PAAT: Physical Activity Analysis Toolbox for the analysis of hip-worn raw accelerometer data in Python

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Summary

The Physical Activity Analysis Toolbox (*paat*) is a versatile Python package designed to analyze physical activity data. It is used in research and health-related fields to process raw acceleration data collected from the hip. It supports importing, cleaning, and preprocessing raw data, and includes algorithms to classify time in bed and non wear time. Furthermore, it supports estimating various physical activity levels such as moderate-to-vigorous physical activity or sedentary behavior, with customizable thresholds from multiple metrics. These estimates can be aggregated and used for further statistical analysis or be used directly for more sophisticated physical activity pattern analysis. Additionally, *paat* is extensible, allowing users to add custom algorithms or modules, and it integrates well with other data analysis tools within the Python ecosystem.

Statement of need

Physical activity is one of the strongest predictors of overall health. Its absence has been linked to various noncommunicable diseases such as cancer, cardiovascular diseases, or diabetes as well as mental diseases like depression or anxiety. Various methods exist to measure physical activity. One of these methods use accelerometers to estimate physical activity. Accelerometers are small body-worn sensors which measure acceleration over time. They have become a popular assessment tool in research and public health as they provide a reasonably cheap but still more objective alternative to surveys while simultaneously keeping the researcher and participant burden low. Accelerometers measure the raw acceleration in ms^{-2} often also expressed as multiples of Earth's gravitation ($1g = 9.80665ms^{-2}$). However, due to historic limitations of on-device storage, the raw acceleration has often been processed to summary metrics like activity counts (Neishabouri et al., 2022). Over the last decade the raw acceleration itself has also gotten into the focus of method development (Van Hees et al., 2016). A fundamental limitation of accelerometry is that many methods are only applicable to a certain wear location and demographic group and often do not generalize beyond that. All wear locations come with advantages and disadvantages. Hip-based accelerometer assessment shows higher correlation with physical activity energy expenditure due to its proximity to the body's center of mass (Swartz et al., 2000) while wrist-worn accelerometers are perceived as less obtrusive and thus has been argued to increase study protocol adherence (Troiano et al., 2014). Unfortunately, separate sets of methods have been developed for different populations, study protocols, and wear locations with most methods and analysis tools focusing on wrist-worn accelerometers.

Today, a plethora of accelerometer packages exist each fulfilling different purposes. The most popular package is GGIR (Migueles et al., 2019) which provides a broad set of well validated raw data methods mainly focusing on wrist-based accelerometry in R. Hammad et al. (2021) implemented *pyactigraphy* to analyze accelerometer activity count and light exposure data.

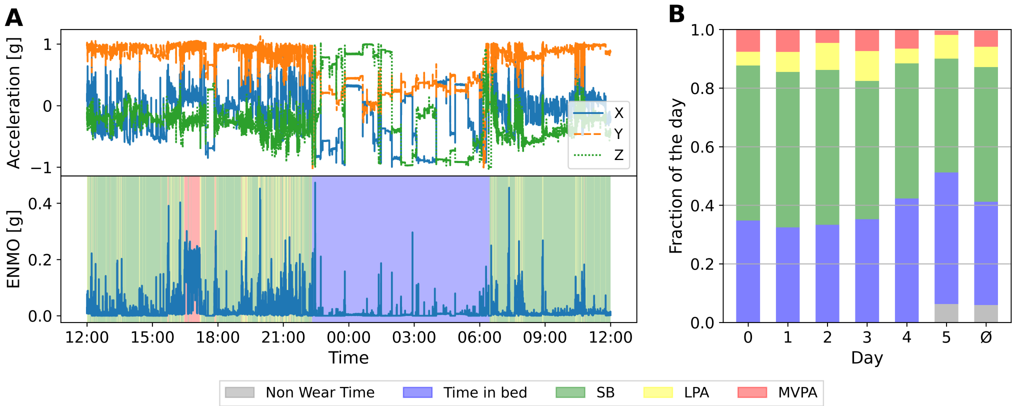

Figure 1: Visualization of the results obtained from *paat*. (A) The package can be used to load and process the raw data (upper row). The loaded data can then be annotated by a variety of methods. The implemented non-wear time and time in bed algorithm exploit raw acceleration data directly. To estimate physical activity, the raw data is reduced to the ENMO of the signal (lower row). Alternatively, also other metrics like MAD can be estimated and used for further processing. (B) Aggregated daily or average (Ø) results can be obtained and then be used for further analyzes.

Actipy provides various file reading and autocalibration functions, but only provide a limited set of methods for the further data analysis (Chan & Doherty, 2024). *SciKit Digital Health (SKDH)* provides a variety of algorithms for deriving clinical features of gait, sit to stand, physical activity, and sleep (Adamowicz et al., 2022). *Paat* is more specific in its focus on hip-placed accelerometer data, but some methods might be also interesting for other packages once they are validated and used more commonly in application.

For that reason, *paat* contains various methods to analyze raw acceleration data from the hip. As many of the methods have only recently been proposed, the primary objective of *paat* is to facilitate validation of these methods on external data. Therefore, we designed the package in a way that all methods can be run in isolation, but can also be combined to create reproducible analysis pipelines. Additionally, we designed the package to be extensible allowing users to easily add custom algorithms or use algorithms from other packages in the same pipeline by structuring it according to the respective applications. By doing that, we also want to facilitate the integration into existing packages and ecosystems.

Use in research

paat has already been used in various studies. Syed et al. (2020), for instance, developed and used the general gt3x reading functionality and implemented and used the NWT algorithm from Van Hees et al. (2011) for a comparison study of different NWT algorithms. Syed et al. (2021) also used the functions to develop a new non-wear time algorithm which is now included in *paat*. Weitz et al. (2024) used the package to load and process the acceleration data to investigate the effect of accelerometer calibration on physical activity in general and MVPA in particular. Weitz, Syed, et al. (2025) used the package to load and process the data in order to train a machine learning model to identify time-in-bed episodes. The developed method is now also included in this package. Weitz, Morseth, et al. (2025) used the package to compare different accelerometer data processing strategies to estimate sedentary time.

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