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Authors: Roman P Kuster [1,2], Wilhelmus J A Grooten [1,3], Daniel Baumgartner [2], Victoria Blom [4,5], Maria Hagströmer [1,3,6], and Örjan Ekblom [4]

1) Division of Physiotherapy, Department of Neurobiology, Care Sciences and Society, Karolinska Institutet, Stockholm (Sweden)
2) Institute of Mechanical Systems, School of Engineering, ZHAW Zurich University of Applied Sciences, Winterthur (Switzerland)
3) Function Area Occupational Therapy and Physiotherapy, Allied Health Professionals, Karolinska University Hospital, Stockholm (Sweden)
4) Åstrand Laboratory of Work Physiology, The Swedish School of Sport and Health Sciences, Stockholm (Sweden)
5) Division of Insurance Medicine, Department of Clinical Neuroscience, Karolinska Institutet, Stockholm (Sweden)
6) Department of Health Promoting Sciences, Sophiahemmet University, Stockholm (Sweden)

Corresponding Author: Roman P Kuster, Technikumstrasse 9, 8401 Winterthur, Switzerland. Mail: roman.kuster@alumni.ethz.ch, Tel.: +41-58-934-6522, Fax: +41-58-935-6522

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Abstract

The ActiGraph has a high ability to measure physical activity, however, it lacks an accurate posture classification to measure sedentary behaviour. The aim of the present study was to develop an ActiGraph (waist-worn, 30Hz) posture classification to detect prolonged sitting bouts, and to compare the classification to proprietary ActiGraph data. The activPAL, a highly valid posture classification device, served as reference criterion.[1]

Both sensors were worn by 38 office workers over a median duration of 9 days. An automated feature selection extracted the relevant signal information for a minute based posture classification. The machine-learning algorithm with optimal feature number to predict the time in prolonged sitting bouts (≥5 and ≥10 minutes) was searched and compared to the activPAL using Bland-Altman statistics. The comparison included optimised and frequently used cut-points (100 and 150 counts-per-minute (cpm), with and without low-frequency-extension (LFE) filtering).

The new algorithm predicted the time in prolonged sitting bouts most accurate (bias ≤7 minutes/day). Of all proprietary ActiGraph methods, only 150 cpm without LFE predicted the time in prolonged sitting bouts non-significantly different from the activPAL (bias ≤18 minutes/day). However, the frequently used 100 cpm with LFE accurately predicted total sitting time (bias ≤7 minutes/day).

To study the health effects of ActiGraph measured prolonged sitting, we recommend using the new algorithm. In case a cut-point is used, we recommend 150 cpm without LFE to measure prolonged sitting, and 100 cpm with LFE to measure total sitting time. However, both cpm cut-points are not recommended for a detailed bout analysis.

Keywords: activPAL, Automated Feature Selection, Bout Analysis, Machine Learning, Posture Prediction, Sedentary Behaviour

Introduction

Sedentary Behaviour (SB, defined as sitting or reclining with ≤1.5 Metabolic Equivalents)[2] is a substantial part of the modern lifestyle, accounting for the vast majority of waking hours.[3] Research has linked SB to a plethora of serious chronic diseases and premature deaths.[4, 5] However, the largest body of evidence is based on imprecise and biased self-reports possibly underestimating the strength of the relationship.[6, 7] The technological improvements in the past years made it feasible to record SB objectively. Nowadays, studies investigating SB use small and lightweight body worn sensors capable to record free-living behaviour over several days.[8] However, the device-based SB measure is not consistent with its definition,[9, 10] and research is far away to stipulate evidence based health recommendations.[11]

Probably the most frequently used sensor to measure SB is the ActiGraph (ActiGraph LCC, Pensacola, USA). The ActiGraph with its proprietary counts-per-minute (cpm) was originally developed to measure physical activity.[12] As there is a growing evidence that SB, in particular the time spent in prolonged bouts, is an independent risk factor for human health,[13-17] ongoing epidemiological studies are interested in measuring both physical activity and SB.[8] While physical activity only depends on the energy expenditure, the definition of SB includes a posture component: sitting or reclining.[2] For this reason, it is of high value for the research community to have an algorithm for the ActiGraph to predict prolonged sitting bouts. In particular, those ≥5 and ≥10 minutes assumed to be most relevant for human health.[17]

To measure sitting, a pragmatic cut-point of <100 cpm for the sensor vertical axis is most frequently used,[18] although there are inconsistent findings whether other cut-points, between 22 to 150 cpm, or machine-learning approaches like the soj3x detect sitting more accurately.[1, 3, 19-21] As the cpm measure does not consider body posture, sophisticated machine-learning algorithms use the ActiGraph raw data to detect sitting.[22, 23] However, these algorithms were developed without considering feature relevance. We therefore do not know whether they extract all relevant signal information to classify posture. It is very common to use extensive feature lists informed by author experience or published algorithms.[21, 24-27] Only a few studies so far investigated feature relevance,[28] but rarely as tool for feature selection,[27, 29] and never in combination with a posture classification algorithm. Furthermore, machine-learning algorithms are typically optimized to have a high sensitivity and specificity to predict posture in a certain predefined window length (typically 1 minute), but not with respect to predict health-relevant bout lengths.[13, 17] Most algorithms were developed in more or less controlled laboratory settings, not covering the true variability of real life.[26, 27, 30] Moreover, many algorithm developments were tailored to special population groups like breast cancer survivor or overweight females. [24, 28]

The aim of the present study was therefore to develop a new ActiGraph posture classification algorithm to detect prolonged sitting bouts in a healthy population with sedentary occupations, and to compare the new algorithm to classifications based on proprietary ActiGraph data.

Materials and Methods

Study Overview

The ActiGraph was calibrated against the activPAL (PAL Technologies, Glasgow, SCO) in a healthy office worker population using machine-learning applied on sensor raw data collected in free-living. To build the algorithm, an automated feature selection based on feature relevance was used. Since poor health outcome is assumed to be related to the time spent in prolonged sitting,[13, 14, 16] a subsequent bout analysis identified the optimal feature number to predict the time in bouts ≥5 and ≥10 minutes.[17] Moreover, optimized cut-points for proprietary ActiGraph data were developed and, together with frequently used existing cut-points and the inclinometer function, included in the bout analysis.

Participants

A convenient sample of 38 participants from the GIH Brain-Health study was used.[31] The Brain-Health Study investigated the association between physical activity pattern and cognition, mental health and sleep in office workers. Participants were recruited from two worksites in the area of Stockholm. Office workers able to perform one week of accelerometer assessment were included. Each participant signed an informed consent prior to study inclusion. Ethical approval to re-use the Brain-Health data was granted by the regional ethics board (DNR 2018/2315-32).

Data Collection

Participants were instructed to wear an ActiGraph wGT3X-BT at the right waist (firmware versions 1.9.1/1.9.2/2.5.0/3.2.1 used, 30 Hz, elastic belt) and an activPAL3 (considered as reference criterion) on the right thigh (firmware 4.2.4, 20 Hz, taped), both attached as recommended by the manufacturers. Participants kept a diary and noted when the ActiGraph was not worn at the waist (e.g. during water based activities, sleep).

Data Preparation

Proprietary software of the sensor manufacturers were used to download sensor data and generate comma separated raw data and event files for the activPAL (activPAL3, v7.2.38), as well as raw data and 1-second episode files with and without low-frequency-extension (LFE) filtering for the ActiGraph (ActiLife, v6.13.3). All files were load into MATLAB 2018a (v9.4, Mathworks Inc., Nattick, USA). Adjacent events in the activPAL event file with the same activity code were summarized and treated as single activities.[32] Subsequently, the following data preparation steps were carried out (for a detailed description see data processing plan in Supporting Information 1): Valid recording time included all days with <95% of the time spent in mode activPAL code, ≥500 steps and ≥12 hours recording. On the first/last day, valid recording time was limited to the time after/before the first/last 45-second non-sedentary activPAL activity. Sleep time was then removed using the Winkler algorithm (Version A) [32]. Since the algorithm is known to underestimate sleep time,[32] step tolerance was increased from 20 to 50 and two additional criteria using the thigh rotation angle around the longitudinal axis applied.[33] Before matching the sensor data, the signals were synchronized as the sensor clocks were out of sync. The offset was neither constant for all sensors nor for a single recording over time. The time course of the offset between the two sensors over each recording was determined by 1) finding the largest cross-correlation between the two normalized sensor x-axes of non-overlapping 3 hour episodes to get the average offset of each 3 hour episode; 2) linear approximation of the offset over all 3 hour episodes; 3) applying the linear approximated offset to the ActiGraph time. Next, ActiGraph non-wear episodes were excluded based on the diary information, sensor contradiction, and prolonged non-wear. Sensor contradiction was defined as the time when the 3 dimensional ActiGraph raw signal remained constant while the activPAL detected a posture change or classified the time as active (ActiGraph likely not worn). Prolonged non-wear was defined as the time when the 3 dimensional ActiGraph raw signal remained constant for ≥90 minutes. Last, to prevent excessive fragmentation of the data with respect to the bout analysis, short episodes between excluded episodes were removed.

Minute Extraction – Valid minutes were extracted in two different ways, one for the algorithm and cut-point development (training minutes) and one for the bout analysis (testing minutes). The training minutes included only minutes with constant activPAL classifications (sitting, standing, and active). All activPAL events ≥1 minute were identified, and as many minutes as possible extracted. An event of e.g. 4.5 minutes of sitting was split in 4 single minutes, the first/last minute starting/ending 15 seconds after/before the event started/ended. The testing minutes were extracted according to daytime (starting at midnight) and included all available minutes on days with ≥10 recording hours, similar as in typical epidemiological studies.[4, 5]

Machine Learning Algorithm Development

Feature Calculation and Selection – A total of 563 ActiGraph signal features were calculated for each training minute, of which 409 in the time and 154 in the frequency domain (see feature table in Supporting Information 2). Features were calculated for each sensor axis and the vector magnitude, the low pass filtered sensor axes and vector magnitude (Butterworth 2nd order, 0.5Hz cut-off), and the 3d angle of the low pass filtered data. To identify the relevance of each signal feature, a random forest classifier programmed in Python was used. The classifier run

100 times, and the 100 most relevant signal features were subsequently inputted into a sequential forward feature selection to get the final feature ranking. A MATLAB bagged classification tree ensemble (using standard properties with five bags) iteratively selected the feature with highest cross-validity on the holdout subjects in each round, similar as in our previous study, [34] until a maximum cross-validity was found. The feature selected in each round was assigned to the corresponding rank.

Algorithm Training – Based on the ranking, the training properties for each feature number were optimized using MATLAB's built-in hyper-parameter optimisation function for learner ensembles (fitcensemble), again using the holdout subject approach. The optimisation searched for the best ensemble learner method (Bag, AdaBoost M2, RUS Boost), split criterion (gdi, twoing, deviance), number of trees (10 to 500), minimum leave size (1 to n/2, n = number of minutes), maximum number of splits (1 to n-1), and learning rate (0 to 1). Further details about the optimisation properties can be accessed online (www.mathworks.com/help/stats/ fitcensemble.html). Subsequently, 38 holdout algorithms were trained for each feature number (one for each subject) and used in the bout analysis to identify the optimal feature number. A detailed description on how classification trees are trained can be found elsewhere.[35]

Optimized Cut-point Development

Beside the machine-learning algorithms, posture classifications based on cpm data for the vertical axis and vector magnitude as well as steps-per-minute were developed, all with and without LFE. The 1-second episode counts and steps were summarized for the extracted training minutes, and cut-points from 0 to 5'000 to identify sitting and standing inspected. Similar as for the machine-learning, the cut-points with highest cross-validity on the holdout subjects were selected and used in the bout analysis to identify the most accurate one.

Bout Analysis

For each testing minute, the selected features as well as the cpm and steps-per-minute were calculated. The trained holdout algorithms (machine-learning) and cut-points (proprietary ActiGraph data) were then used to predict body posture of each minute. All ActiGraph predictions as well as the activPAL reference criterion (the proprietary event file) were subsequently aggregated in sitting and standing bouts of certain lengths for each day and subject. A sitting/standing bout was defined as the time the prediction model/activPAL event file classified a person continuously in sitting/standing, without the allowance of any other body posture or walking. Additionally, the two most frequently used cpm cut-points, 100 and 150 for the vertical axis,[18] and the inclinometer function were included in the bout analysis (all with and without LFE). For the inclinometer function, each testing minute was assigned to the most dominant posture. Note that the proprietary activPAL event file uses another resolution (0.1 seconds) for the behaviour classification than the developed ActiGraph prediction models (60 seconds).

Evaluation and Statistics

Data Preparation – After rejecting the normal distribution with Lilliefors test, descriptive results for data preparation are presented with median (interquartile-range).

Algorithm and Cut-point Development - To analyse cross-validity, the balanced holdout sensitivity and specificity, which is the average of all sensitivities and specificities over all holdout subjects, was used. For the machine-learning, the balanced sensitivity and specificity was weighted according to the fraction of each behaviour in the training data. For the proprietary ActiGraph data, the cut-points to detect sitting and standing were searched independently. Accordingly, the balanced sensitivity and specificity was calculated for each posture separately. The holdout approach (also called leave-one-subject-out) trained the algorithm/cut-point on all but one subject (the holdout), and used the trained algorithm/cut-point to predict the posture on the holdout subject. This procedure was repeated until every subject served once as holdout, and the cross-validity was calculated among all holdout predictions.

Bout Analysis - With respect to detrimental health effects of prolonged sitting,[13-17] the daily time spent in sitting bouts ≥5min and ≥10min was considered most important.[17] Accordingly, the algorithm and cut-point with lowest absolute bias to predict the time spent in these bouts was selected. Additional bout lengths and number of bouts per day are presented to inspect the prediction performance in detail. For standing, there is no evidence that certain bout lengths are more relevant for health than others are. Accordingly, only total time spent standing was analysed. Bias was calculated according to Bland-Altman statistics by subtracting the activPAL reference criterion from the ActiGraph holdout prediction.[36] In case the bias depended on the mean, the regression approach was used. To simplify comparison, data is in either case (standard or regression approach) presented at the mean of both methods with bias and standard error. Significant differences of the ActiGraph methods to the activPAL were detected using the 95% confidence interval of the bias.

Results

Subjects of the present analysis were 25 men and 13 women. Mean ±SD was 71.2 ±10.2 kg for body mass and 42.3 ±8.4 years for age. Subjects wore the sensors for 9 (0) days (median with inter-quartile range in brackets). Sensor offset at first valid data entry was 5.9 (8.7) seconds and increased with 1.0 (1.3) seconds a day. Data preparation and minute extraction resulted in 200'704 training minutes (3'345 hours) and 255'569 testing minutes (4'260 hours). The posture in which the time was spent is shown in Table 1.

Machine Learning Algorithm - The automated feature selection identified 26 relevant signal features (maximum cross-validity), for each of which an algorithm was trained (see feature ranking information in Supporting Information 2). However, the lowest absolute bias to predict the sitting time in bouts ≥5 and ≥10 minutes was found for the algorithm with 14 features. This algorithm combined 16 decision trees and predicted the time non-significantly different from the activPAL (Table 2, absolute bias ≤7 minutes). The detailed bout analysis (from <5 to ≥30 minutes, Table 2) shows that the time and number of bouts <15 minutes was overestimated by the algorithm, while longer bouts were accurately predicted. For standing, the bias was non-significantly different from the activPAL (Table 2).

Optimised Cut-points - All optimised cut-points for proprietary ActiGraph data (cut-points shown in Table 2) significantly underestimated the time in sitting bouts ≥5 and ≥10 minutes, except steps-per-minute without LFE (accurate for bouts ≥10 minutes, overestimation for bouts ≥5 minutes, Table 2). The detailed bout analysis uncovers that the time and number of short bouts was generally overestimated and long bouts generally underestimated. For standing, the optimised cpm cut-points for data without LFE predicted the time non-significantly different from the activPAL, but the bias depended on total standing time (marked with † in Table 2).

Existing Cut-points and Inclinometer Function – The existing cut-points for proprietary ActiGraph data significantly underestimated the time in the two bout lengths, except 150 cpm without LFE (absolute bias ≤18 minutes, Table 3). However, the 100 cpm with LFE accurately predicted total sitting time without consideration of a minimum bout length. The detailed bout analysis shows again that short bouts were generally overestimated and long bouts generally underestimated, both mostly significant (Table 3). The inclinometer function significantly underestimated the time in the two bout lengths as well as total sitting and standing time.

Discussion

This study developed a new posture classification algorithm for ActiGraph raw data to predict the time spent in prolonged sitting bouts as well as total standing time. The posture prediction of the new algorithm does not differ from the activPAL. For sitting, the bias was <0.0% for bouts ≥5 minutes and -1.8% for bouts ≥10 minutes. For standing, the bias was -4.9% for total time without consideration of a minimum bout duration. The algorithm to predict the posture directly from the ActiGraph raw data file as exported by ActiLife is provided on MATLAB Central File Exchange (URL is inserted provided that your journal approves the publication).

The study also optimised cut-points for proprietary ActiGraph data. Of these, there was only one accurately predicting the time spent in sitting bouts ≥10 minutes: the step count with a cut-point of 3 steps-per-minute (without LFE). All others substantially underestimated prolonged sitting. For standing, the developed cpm cut-points without LFE accurately predicted total time (vertical axis and vector magnitude). However, the longer the time spent standing the larger the bias.

Moreover, two frequently used existing cpm cut-points were included in the bout analysis: 100 and 150 cpm on the vertical axis.[18] While the 150 cpm without LFE accurately predicted the time in prolonged sitting bouts (bias of ≤18 minutes or ≤4.6%), all others underestimated prolonged sitting. However, 100 cpm on the vertical axis with LFE very accurately predicted the total time spent sitting (bias of ≤7 minutes or ≤1.4%). The result for the 100 cpm with LFE is in line with Matthews et al. 2018 and the overestimation of short bouts (<20 minutes) and underestimation of long bouts (≥30 minutes) in line with Kerr et al. 2018.[3, 24] The results for the 150 cpm to detect prolonged sitting is in line with the recommendation in Kim et al. 2015.[1] However, due to the significant overestimation of bouts <25 minutes and underestimation of bouts ≥30 minutes, a detailed bout analysis is not recommended with the 150 cpm.

For all cpm cut-points, there was a substantial difference between the data with and without LFE, highlighting that the decision whether LFE is used or not has a great bearing, and should future studies sensitize to report the use of LFE.[18] Although the results of the existing cut-points (Table 3) were not directly compared to the optimised cut-points for methodological reasons (Table 2), it is evident that the optimised cut-points performed worse in the bout analysis despite the slightly higher balanced sensitivity and specificity (see cross-validity table in Supporting Information 3). The existing cut-points had far higher sensitivities (+18%) and far lower specificities (-20%) to detect sitting. From this, we conclude that sensitivity and specificity is not a universal measure to infer to the accuracy in the bout analysis. Future studies developing new algorithms to measure prolonged sitting might therefore consider the use of other optimisation criteria than balanced sensitivity and specificity, combine it as in this study with a subsequent bout analysis, or weight the sensitivity more than the specificity. In our data set, a weighting factor between 1.16 and 1.85 for sensitivity would have turned the best method for proprietary ActiGraph data to predict total sitting time (100 cpm on the vertical axis with LFE) also into the one with highest balanced sensitivity and specificity.

The ActiGraph inclinometer function performed worst and underestimated prolonged sitting as well as total standing time by more than 2 hours a day or -32 to -54%. For total sitting time, our data (bias of -21% and -22%) is in line with Kim et al 2015 who compared the inclinometer function to an automated wearable camera.[1]

Methodological Consideration

The machine-learning algorithm development started with an extensive feature number (563) calculated for an immense amount of training data (200’704 minutes) collected in entirely free-living over several days. The data was labelled with the activPAL, a well-known and highly valid sensor to measure body posture that is seen as the method of choice to measure sitting in free-living.[1, 20, 37] Before building the algorithm, a random forest classifier in combination with a sequential forward feature selection identified the most relevant signal features. Although machine-learning is able to minimize the impact of non-relevant signal features on the predicted output, this approach was key to end up with an algorithm having only a few features with limited complexity despite the good bout performance. Our algorithm uses 14 features in combination with 16 trees, while other algorithms use more than 40 features with 500 trees.[24, 35] In a general sense, an algorithm with only a few features and simple architecture is less prone to overfitting and thus more likely to have a better generalizability than an algorithm with many features and complex architecture, although the algorithm with many features typically performs better on the training data.[38] In this regard, we recommend to develop algorithms with as few features as necessary, and to treat each feature for each signal dimension independently to ensure the algorithm performance is not reduced with non-relevant and/or redundant features.[39] Our final algorithm e.g. uses the signal power of the sensor y-axis, but not the signal power of the other two sensor axes. For this reason, we recommend to forego predefined feature lists and to use an automated selection procedure. Interestingly, the algorithm uses only 2 features from the low-pass filtered data, but 12 features from the non-filtered raw data (see Supporting Information 2). While the low-pass filtered acceleration signal reflects the waist orientation versus gravity (which is often referred to as inclinometer function) that is sensitive to body shape and sensor placement, the non-filtered data reflects waist movements and is less sensitive to body shape and sensor placement. Accordingly, the presented algorithm primarily detects the different motion pattern of the waist while sitting and standing, and not a different waist orientation.

After optimising the training properties for each feature number, the algorithms were developed with the training minutes and evaluated on the testing minutes. The clear distinction between training and testing minutes further helped to limit the algorithm complexity and prevent overfitting. For this reason, the algorithm with 14 features was selected, although the one with 26 had the highest cross-validity in the training data, again supporting our observation that a high cross-validity does not imply a good bout performance. Although the two data sets (training: minutes with constant activPAL classification, testing: all minutes on days with ≥10 hours) are not independent of each other as they use the same data recording and subjects, the start times of the minutes were always different and thus the features not congruent. Even more importantly, 28% of the testing minutes contained more than one activPAL posture classification, similar as the data of a typical field study. The combination with the holdout subject approach makes the algorithm to a large degree independent of the training minutes and increases its generalizability. Nevertheless, a future study using the presented algorithm should use exactly the same sensor settings: mounting the ActiGraph wGT3X-BT at the right waist with an elastic belt and record with 30Hz. However, the study recorded data over several days, and the raw data looks like the sensors were not always worn in the same way (e.g. upside down). For this reason, the results of this study should not be compared to studies collecting data on a daily basis in the presence of a researcher.[1] Since the ActiGraph raw data is already pre-processed, we do not know whether our algorithm depends on the ActiLife software version used in this study.

The Bland-Altman comparison used the data of each device similar as a typical field study does: The proprietary activPAL event file with a resolution of 0.1 seconds, and the ActiGraph predictions on a minute-by-minute level. The bout comparison is therefore questionable for very short bouts (<1 minute) as the ActiGraph might fail to detect them. However, there is some evidence that prolonged bouts are health-relevant, and >90% of the daily sitting time was spent in bouts ≥5 minutes (activPAL data, Table 2). We therefore accepted this limitation for very short bouts but were able to use the sensors exactly the way as they are used in field studies. From a health perspective, we do not feel that sitting bouts <1 minute are of critical importance.

Furthermore, the ActiGraph step count (without LFE) allows for 2 steps per minute although the minute is still classified as sitting. This might imply that different sitting bout definitions were used in this study, which was not the case. The fact that the ActiGraph records 2 steps in a minute does not mean that a subject actually took 2 steps. We quite often noticed single steps in a minute, even though the activPAL classified the entire minute as sitting. Accordingly, the ActiGraph step count should be interpreted with caution when only a handful of steps are recorded.

Unless the algorithm is tested in another study population than office workers, its application in other populations should take place with caution. Our office worker spent 8.0 hours a day sitting in 47 bouts, of which almost 50% in bouts ≥30 minutes (activPAL data). The female breast cancer survivors in Kerr et al. 2018 spent 8.1 hours a day sitting in 49 bouts, of which approximately 56% in bouts ≥30 minutes (activPAL data).[24] The NHANES 2003-2006 study population in Kim et al. 2015 spent 8.0 hours a day sitting in 93 bouts, of which only 20% in bouts ≥30 minutes (ActiGraph data with 100 cpm cut-point on the vertical axis).[17] However, if comparing the NHANES data to the 100 cpm in this study (without LFE), our subjects spent 8.4 hours a day sitting in 76 bouts, of which only 26% in bouts ≥30 minutes. Thus, it seems that our office workers are not fundamentally different from other study populations, but we do not know whether they are representative. The office workers in Keown et al. 2018 spent 9.8 hours a day sitting in 49 bouts, of which 67% in bouts ≥30 minutes (activPAL data).[40] However, the comparison to NHANES data highlights that using the 100 cpm on the vertical axis without LFE is not the preferred choice to analyse the time in and number of sitting bouts. Even the 150 cpm does not allow such a detailed analysis.

This study developed an algorithm to detect prolonged sitting bouts since there is some evidence that long-lasting, uninterrupted sitting might have detrimental health effects.[13, 14, 16] To date, we do not know which bout length separates detrimental sitting from non-detrimental sitting. One frequently cited study reports that either 5 or 10 minutes could be a reasonable choice, especially as compared to no minimum bout length.[17] Unfortunately, the study used the 100 cpm on the vertical axis to detect sitting bouts. As can be seen in our data (Table 3), the 100 cpm is not appropriate to detect sitting bouts, and further research is warranted to identify what separates detrimental from non-detrimental sitting. For this reason, we decided to treat bouts ≥5 and ≥10 minutes equal, even though bouts longer than 10 minutes are included twice. In regard of the bout length, we decided to develop a minute-based posture classification. Other authors used shorter durations of e.g. 5 seconds on a very similar dataset to better handle posture changes within a minute.[24] In our data set, 28% of all testing minutes contained at least one posture change, while 72% were spent in the same posture. There is some evidence that reducing the window size reduces cross-validity,[23] with unknown effects on the bout analysis. However, we felt that reducing the window size is superfluous for an algorithm aiming to detect prolonged sitting bouts. A shorter window size increases the computational demands that could be a severe limitation for large data sets. However, the minute based approach might partially explain the new algorithm's overestimation of short bouts.

The combined analysis of two sensors requires that they record synchronously. However, we noticed a substantial offset between the two sensor clocks. The start offset could be a consequence of using different clocks (i.e. computers) to initialise the sensors, and the increasing offset must be a consequence of inexact sensor frequency. We could not find evidence that other studies observed the same issue, but recommend future studies to inspect the raw data in detail and ensure their synchronicity.

The feature calculation of the final algorithm does not allow to straightforward convert the MATLAB code into a universal computer language like C++ since MATLAB specific functions are used. Thus, the use of the algorithm requires a MATLAB license including two toolboxes (signal processing, statistics and machine learning), all together resulting in an annual or perpetual license fee of 600 or 1200 USD. Compared to available freeware, however, the advantages of MATLAB clearly outweighed the disadvantages for this project. Given the costs of the ActiGraph sensors for large field studies, we do not consider the license fee to be a serious limitation. The final algorithm published on MATLAB Central File Exchange (URL is inserted provided that your journal approves the publication) directly predicts the posture from the ActiGraph raw data csv-file and creates a new csv-file in the same data format. The algorithm can be used even without previous MATLAB experience.

Practical Implications

The results of this study show that there is no single ActiGraph method accurately predicting the sitting time in certain bout length as well as total sitting time. We therefore recommend future studies to choose a method depending on the study aim. To analyse the total sitting time regardless of a minimum bout duration, our recommendation is to use the 100 cpm cut-point with LFE. To analyse prolonged sitting, our recommendation is to use the developed machine-learning algorithm or the 150 cpm without LFE. The machine-learning algorithm is the most accurate choice, and allows for a very detailed analysis of bouts ≥15 minutes (time in and number of bouts) that should be avoided with the 150 cpm. Moreover, the algorithm includes an accurate total standing time prediction. For the cut-point methods, the study highlights that the decision whether LFE is used or not is of utmost importance and should be explicitly reported. Regarding the future algorithm development to detect prolonged sitting, we recommend considering also other optimisation criteria than sensitivity and specificity with respect to an accurate bout prediction. The present study analysed the classification capability of the ActiGraph GT3X to detect prolonged sitting, which should not be equated with SB. For SB, the sitting classification must be combined with an activity classification and other cut-points than those investigated in this study might solve the SB classification better.

Perspective

To study the health effects of ActiGraph measured prolonged sitting, we recommend using the new algorithm available on MATLAB Central File Exchange. In case a cpm cut-point should be use, the 150 cpm without LFE is the best choice. To analyse total sitting time without consideration of a minimum bout length, the 100 cpm cut-point is the most appropriate choice only in combination with LFE data. However, we do not recommend using the cpm cut-points for a detailed sitting bout analysis. Further research is warranted to validate the new algorithm in an independent sample and different population.

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Tables

Table 1: Overview of the recorded time, data preparation, and time used for the algorithm/cut-point development (training) and the bout analysis (testing data). Absolute time in hours per subject except sleep (hours per night), relative time in percentage of total time per subject. Indicated is the median with interquartile-range (iqr).

	Absolute Time [hours/subject]		**Relative Time [%]**	
	Median (iqr)	Range	Median (iqr)	Range
Valid Recording Time	200.7 (7.3)	[81.3 - 224.2]		
- Sleep	8.5 (1.3)	[6.9 - 10.6]		
- ActiGraph Non-Wear	8.2 (11.5)	[2.1 - 39.5]		
- Short Episode	0.9 (1.1)	[0.0 - 3.6]		
Remaining Time	121.3 (15.6)	[37.1 - 149.6]		
Training Data	90.2 (15.1)	[30.3 - 111.7]		
- Sitting	62.2 (14.9)	[22.8 - 94.3]	72.6 (15.3)	[49.8 - 91.3]
- Standing	17.3 (11.8)	[5.8 - 37.7]	21.0 (10.9)	[6.0 - 38.8]
- Active	6.5 (5.5)	[1.5 - 13.1]	7.2 (5.6)	[2.7 - 15.5]
Testing Data	114.3 (24.6)	[31.5 - 149.4]		
- Sitting	60.7 (19.5)	[20.9 - 98.7]	55.4 (13.4)	[38.4 - 78.2]
- Standing	36.3 (14.1)	[8.0 - 58.8]	31.5 (10.9)	[13.8 - 44.7]
- Active	15.2 (8.3)	[2.6 - 26.4]	13.6 (4.9)	[8.0 - 21.7]

The training data contains only minutes with constant activPAL classification, the testing data contains all minutes on days with ≥10 hours.
Abbreviations: interquartile-range (iqr)

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Table 2: Bias of the machine-learning algorithm and the optimised cut-points for proprietary ActiGraph data to the activPAL (reference criterion). Indicated is the mean ±standard error for the reference criterion, and bias ±standard error for the ActiGraph methods. Time in minutes per day.

	Reference Criterion	Machine Learning Algorithm	y_{cpm}	$y_{cpm(LFE)}$	VM_{cpm}	$VM_{cpm(LFE)}$	Step	$Step_{LFE}$
Sitting			< 16 cpm	< 23 cpm	< 69 cpm	< 170 cpm	< 3 spm	< 5 spm
Time in Bout								
- ≥5	441.2 ±12.7	0.2 ±6.6	-185.6 ±13.6 *	-190.2 ±13.9 *	-168.9 ±14.9 *	-126.0 ±15.4 *	38.5 ±11.6 *	-101.5 ±13.8 *
- ≥10	397.4 ±12.6	-7.1 ±7.4	-234.9 ±13.1 *	-237.7 ±13.1 *	-223.2 ±14.5 *	-176.9 ±15.6 *	6.5 ±11.9	-132.2 ±13.2 *
- total	481.7 ±12.5	17.6 ±6.7 *	-98.7 ±12.5 *	-109.9 ±13.5 *	-86.4 ±13.1 *	-57.2 ±13.9 *	80.4 ±11.5 *	-55.4 ±14.1 *
- <5	40.4 ±2.1	17.5 ±2.7 *	86.9 ±3.6 * (†)	80.4 ±3.5 * (†)	82.5 ±3.4 * (†)	68.8 ±3.2 * (†)	42.0 ±2.3 * (†)	46.1 ±2.8 *
- 5-9	43.8 ±1.8	7.3 ±1.9 *	49.3 ±3.5 * (†)	47.5 ±3.6 * (†)	54.3 ±3.3 * (†)	50.9 ±3.0 * (†)	32.0 ±2.2 * (†)	30.7 ±3.0 * (†)
- 10-14	42.2 ±1.6	5.2 ±1.5 *	11.8 ±2.9 * (†)	10.6 ±3.0 * (†)	14.9 ±3.1 * (†)	23.3 ±2.8 * (†)	21.0 ±2.1 * (†)	13.9 ±2.2 * (†)
- 15-19	43.9 ±2.0	-1.6 ±2.3	-10.1 ±2.7 *	-11.3 ±2.8 *	-6.7 ±2.9 * (†)	-1.0 ±3.1 (†)	9.3 ±2.5 *	3.3 ±2.7
- 20-24	37.8 ±2.3	0.2 ±2.0	-18.9 ±3.3 *	-18.3 ±3.3 *	-17.7 ±3.5 *	-9.8 ±3.6 *	5.7 ±2.4 *	-3.2 ±2.8
- 25-29	37.7 ±2.2	-3.1 ±1.7	-23.7 ±2.3 * (†)	-23.6 ±2.3 * (†)	-21.3 ±2.5 *	-18.4 ±2.9 *	0.7 ±2.0	-12.2 ±2.5 *
- ≥30	235.9 ±11	-8.0 ±7.7	-194.0 ±7.9 * (†)	-195.1 ±7.9 * (†)	-192.4 ±8.0 * (†)	-171.0 ±10.2 *	-30.3 ±10.3 *	-134.0 ±10.6 *
Number of Bouts								
- ≥5	19.4 ±0.5	2.0 ±0.3 *	4.0 ±0.9 * (†)	3.5 ±1.0 * (†)	5.3 ±0.9 * (†)	6.7 ±0.8 * (†)	8.1 ±0.6 *	4.2 ±0.8 * (†)
- ≥10	13.4 ±0.4	0.4 ±0.2	-4.4 ±0.6 * (†)	-4.6 ±0.6 * (†)	-3.8 ±0.6 * (†)	-1.7 ±0.6 * (†)	2.7 ±0.4 *	-1.1 ±0.5 *
- total	46.7 ±1.7	8.4 ±2.2 *	46.4 ±2.9 * (†)	42.9 ±2.8 * (†)	45.0 ±2.7 * (†)	38.3 ±2.4 * (†)	26.3 ±1.7 *	25.1 ±2.1 *
- <5	27.3 ±1.5	6.4 ±2.0 *	42.4 ±2.5 * (†)	39.5 ±2.4 * (†)	39.7 ±2.4 * (†)	31.6 ±2.2 * (†)	18.2 ±1.4 *	20.9 ±1.7 *
- 5-9	6.0 ±0.3	1.6 ±0.3 *	8.4 ±0.5 * (†)	8.0 ±0.5 * (†)	9.0 ±0.5 * (†)	8.4 ±0.4 * (†)	5.4 ±0.3 * (†)	5.3 ±0.4 * (†)
- 10-14	3.4 ±0.1	0.6 ±0.1 *	1.2 ±0.2 * (†)	1.1 ±0.2 * (†)	1.5 ±0.2 * (†)	2.2 ±0.2 * (†)	1.9 ±0.2 * (†)	1.4 ±0.2 * (†)
- 15-19	2.5 ±0.1	0.0 ±0.1	-0.5 ±0.2 *	-0.6 ±0.2 *	-0.3 ±0.2 (†)	0.0 ±0.2 (†)	0.6 ±0.1 *	0.3 ±0.2
- 20-24	1.7 ±0.1	0.1 ±0.1	-0.8 ±0.2 *	-0.8 ±0.1 *	-0.8 ±0.2 *	-0.4 ±0.2 *	0.3 ±0.1 *	-0.1 ±0.1
- 25-29	1.4 ±0.1	-0.1 ±0.1	-0.9 ±0.1 * (†)	-0.9 ±0.1 * (†)	-0.8 ±0.1 *	-0.7 ±0.1 *	0.0 ±0.1	-0.4 ±0.1 *
- ≥30	4.4 ±0.2	-0.1 ±0.1	-3.4 ±0.2 * (†)	-3.4 ±0.2 * (†)	-3.4 ±0.2 * (†)	-2.9 ±0.2 *	-0.3 ±0.2	-2.2 ±0.2 *
Standing			< 403 cpm	< 398 cpm	< 1379 cpm	< 1484 cpm	< 11 spm	< 42 spm
Time in Bout								
- total	261.5 ±10.4	-12.7 ±6.4	-13.5 ±9.8 (†)	-23.8 ±11.5 * (†)	-6.5 ±10.7 (†)	-44.9 ±12.7 *	-141.8 ±7.5 * (†)	60.8 ±13.4 *

Positive bias indicates an overestimation, negative an underestimation. Significant differences to the reference criterion marked with *, biases depending on the time/number in bout indicated with † (regression approach used to calculate bias).
Abbreviations: vertical sensor axis (y), counts-per-minute (cpm), steps-per-minute (spm), low-frequency-extension filtering (LFE), vector magnitude (VM).

Table 3: Bias of the existing ActiGraph methods (counts-per-minute (cpm) and inclinometer function) to the activPAL (reference criterion). Indicated is the mean ±standard error for the reference criterion, and bias ±standard error for the ActiGraph methods. Time in minutes per day.

	Reference Criterion	y_{cpm}	$y_{cpm(LFE)}$	y_{cpm}	$y_{cpm(LFE)}$	Inclinometer	$Inclinometer_{LFE}$
Sitting		< 100 cpm	< 100 cpm	< 150 cpm	< 150 cpm		
Time in Bout							
- ≥5	441.2 ±12.7	-24.4 ±10.6 *	-59.4 ±11.5 *	14.5 ±9.8	-12.9 ±10.4	-148.3 ±20.2 *	-143.3 ±20 *
- ≥10	397.4 ±12.6	-67 ±11.6 *	-105.3 ±12.4 *	-18.4 ±10.2	-49.6 ±11.0 *	-180.3 ±19.5 *	-175.5 ±19.7 *
- total	481.7 ±12.5	23.3 ±10.7 *	-6.8 ±11.1	54.4 ±10.5 *	28.4 ±10.6 *	-105.8 ±19.6 *	-100.4 ±19.2 *
- <5	40.4 ±2.1	47.7 ±2.7 * (†)	52.6 ±2.7 * (†)	39.9 ±2.7 *	41.2 ±2.7 *	42.6 ±3.4 * (†)	43 ±3.4 * (†)
- 5-9	43.8 ±1.8	42.6 ±2.5 * (†)	45.9 ±2.5 * (†)	32.9 ±2.3 * (†)	36.8 ±2.3 * (†)	32 ±2.6 * (†)	32.2 ±2.6 *
- 10-14	42.2 ±1.6	28.6 ±1.8 * (†)	28.6 ±2 * (†)	23.3 ±2.0 * (†)	25.0 ±1.7 * (†)	10.7 ±2.5 * (†)	10.8 ±2.6 * (†)
- 15-19	43.9 ±2.0	12 ±2.7 * (†)	6.9 ±2.8 *	13.3 ±3.0 * (†)	11.8 ±3.1 *	-7.1 ±3.2 *	-5.8 ±3.1
- 20-24	37.8 ±2.3	2.8 ±2.6	-1.1 ±3.2	5.6 ±2.1 *	4.5 ±2.2 *	-10.6 ±2.9 *	-10.7 ±2.7 *
- 25-29	37.7 ±2.2	-4.4 ±2.9	-10.4 ±2.8 *	0.3 ±2.4	-2.9 ±2.7	-18.8 ±2.9 *	-18.6 ±2.9 *
- ≥30	235.9 ±11	-106 ±10.1 *	-129.3 ±9.8 *	-60.8 ±10.0 *	-88.0 ±9.6 *	-154.6 ±14.1 *	-151.3 ±14.4 *
Number of Bouts							
- ≥5	19.4 ±0.5	8.8 ±0.6 * (†)	8.3 ±0.6 * (†)	8.2 ±0.6 *	8.2 ±0.6 *	2.6 ±0.8 * (†)	2.7 ±0.8 * (†)
- ≥10	13.4 ±0.4	1.8 ±0.4 *	0.7 ±0.5	2.6 ±0.4 *	2.0 ±0.4 *	-3 ±0.6 * (†)	-2.8 ±0.6 * (†)
- total	46.7 ±1.7	29.2 ±2.1 *	30.8 ±2.2 *	24.8 ±2.0 *	25.1 ±2.0 *	18.7 ±2.4 *	18.9 ±2.4 *
- <5	27.3 ±1.5	20.4 ±1.8 *	22.5 ±1.9 *	16.6 ±1.7 *	17.0 ±1.6 *	16.2 ±2.3 *	16.2 ±2.4 *
- 5-9	6.0 ±0.3	7 ±0.3 * (†)	7.6 ±0.4 * (†)	5.5 ±0.3 * (†)	6.2 ±0.3 * (†)	5.5 ±0.4 * (†)	5.6 ±0.4 *
- 10-14	3.4 ±0.1	2.6 ±0.2 * (†)	2.6 ±0.2 * (†)	2.1 ±0.2 * (†)	2.3 ±0.1 * (†)	1.1 ±0.2 * (†)	1.1 ±0.2 * (†)
- 15-19	2.5 ±0.1	0.8 ±0.2 * (†)	0.5 ±0.2 *	0.9 ±0.2 * (†)	0.8 ±0.2 *	-0.3 ±0.2	-0.3 ±0.2
- 20-24	1.7 ±0.1	0.2 ±0.1	0 ±0.1	0.3 ±0.1 *	0.2 ±0.1 *	-0.4 ±0.1 *	-0.4 ±0.1 *
- 25-29	1.4 ±0.1	-0.1 ±0.1	-0.4 ±0.1 *	0.0 ±0.1	-0.1 ±0.1	-0.7 ±0.1 *	-0.7 ±0.1 *
- ≥30	4.4 ±0.2	-1.6 ±0.2 *	-2 ±0.2 *	-0.7 ±0.2 *	-1.2 ±0.2 *	-2.6 ±0.2 *	-2.5 ±0.3 *
Standing							
Time in Bout							
- total	261.5 ±10.4	-	-	-	-	-140.8 ±19.1 * (†)	-138.6 ±19.2 * (†)

Positive bias indicates an overestimation, negative an underestimation. Significant differences to the reference criterion marked with *, biases depending on the time/number in bout indicated with † (regression approach used to calculate bias).
Abbreviations: vertical sensor axis (y), counts-per-minute (cpm), low-frequency-extension filtering (LFE).

List of Supporting Information Files

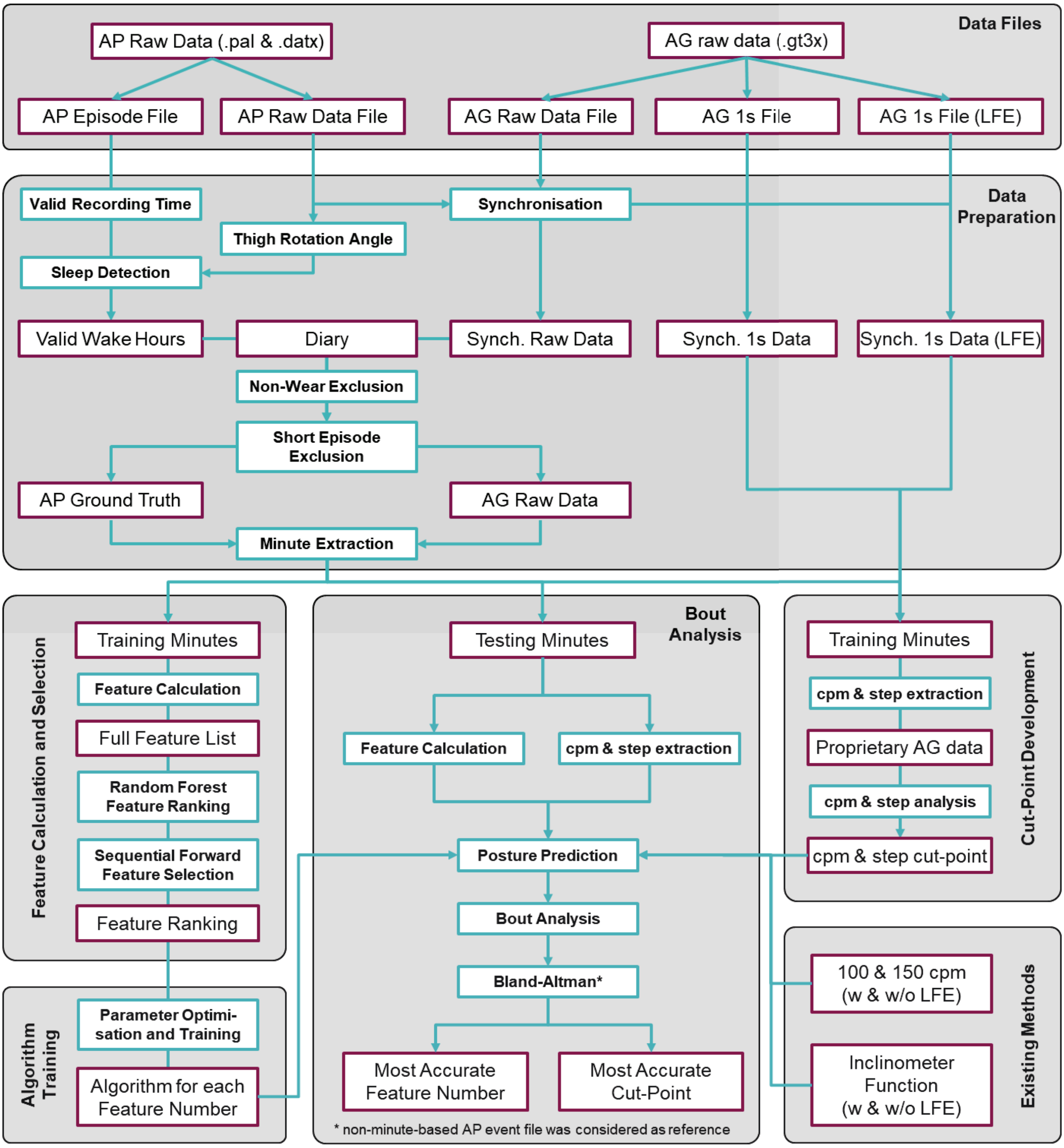
Supporting Information 1. Data processing plan including detailed data preparation description (.pdf)

Supporting Information 2. Feature table with ranking information and MATLAB code on how to calculate the features (.pdf)

Supporting Information 3. Cross-validity table of all presented methods (.pdf)

This is the accepted version of the appendix of the following article: Kuster, R.P.; Grooten, W.J.A.; Baumgartner, D.; Blom, V.; Hagströmer, M.; Ekblom, Ö. Detecting Prolonged Sitting Bouts with the ActiGraph GT3X. Scand. J. Med. Sci. Sports 2020, 30, 572-582, which has been published in final form at https://onlinelibrary.wiley.com/doi/full/10.1111/sms.13601.

Supporting Information 1: Data processing plan for acitvPAL (AP) and ActiGraph (AG) data, including detailed data preparation description (bottom).



Valid Recording Time
A valid day consists of (criteria applied to activPAL (AP) data):
- <95% of day spent in mode AP Code
- ≥500 steps
- ≥12 hours recorded

On first/last valid day:
- recording start/stop defined by first/last 45-second non-Sedentary AP activity

Sleep Detection
Longest AP Sedentary Bout from noon to noon, expanded if surrounding 15 minute window contains:
1) AP Sedentary ≥2 hours
2) AP Sedentary ≥0.5 hours & ≤50 steps
3) AP Standing between Sleeping and Sedentary with 0 steps
4) AP Sedentary with thigh rotation >65° & ≤50 steps
5) AP Sedentary ≥15 min with thigh rotation >65° & ≤100 steps (applied to surrounding 60 min)

1-3) Winkler et al. 2016 (32); 4-5) Lyden et al. 2016 (33)

Non-Wear Exclusion
Each AP episode overlapping an AG episodes ≥1 second with constant AG signal on all sensor axes excluded if:
- AP recorded posture change
- AP classified the episode as Active
- AG episode ≥90 min

Self-Reported: Time excluded if participants reported the AG was not worn (diary).

Thigh Rotation Angle
Orientation of the thigh along its longitudinal axis versus vertical room axis (Lyden et al. 2016, 33; used to detect sleep)
- Sitting/Standing ≈ 0°
- Lying on the side ≈ ± 90°
- Lying on the stomach ≈ 180°

Synchronisation
Find largest cross-correlation between normalized sensor x-axes of non-overlapping 3 hour bouts, maximum 2 minute lag. Delay linear approximated and applied to ActiGraph (AG) time.

Short Episode Exclusion
Time between two excluded episodes if:
- <5 min
- <10 min & both excluded episodes ≥2 min
- <60 min & shorter than both excluded episodes, each ≥10 min

Supporting Information 2 – Table 1: Table of all features including ranks for the top 100. From all 563 features, the 100 most relevant ones (identified by the random forest classifier) are indicated with the rank of the sequential forward feature selection. The final algorithm uses the 14 top ranked features (rank marked in bolt). Of these, 4 were selected from the vector magnitude and z-axis, respectively, 3 from the x-axis, 2 from the y-axis, and 1 from the dynamic time warping between x- and y-axis. Most features are based on the raw data (12) and 2 on the filtered data. No feature based on the 3d-angle was included in the final algorithm.

Features	raw data							filtered data				filtered angles			time	usage count	
Time Domain	x	y	z	VM	xy	xz	yz	x	y	z	VM	x	y	z			
1st Percentile				88						66				17			3
5th Percentile				39						76				91			3
10th Percentile			52	93						62				70			4
25th Percentile			43	98						18							3
50th Percentile (Median)			29											51			2
75th Percentile				83													1
90th Percentile				97													1
95th Percentile				25													1
99th Percentile				59													1
Inter-quartile range				36													1
Minimum				92						**2**						1	2
Maximum				19													1
Range		32		100													2
Mean			**5**							67				99		1	3
Standard Deviation (SD)				82													1
Coefficient of Variation (CV)				46													1
Skewness				49													1
Kurtosis				**4**												1	1
Summed absolute Signal Change from Frame to Frame	27	64	22	35				26	47		38	33					8
Lag 1 Frame Autocorrelation											61						1
Lag 1 Second Autocorrelation																	0
3rd Moment				**1**												1	1
4th Moment				40													1
Number of Peaks											42						1
Number of Prominent Peaks	**10**	60	54	50					65		23					1	6
entropy				95													1
Number of Zero-Crossings																	0
Mean Time between adjacent Zero-Crossings																	0
Median Time between adjacent Zero-Crossings																	0
SD of the Time between adjacent Zero-Crossings																	0
Number of Median-Crossings									31								1
Mean Time between adjacent Median-Crossings																	0
Median Time between adjacent Median-Crossings																	0
SD of Time between adjacent MedianCrossings																	0
Dynamic Time Warping (DTW) between Axes					**3**											1	1
DTW between 1st Derivative of the axes					20	86	37										3
Covariance between axes					79												1
Correlation between axes					24												1
Daytime															21		1
SD of all non-overlapping 5 Seconds Mean																	0
SD of all non-overlapping 5 Seconds CV				85													1
Frequency Domain																	
Mean Frequency		78	15	96							16						4
Power at Mean Frequency ±0.1Hz		63	73	57					68	**11**			58	45		1	7
Median Frequency				44													1
Power at Median Frequency ±0.1Hz		80	55						90	53			30	48			6
Mean Frequency between 0.3 to 3Hz		56															1
Power at Mean Frequency ±0.1 Hz between 0.3 to 3Hz																	0
Median Frequency between 0.3 to 3Hz		28									41						2
Power at Median Frequency ±0.1Hz between 0.3 to 3 Hz																	0
Total Signal Power		**9**	71						77	89			74	84		1	6
Power below 0.3 Hz		94	75						69	87			72				5
Power between 0.3 and 3 Hz	**13**	**12**		**6**												3	3
Power above 3 Hz	**8**	34	**7**	**14**												3	4
Harmonic Power				81													1
Harmonic Frequency																	
Usage Count																	
top 14 (final algorithm)	3	2	2	4	1					2						14	
top 100	4	12	12	28	4	1	1	1	7	10	6	1	4	8	1		100

Supporting Information 2 – Table 2: Instructions and MATLAB code to calculate the signal features. * marks features for which NaN and ±Inf were replaced with zero.

	Dimensions	Instructions / MATLAB Code
	rawdata: RAWDATA(:,1:3)	x, y, and z, as recorded
	vector magnitude: RAWDATA(:,4)	= sqrt(RAWDATA(:,1).^2+RAWDATA(:,2).^2+RAWDATA(:,3).^2)
	filtered data: RAWDATA(:,5:8)	= filter(b,a, RAWDATA(:,1:4)); with CutoffFreq = 0.5; sampfreq = 30; [b,a] = butter(2,CutoffFreq / (sampfreq/2));
	filtered angle x: [~,RAWDATA(:,9),~]	= cart2sph(RAWDATA(:,6),RAWDATA(:,7),RAWDATA(:,5));
	filtered angle y: [~,RAWDATA(:,10),~]	= cart2sph(RAWDATA(:,7),RAWDATA(:,5),RAWDATA(:,6));
	filtered angle z: [~,RAWDATA(:,11),~]	= cart2sph(RAWDATA(:,5),RAWDATA(:,6),RAWDATA(:,7));
	Minute Data	
	Start frame of each minute (frameID)	= 1:1800:(NumberOfMinutes-1)*1800;
	Data of each Minute (MinData)	= RAWDATA(minuteID:minuteID+1799,dimension) % for dimension = 1:11;
#	**Features**	
	Time Domain	
11	1st Percentile	prctile(MinData,1);
11	5th Percentile	prctile(MinData,5);
11	10th Percentile	prctile(MinData,10);
11	25th Percentile	prctile(MinData,25);
11	50th Percentile (Median)	prctile(MinData,50);
11	75th Percentile	prctile(MinData,75);
11	90th Percentile	prctile(MinData,90);
11	95th Percentile	prctile(MinData,95);
11	99th Percentile	prctile(MinData,99);
11	Inter-quartile range	iqr(MinData)
11	Minimum	min(MinData);
11	Maximum	max(MinData);
11	Range	max(MinData) - min(MinData);
11	Mean	nanmean(MinData);
11	Standard Deviation (SD)	nanstd(MinData);
11	Coefficient of Variation (CV) *	nanstd(MinData)./nanmean(MinData);
11	Skewness *	skewness(MinData);
11	Kurtosis *	kurtosis(MinData);
11	Summed absolute Signal Change from Frame to Frame	sum(abs(diff(MinData)));
11	Lag 1 Frame Autocorrelation *	lag = autocorr(MinData,sampfreq); lag(2);
11	Lag 1 Second Autocorrelation *	lag = autocorr(MinData,sampfreq); lag(sampfreq+1);
11	3rd Central Moment	moment(MinData(isnan(MinData)~=1),3);
11	4th Central Moment	moment(MinData(isnan(MinData)~=1),4);
11	Number of Peaks	length(findpeaks(MinData ,'Threshold',1e-4,'MinPeakHeight', mean(MinData) + (max(MinData)-min(MinData))/4));
11	Number of Prominent Peaks	length(findpeaks(MinData ,'Threshold',1e-6,'MinPeakProminence', (max(MinData)-min(MinData))/4));
11	entropy	entropy(MinData);
11	Number of Zero-Crossings	C = midcross(MinData(isnan(MinData)~=1),sampfreq); length(C);
11	Mean Time between adjacent Zero-Crossings	if size(C,1) < 2; 60; else; mean(diff(C)); end
11	Median Time between adjacent Zero-Crossings	if size(C,1) < 2; 60; else; median(diff(C)); end
11	SD of the Time between adjacent Zero-Crossings	if size(C,1) < 2; 0; else; std(diff(C)); end
11	Number of Median-Crossings	zci = @(MinData) find(MinData(:).*circshift(MinData(:), [-1 0]) <= 0); C = zci(MinData); length(C);
11	Mean Time between adjacent Median-Crossings	if size(C,1) < 2; 60; else; mean(diff(C)); end
11	Median Time between adjacent Median-Crossings	if size(C,1) < 2; 60; else; median(diff(C)); end
11	SD of Time between adjacent MedianCrossings	if size(C,1) < 2; 0; else; std(diff(C)); end
3	Dynamic Time Warping (DTW) between Axes	dtw(MinData(:,1), MinData(:,2)); % for x-y, (:,1) and (:,3) for x-z, (:,2) and (:,3) for y-z
3	DTW between Signal Changes from Frame to Frame	dtw(diff(MinData(:,1)), diff(MinData(:,2))); % for x-y, (:,1) and (:,3) for x-z, (:,2) and (:,3) for y-z
3	Covariance between axes	CovTemp = nancov(MinData(:,1:3)); CovTemp(1,2) % for x-y; CovTemp(1,3) % for x-z; CovTemp(2,3) % for y-z;
3	Correlation between axes	corr(MinData(:,1),MinData(:,2)); % for x-y, (:,1) and (:,3) for x-z, (:,2) and (:,3) for y-z
1	Daytime	TIMESINCEFIRSTDAY(frameID,1) - floor(TIMESINCEFIRSTDAY(frameID,1));
11	SD of all non-overlapping 5 Seconds Mean	for i = 1:12; TempMean(i) = nanmean(MinData((i-1)*150+1:(i-1)*150+150,:)); end; std(TempMean)
11	SD of all non-overlapping 5 Seconds CV	for i = 1:12; TempStd(i) = nanstd(MinData((i-1)*150+1:(i-1)*150+150,:)); TempCV(i) = TempStd(i) ./ TempMean(i); end; std(TempCV)
	Frequency Domain	
11	Mean Frequency *	MeanFreq = meanfreq(MinData,sampfreq);
11	Power at Mean Frequency ±0.1Hz	L = [MeanFreq-0.1 MeanFreq+0.1]; if L(1) < 0; L(2) = L(2)+abs(L(1)); L(1) = 0; end; if L(2) > 15; L(1) = L(1) - (L(2)-15); L(2) = 15;end; bandpower(MinData,sampfreq,L);
11	Median Frequency *	MedFreq = medfreq(MinData,sampfreq);
11	Power at Median Frequency ±0.1Hz	L = [MedFreq-0.1 MedFreq+0.1]; if L(1) < 0; L(2) = L(2)+abs(L(1)); L(1) = 0; end; if L(2) > 15; L(1) = L(1) - (L(2)-15); L(2) = 15;end; bandpower(MinData,sampfreq,L);
11	Mean Frequency between 0.3 to 3Hz *	MeanFreqLow = meanfreq(MinData,sampfreq,[0.3 3]);
11	Power at Mean Frequency ±0.1 Hz between 0.3 to 3Hz	L = [MeanFreqLow-0.1 MeanFreqLow+0.1]; if L(1) < 0; L(2) = L(2)+abs(L(1)); L(1) = 0; end; if L(2) > 15; L(1) = L(1) - (L(2)-15); L(2) = 15;end; bandpower(MinData,sampfreq,L);
11	Median Frequency between 0.3 to 3Hz *	MedFreqLow = medfreq(MinData,sampfreq,[0.3 3]);
11	Power at Median Frequency ±0.1Hz between 0.3 to 3 Hz	L = [MedFreqLow-0.1 MedFreqLow+0.1]; if L(1) < 0; L(2) = L(2)+abs(L(1)); L(1) = 0; end; if L(2) > 15; L(1) = L(1) - (L(2)-15); L(2) = 15;end; bandpower(MinData,sampfreq,L);
11	Total Signal Power	bandpower(MinData,sampfreq,[0 15]);
11	Power below 0.3 Hz	bandpower(MinData,sampfreq,[0 0.3]);
11	Power between 0.3 and 3 Hz	bandpower(MinData,sampfreq,[0.3 3]);
11	Power above 3 Hz	bandpower(MinData,sampfreq,[3 15]);
11	Harmonic Power *	[~,harmpow,~] = thd(MinData,sampfreq); harmpow(1);
11	Harmonic Frequency *	[~,~,harmfreq] = thd(MinData,sampfreq); harmfreq(1);

Supporting Information 3: Cross-validity table for all optimized and existing methods to detect sitting, standing, and being active, including cut-off for the cut-off based methods (in counts-per-minute (cpm) and steps per minute (spm)). The balanced sensitivity and specificity (Balanced) is the mean of sensitivity and specificity over the indicated/all posture. Data analysed on a subject-by-subject level and averaged over all subjects with median and non-parametric 95% confidence interval in brackets (after rejecting normal distribution with Lilliefors test). The activPAL served as reference criterion.

		Cut-Off		**Overall**	**Sitting**			**Standing**			**Active**		
		Sitting	Standing	Balanced	Balanced	Sensitivity	Specificity	Balanced	Sensitivity	Specificity	Balanced	Sensitivity	Specificity
	ML Algorithm	-	-	90.4 [87.9 - 92.4]	87.8 [84.0 - 90.7]	95.6 [94.7 - 97.2]	79.6 [74.0 - 85.2]	85.2 [79.8 - 87.6]	74.8 [65.5 - 78.8]	96.1 [95.0 - 97.4]	99.2 [98.9 - 99.5]	98.4 [97.9 - 99.1]	99.9 [99.9 - 100.0]
optimized methods	**y_{cpm}**	< 16 cpm	< 403 cpm	76.9 [74.5 - 78.0]	71.1 [66.9 - 73.2]	72.0 [67.3 - 77.7]	68.6 [63.1 - 77.7]	63.9 [61.6 - 66.5]	53.6 [47.4 - 58.9]	75.9 [72.1 - 80.2]	96.9 [95.8 - 97.5]	96.3 [93.2 - 97.8]	97.6 [96.9 - 98.5]
optimized methods	**$y_{cpm(LFE)}$**	< 23 cpm	< 398 cpm	76.7 [74.5 - 78.4]	71.4 [67.1 - 73.7]	71.8 [66.8 - 76.1]	71.8 [66.3 - 80.2]	63.8 [60.5 - 66.2]	54.9 [48.6 - 60.3]	74.8 [71.8 - 78.8]	96.6 [96.0 - 97.3]	97.2 [95.4 - 98.9]	97.0 [95.9 - 97.9]
optimized methods	**VM_{cpm}**	< 69 cpm	< 1379 cpm	76.6 [74.1 - 77.7]	69.8 [65.8 - 71.8]	71.7 [69.3 - 77.4]	66.4 [55.5 - 74.1]	62.8 [60.6 - 65.2]	51.2 [41.3 - 58.7]	76.0 [72.6 - 80.8]	97.8 [97.2 - 98.3]	97.3 [96.0 - 98.7]	98.5 [98.1 - 98.7]
optimized methods	**$VM_{cpm(LFE)}$**	< 170 cpm	< 1484 cpm	75.9 [73.2 - 76.9]	69.0 [64.4 - 72.1]	76.9 [74.5 - 82.9]	59.6 [49.4 - 67.9]	61.1 [57.9 - 62.4]	39.9 [33.1 - 51.0]	81.2 [77.7 - 84.6]	97.8 [97.5 - 98.3]	97.8 [96.8 - 99.0]	98.2 [97.6 - 98.4]
optimized methods	**Step**	< 3 spm	< 11 spm	70.7 [69.7 - 72.3]	61.6 [59.9 - 66.5]	95.2 [94.6 - 96.1]	29.8 [25.2 - 40.9]	51.9 [51.2 - 52.7]	8.0 [7.0 - 11.3]	96.0 [95.5 - 96.7]	98.6 [98.1 - 99.1]	97.7 [96.3 - 98.8]	99.7 [99.6 - 99.8]
optimized methods	**$Step_{LFE}$**	< 5 spm	< 42 spm	75.5 [72.6 - 78.1]	66.5 [62.2 - 71.6]	76.8 [73.7 - 80.8]	57.7 [49.5 - 66.5]	61.2 [56.9 - 63.3]	43.4 [35.2 - 49.6]	79.6 [77.5 - 83.1]	99.4 [99.2 - 99.7]	99.4 [98.9 - 99.8]	99.8 [99.4 - 99.8]
existing methods	**y_{cpm}**	< 100 cpm	-	-	67.8 [64.3 - 72.3]	90.7 [88.7 - 92.7]	45.3 [38.0 - 55.6]	-	-	-	-	-	-
existing methods	**$y_{cpm(LFE)}$**	< 100 cpm	-	-	70.1 [65.7 - 73.7]	87.1 [84.5 - 89.7]	54.1 [44.7 - 63.2]	-	-	-	-	-	-
existing methods	**y_{cpm}**	< 150 cpm	-	-	66.6 [63.2 - 71.4]	94.2 [93.0 - 95.3]	39.3 [32.0 - 49.5]	-	-	-	-	-	-
existing methods	**$y_{cpm(LFE)}$**	< 150 cpm	-	-	68.5 [65.0 - 72.8]	91.9 [90.7 - 93.7]	45.2 [37.9 - 57.1]	-	-	-	-	-	-
existing methods	**Inclinometer**	-	-	-	33.8 [29.6 - 43.9]	27.4 [23.4 - 32.4]	44.5 [33.6 - 58.2]	47.3 [45.6 - 48.1]	0.9 [0.3 - 2.9]	90.5 [86.4 - 93.9]	-	-	-
existing methods	**$Inclinometer_{LFE}$**	-	-	-	33.5 [29.4 - 43.7]	27.5 [23.5 - 32.5]	43.8 [33.5 - 57.7]	47.3 [45.6 - 48.1]	0.9 [0.3 - 2.9]	90.5 [86.3 - 93.9]	-	-	-

Abbreviations: machine learning (ML), vertical axis (y), counts-per-minute (cpm), low-frequency-extension (LFE), vector magnitude (VM), steps-per-minute (spm)