




# KielMAT: Kiel Motion Analysis Toolbox - An Open-Source Python Toolbox for Analyzing Neurological Motion Data from Various Recording Modalities

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## Software

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## Summary

The Kiel Motion Analysis Toolbox (KielMAT) is an open-source Python-based toolbox designed for processing human motion data, following open-science practices. KielMAT offers a range of algorithms for the processing of motion data in neuroscience and biomechanics and currently includes implementations for gait sequence detection, initial contact detection, physical activity monitoring, sit to stand and stand to sit detection algorithms. These algorithms aid in identifying patterns in human motion data on different time scales. The KielMAT is versatile in accepting motion data from various recording modalities, including IMUs that provide acceleration data from specific body locations such as the pelvis or wrist. This flexibility allows researchers to analyze data captured using different hardware setups, ensuring broad applicability across studies. Some of the toolbox algorithms have been developed and validated in clinical cohorts, allowing extracted patterns to be used in a clinical context. The modular design of KielMAT allows the toolbox to be easily extended to incorporate relevant algorithms which will be developed in the research community. The toolbox is designed to be user-friendly and is accompanied by a comprehensive documentation and practical examples, while the underlying data structures build on the Motion BIDS specification ([Jeung et al., 2024](#)). The KielMAT toolbox is intended to be used by researchers and clinicians to analyze human motion data from various recording modalities and to promote the utilization of open-source software in the field of human motion analysis.

## Statement of need

Physical mobility is an essential aspect of health, as impairment in mobility is associated with reduced quality of life, falls, hospitalization, mortality, and other adverse events in many chronic conditions. Traditional mobility measures include patient-reported outcomes, objective clinical assessments, and subjective clinical assessments. These measures are linked to the perception and capacity aspects of health, which often fail to show relevant effects on daily function at an individual level ([Maetzler et al., 2021](#)). Perception involves surveys and patient-reported outcomes that capture how individuals feel about their own functional abilities, while capacity refers to clinical assessments of an individual's ability to perform various tasks. To complement both patient-reported (perception) and clinical (capacity) assessment approaches, digital health technology (DHT) introduces a new paradigm for assessing daily function. By using

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39 wearable devices, DHT provides objective insights into an individual's functional performance,  
40 directly linking it to the International Classification of Functioning, Disability and Health (ICF)  
41 framework (Üstun et al., 2003; World Health Organization, 2001) for assessing how people  
42 perform in everyday life activities. (Buckley et al., 2019; Celik et al., 2021; Fasano & Mancini,  
43 2020; Hansen et al., 2018; Maetzler et al., 2021; Warmerdam et al., 2020). DHT allows an  
44 objective impression of how patients function in everyday life and their ability to routinely  
45 perform everyday activities (Buckley et al., 2019; Celik et al., 2021; Hansen et al., 2018).  
46 Nonetheless, due to several persisting challenges in this field, current tools and techniques are  
47 still in their infancy (Micó-Amigo et al., 2023a). Many studies often used proprietary software  
48 to clinically relevant features of mobility. The development of easy-to-use and open-source  
49 software is imperative for transparent features extraction in research and clinical settings.  
50 KielMAT addresses this gap by providing software for human mobility analysis, to be used  
51 by motion researchers and clinicians, while promoting open-source practices. The conceptual  
52 framework builds on Findable, Accessible, Interoperable and Reusable (FAIR) data principles to  
53 encourage the use of open source software as well as facilitate data sharing and reproducibility  
54 in the field of human motion analysis (Wilkinson et al., 2016). The KielMAT comprises several  
55 modules which are implemented and validated with different dataset and each serving distinct  
56 purposes in human motion analysis:

- 57 1. Gait Sequence Detection (GSD): Identifies walking bouts to analyze gait patterns and  
58 abnormalities, crucial for neurological and biomechanical assessments.
- 59 2. Initial Contact Detection (ICD): Pinpoints the moment of initial foot contact during  
60 walking, aiding in understanding gait dynamics and stability.
- 61 3. Physical Activity Monitoring (PAM): Determines the intensity level of physical activities  
62 based on accelerometer signals.

63 These modules are pivotal because they enable researchers and clinicians to extract meaningful  
64 insights from motion data captured in various environments and conditions. These modules  
65 are designed to process data from wearable devices, which offer distinct advantages over vision-  
66 based approaches. Wearable devices such as IMUs provide continuous monitoring capabilities,  
67 enabling users to wear them throughout the day in diverse settings without logistical constraints  
68 posed by camera-based systems.

## 69 State of the field

70 With the growing availability of digital health data, open-source implementations of rele-  
71 vant algorithms are increasingly becoming available. From the Mobilise-D consortium, the  
72 recommended algorithms for assessing real-world gait were released, but these algorithms  
73 were developed in MATLAB, that is not free to use (Micó-Amigo et al., 2023b; Mobilise-D  
74 Consortium, 2019). Likewise, an algorithm for the estimation of gait quality was released, but  
75 it is also only available in MATLAB (Schooten, 2016; The MathWorks Inc., 2022). Alter-  
76 natively, open-source, Python packages are available, for example to detect gait and extract  
77 gait features from a low back-worn inertial measurement unit (IMU) (Czech & Patel, 2019),  
78 or from two feet-worn IMUs (Küderle et al., 2024). These advancements facilitate broader  
79 accessibility and usability across research and clinical applications. Additionally, innovative  
80 approaches like Mobile GaitLab focus on video input for predicting key gait parameters such  
81 as walking speed, cadence, knee flexion angle at maximum extension, and the Gait Deviation  
82 Index, leveraging open-source principles and designed to be accessible to non-computer science  
83 specialists (Kidziński et al., 2020a, 2020b). Moreover, tools such as Sit2Stand and Sports2D  
84 contribute to this landscape by offering user-friendly platforms for assessing physical function  
85 through automated analysis of movements like sit-to-stand transitions and joint angles from  
86 smartphone videos (Sports2D) (Boswell et al., 2023; Pagnon, 2023). KielMAT builds forth  
87 on these toolboxes by providing a module software package that goes beyond the analysis  
88 of merely gait, and extends these analyses by additionally allowing for the physical activity

89 monitoring (Van Hees et al., 2013) and other daily life-relevant movements, such as sit-to-stand  
90 and stand-to-sit transitions (Pham et al., 2017) as well as turns (Pham et al., 2018).

## 91 Provided Functionality

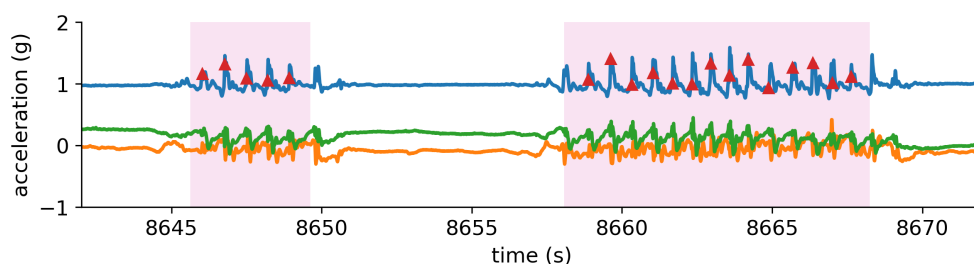
92 KielMAT offers a comprehensive suite of algorithms for motion data processing in neuroscience  
93 and biomechanics. Currently, the toolbox includes implementations for gait sequence detection  
94 (GSD) and initial contact detection (ICD), whereas algorithms for postural transition analysis  
95 (Pham et al., 2017) and turns (Pham et al., 2018) are under current development. KielMAT  
96 is built on principles from the Brain Imaging Data Structure (BIDS) (Gorgolewski et al., 2016)  
97 and for the motion analysis data are organized similar to the Motion-BIDS specifications (Jeung  
98 et al., 2024).

## 99 Dataclass

100 Supporting the data curation as specified in BIDS, data are organized in recordings, where  
101 recordings can be simultaneously collected with different tracking systems (e.g., an camera-  
102 based optical motion capture system and a set of IMUs). A tracking system is defined as a  
103 group of motion channels that share hardware properties (the recording device) and software  
104 properties (the recording duration and number of samples). Loading of a recording returns  
105 a KielMATRecording object, that holds both data and channels. Here, data are the actual  
106 time series data, where channels provide information (meta-data) on the time series type,  
107 component, the sampling frequency, and the units in which the time series (channel) are  
108 recorded.

## 109 Modules

110 The data can be passed to algorithms that are organized in different modules, such as GSD  
111 and ICD. For example, the accelerometer data from a lower back-worn IMU can be passed to  
112 the gait sequence detection algorithm (Paraschiv-Ionescu et al., 2020, 2019). Next, the data  
113 can be passed to the initial contact detection algorithm (Paraschiv-Ionescu et al., 2019) to  
114 returns the timings of initial contacts within each gait sequence (Figure 1).



115  
116 Figure 1: A representative snippet of acceleration data from a low back-worn with the detected  
117 gait sequences (pink-shaded background) and the detected initial contacts (red triangles).

## 118 Installation and usage

119 The KielMAT package is implemented in Python ( $\geq 3.10$ ) and is freely available under a  
120 Non-Profit Open Software License version 3.0. The stable version of the package can be  
121 installed from PyPI.org using `pip install kielmat`. Users and developers can also install  
122 the toolbox from source from GitHub. The documentation of the toolbox provides detailed  
123 instructions on [installation](#), [conceptual framework](#) and [tutorial notebooks](#) for basic usage and

124 specific algorithms. Data used in the examples have been collected in accordance with the  
125 Declaration of Helsinki.

## 126 How to contribute

127 KielMAT is a community effort, and any contribution is welcomed. The project is hosted on  
128 <https://github.com/neurogeriatricskiel/KielMAT>. In case you want to add new algorithms, it  
129 is suggested to fork the project and, after finalizing the changes, to [create a pull request from](#)  
130 [a fork](#).

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134 competing interests.

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