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ACTman: Automated preprocessing and analysis of actigraphy data

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ABSTRACT

Objectives: To introduce a novel software-library called Actigraphy Manager (ACTman) which automates labor-intensive actigraphy data preprocessing and analyses steps while improving transparency, reproducibility, and scalability over software suites traditionally used in actigraphy research practice.

Design: Descriptive.

Methods: Use cases are described for performing a common actigraphy task in ACTman and alternative actigraphy software. Important inefficiencies in actigraphy workflow are identified and their consequences are described. We explain how these hinder the feasibility of conducting studies with large groups of athletes and/or longer data collection periods. Thereafter, the information flow through the ACTman software is described and we explain how it alleviates aforementioned inefficiencies. Furthermore, transparency, reproducibility, and scalability issues of commonly used actigraphy software packages are discussed and compared with the ACTman package.

Results: It is shown that from an end-user perspective ACTman offers a compact workflow as it automates many preprocessing and analysis steps that otherwise have to be performed manually. When considering transparency, reproducibility, and scalability the design of the ACTman software is found to outperform proprietary and open-source actigraphy software suites. As such, ACTman alleviates important bottlenecks within actigraphy research practice.

Conclusions: ACTman facilitates the current transition towards larger datasets containing data of multiple athletes by automating labor-intensive preprocessing and analyses steps within actigraphy research. Furthermore, ACTman offers many features which enhance user-convenience and analysis customization, such as moving window functionality and period selection options. ACTman is open-source and thus fully verifiable, in contrast with many proprietary software packages which remain a *black box* for researchers.

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Practical implications

- The feasibility of large scale actigraphy studies is often constrained by the associated analysis software.
- Open-source actigraphy software makes actigraphy analysis more transparent and verifiable.
- Automated batch processing of actigraphy data allows researchers to study more and longer datasets from multiple athletes in less time, while reducing human error.

1. Introduction

Over the years, actigraphy has gained popularity as it allows researchers to study athletes and regular participants in their own living environment, with minimal disturbance.¹ Actigraphy is considered to assess more ecological valid measures of physical activity, sleep duration, and circadian rhythm compared to subjective measures as it minimizes the risk of recall and social desirability bias.^{2,3} Although *polysomnography* is the golden standard in sleep research,⁴ its invasive nature and high costs make it an unfeasible method when studying large samples of multiple athletes in ecological valid daily life settings for longer periods of time (i.e. weeks, months). *Actigraphy* on the other hand, is

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non-invasive, relatively cheap, and easy to use.^{3–5} In actigraphy studies, participants often continuously wear wireless, lightweight, accelerometers that measure (tri-axial) movement in small intervals (and thus high resolution). Such accelerometers have been validated against polysomnography (PSG) and are an accepted alternative for long-term sleep assessment during daily life.^{3,4,6} The usefulness of actigraphy in studying circadian rhythms is supported by the finding that actigraphy-defined sleep-wake cycles accurately predicted sleep-wake cycles defined by simultaneously measured polysomnography.⁷

However, while accelerometer hardware is important, the software required for subsequent analyses plays an often overlooked role in determining whether the analysis of large data sets is feasible and whether the results are of sufficient quality. There is a limited number of software packages which cater towards the actigraphy researcher. The most common is the default software included with some actigraphy devices. Examples hereof are the *MotionWare* software, included with the MotionWatch 8 accelerometer, and the *Actiware* software, included with the Philips Actical and Actiwatch 2 accelerometers.^{1,8} Next to the proprietary software, there are a limited number of open-source alternatives, for example: *nparACT*,⁹ *acc*,¹⁰ and *GGIR*¹¹ for R statistical software.¹²

There are, however, some limitations to existing software suites regarding *transparency*, *reproducibility*, and *scalability*. Transparency can be defined as the availability and complete observability of the source code of the software for all stakeholders. Moreover, transparency is found to be a crucial software design choice that influences stakeholder behavior.^{13,14} Making the source code transparent thus makes it *verifiable* and *auditable*. Relevant and easily checkable indicators of transparency are whether the software is open-source; and whether the software has a public code repository where the full source code is available and observable.

Reproducibility is defined as being able to obtain identical numeric results at a later time point while using the same data,¹⁵ and is regarded to be one of the defining characteristics of science.^{16,17} Indeed, reproducibility and transparency are closely related as a lack of transparency hinders identification of the root causes for low reproducibility. Furthermore, a lack of reproducibility can be caused by human error. For example, consider two actigraphy researchers named Alice and Bob. Alice originally conducted a study collecting actigraphy data of one athlete for 365 days using actigraphy. Alice then uses a software suite to run the analyses which requires her to manually input the athlete's bed and wake up times from a pen-and-paper sleep-log. As Alice is very focused and precise she inputs the information from the sleep-log into the software without error and after running the analyses receives a set of results. Bob, on the other hand, read about Alice's results and decides to try to reproduce them. While Bob is also very dedicated, he unintentionally mixed up some times from the sleep-log when inputting these manually into the actigraphy software. Hence, as he tries to replicate Alice's results Bob will find deviating results meaning that he could not fully reproduce the results reported by Alice. However, this lack of reproducibility is caused by human error, not deficiencies in theory or experimental design. Given this example the importance of reducing human error to improve reproducibility becomes clear. Moreover, it was found that humans are especially susceptible for making errors during repetitive and monotonous tasks, while automation is regarded as a method to reduce such human error and thus improve reproducibility.^{18,19} A relevant indicator of reproducibility is how much monotonous manual processes are automated to prevent human error.

Scalability is defined as the ability to process an increasing amount of work and elements, while facilitating effortless enlargement.^{20,21} Given such a definition, a scalable process will

keep performing at an acceptable level under load while the performance of a less scalable process will deteriorate, possibly causing longer turnaround times and/or increased error rates. Moreover, less scalable processes will require large amounts of work to add improvements, while a scalable process is designed with ease of implementation in mind. Relevant indicators of scalability are, for example, the ease of adaptability of the process to interact with and support new types of hardware, and the degree to which performance under increased workload is bounded by manual processing steps.

To address these issues, we developed the *Actigraphy Manager* (ACTman) software-library (software repository available online²²) for the statistical programming language R.¹² ACTman automates preprocessing and analysis of actigraphy data, thereby automatically performing a multitude of labor-intensive tasks usually done by hand. ACTman aims to improve transparency, reproducibility, and scalability over existing actigraphy software packages by offering a solution that is open-source, automates monotonous manual processes, and is easily expandable. Moreover, the data preprocessing steps in ACTman add functionalities which can benefit actigraphy researchers, for example: (1) the possibility for selecting a subset of the data from a specific time period, (2) removing tails of zero activity, (3) binning the data into 60 s epochs, (4) reformatting dates and times to a standardized format, (5) plotting 48-h or 24-h actograms, (6) offering moving window functionality, that is, being able to analyze a distinct period, for example 14 days, in a larger dataset and then moving this period forward in user-defined steps while iterating the analysis, and (7) being able to take plain marker button data and automatically convert this into a machine-readable sleep-log which can then be used in subsequent sleep analyses.

ACTman automatically preprocesses input data into a uniform file format for subsequent analyses. ACTman currently supports two actigraphs, namely the MotionWatch 8 (*CamNTEch*), and the Actiwatch 2 (*Philips Respironics*), while offering a scriptable framework which can be readily extended to include other actigraphs. After the preprocessing steps ACTman applies validated sleep and circadian algorithms in order to calculate commonly used output variables. The major and novel contribution of ACTman is that it offers researchers both a comprehensive actigraphy software solution for automating necessary preprocessing steps, as well as a tool for calculating validated circadian rhythm and sleep analysis output measures. Moreover, replacing manual preprocessing by automated preprocessing reduces chances for human error.

2. Methods

The main goal of the ACTman data preprocessing part is transforming device-specific data into generic data files (also see Fig. 1). These generic data files are then used for subsequent sleep or circadian rhythm analyses.

During preprocessing, ACTman first indexes all the actigraphy data files and sleep-logs in the specified working directory. Thereafter, the actigraphy data files are read and transformed into a data frame, out of which only relevant data columns (date, time, and activity) are extracted. Reading in the actigraphy data files requires a device-specific approach as the native layout of these actigraphy files differs per device. ACTman then checks if the data is binned in epochs of 60 s; a common epoch length required for various actigraphy analyses. If 30 s epochs are found instead, ACTman will automatically bin these into 60 s epochs. Then, the dates and times are combined and reformatted into a standardized format (e.g. 2019-01-31 12:30:00). Hereafter, a check for missing data is performed and the user is informed when the dataset contains a considerable amount of missings. If missing data is found and the

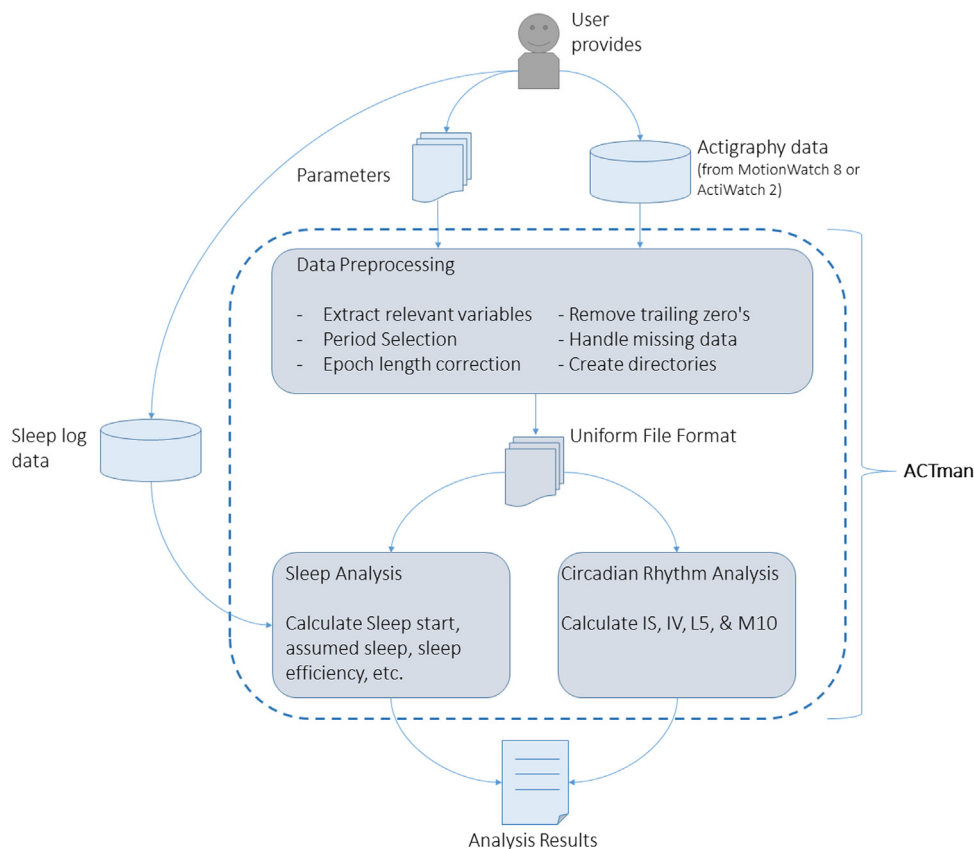


Fig. 1. Overview of ACTman information flow. The dotted line delineates the ACTman software. First, the data from either the MotionWatch 8 or the Actiwatch 2 is entered into the data-preprocessing module to obtain a uniform file format for use in subsequent analyses. Thereafter, the data in the uniform file format is used as input for the circadian rhythm analysis or the sleep analysis. If sleep analysis is required, the data from the sleep-log is read in and used in the subsequent analyses.

user has specified to omit missing values, then these are removed in a row wise manner wherein incomplete cases are also removed. The user can also specify missings to be imputed using predictive mean matching.²³ In the next step it is checked if there is activity in the tail of the dataset, as researchers can sometimes forget to immediately stop the actigraph after receiving it from the athlete. If such chunks of trailing zeroes are found, they are removed from the dataset. Hereafter a new folder is created within the working directory wherein the processed actigraphy files are saved for use in subsequent analyses.

Regarding circadian rhythm analysis, the literature describes both parametric as well as non-parametric methods.⁵ In the ACTman R-package, we chose to implement non-parametric methods as they do not require any a priori assumptions about the waveform of the activity data. Seven commonly used, well-established non-parametric variables are implemented in ACTman. These are inter-daily stability (IS; the stability of the rhythm from day to day), intra-daily variability (IV; the fragmentation of the rhythm), total activity of the ten most active (M10) and five least active hours (L5), onset times for M10, and onset times for L5. Their calculation is explained in detail elsewhere.^{5,24}

Sleep measurements in actigraphy studies are often accompanied by a sleep-log, either in digital or paper-and-pencil form, in which times for going to bed and waking up are logged. ACTman automatically reads data from digital sleep-logs and combines these with the data from the actigraph for the sleep analysis. Sleep identification is performed by calculating per epoch whether the subject is asleep or awake. To attain this, activity scores are created based on the total activity counts of the specified epoch and its direct neighbors, through the use of weighted factors specific to the epoch length.²⁵

The performance of ACTman in comparison with alternative software suites will be illustrated and evaluated by presenting *use case descriptions* for a common actigraphy task, namely performing sleep analysis. By describing software using use case descriptions, we can systematically clarify interactions between the software and its users while also highlighting workflow.²⁶ Furthermore, ACTman will be evaluated regarding transparency, reproducibility, and scalability using the aforementioned indicators, while being compared to existing proprietary software. By doing so, we illustrate important inefficiencies in actigraphy processing and analyses. A short description regarding software runtimes and analysis output is available in the supplementary materials.

3. Results

Tables 1 and 2 show use case descriptions for performing sleep analysis in two different actigraphy software packages, respectively MotionWare and ACTman. The dataset contained multiple days, which thereby provided options for both single- and multi-repetition analyses. A comparison of both tables reveals that the basic flow of the MotionWare software includes more manual steps requiring user input, which further increases as the analysis gets repeated over multiple days. Moreover, as the MotionWare software can only perform sleep analysis one day at a time, user workload will increase strongly when multiple nights of sleep are analyzed. In such a case, the user will need to repeat steps 11 till 16 until all required nights are analyzed. Such a requirement for manual involvement forms a bottleneck in facilitating actigraphy research in larger datasets as preprocessing and analysis performance is then ultimately bounded by the user performing manual tasks. Conversely, the ACTman package does not require additional

Table 1

Use case description of performing sleep analysis with the MotionWare software on a single dataset with multiple days.

Perform sleep analysis (in MotionWare)
Brief description: The actor preprocesses an actigraphy dataset of multiple days and performs a sleep analysis to obtain reportable results
Actors: Researcher, athlete and/or coach, student
Preconditions: The to be analyzed actigraphy files and corresponding sleep logs are available on the actor's computer
Basic flow of events:
1 The actor starts the system
2 The system authenticates the actor and starts a session
3 The actor locates and opens the actigraphy data file using the system
4 The system returns a selectable icon of the actigraphy data file
5 The actor clicks the <i>Sleep Analysis</i> button
6 The system returns a plot of every day available in the actigraphy data
7 The actor chooses <i>Tools > Sleep Summary Table</i> to open the sleep log window
8 The actor manually inputs the bed- and wakeup times of all days to be included in the analysis from the sleep diary into the system's sleep log window
9 The actor saves the changes made in the sleep log window
10 The systems returns to the plot of every day available in the actigraphy data
11 The actor selects the required period by double-clicking and holding the left mouse button while dragging and scrolling the selection tool downwards over the plotted actigraphy data
12 The system returns a summary view of the selected period
13 The actor chooses the <i>Sleep</i> option from the <i>Analysis Function</i> menu
14 The actor manually drags two markers, indicating bed- and wake up time, over the plot of the actigraphy data to the times corresponding to those in the sleep log
15 The system calculates and returns sleep analysis results
16 The actor transfers the sleep analysis results by copy-pasting the results into a text editor, or writing them down
17 The actor leaves the system
Extensions:
3a. The system cannot authenticate the actor
• The system informs and halts the actor
8a. Bed- and wakeup times from sleep diary are not available.
• Sleep analysis cannot be correctly performed and current night has to be skipped
16a. The actor requires the analysis of a longer period than the one day processed and analyzed up until now
• The actor repeats steps 11 till 16 until the whole required period is preprocessed and analyzed.
Post-conditions: Results are outputted on-screen and have to be transferred to another software program for saving and formatting
Special requirements: The actor has acquired the required licenses and registration to use the software

manual steps for every extra night of sleep, as it automates such preprocessing steps.

Regarding reproducibility, we identified that automation of monotonous manual processes decreases human error and facilitates better reproducibility rates. The aforementioned use case descriptions have furthermore shown that the ACTman workflow does automate processes in actigraphy research that previously required large amounts of monotonous manual labour. Especially when compared to steps 11 till 16 in the MotionWare use case description, we can see that the ACTman package substantially alleviates the workload for the actigraphy researcher. As such, by using ACTman, actigraphy researchers can decrease chances for human error which facilitates better reproducibility rates.

For transparency it is important that code is available and observable, hence we evaluated transparency by reporting whether the compared software packages are open-source and whether there is a repository where stakeholders can find the full source code. As making a software package open-source instead of proprietary is often a dedicated design choice, both the ACTman package as well as alternatives such as nparACT⁹ are necessarily transparent in this sense. For example, both have easy to find repositories

Table 2

Use case description of performing sleep analysis with the ACTman software on a single dataset with multiple days.

Perform Sleep analysis (in ACTman)
Brief description: The actor preprocesses an actigraphy dataset of multiple days and performs a sleep analysis to obtain reportable results
Actors: Researcher, athlete and/or coach, student
Preconditions: The to be analyzed actigraphy files and corresponding sleep logs are available on the actor's computer
Basic flow of events:
1 The actor starts the system
2 The system starts a session
3 The actor specifies the path where the actigraphy files are located
4 The actor runs the ACTman script
5 The system preprocesses the data into a uniform file format
6 The system reads in the sleep diary
7 The system performs the sleep analysis
8 The system returns the sleep analysis results in a dedicated spreadsheet file
9 The actor leaves the system
Extensions:
4a. The actor requires the sleep analysis of a longer period than one day.
• When the corresponding user-defined parameters are provided, the system automatically performs the required analysis over multiple days.
6a. Bed- and wakeup times from sleep diary are not available.
• The system searches for a marker button file instead and, when available, uses that to generate the sleep log, otherwise the system informs the actor
Post-conditions: A preprocessed dataset is created and used to perform the sleep analysis. Results are outputted in a dedicated results file and on-screen
Special requirements: none

where the source code is available for stakeholders.^{22,27} Conversely, proprietary actigraphy software is by definition not as transparent, thereby obscuring the exact workings of the software from stakeholders. Such obscurity can have substantial ramifications as it could take a long time before bugs in calculations are caught, if ever. The open-source actigraphy software packages, on the other hand, are fully verifiable, even offering users to make their own improvements and expansions of the software, where needed.

When considering scalability, the ability of a software package to accommodate an increasing amount of work and to support new types of hardware were identified as important characteristics. Here, software suites which require user input in many of the processing steps are necessarily limited in the amount of actigraphy files they can process within a set time period. Hence, scalability of these software suites is ultimately bounded by how quick a researcher can manually process actigraphy files without error; thus constituting a human-bound scaling limit. As such, the ACTman package, which automate these manual steps, is more scalable as its performance under increased workload is not bounded by manual processing steps. Another feature of scalability in actigraphy software is being able to support multiple types of actigraphy hardware. Here, proprietary software suites are at a disadvantage as they only offer dedicated support for one device, or in the best case, for multiple related devices from the same manufacturer. In this case, open-source packages could theoretically offer better scalability then proprietary ones as they are not per se constrained to one type of actigraph device or manufacturer. However, many open-source actigraphy packages do cater only to one specific device (e.g., the "ActivityIndex" R-package²⁸) or require actigraphy data which is already preprocessed into a specific data format (e.g., the "nparACT" R-package⁹), thereby limiting their scalability. ACTman on the other hand, preprocesses actigraphy files into a uniform format which is then used for subsequent analyses. This allows for easy support of other actigraphy devices as adding support for a new device would only require adding a module to read the device output files and transform it to the uniform file format. This not only future-proofs the ACTman package, but also allows for hetero-

geneous test environments of different actigraph devices, in which the processing of data is guaranteed to be the same.

4. Conclusions & discussion

In this paper we introduced ACTman; a R-library which automates various data preprocessing steps and performs circadian rhythm and sleep analysis. ACTman is thereby able to quickly process data from two actigraphs, the MotionWatch 8 and the Actiwatch 2, into a generic file format which are then analyzed. The ACTman package thereby tackles existing issues in actigraphy research regarding transparency, reproducibility, and scalability. By offering transparent source code and a public repository, ACTman guarantees stakeholders that the code is both auditable and verifiable. This is in contrast with many proprietary software packages which obscure their source code and thus prevent stakeholders from identifying possible issues. Furthermore, as ACTman is open-source it allows stakeholders to use and modify the ACTman source code for their own specific goals and contexts. Hence, the ACTman code could thus serve as a stepping stone for other developers to create novel actigraphy applications.

Additionally, we identified an important bottleneck in actigraphy research; namely that with common actigraphy software, quality and speed of both preprocessing and analysis is ultimately constrained by user performance in conducting specific manual tasks. This bottleneck was exemplified by presenting a use case description of actigraphy software which requires a large amount of manual involvement, and the ACTman R-package which automates most of such manual tasks. ACTman thereby also tackles an important threat to producing reproducible results, namely human error, which is especially common during repetitive and monotonous tasks, such as those normally required when processing and analyzing actigraphy data. Automating such repetitive and monotonous steps also improves scalability of actigraphy research, which can support the current trend in actigraphy research towards longer datasets including large numbers of athletes measured over extended time periods. Moreover, as ACTman transforms data into a generic data format prior to analyses, it is receptive for extensions to include various other actigraphs. Moreover, this design offers researchers heterogeneous test environments for different actigraphs, wherein data processing steps are guaranteed to be the same. In addition to these main points, ACTman offers actigraphy researchers a suite of additional features, including: comprehensive moving window functionality with a large degree of user customization, the ability to convert marker button presses to a sleep-log, and actigraphy plotting options.

There are, however, some limitations of the current work. For example, proprietary software packages often include extensive graphical user interfaces (GUI), which are easy to use for novel users, whereas open-source software sometimes lack refined user interfaces. This is also the case for ACTman, especially when compared to software such as MotionWare. However, as the R programming language is commonly used amongst sport researchers and data analysts, and offers extensive community tech support, this is not expected to deter its use. Moreover, R-users routinely use R through integrated development environments, such as R studio, which add functional user interfaces. A second limitation is that ACTman currently only offers calculation of non-parametric circadian rhythm variables, whereas parametric methods such as acrophase, MESOR (Midline Statistic of Mean), and cosinor analysis could bring complementary information. However, we prioritized non-parametric methods as they do not require any assumptions on the waveform underlying the rest-activity circadian rhythm.

In summary, the current paper presented the ACTman R-library, which aims at facilitating large scale actigraphy research with the MotionWatch 8 (CamNTEch) and the Actiwatch 2 (Philips

Respironics) actigraphs. ACTman realizes this by taking away an important hurdle in actigraphy data processing, namely its current labor intensity, while addressing transparency, reproducibility and scalability issues. ACTman thereby offers sport and actigraphy researchers a software solution that improves on many common inefficiencies in current actigraphy software libraries.

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Appendix A. Supplementary data

Supplementary material related to this article can be found, in the online version, at doi:<https://doi.org/10.1016/j.jsams.2019.11.009>.

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