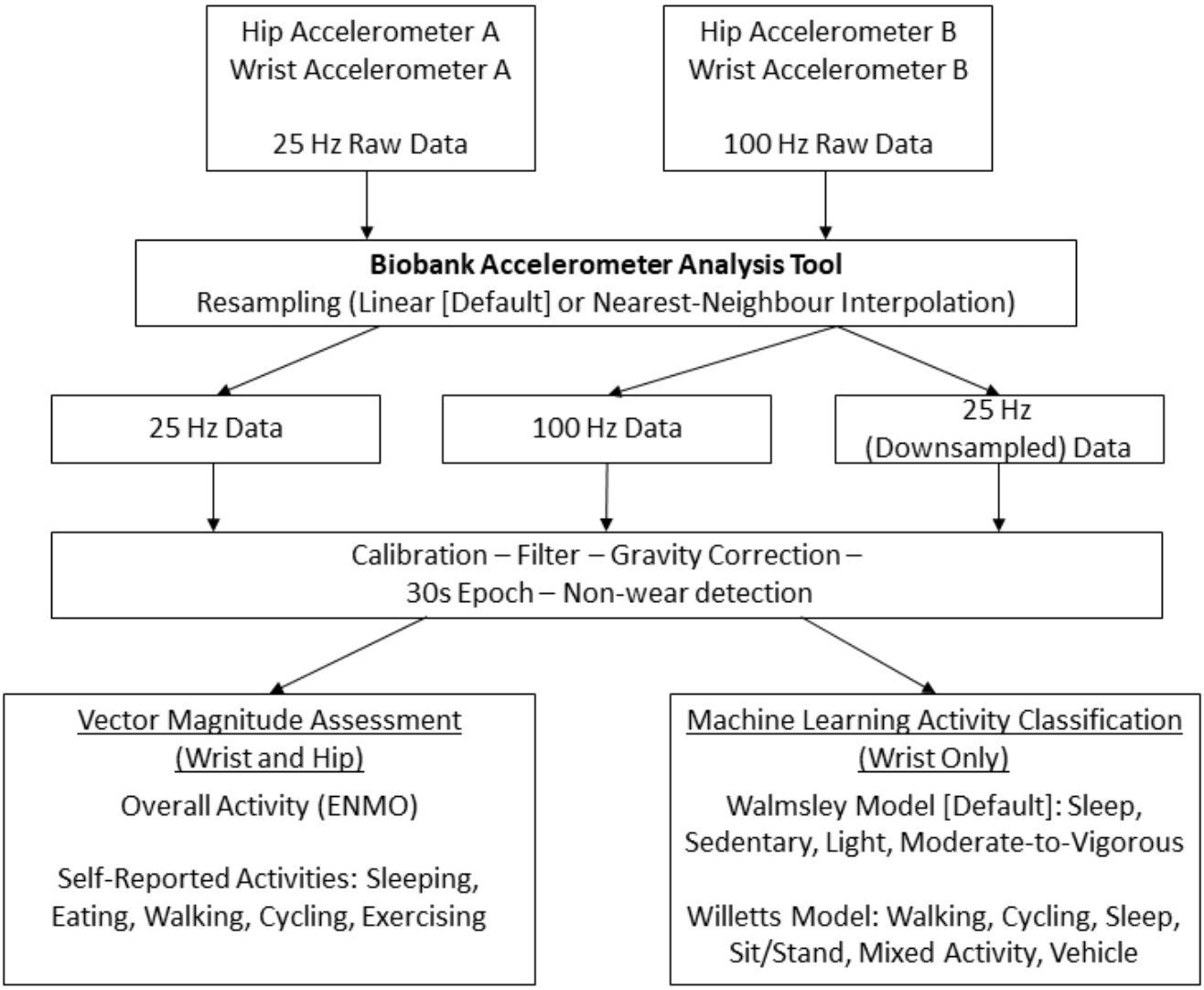

54 enrolled participants
3 participants with <20 hours wrist wear time were removed
51 valid sets of wrist-worn activity data
9 participants with <20 hours hip wear time were removed
45 valid sets of hip-worn activity data

Figure 1



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690 **Figure 2a**

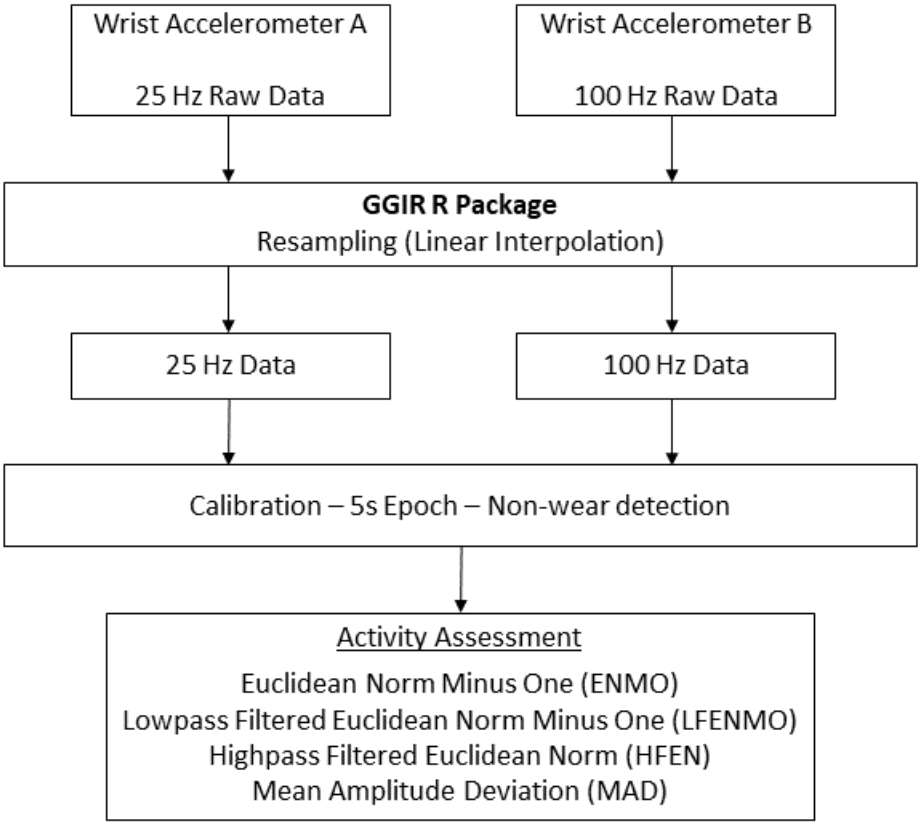
Wrist Accelerometer A
25 Hz Raw Data
Wrist Accelerometer B
100 Hz Raw Data
GGIR R Package
Resampling (Linear Interpolation)
25 Hz Data
100 Hz Data
Calibration – 5s Epoch – Non-wear detection
Activity Assessment
Euclidean Norm Minus One (ENMO)
Lowpass Filtered Euclidean Norm Minus One (LFENMO)
Highpass Filtered Euclidean Norm (HFEN)
Mean Amplitude Deviation (MAD)

Figure 2b

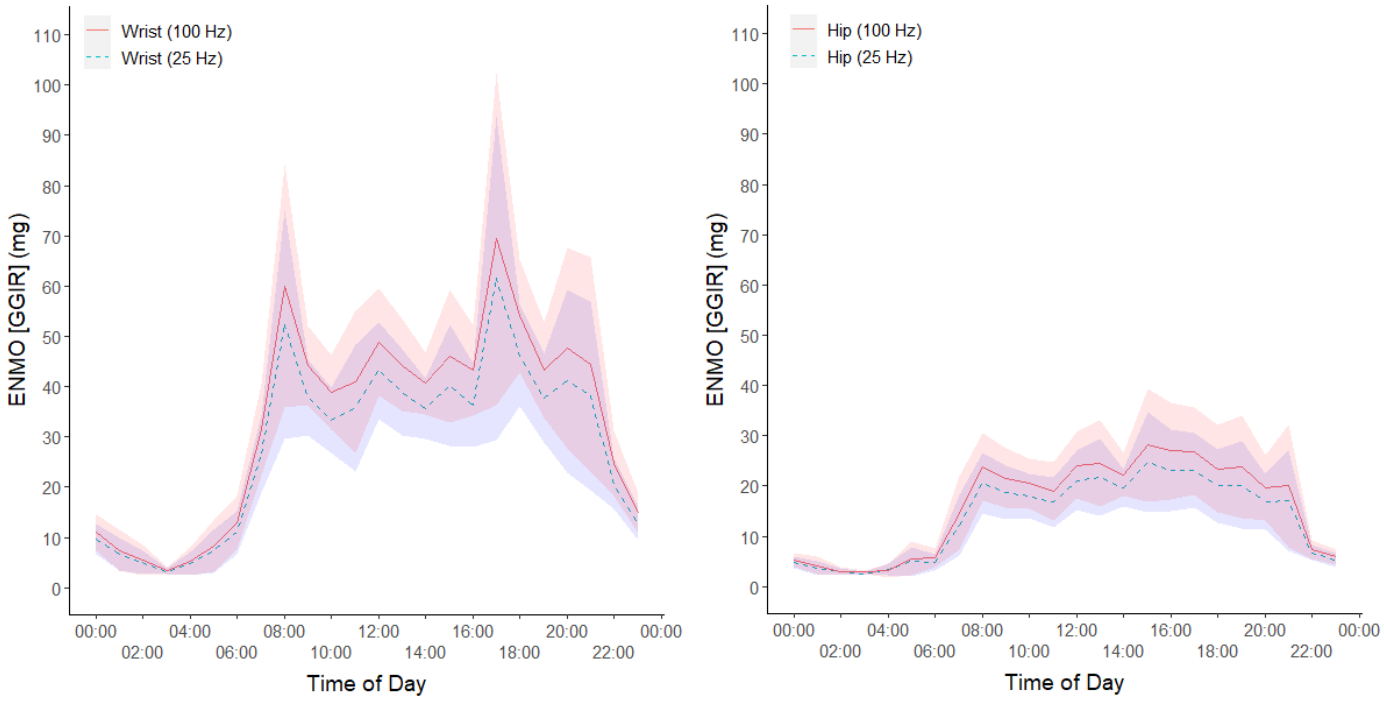

Figure 3

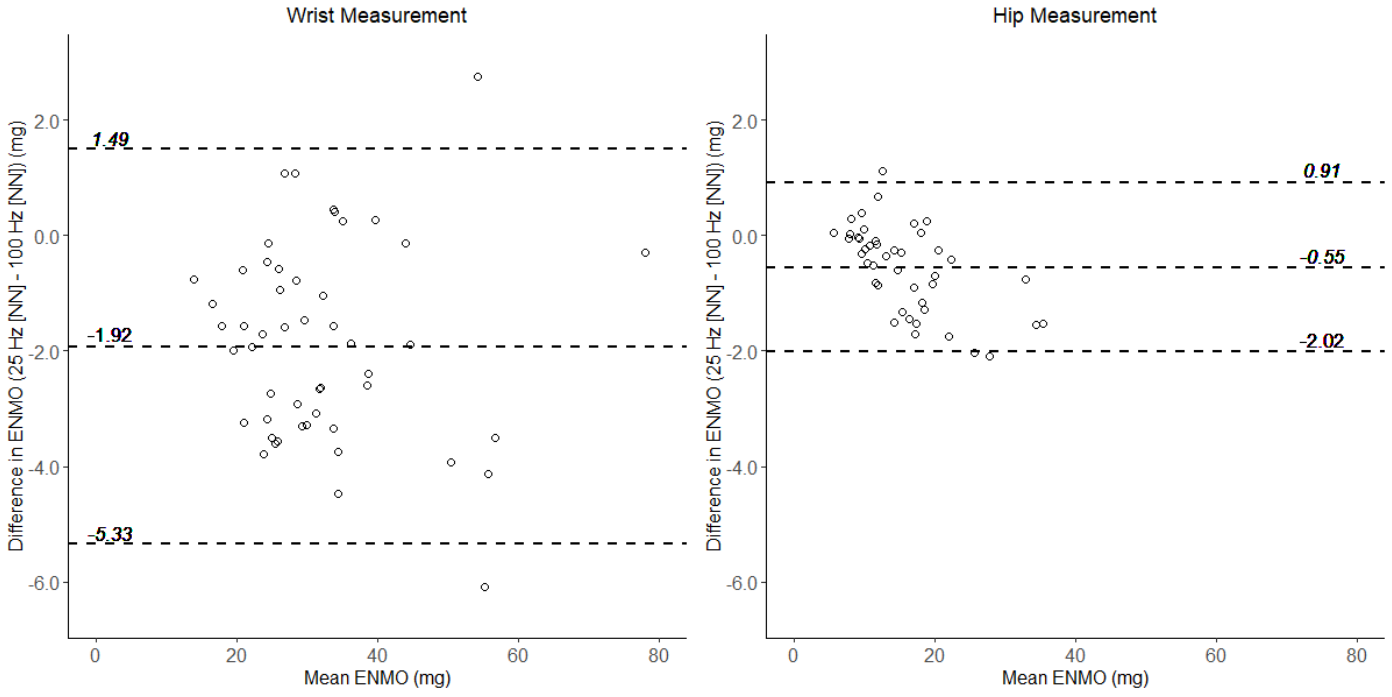

Figure 4

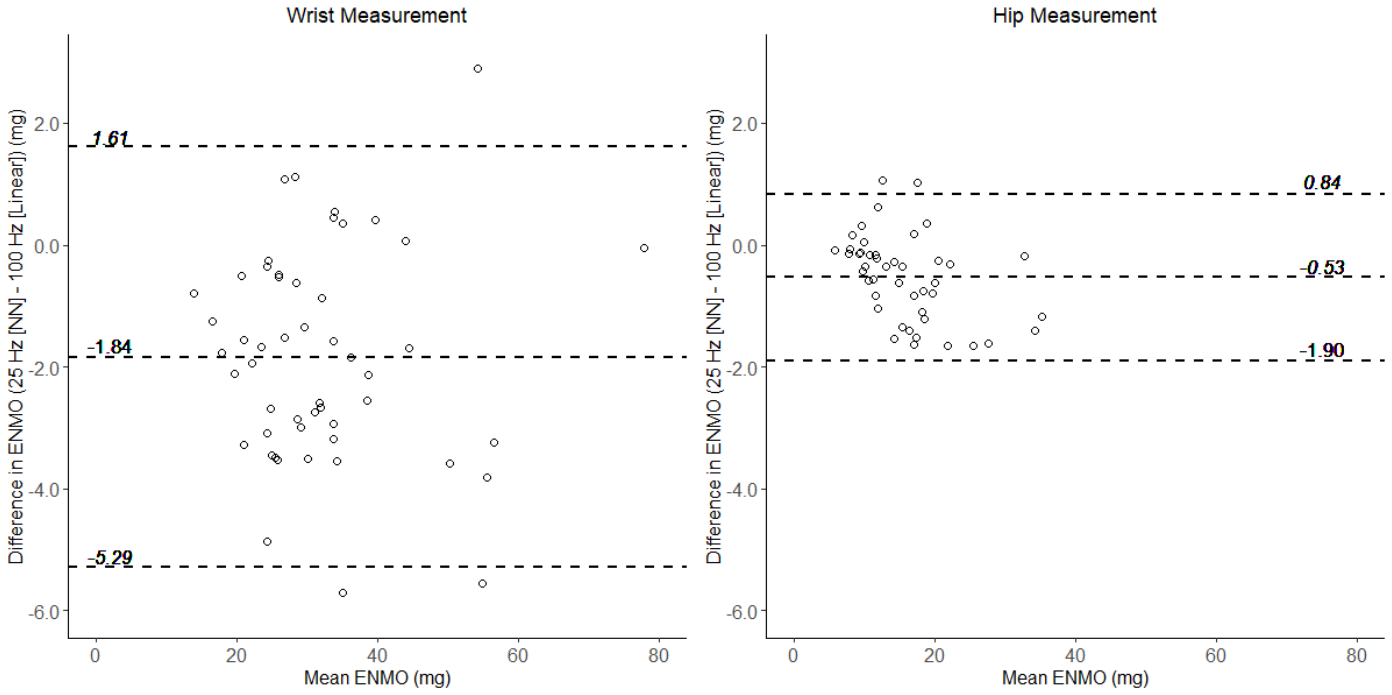

Figure 5

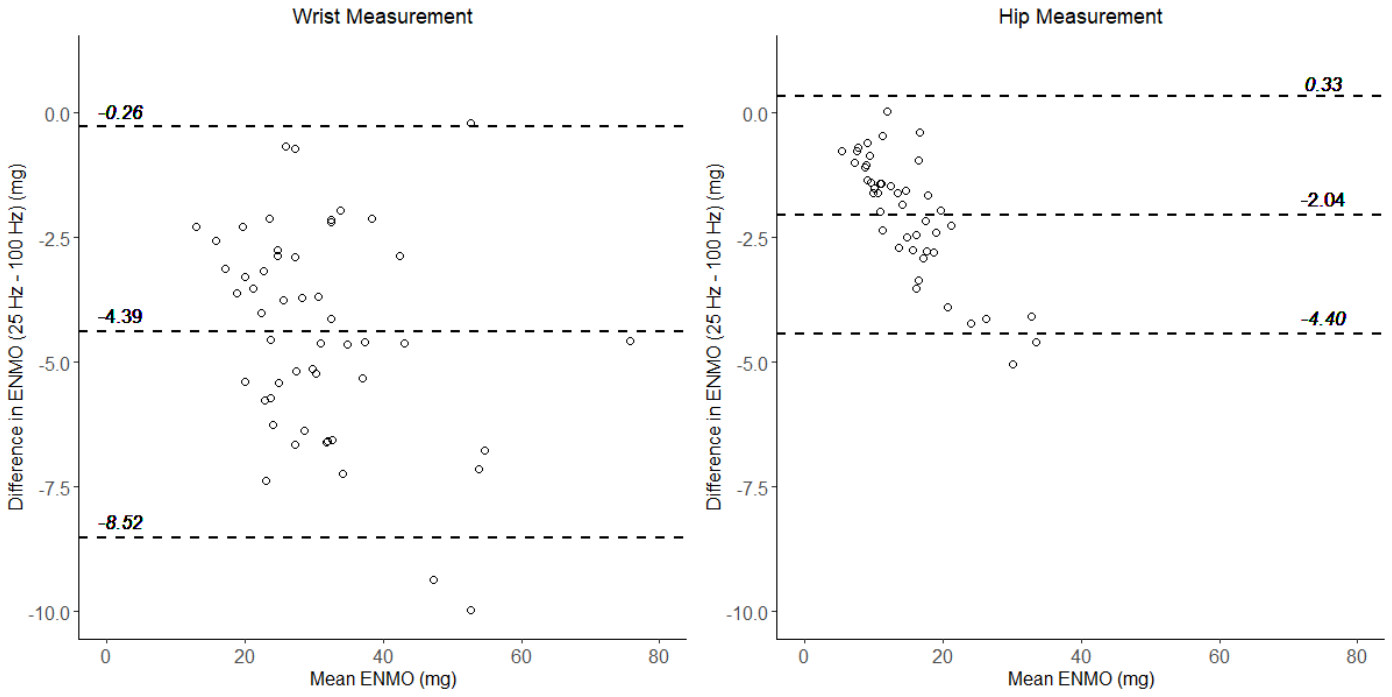

Figure 6

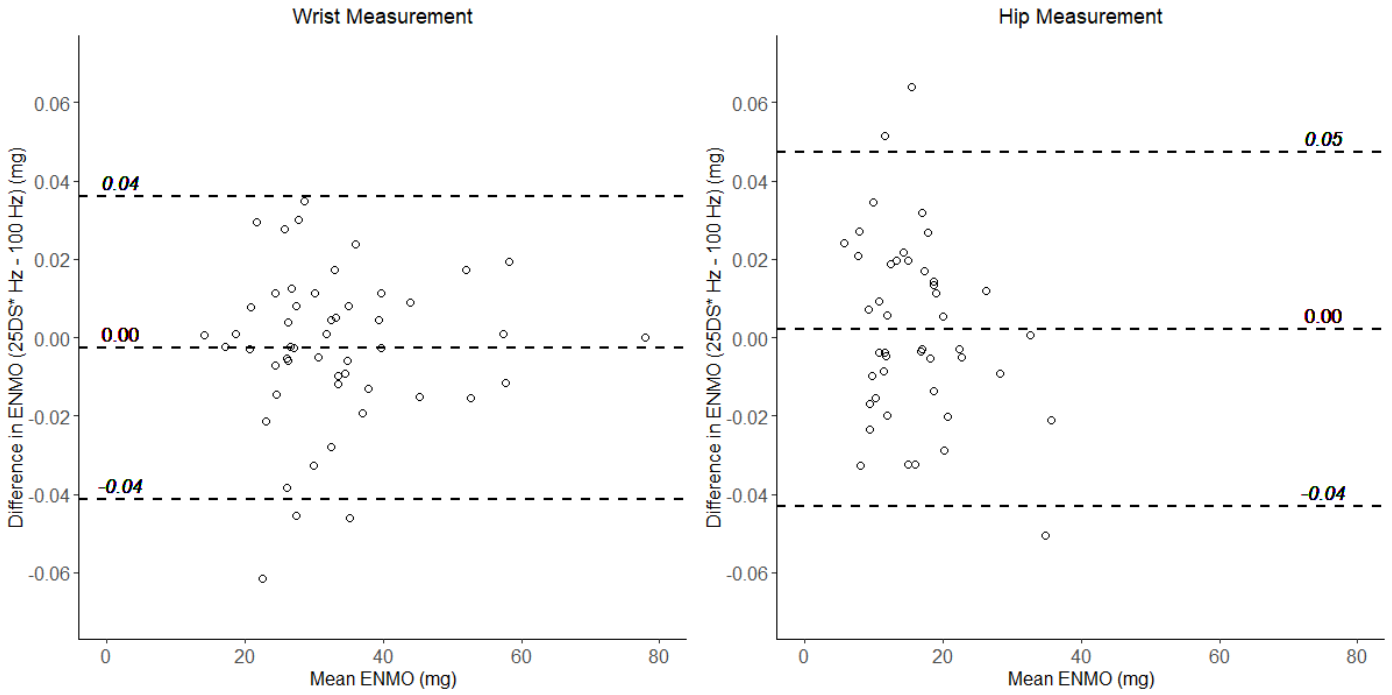
Wrist Measurement
Hip Measurement
Difference in ENMO (25DS* Hz - 100 Hz) (mg)
Mean ENMO (mg)
0.04
0.00
-0.04
0.05
0.06
0.04
0.02
0.00
-0.02
-0.04
-0.06
0
20
40
60
80

Figure S1