pyActigraphy: open-source python package for actigraphy data visualisation and analysis

Grégory Hammad^{a,*}, Mathilde Reyt^{a,b}, Nikita Beliy^a, Marion Baillet^a, Michele Deantoni^a, Alexia Lesoinne^a, Vincenzo Muto^a, Christina Schmidt^{a,b}

^a*GIGA-CRC In vivo Imaging, University of Liège, Liège, Belgium*

^b*Psychology and Neurosciences of Cognition, Faculty of Psychology, University of Liège, Liège, Belgium*

Abstract

Over the past 40 years, actigraphy has been used to study rest-activity patterns in circadian rhythm and sleep research. Furthermore, considering its simplicity of use, there is a growing interest in the analysis of large population-based samples, using actigraphy. Here, we introduce *pyActigraphy*, a comprehensive toolbox for data visualization and analysis including multiple sleep detection algorithms and rest-activity rhythm variables. This open-source python package implements methods to read multiple data formats, quantify various properties of rest-activity rhythms, visualize sleep agendas, automatically detect rest periods and perform more advanced signal processing analyses. The development of this package aims to pave the way towards the establishment of a comprehensive open-source software suite, supported by a community of both developers and researchers, that would provide all the necessary tools for in-depth and large scale actigraphy data analyses.

Keywords: actigraphy, sleep, circadian rhythm, rest, activity, open-source, python

*Corresponding author.

Email addresses: `gregory.hammad@uliege.be` (Grégory Hammad), `mathilde.reyt@uliege.be` (Mathilde Reyt), `nikita.beliy@uliege.be` (Nikita Beliy), `marion.baillet@uliege.be` (Marion Baillet), `michele.deantoni@uliege.be` (Michele Deantoni), `alexia.lesoinne@uliege.be` (Alexia Lesoinne), `vincenzo.muto@uliege.be` (Vincenzo Muto), `christina.schmidt@uliege.be` (Christina Schmidt)

Required Metadata

Current code version

Nr.	Code metadata description	Please fill in this column
C1	Current code version	v1.0
C2	Permanent link to code/repository used for this code version	https://github.com/ghammad/pyActigraphy
C3	Code Ocean compute capsule	
C4	Legal Code License	GPL-3.0
C5	Code versioning system used	Git
C6	Software code languages, tools, and services used	Python 3
C7	Compilation requirements, operating environments & dependencies	
C8	If available Link to developer documentation/manual	
C9	Support email for questions	gregory.hammad@uliege.be

Table 1: Code metadata (mandatory)

1. Motivation and significance

Actigraphy consists in continuous movement recordings, using small watch-like accelerometers that are usually worn on the wrist or on the chest. As recordings can last several days or weeks, this technique is an adequate tool for in-situ assessments of the locomotor activity and the study of rhythmic rest-activity patterns. Consequently, it has been used in the field of sleep and circadian rhythm research [1] to assess night-to-night variability in estimated sleep parameters as well as rest-activity rhythm integrity. For example, intradaily variability has been associated with both cognitive and brain ageing [2, 3], while sleep fragmentation, as quantified by probability transitions from rest to activity during night-time, has been linked to cognitive performances [4] as well as to increased risks for Alzheimer’s disease [5].

However, the generalization of the findings made by this technic remains difficult; researchers either develop specific, often closed-source, data processing pipeline and/or analysis scripts, which are time-consuming, error prone and make the reproducibility of the analyses difficult, or they rely on commercial toolboxes that are not only costly but also act as black boxes. In addition, cumbersome manual data preprocessing, such as cleaning, hampers large scale analyses, which are mandatory for reliable and generalizable results.

In 2012, the UK Biobank decided to add 7-day actimetry-derived physical activity data collection. However, only a reduced set of sleep estimates has been extracted yet from this dataset to identify different rest-activity phenotypes and link them to pathology of genetic background (e.g. [6, 7]).

We thus argue that there is a need for a comprehensive and open-source toolbox for actigraphy data analysis. This motivated the development of the *pyActigraphy* package.

2. Software description and documentation

The *pyActigraphy* package is written in Python 3 (Python Software Foundation, <https://www.python.org/>) and is available from the Python Package Index (PyPI) repository. Its source code is hosted by Github and the Zenodo platform [8]. The online documentation of the *pyActigraphy* package contains a detailed description of the attributes and methods of its various modules and is meant to be used as complementary material of the current paper. In addition, more than a dozen of tutorials are made available online (<https://ghammad.github.io/pyActigraphy/tutorials.html>) to illustrate how to use the multiple features of the package, described in this paper. These tutorials are based on example data files that are provided with the package itself.

2.1. Reading native actigraphy files

The *pyActigraphy* package provides a unified way to read several actigraphy file formats. Currently, it supports files from:

- wGT3X-BT, Actigraph (.agd file format only);
- Actiwatch 4 and MotionWatch 8, CamNtech;
- ActTrust 2, Condor Instruments;
- Daqtometer, Daqtix;
- Actiwatch 2 and Actiwatch Spectrum Plus, Philips Respironics.

For each file format, a dedicated class has been implemented to extract the corresponding actigraphy data, as well as the associated meta-data. These classes inherit from a base class implementing the various functionalities of the *pyActigraphy* package. In addition, the package allows users to read actigraphy recordings, either individually, for visual inspection for example, or by batch, for analysis purposes.

54 2.2. Masking and cleaning data

55 Before analysing the data, spurious periods of inactivity, where the acti-
 56 graph was most likely removed by the participant, need to be discarded from
 57 the activity recordings. The *pyActigraphy* package implements a method to
 58 automatically mask continuous periods of total inactivity. User-defined pe-
 59 riods of masking can also be specified, either manually or in a specific file.
 60 In addition to temporary actigraph removals, another usual source of artifi-
 61 cial inactivities arises when the recordings start before and/or end after the
 62 actigraph is actually worn by the participant. Upon reading an actigraphy
 63 file, the *pyActigraphy* package allows users to discard such inactivity peri-
 64 ods by specifying a start and a stop timestamp. The data collected outside
 65 this time range are not analysed. These timestamps can also be specified
 66 by batch by using a simple log file where each line should correspond to the
 67 participant's identification. This file is then processed to automatically apply
 68 such boundaries to the corresponding actigraphy file read by the package.

69 2.3. Activity profile and onset/offset times

70 In circadian rhythm and sleep research, profile plots of the mean daily
 71 activity of actigraphy recording provides a visual tool to assess the overall
 72 rest-activity pattern, as well as recurrent behaviours such as naps. This pro-
 73 file is obtained by averaging consecutive data points that are 24h apart, over
 74 the consecutive days contained in the recording. The *pyActigraphy* package
 75 provides methods to construct this profile (Fig 1). In addition, it provides
 76 two methods to calculate and anchor these 24-hour profiles to the average
 77 activity onset and offset times of a given individual in order to ease group av-
 78 eraging. These activity onset and offset times are defined as the time points
 79 where the relative difference between the mean activity before and after this
 80 time point is maximal and minimal, respectively.

81 2.4. Visualization of sleep agenda

82 In both sleep research and medicine, a sleep diary is usually given with
 83 an actimeter to allow participants to report sleep episodes (duration and
 84 timing) as well as the subjective assessment of sleep quality for example. It
 85 allows comparisons between data recorded by an actigraph and the subjective
 86 perception of the individual wearing the device. In medical fields, sleep
 87 diaries are commonly recommended in order to help doctors in the diagnosis
 88 and treatment of sleep-wake disorders. The *pyActigraphy* package allows
 89 users to visualize and analyse sleep diaries, encoded as .ods or .csv files. Each
 90 row of these files indicates a new event, characterized by a type, a start time
 91 and an end time. A summary function provides descriptive statistics (mean,
 92 std, quantiles, ...) for each type of events. For convenience and considering

Figure 1: Visualisation example of average daily profiles obtained with *pyActigraphy* using example files included in the package.

the current interests of the researchers involved in the development of the package, four types (active, nap, night, no-wear) are implemented by default when a sleep diary is read. However, the *pyActigraphy* package allows users to remove or customize these types and add new ones. As shown in Fig. 2, the visualization of the sleep diary is allowed through the use of the python plotting library “plotly” [9]. Each event found in the sleep diary is associated with a plotly “shape” object that can be overlaid with the actigraphy data in order to visually assess the adequacy between the subjective reports and their objective counterparts.

2.5. Rest-activity rhythm variables

Non-parametric rest-activity variables can easily be calculated with the *pyActigraphy* package. The list of such variables includes:

- the interdaily stability (IS) and the intradaily variability (IV) [10], which quantify the day-to-day variance and the activity fragmentation, respectively;
- the relative amplitude (RA) [11], which measures the relative difference between the mean activity during the 10 most active hours (M10) and the 5 least active ones (L5).

In addition, *pyActigraphy* implements the mean IS and IV variables, namely ISm and IVm [12], obtained by averaging IS or IV values calculated with

Figure 2: Visualization example of actigraphy data, overlaid with periods (green: nap, grey: night, red: device not worn) reported in the sleep diary example file included in the package.

113 data resampled at different frequencies. Finally, the *pyActigraphy* package
 114 allows users to calculate the values of the IS(m), IV(m) and RA variables for
 115 consecutive, non-overlapping time periods of user-defined lengths. Upon call-
 116 ing the corresponding function, users can specify the resampling frequency, if
 117 the data must be binarized before calculation, as well as the threshold used
 118 to binarize the data.

119 2.6. Fragmentation of rest-activity patterns

120 The *pyActigraphy* package implements rest-activity state transition prob-
 121 abilities, k_{RA} and k_{AR} [13]. These variables quantify the fragmentation of the
 122 rest-activity pattern fragmentation; based on a probabilistic state transition
 123 model, where epochs with no activity are associated to a “rest” state (R) and
 124 to an “active” state (A) otherwise, the k_{RA} variable is associated with the
 125 probability to transition from a sustained “rest” state to an “active” state
 126 and the k_{AR} variable is associated with the probability to transition from a
 127 sustained “active” state to a “rest” state. The *pyActigraphy* package allows
 128 users to restrict the computation of the k_{RA} and k_{AR} variables to specific
 129 period of the day. For example, to target sleep periods, users may specify
 130 the activity offset and onset times (see section 2.3), as derived from indi-
 131 vidual activity profiles, as time boundaries. In the case of the k_{RA} variable,
 132 this would provide a quantification of the sleep fragmentation, adapted to a

133 subject's specific rest periods.

134 2.7. Rest-activity period detection

135 The *pyActigraphy* package implements several rest-activity detection al-
136 gorithms, which can be classified into two broad classes:

- 137 • Epoch-by-epoch rest/activity scoring algorithms: Cole-Kripke's [14],
138 Oakley's [15], Sadeh's [16] and Scripps' [17] algorithms. The idea un-
139 derlying these algorithms is to convolve the signal contained in a sliding
140 window with a pre-defined kernel. Most algorithms use gaussian-like
141 kernels. If the resulting value is higher than a certain threshold, then
142 the epoch under consideration, usually the one located at the centre of
143 the sliding window, is classified as active and as rest, otherwise. Fi-
144 nally, the window is shifted forward by one epoch and the classification
145 procedure is repeated.
- 146 • Detection of consolidated periods of similar activity patterns: Cre-
147 spo's [18] and Roenneberg's [19] algorithms. These two algorithms are
148 fundamentally different from the epoch-by-epoch scoring algorithm as
149 they intend to detect, at once, consolidated periods of rest. One ad-
150 vantage of this class of algorithms is that it provides a start and a stop
151 time for each period classified as rest.

152 As illustrated in Fig. 3, these algorithms have been implemented to return a
153 binary time series: 0 being rest or activity depending on the definition made
154 in the original article describing the detection algorithm.

155 Based on the aforementioned algorithms, the *pyActigraphy* package al-
156 lows also the computation of a sleep regularity profile which quantifies the
157 probability for the participant to be in the same state (rest or active) at
158 any daytime point on a day-by-day basis. From this 24h profile, the sleep
159 regularity index (SRI) [20, 21] can be calculated as the product of theses
160 probabilities over all the time bins.

161 Finally, using the detection algorithms of the latter class, the *pyActig-*
162 *raphy* package allows the computation of the sleep midpoint as described
163 in [21].

164 2.8. Advanced signal processing

165 The *pyActigraphy* package makes available additional functions for more
166 advanced analyses of actigraphy recordings:

Figure 3: Visualization example of actigraphy data, overlaid with periods scored as “active” (0) or “rest” (1) by Roennberg’s algorithm [19] for two different settings (full line: default parameter values, dash line: with a threshold set at 0.25 of the activity trend).

- Cosinor [22]: the idea of a Cosinor analysis is to estimate some key parameters of the actigraphy count series by fitting these data with a (co)sine curve:

$$Y(t) = M + A * \cos\left(\frac{2\pi}{T} * t + \phi\right)$$

where M is the MESOR (Midline Statistic Of Rhythm), A is the amplitude of the oscillations, T is the period and ϕ is the acrophase. The fit procedure provides estimates of these parameters which can then help to characterize the 24h rest-activity rhythm of an individual.

- Detrended Fluctuation Analysis (DFA) [23, 24]: human activity exhibits a temporal organization characterised by scale-invariant (fractal) patterns over time scales ranging from minutes to 24 hours. This organization has been shown to be degraded with aging and dementia [25]. The DFA method allows the quantification of this scale-invariance and comprises four steps:

1. Signal integration and mean subtraction
2. Signal segmentation
3. Local detrending of each segment
4. Computation of the q-th order fluctuations

181 All these steps have been implemented in the DFA class of *pyActigra-*
182 *phy* .

183 • Functional linear modelling (FLM) [26]: it consists in converting dis-
184 crete measures to a function or a set of functions that can be used for
185 further analysis. In most cases, the smoothness of the resulting function
186 is under control, which ensures the derivability of this function. Three
187 techniques are available in *pyActigraphy* to convert the actigraphy data
188 to a functional form:

- 189 – Fourier expansion
- 190 – B-spline interpolation
- 191 – Smoothing

192 In the context of actigraphy, functional linear modelling and analysis
193 have been successfully applied to link sleep apnea and obesity to specific
194 circadian activity patterns [27].

195 • Locomotor inactivity during sleep (LIDS) [28]: the analysis of the lo-
196 comotor activity during sleep revealed a rhythmicity that mimics the
197 ultradian dynamic of sleep. This type of analysis opens new opportu-
198 nities to study, *in situ*, sleep dynamics at a large scale and over large
199 individual time periods. The LIDS class implements all the necessary
200 functions to perform the analysis of the LIDS oscillations:

- 201 – sleep bout filtering
- 202 – non-linear conversion of activity to inactivity
- 203 – extraction of the characteristic features of the LIDS oscillations
204 via a cosine fit

205 • Singular spectrum analysis (SSA) [29, 30]: this technic allows the de-
206 composition of a time series into additive components and the quantifi-
207 cation of their respective partial variance. In the context of actigraphy,
208 SSA can be used to extract the signal trend as well as circadian and
209 ultradian components separately. The latter is relevant in human sleep
210 research because sleep is not only alternating with wakefulness over the
211 24-hour cycle, but also exhibits an ultradian modulation, as mentioned
212 previously. For example, a SSA analysis has been used to reveal al-
213 terations of the ultradian rhythms in insomnia [31]. All the necessary
214 steps for the SSA and related functions, namely the embedding, the
215 singular value decomposition, the eigentriple grouping and the diago-
216 nal averaging, are implemented in the SSA class. Since the subsequent

calculations can be computationally intensive, the class implementation uses the open-source compiler Numba [32] for a direct translation of the functions to machine code and therefore improve their execution speed by several orders of magnitudes.

2.9. Online documentation and tutorials

The online documentation of the *pyActigraphy* package contains instructions to install the package, as well as informations about the authors and the code license. It also contains a detailed description of the attributes and methods available in the *pyActigraphy* package, which is generated automatically from source code annotations. In order to keep the documentation up to date with the latest developments of the package, the documentation is automatically generated anew and made available online for each new release. Finally, the online documentation offers several tutorials, illustrating the various functionalities of the package. These tutorials are generated from Jupyter notebooks [33] that are included in the *pyActigraphy* package itself, so that they can be used by any user to reproduce and practice the various functionalities of the *pyActigraphy* package in an interactive and user-friendly environment. As input data, the tutorials use real example data files that are included in the package for illustration and testing purposes. In total, 13 examples are included.

3. Illustrative Examples

As mentioned in section 2.9, the functionalities of the *pyActigraphy* package are illustrated in several notebooks that act as tutorials and are part of the online documentation. Nonetheless, this section provides two examples on how to read and analyse actigraphy files.

3.1. Basic example

The source code in Listing 1 is used to read multiple actigraphy files at once and calculate the rest-activity variables mentioned in sections 2.5 and 2.6. In this example, the results are simply printed but can be reused for further analyses.

Listing 1: Basic example

```
#Import packages
import pyActigraphy, os
#Define path to example files
#(included in the pyActigraphy package)
fpath = os.path.join(
```

```

252         os.path.dirname(pyActigraphy.__file__), 'tests/data/'
253     )
254
255     #Read all Actiwatch 4 (CamNtech) files in the test directory:
256     raw = pyActigraphy.io.read_raw(
257         fpath+'example_0[0-9].AWD',
258         reader_type='AWD'
259     )
260
261     #Most functions can be accessed through this "raw" object.
262
263     #Ex: calculate non-parametric rest-activity variables
264     ISs = raw.IS()
265     IVs = raw.IV()
266
267     #Ex: calculate the probability to transition
268     #from Rest to Active
269     kRAs = raw.kRA(0)
270
271     #Print the results for all files
272     print('Subject_ID; IS; IV; kRA')
273     for k in myIS.keys():
274         print('{ }; {:.2f}; {:.2f}; {:.2f}'.format(
275             k, ISs[k], IVs[k], kRAs[k])
276         )

```

277 3.2. Advanced example

278 In Listing 2, a more complex example is provided. It illustrates how to fit
279 actigraphy data with a cosinor model (section 2.8). In addition, the data are
280 decomposed into several components via singular spectrum analysis (SSA)
281 and the component whose pseudo-period is close to 24h is extracted.

Listing 2: Advanced example

```

282 #Import packages
283 import pyActigraphy, os
284 from pyActigraphy.analysis import Cosinor, SSA
285 #Define path to an example file
286  #(included in the pyActigraphy package)
287 fpath = os.path.join(
288     os.path.dirname(pyActigraphy.__file__), 'tests/data/'
289 )

```

```

290
291 #Read all Actiwatch 4 (CamNtech) files
292 #in the test directory:
293 raw = pyActigraphy.io.read_raw_awd(fpath+'example_01.AWD')
294
295 #Initialize a Cosinor model object.
296 myCosinor = Cosinor()
297 # and fit it to the data
298 results = myCosinor.fit(raw, verbose=True)
299 #Inspect results
300 results.params.pretty_print()
301 # Cosinor model with parameters set to their estimated values
302 cosinor_fit = cosinor.best_fit(raw, results.params)
303
304 #Initialize a SSA object with the 'raw' object
305 mySSA = SSA(raw.data, window_length='24h')
306 # and fit it to the data
307 mySSA.fit()
308 #Inspect the singular values
309 mySSA.lambda_s
310 #Calculate the weighted correlation matrix
311 #for the first 10 components
312 w_corr_mat = mySSA.w_correlation_matrix(10)
313
314 #Based on the results of the weighted correlation matrix,
315 #it is straightforward to realize that
316 #the first and second SSA components
317 # ( $X_{\tilde{}}$ ) are strongly correlated and need to be merged.
318 circ = mySSA.X_tilde([1,2])

```

319 The result of the Cosinor model, as well the circadian SSA component
320 extracted from the data can then be used for further analyses or simply
321 plotted for visual inspection (Fig. 4).

322 More generally, complete informations on each function can accessed
323 through the usual python “help” command or through the online documen-
324 tation.

325 4. Impact

326 Even though actigraphy has been used in the field of sleep and chronobi-
327 ology research for the past 40 years, there is, to our knowledge, no compre-
328 hensive open-source analysis package for actigraphy data that would allow

Figure 4: Vizualisation example.

users to read various data format, perform the necessary data cleaning as well as some more advanced data analysis within a single framework. This is all the more necessary as it would improve the reproducibility of research outcomes by limiting the proliferation of private analysis codes [35]. It would also allow users to perform more complex analyses and therefore make optimal use of actigraphy data that are often part of costly multi-modal data acquisition protocols. Such analysis package would also help to reduce error rates by alleviating the burden of manual data processing that hampers the processing of large-scale actigraphy datasets. The emergence of nation-wide biobanks, which would be crucial for understanding public health issues such as the impact of daylight time saving changes or chronic sleep deprivation, should be matched by the emergence of appropriate analysis tools. Besides, facilitating the access to such analysis tools for actigraphy data would benefit other fields of neuroscience. For example, there are evidence for a link between human brain structure and the locomotor activity, whether it is the total amount of activity [36, 37], the sleep fragmentation [38] or the integrity of the circadian rhythmicity [3, 39]. Human brain functions are also modulated by circadian and/or seasonal rhythmicity [40, 41]. Therefore, a precise assessment of rhythmicity, as allowed by actigraphy, is crucial for functional brain imaging and cognitive studies too. This is one of many examples that emphasize the benefit of extending the use of actigraphy outside the field of sleep and circadian research.

5. Conclusions

We present the *pyActigraphy* toolbox, an open-source python package for actigraphy data visualisation and analysis which offers functionalities to automatise data pre-processing, read large file batches and implement various metrics and techniques for the analysis of actigraphy data. By developing the *pyActigraphy* package, we not only hope to facilitate data analysis but also foster research using actimetry and drive a community effort to improve this open-source package and develop new variables and algorithms.

6. Conflict of Interest

We wish to confirm that there are no known conflicts of interest associated with this publication and there has been no significant financial support for this work that could have influenced its outcome.

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586 Current executable software version

587 Ancillary data table required for sub version of the executable software:
 588 (x.1, x.2 etc.) kindly replace examples in right column with the correct
 589 information about your executables, and leave the left column as it is.

Nr.	(Executable) software meta-data description	Please fill in this column
S1	Current software version	v1.0.
S2	Permanent link to executables of this version	https://github.com/ghammad/pyActigraphy/releases
S3	Legal Software License	GPL-3.0
S4	Computing platforms/Operating Systems	Linux, OS X, Microsoft Windows
S5	Installation requirements & dependencies	Python 3.6
S6	If available, link to user manual - if formally published include a reference to the publication in the reference list	https://ghammad.github.io/pyActigraphy/
S7	Support email for questions	gregory.hammad@hotmail.fr

Table 2: Software metadata (optional)