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ORIGINAL PAPER

G.A.I.T: gait analysis interactive tool a pipeline for automatic detection of gait events across different motor impairments

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Abstract

We introduce an open-access tool capable of automatically extracting the timing of gait events during unconstrained locomotion across different neuromotor impairments. The gait analysis interactive tool is conceived as an assistant for gait assessment studies, both in healthy participants or in people with motor impairments affecting gait symmetry, regularity, or balance, as usually encountered in patients with neurological disorders. Our open-access pipeline makes it possible to automatically identify the time of key gait events (heel strike, toe off) from a single gyroscope axis (lateral mid-axis), simplifying experimental protocols, and can easily be used in everyday life conditions. The code is user-friendly and interactive. At each stage of analysis, it allows for possible adjustments and manual corrections of undetected or mismatched events. To implement, test, and validate our algorithm, we used three different databases of gait recordings that span from healthy subjects to patients affected by Parkinson's disease. The pipeline consists of three main sections that allow us to segment, identify, and eventually correct the events within the gait cycle. The algorithm achieved an average accuracy of 99.23% over healthy participants, either with average weight or overweight, and a performance of 94.84% over patients with Parkinson's disease. Even if gait analysis is a widely studied problem, so far, no open-source algorithm is available. The present work provides an easy tool capable of working with a minimum set of sensors and without any expensive platform or camera-based system. Employing three databases widely different for the environment, and for the subjects' age and motor impairments highlights the versatility of our approach.

Keywords Gait · Automatic gait cycle events recognition · Gait cycle analysis · Parkinson · IMU

1 Introduction

Gait Analysis refers to the study of human locomotion during walking. It plays an essential role in detecting abnormalities in human walking style [1]. The gold standard systems for monitoring human gait, in terms of higher accuracy,

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are camera-based 3D motion capture systems and instrumented walkways. However, these systems are expensive, require ample room to operate, and demand trained professionals to run them [2]. Therefore, they are suitable only for hospitals or hospital-like settings, such as specialized gait analysis clinics or research centers. These characteristics make the systems rare and inaccessible to most patients and cannot be used in an ecological environment. As a result, in recent years, pervasive gait assessment systems emerged that could be easily deployed in non-hospital settings (such as homes or small private clinics). Indeed, there are plenty of wearable devices based on 3D Inertial Measurement Units (IMUs) [3, 4] and foot pressure sensors [5], which are generally used to measure various characteristics of human gait and monitoring motor deficits in post-surgery [6], fall detection [7], athletes'performance evaluations [8], self-detection of elderly's daily activities [9], or in neurodegenerative diseases [10–12]. Many are also the algorithms devoted to determining gait-specific characteristics: zero velocity detection, Kalman filters or the combination of both [2], the use of different machine learning techniques [13, 14] or simple peak detection methods [15]. However, in all the works cited above, data analysis was performed individually by single groups and tuned to the specific data collection. In particular, there was no general-purpose tool that could support researchers in identifying with very high accuracy key gait events both in healthy subjects and patients with different motor impairments from the simple data acquired by IMU. Here, we present a graphical open-access tool http://github.com/matteonocilli/GAIT-tool that automatically identifies heel strikes (HS) and toe-off (TO) events during gait acquired with two IMUs positioned on the foot of the subject under evaluation. We implemented the algorithm based on the signal gathered from a single gyroscope axis (lateral mid-axis), which has been validated on healthy normal-weight and overweight patients, with an average accuracy of 99.23%, and tested on patients with Parkinson's Disease (PD) with an averaged accuracy of 94.84%. The tool allows the user to interact quickly and intuitively to adjust event timing in case of possible mismatch. Moreover, it is possible to combine the inertial signals with EMG sensors as an additional aid for determining the gait cycle timing in patients severely affected.

2 Data

To implement, test, and validate our algorithm, we used three different databases of gait recordings (MeDiTech, BIOLAB,.NR) that span from healthy subjects to patients affected by Parkinson's disease. Overall, data comes from 41 subjects (17 normal-weight, 10 overweight, and 14 with Parkinson's disease, Table 1). Each participant gave written informed consent prior to the experiment, according to the declaration of Helsinki. The MeDiTech has been used to implement the algorithm. The BIOLAB, which comprises data from healthy and obese subjects, was used as the gold standard for validating the algorithm. Finally, to verify the algorithm's robustness, we tested it with the.NR database, which is based on Parkinson's disease patients. Indeed, Parkinson's disease significantly affects the motor abilities of the patients altering their gait pattern [16–18], which translates into morphological differences in the signal compared with a nonpathological one (Fig. 1).

2.1 MeDiTech database

We recorded data from 5 subjects in our lab, considering them as a control group. The experiments were performed in an internal hallway of the MeDiTech institute at the University of Applied Sciences and Arts of Southern Switzer-

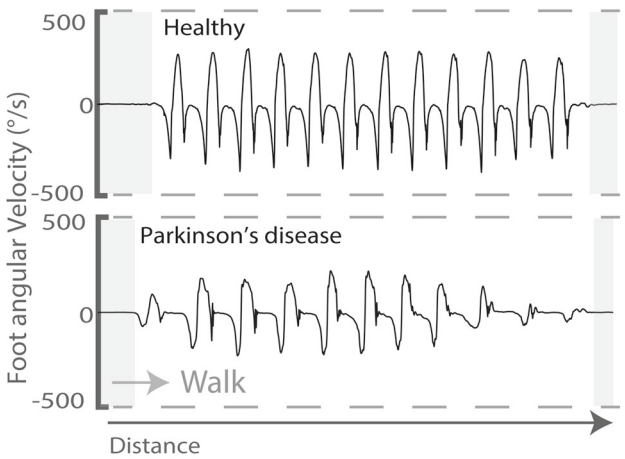

Fig. 1 Gyroscopic acquisition from the x-axis of a healthy subject belonging to the MediTech database and from a patient with severe motor impairments belonging to the.NR database

Table 1 Demographics of MeDiTech, BIOLAB and .NR databases

	MeDiTech (N = 5)	BIOLAB (N = 22)	.NR (N = 14)
Age (years)	26.8 ± 1.8	25.9 ± 1.9	64.4 ± 6.0
Height (cm)	180 ± 11.2	177.85 ± 8.2	–
UPDRS (ptlll)	–	–	38.5 ± 20.1
Sex (M/F)	4/1	22/0	8/6

TTO total toe-off, *DTO* detected toe-off, *THS* total heel-strike, *DHS* detected heel-strike

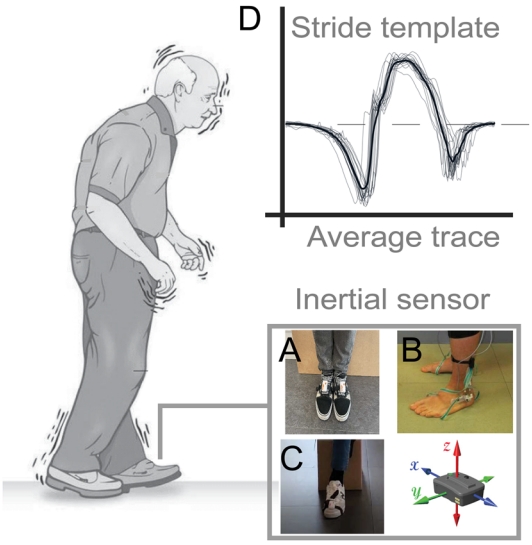

Fig. 2 **a** Picture of the placement of the IMU sensor for subjects of MediTech database; **b** picture of the placement of the IMU sensor for subjects of BIOLAB database; **c** picture of the placement of the IMU sensor for subjects of.NR database; **d** averaged stride template used for the gait segmentation phase

land (SUPSI). One IMU (Shimmer3 IMU Unit, Shimmer Research Ltd, Ireland) was placed at each tip of the subject's feet (Fig. 2a). The sensors were programmed to sample at 51.2 Hz. Subjects were instructed to stand for approximately 3 s before initiating a sustained bout of walking at their comfortable speed (ten steps). When arriving at the end of the bout, patients were instructed to stop and stand still for another 3 s before performing a U-turn and starting again for the last ten steps.

2.2 BIOLAB database

Data were collected in a previous study at the BIOLAB of the Department of Electronics and Telecommunications of the Polytechnic of Turin [5, 19]. The study involved twenty-two male volunteers, comprising twelve individuals with normal weight and ten individuals who were either overweight or obese. Data were acquired using two IMUs (TSDN121, ATR Promotions, Kyoto, Japan), attached to the lateral malleolus (Fig. 2b). In addition, three footswitches ($10 \times 10 \times 0.5$ mm, activation force: 3N) were positioned under the rear portion of the heel and the first and fifth metatarsal heads. Experiments were conducted indoor in a well-lit room and the participants walked at a self-comfort speed over a straight path of 14 m.

2.3 .NR database

Gait disorders are commonly observed in people with advanced Parkinson's disease (PD), who develop asymmetrical and disjoined gait caused by symptoms such as tremor, bradykinesia, postural rigidity, and freezing of gait [16–18, 20]. From a spatiotemporal point of view, the most important feature of PD gait is the reduction in stride length, often accompanied by a decrease in gait speed and an increase in double support duration [21, 22]. They also have limited hip flexion, inadequate knee extension, or absent heel strike. Fourteen patients affected by Parkinson's disease were recruited in a different study at the Department of Clinical Neurosciences, Lausanne University Hospital (CHUV). All patients received bilateral deep brain stimulation (DBS) leads (Medtronic 3389, Medtronic, USA) and were recorded in the five days after their surgery. All experiments were approved by the Ethical Committee of the Canton de Vaud, Switzerland (Reference PB 2017-00064). Recordings were performed in the gait lab using an optoelectronic motion capture system (Vicon, UK) that measured the 3D positions of key body joints. Kinematic data were complemented by bilateral triaxial inertial measurement unit (IMU) sensors (Delsys, MA, USA) attached to the patient's shoes (Fig. 2c), recording raw gyroscope signals from the right and left feet (sampling frequency: 148 Hz). All patients were in OFF medication and OFF stimulation conditions. Patients were instructed to stand for about 3 s before initiating a sustained bout of walking on a straight line of around 15 ms at their comfortable speed. When arriving at the end of the bout, patients were instructed to stop and stand for another 3 s before doing a U-turn and starting again [11].

3 Methods

The algorithm was developed in MATLAB® R2022a and allows extracting the TO and HS succession during walking from the angular velocity recorded by the gyroscope around the mid-lateral axis, which detects plantar and dorsi-flection movements of the ankle. The position of the inertial sensor on the foot does not significantly affect the morphology of the signal, except for changes in amplitude. Indeed, in the three databases used for the algorithm's implementation, validation, and testing, the sensors are placed at three distinct locations on foot, on the toe, in the instep, and on the malleolus, respectively. The tool can be divided into four sections: data loading, gait segmentation, main events detection, and manual correction phase.

3.1 Data loading and smoothing

The first step in the pipeline involves loading the data, verifying the sensor's orientation, and selecting the IMU channel for analysis. If an electromyogram signal is present, it can also be loaded to assist during the inspection phase. To enhance signal quality, a moving average filter can be applied

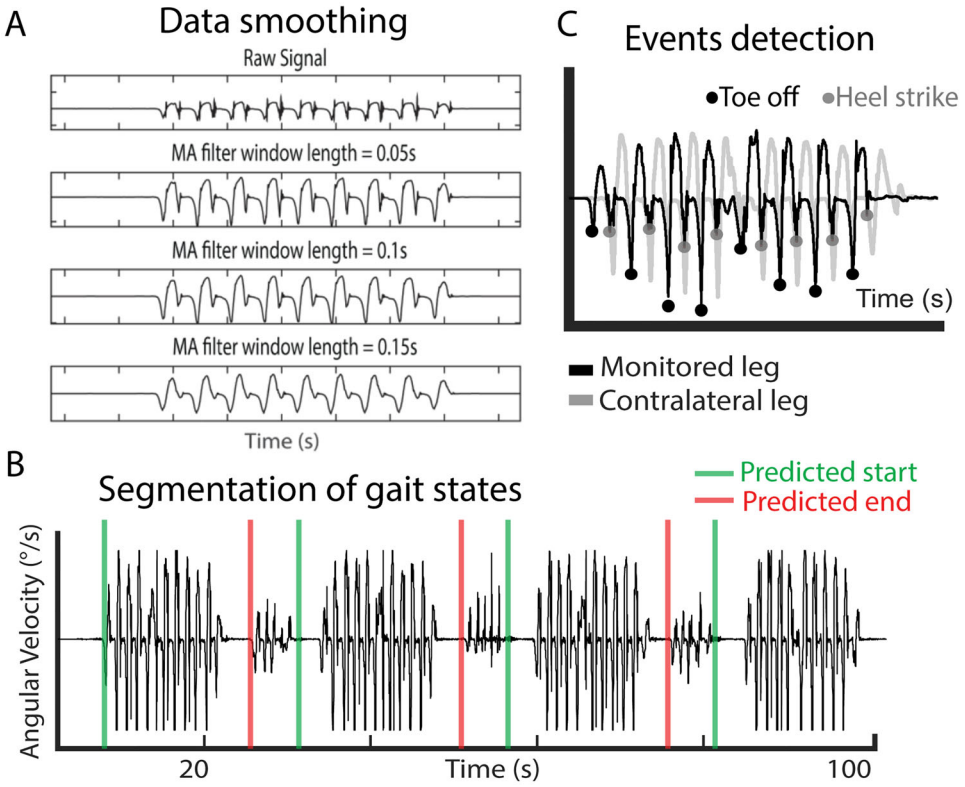

Fig. 3 **a** Data smoothing step of the pipeline. Different filters are proposed to the user to improve the quality of the shape of the gyroscopic signal; **b** segmentation phase, in case the task requires pauses or changes in direction the pipeline proceeds with a segmentation; **c** for each segment TOs and HSs are detected

to reduce potential vibration or noisy peaks. Signals can fluctuate due to various factors, including sensor sensitivity, attachment method, foot vibrations during ground contact, and suboptimal sensor placement. This technique smooths data by averaging sequential points over a chosen window size. The algorithm displays both raw and filtered signals for user selection (Fig. 3a).

3.2 Gait segmentation

Due to the confined spaces in which signals are usually recorded or the need to remain within ranges of the acquisition system, several changes in direction occur during gait that often consist of the alternating of walking and pauses followed by rotations. To recognize and isolate the walking task, we use a pattern computed by averaging the signal of a gait cycle (20 steps) gathered from a healthy subject (Fig. 2d). Based on this pattern, the tool recognizes the different portions of the walking task inside the whole gait task and presents them to the user, separated by markers identifying the beginning and the end of each repetition (Fig. 3b). During this phase, a gait cycle is identified through the cross-correlation $y(t)$ between the gyroscopic signal $x(t)$ and the aforementioned stride template $z(t)$. The peaks of the cross-correlation output above a threshold ($Th = 2.5 * \sigma$) are considered gait cycles. However, selecting peaks based only on amplitude is insufficient for gait segmentation because peaks can also occur when the patient turns to start a new repetition. Therefore, it is essential to distinguish between peaks related to walking and those related to turning. At the end of each repetition, the patient briefly stops, turns around, and stands still before starting the next repetition. To identify this pause, we calculate the mean distance between all amplitude-detected peaks. When the distance between two consecutive peaks exceeds twice the mean value, it indicates a pause, thereby allowing for gait segmentation.

3.3 Detection of the main events

Successively, the tool proceeds with the TO and HS detection within the constraints imposed in Sect. 3.2 and returns the timing related to these events. Detection is achieved by identifying the broad peak that characterizes the swing phase. For a healthy subject, it corresponds to the complete detachment of the foot from the ground and it is between TO and HS, which are the preceding and the following minimum, respectively. A detailed examination reveals that the amplitudes of swing peaks often differ from those of heel strike and toe-off peaks. To accurately and consistently detect swing peaks without mistakenly identifying other events, a threshold Th was set at 2.5 times the value of the standard deviations ($Th = 2.5 * \sigma$). This threshold was established through a combination of empirical analysis and simulations top recisely identify swing peaks in the gyroscopic signal.

Further detection of the zero-crossing points of the signal, previously deprived of any off set, allows for determining the position of the two local minima. This was done as a second control to avoid the recognition of local minima, TO and HS correspond to a change in the sign of the speed in the gyroscopic signal (Fig. 3c).

3.4 Manual correction phase

This tool was conceived to provide automatic labeling of main gait events, and it can be shared and adapted to various acquisition protocols. Moreover, it is possible to accept or manually modify the outputs of all processing stages. First, it gives the chance to visualize the signal and, eventually, invert its rotation axis to make the swing peak concurrent with the positive direction. Then, the constraints identified in Sect. 3.2 can be relocated. Finally, the tool allows adding, deleting, or modifying the TO and HS labels (accurate instructions are provided in GitHub).

4 Results

Firstly, we tested our algorithm on the MeDiTech database, considered as the control group. We used one subject as a trial to calibrate the detection and the other four as a preliminary test, reaching an accuracy of 100%, according to careful inspection by two experts. Then, it was validated using the BIOLAB database as the gold standard since it includes both IMU data and data from footswitches (ground truth) that identify all gait events with their exact timing. We ran our algorithm on the IMUs recordings, and the detected HS and TO were compared with the ground truth. All erroneous or undetected events were considered errors. As reported below, we achieved an accuracy greater than 99% in both events for both feet.

Table 2 Matching performance on PD data

ID	TTO	DTO	%DTO	THS	DHS	%DHS
PD1	209	208	99.52	209	208	99.52
PD2	107	105	97.20	107	102	93.43
PD3	217	209	96.31	217	204	94.00
PD4	138	138	100.00	138	138	100.00
PD5	141	137	97.16	141	137	97.16
PD6	167	165	98.80	167	155	92.81
PD7	122	122	100.00	122	122	100.00
PD8	154	128	83.11	154	128	83.11
PD9	134	133	99.25	134	133	99.25
PD10	165	165	100.00	165	165	100.00
PD11	211	201	90.99	211	201	90.99
PD12	132	128	96.97	132	123	93.18
PD13	182	168	92.31	182	163	89.56
PD14	130	117	90.00	130	117	90.00

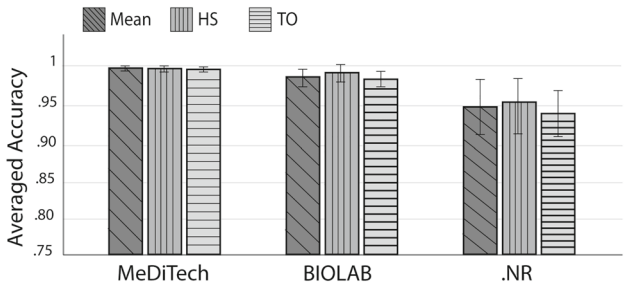

Fig. 4 Overall performance across the three databases: MeDiTech $n = 200$ (100 HS, 100 TO); BIOLAB $n = 12,834$ (6417 HS, 6417 TO);.NR $n = 4418$ (2209 HS, 2209 TO)

- Right Foot Heel-Strike: 99.52% $\pm$ 1.41
- Left Foot Heel-Strike: 99.07% $\pm$ 1.59
- Right Foot Toe-Off: 99.42% $\pm$ 1.63
- Left Foot Toe-Off: 98.92% $\pm$ 1.74

Also, in the case of the PD data, the results are very satisfactory (see Table 2), although the matching rates are slightly lower than those for patients without motor deficits. We obtained an average matching rate for TOs of 95.68% $\pm$ 4.95 while the rate drops to 94.00% $\pm$ 5.35 for HSs. In both validation and test phases, we dry-run the algorithm without any further adjustment offered by the tool (Fig. 4).

5 Discussion

The results show that the algorithm can correctly detect almost all events of interest based only on the gyroscopic signal referred to the mid-lateral axes of the ankle joint. Moreover, it is robust against the morphology of the signal, from healthy to PD subjects, and transparent to the IMU placement on foot. Indeed, in the data collected in the MeDiTech database, we used the same protocol and sensor positions as in the .NR database. In both cases, we placed two IMU sensors centrally on the instep. Although a different position was used in the BIOLAB database, it still achieved a very high average accuracy. As seen from Table 2, the algorithm's average performance is highly impacted by PD8, which has a matching accuracy of 83.11% for both events. In that patient, we encountered the highest number of undetected events due his severe gait impairments when unmedicated. The analysis was more challenging than in similar cases because the patient used a walking stick, which interfered with the swing phase. Often, the patient dragged his foot, complicating the gyroscope's event detec-

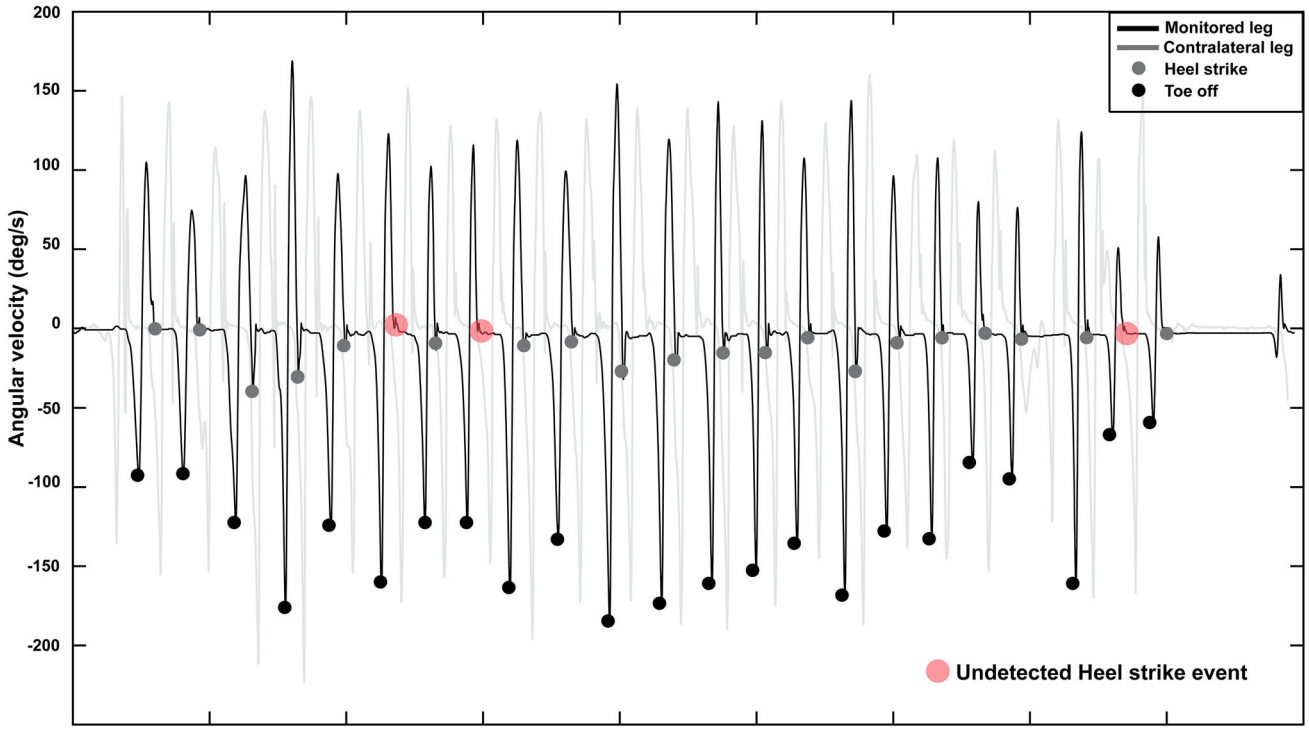

Fig. 5 Automatic event detection failure during the analysis of PD8

tion (Fig. 4). Considering all other patients, the average accuracy increases to 96.81% ± 3.51 for TO and 95.38% ± 4.52 for HS. The tool follows a continuous flow from selecting the signal to be analyzed to the final results, offering a sequence of graphical outputs summarizing the steps outlined in Sect. 3. It allows the user to intervene in case of possible mismatches or errors determined by the automatic event detection algorithm. There is always the possibility to adjust the results through easy interactive steps. Moreover, it outputs all timing data of each single gait phase. Furthermore, in the case of signal morphology hardly affected by the subject's disease, it is possible to visualize the EMG data, if present, together with the gyroscopic mid-lateral axis to select the events more accurately.

6 Conclusion and future work

In this work, an algorithm was developed to automatically detect major gait cycle events only using inertial sensors. This detection algorithm is embedded within a pipeline that allows the user to load the data, visually choose the smoothing of the raw signal, and modify, if desired, the outputs manually. Future works may include testing the pipeline on other motor tasks such as overcoming obstacles, climbing stairs, walking uphill or downhill, or at different speeds. Summing up, the impact of this tool relies on its easy handling, open-access availability, and the simplicity of the measurement setup, only one gyroscopic signal, guaranteeing excellent performance even with PD patients.

6.1 Freezing of gait episodes

Freezing of Gait (FoG) is one of the most debilitating motor symptoms that can affect patients with PD during the progression of the disease [23]. When we tested the algorithm on the .NR database, one patient exhibited severe FoG episodes if unmedicated. During these episodes, defined by an expert, the patient's feet were glued to the ground. In Fig. 6a, we report the segmentation results, and in Fig. 6b, the automatic event detection. Even during FoG episodes, if the patients managed to drag their feet, resulting in activity in the gyroscope, the tool was able to distinguish that activity from normal walking. After inspecting the results, we can state that movements related to shaking or turning are not recognized as walking.

Author Contributions MN, SS implemented the code conceived the study. MN, MGVA, and EMM acquired the data. MN and SS performed kinematics data analyses. EMM, and AP analysed the algorithm performance. EMM recruited patients and performed clinical evaluations, MG and AV made available the BIOLAB dataset including signal pre-processing recruited patients and performed clinical evaluations. EMM and SS prepared the figures. MN, SS, EMM and NLP wrote the manuscript. All authors contributed to its editing. AP supervised all aspects of the work.

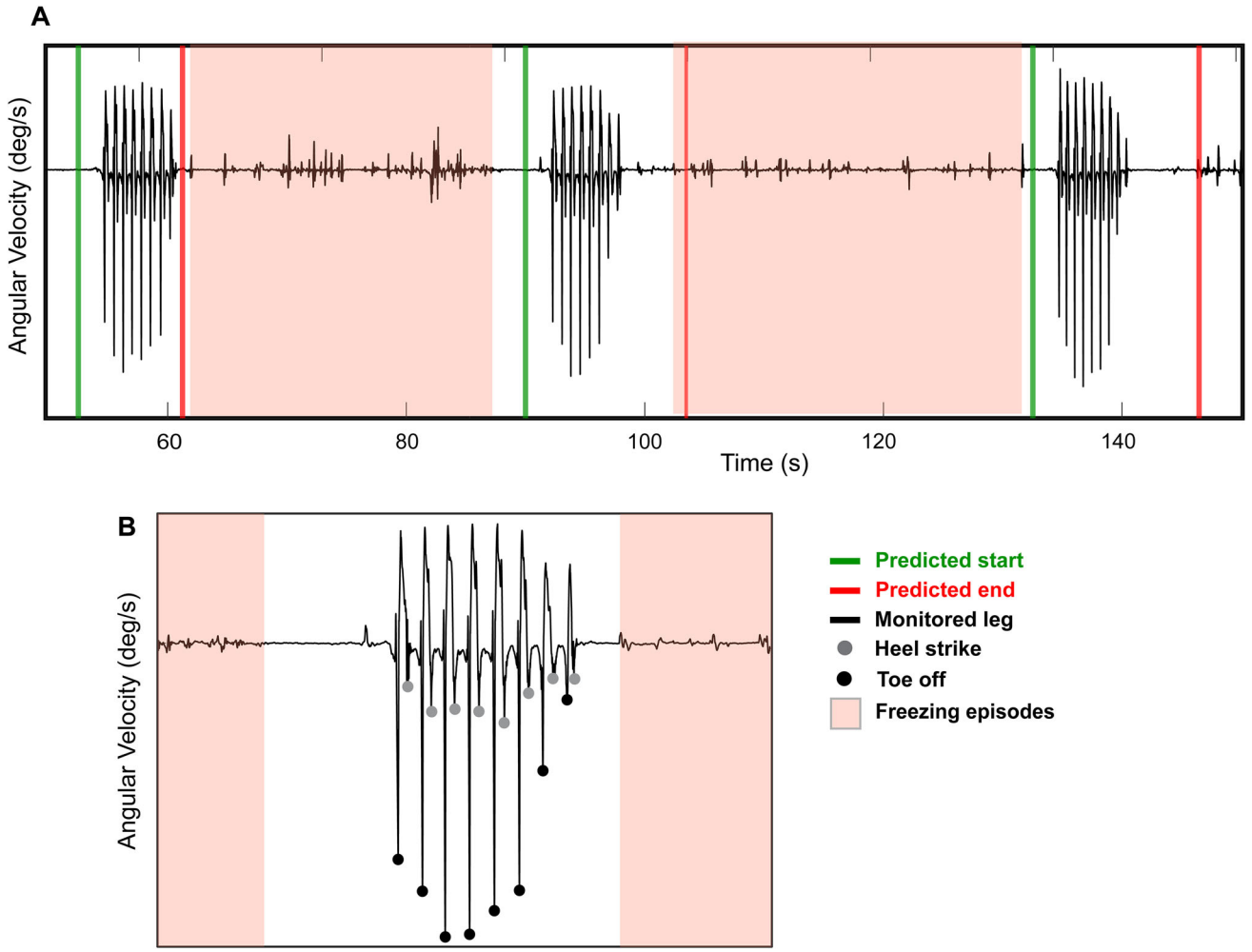

Fig. 6 **a** Segmentation result and **b** Events detection during gait of the patient affected by FoG from .NR database. Inpink the episodes marked by the neurologist

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Declarations

Competing interests The authors declare no competing interests.

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