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Automated detection of gait initiation and termination using wearable sensors

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ABSTRACT

This paper presents algorithms for detection of gait initiation and termination using wearable inertial measurement units and pressure-sensitive insoles. Body joint angles, joint angular velocities, ground reaction force and center of plantar pressure of each foot are obtained from these sensors and input into supervised machine learning algorithms. The proposed initiation detection method recognizes two events: gait onset (an anticipatory movement preceding foot lifting) and toe-off. The termination detection algorithm segments gait into steps, measures the signals over a buffer at the beginning of each step, and determines whether this measurement belongs to the final step. The approach is validated with 10 subjects at two gait speeds, using within-subject and subject-independent cross-validation. Results show that gait initiation can be detected timely and accurately, with few errors in the case of within-subject cross-validation and overall good performance in subject-independent cross-validation. Gait termination can be predicted in over 80% of trials well before the subject comes to a complete stop. Results also show that the two sensor types are equivalent in predicting gait initiation while inertial measurement units are generally superior in predicting gait termination. Potential use of the algorithms is foreseen primarily with assistive devices such as prostheses and exoskeletons.

1. Introduction

A number of devices have been developed to enhance or restore lower limb motor function. Such systems include exoskeletons [1] and active prostheses [2]. They are commonly equipped with advanced control algorithms that utilize sensors to better interact with both the human body and the environment [3]. For instance, the Hybrid Assistive Limb exoskeleton uses accelerometers, gyroscopes and potentiometers to measure joint angles [4] while the MIT exoskeleton measures hip and knee angles using rotary potentiometers [5].

In addition to sensors built into the assistive device, wearable sensors such as footswitches and accelerometers can be mounted on the user's body, supplementing information available from the device [6]. Such wearable sensors have already been used in general gait analysis and activity recognition. They can, for instance, detect falls [7] or events during cyclic gait [8].

Body- or device-mounted sensors thus allow assistive devices to detect and respond to the user's intentions [9]. In such circumstances, intentions should be detected quickly and anticipate the movement; it is not useful to, for example, determine that users want to stop once they have already done so. In our paper, we focus on the use of wearable sensors for intention detection during two events: gait initiation and gait termination.

Gait initiation represents the transition from quiet standing to steady-state gait. It is first characterized by anticipatory postural adjustments where the center of pressure is shifted [10]. Following these adjustments, the foot leaves the ground. The biomechanics of gait initiation have been studied in healthy and pathological subjects [11,12]. During gait termination, a person transitions from steady-state gait to a standing posture. This process is characterized by increased braking forces of the lead foot and reduced trail foot pushoff during the final steps. The biomechanics of gait termination have also been studied in healthy and pathological subjects [13–15]. Notably, termination strategies vary depending on gait velocity and whether termination is planned or unplanned [13].

Though extensive analyses have been performed on gait initiation and termination, less work has been done on their automated detection. Automated detection would let assistive devices react

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rapidly to desired gait starting or stopping, allowing smooth transition between rest and steady-state gait. However, such detection is significantly more difficult than detection of events during steady-state gait. Steady-state gait algorithms [16,17] can take advantage of the cyclic nature of gait and roughly predict the next event (e.g. heel-strike) based on the time of the previous one. Gait initiation and termination, on the other hand, can in principle occur at any time.

Gait initiation has already been detected with a simple threshold-based algorithm [18]. A more complex algorithm was used in our previous work [19], but focused on nonwearable sensors. Even less work has been done on detection of gait termination, but it should be possible to detect the transition to the quiet standing posture before it has completed.

This paper comprises the development and validation of algorithms for detection of gait initiation and termination using two types of wearable sensors: inertial measurement units and pressure-sensitive insoles. The ultimate goal is to use such technology to control devices for lower limb motion assistance or replacements such as robotized orthoses and prostheses. However, as the technology is still relatively untested, we decided to first conduct a proof-of-concept study with healthy subjects in order to better understand how much information can be obtained from the wearable sensors, as well as to prototype the supervised machine learning algorithm that detects intended gait initiation and termination. Since the implementation is a proof of concept, we omitted some constraints an assistive device would have. We used a larger number of inertial measurement units, which would be downscaled for a final application. We performed data analysis on a personal computer, though a final application would utilize a body-worn computer. The machine learning algorithm was evaluated offline using prerecorded data, and this constitutes the majority of the paper. An online implementation was tested afterwards to demonstrate its feasibility. It is briefly reported in the discussion, but is not the main focus of the study.

A preliminary analysis of the data presented in this paper was shown at the BioRob 2012 conference [20]. The detection algorithms presented in this paper have been significantly improved over the prior publication, providing higher accuracy and better suitability for real-time use. We also present a more detailed description of the approach and deeper analysis of the results.

2. Experiment description

2.1. Subjects

Ten male subjects with no physical or cognitive abnormalities that would affect gait participated in the study. Their age was 33.1 ± 13.2 years, their weight was 75.0 ± 7.4 kg, and their height was 174.1 ± 3.8 cm. Their European shoe sizes were between 41 and 43. All subjects signed an informed consent form after the purpose and procedure of the experiment had been explained to them.

2.2. Hardware

Two types of wearable sensors were used to measure gait: inertial measurement units (IMUs) and pressure-sensitive shoe insoles (Fig. 1). Signals from all sensors were sent wirelessly at 100 Hz using IEEE protocol 802.15.4 to a receiver unit in parallel. They were sampled serially at 100 Hz by the receiver and sent to the analysis computer over a local network using UDP. In worst-case situations, the global transmission delay is 20 ms. No onboard data processing was done since the sensors do not have sufficient capability.

A single IMU contains a triaxial accelerometer (STmicroelectronics LIS3LV02DL), gyroscope (Invensense IMU-3000) and magnetometer (Honeywell HMC5843). Outputs from these individual sensors are combined to obtain the IMU orientation. Nine IMUs were used in total. One was placed on each foot, shank, thigh and upper arm. A ninth IMU was placed on the back. The IMUs were validated, in terms of measurement range and accuracy, in a previous paper [21].

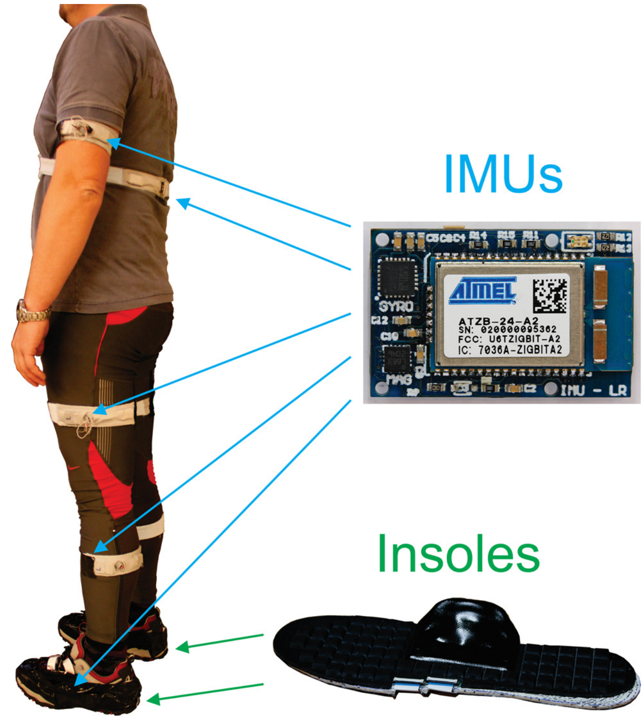

Fig. 1. A subject (left) wearing bands containing inertial measurement units (top right, actual size 30 mm × 20 mm × 5 mm) and sneakers containing insoles (bottom right).

The sensorized insoles are placed inside normal sneakers and measure the pressure distribution between the foot and ground using 64 optoelectronic pressure sensors. The technology was developed in-house and first used in pressure-sensitive cuffs [22], then adapted for insoles. This specific design has been validated [23,24] and requires no user-specific calibration.

2.3. Measurement protocol

The protocol was first explained to the subjects. Then, IMUs and insoles were placed on the body. An IMU calibration was performed by having the subject stand still for 5 s and then perform a few simple motions [21]. This allowed us to establish the starting orientations of all IMUs as well as define the joint rotation axes. For instance, knee flexion and extension were used to define the knee axis. This calibration procedure was adapted from Favre et al. [25].

Each subject performed 40 gait trials. A trial began with gait initiation and ended with gait termination. The trials were split into two 20-trial blocks: normal gait and fast gait. This was done since gait strategies depend on gait velocity [13]. The two blocks were done in random order. Subjects were instructed to walk at a moderate pace (normal gait) and a brisk, rapid pace (fast gait).

Each trial began with the subject standing still for 5 s at one end of the room. Once a signal was given, the subject waited at least 2 s, then walked across the room and stopped at the other end. The subject was allowed to wait longer if desired, ensuring that posture changes preceding gait initiation were not due to e.g. startle responses to the experimenter's signal. The exact area where the subject should stop was not marked in order to allow natural

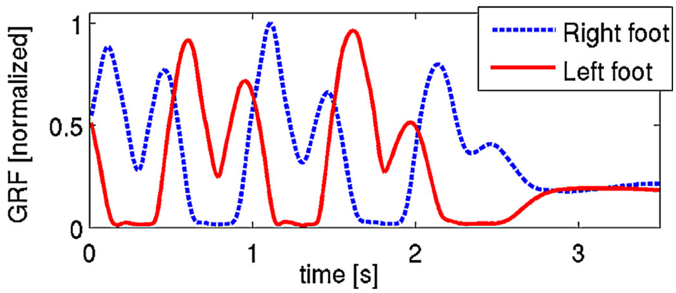

Fig. 2. Ground reaction force of the left and right foot during gait termination (final step and four preceding steps). Both forces are normalized to the maximum value measured during the trial. Two peaks can be seen for each step, the first representing heel-strike and the second representing toe push-off.

gait termination. Once the subject had stopped, waited for 5 s, then returned to the initial spot.

2.4. Data processing

Data from IMUs and insoles were processed offline. For each IMU, a Kalman filter was used on the accelerometer, gyroscope and magnetometer outputs to obtain the IMU orientation. From multiple IMUs, joint angles and joint angular velocities in the sagittal plane were calculated for both ankles, knees and hips. This resulted in 12 signals from IMUs (6 angles + 6 angular velocities). The filtering and joint angle calculation are described in our previous paper [21]. The maximum expected error of one IMU's orientation is 3° compared to an optical reference system. On average, one computational step of a single Kalman filter requires 120 μs while joint angle calculation takes 12 μs on a 1-GHz personal computer. In offline processing, Kalman filtering was done for one IMU after another, though in online applications all filters could be run in parallel.

For each insole, the center of plantar pressures (COP) along the antero-posterior direction and the total vertical ground reaction force (GRF) were calculated. This resulted in 4 signals from the two insoles (2 GRF + 2 COP). An example of GRF during gait termination, normalized with respect to the maximum value, is shown in Fig. 2. Insole processing is done in parallel to IMU Kalman filtering. It consists of 2nd-order lowpass Butterworth filtering (cutoff: 10 Hz) followed by Laplacian smoothing to obtain the meshed pressure surface. These calculations require less than 100 μs.

All signals (12 from IMUs, 4 from insoles) are used to train the classifiers in Sections 2.5 and 2.6. However, as the classifiers are based on classification trees, which only select an optimal subset of inputs, some signals may not be needed for the final classifier.

2.5. Early detection – gait initiation

The gait initiation detection algorithm's goal is to detect two events: onset and toe-off (Fig. 3). Onset is the first detectable change from the quiet standing state while toe-off occurs when the entire foot leaves the ground. Onset occurs about 0.5 s before the foot starts leaving the ground [18]. Detecting it would allow gait initiation to be detected very early. Toe-off should be easily detectable using insoles and represents a more reliable, but later event.

To detect the events, signals are classified into one of three phases: before onset, between onset and toe-off, or after toe-off. This is done with classification trees, a supervised learning method [26]. A tree uses previously recorded training data to learn a branching structure of IF-THEN rules that separate data into classes. Its main strength is robustness with regard to the number of inputs.

Two classification trees were created:

- The first classification tree is active when recording begins. It classifies each sample as either before or after onset.
- Once a sample is classified as after onset, the next three samples must also be classified as 'after onset'. Otherwise, the output is ignored and onset is considered to not have occurred. This prevents brief noise from affecting the results.
- If four consecutive samples are classified as 'after onset', onset is considered detected at the fourth sample. The first classification tree is then ignored and the second tree is activated.
- The second tree classifies each sample as either before or after toe-off. As with the first tree, four samples must be classified as 'after toe-off' before toe-off is considered detected.

As data was analyzed offline, cross-validation was used to evaluate detection accuracy (Section 2.7.1).

2.6. Early detection – gait termination

The principle of detecting gait termination is as follows: gait is first segmented into individual steps. At the beginning of each step, the algorithm records signals for a certain amount of time ('buffer') and uses them to determine whether this step is the final step. This principle was chosen since early measurements showed that signals during the final step are noticeably different from previous steps, but the second-to-final step is difficult to distinguish from steady-state gait.

Segmentation into steps is done using a simple insole-based algorithm. We consider one step to end and the next to begin when GRF of one insole exceeds the GRF of the other; i.e. when weight shifts from one leg to the other. This criterion was chosen over the criterion of GRF dropping to near zero (which was more sensitive to sensor noise).

At the beginning of each step, signals are recorded for a preset buffer. The length of this buffer is important; a shorter buffer would allow gait termination to be detected earlier but would give the detection algorithm less data to work with. Multiple buffer lengths were tested: 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.75 and 1 s. Essentially, the buffer represents the interval from the beginning of a step to when the algorithm decides whether gait termination is occurring.

Once signals have been recorded, they are assigned to the »swing« or »stance« leg in each step. For instance, if the left leg moves forward during a step, IMU and insole signals from the left leg are assigned to the swing leg while those from the right leg are assigned to the stance leg. Assuming gait symmetry, this allows the same detection algorithm to be used regardless of which leg makes the final step.

Several features are extracted from each signal in the buffer: the mean, median, standard deviation, range (maximum–minimum), skewness, and kurtosis. These features are classified using a classification Tree [26], which outputs whether the step is a final step. The approach is again trained with prerecorded data. As data were analyzed offline, cross-validation was used (Section 2.7.1).

2.7. Algorithm performance evaluation

2.7.1. Cross-validation

Since data were recorded and processed offline before detection algorithms were developed, detection accuracy must also be evaluated offline. However, detection rules should not be trained and tested on the same data, as this would not give a proper accuracy estimate. A good estimate can be obtained using cross-validation, a common method of evaluating the accuracy of supervised learning algorithms offline. The detection algorithms are first trained on a subset of the available data. They are then tested on a different subset of the data, ensuring generalizability to new data.

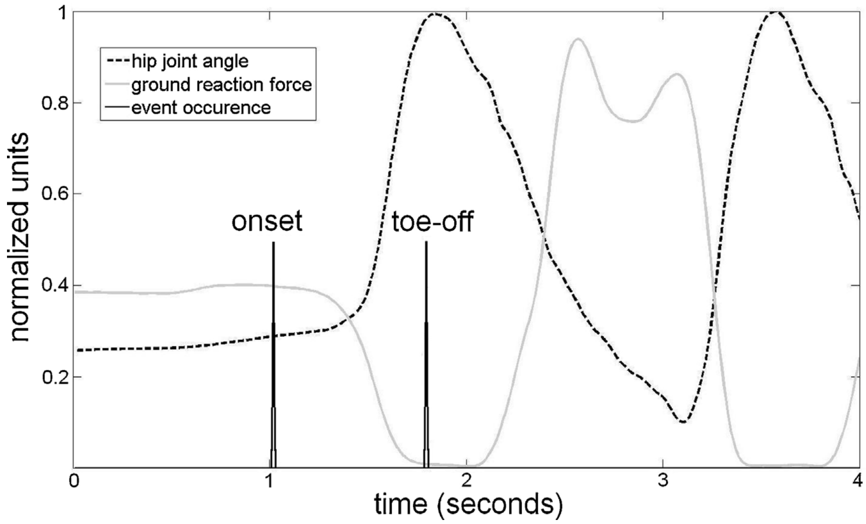

Fig. 3. Hip joint angle and ground reaction force of the leading leg during gait initiation, with onset and toe-off marked.

A more specific cross-validation method is leave-one-out cross-validation. In this approach, the entire dataset is split into subsets corresponding to either different trials or different subjects. The detection algorithm is trained on all but one subset and tested on the remaining subset. The process is repeated as many times as there are subsets, with each serving as the 'test' subset once. The final result is the overall accuracy across all test subsets.

As mentioned above, two types of leave-one-out cross-validation are performed: within-subject and subject-independent. The within-subject case represents detection tailored to each subject while the subject-independent case represents detection based on rules obtained from other subjects. Both are performed separately for only normal trials, for only fast trials, and for both normal and fast trials. This allows us to analyze the algorithms' performance both with a relatively constant gait speed and with a wider range of possible gait speeds.

In the within-subject case, algorithms are validated for each subject separately. For each subject, the training subset consists of all but one trial (19 trials if one gait speed is included; 39 trials if both speeds are included) from the subject while the test subset consists of the remaining 1 trial. The algorithm is trained and tested as many times as there are trials). This process is performed for each subject, and the final result is the overall result across all trials from all subjects.

In the subject-independent case, data from different subjects are combined. The training subset consists of trials from 9 subjects (180 trials if one gait speed is included; 360 trials if both speeds are included) while the test subset consists of trials from the remaining subject. The algorithm is trained and tested 10 times (once per test subject). The final result is the overall result across all trials from all subjects.

2.7.2. Evaluation metrics – gait initiation

In gait initiation, the goal is to identify two events in each trial: gait onset and toe-off. In order to obtain a reference, all trials are analyzed by a gait expert who marks the two events. Onset is determined entirely manually, with the expert looking at all signals and using his subjective judgment to determine the onset. Toe-off is first roughly determined by a simple automatic algorithm (when the pressure measured by an insole drops to near zero) and then corrected by the expert.

The accuracy of gait initiation detection is evaluated by first calculating the percentage of trials in which an event is not detected at all. These are reported in the results as undetected events and excluded from accuracy calculation. For the remaining trials, the mean and median absolute error (AE) are calculated: the mean and median absolute time difference between events marked by the expert and events marked by the algorithm.

2.7.3. Evaluation metrics – gait termination

In gait termination, the goal is to classify the final step as early as possible without misclassifying any preceding steps. For each step of a trial, there are three possible outcomes:

- true positive: algorithm correctly classifies a final step;
- false negative: algorithm misclassifies a final step as a nonfinal step;
- false positive: algorithm misclassifies a nonfinal step as a final step.

The accuracy of gait termination detection is evaluated as the percentage of correctly classified trials. An entire trial is classified correctly if the algorithm produces no false negatives or false positives. To reduce the amount of processing, only the last five steps of a trial are used in evaluation.

3. Results

3.1. Gait initiation

Table 1 shows results for gait onset and toe-off detection. An example of the optimal subject-independent classification tree for onset detection with IMUs is shown in Fig. 4. It was trained using both normal and fast trials. It initially checks the hip angular velocity and knee angle. If both are low, onset has not occurred. If both exceed a threshold, onset has occurred if either knee angular velocity or hip angle is sufficiently high. The process essentially measures anticipatory postural adjustments [10,18] where the COP is shifted by moving the hips and knees prior to lifting the foot. The most important movement is in the hip joint; if it has not begun moving sufficiently rapidly, onset has not occurred.

3.2. Gait termination

The duration of a step (averaged across subjects) was 0.60 ± 0.07 s during normal gait and 0.48 ± 0.06 s during fast gait. An example of the optimal subject-independent classification tree for gait termination detection with IMUs and insoles is shown in

Table 1
Mean and median absolute error (AE) for detection of gait onset and toe-off, as well as the percentage of trials where an event was not detected. Results are given separately for within-subject and subject-independent detection. They are further sorted according to type of sensor and trial speed.

	IMUs		Insoles		Both	
	Onset	Toe-off	Onset	Toe-off	Onset	Toe-off
Within-subject						
Normal trials						
Mean AE (s)	0.13	0.09	0.44	0.28	0.14	0.09
Median AE (s)	0.07	0.03	0.12	0.06	0.07	0.03
% undetected	0.0	0.0	2.9	1.5	2.9	2.9
Fast trials						
Mean AE (s)	0.10	0.06	0.24	0.20	0.11	0.08
Median AE (s)	0.07	0.03	0.05	0.05	0.05	0.04
% undetected	0.0	0.0	1.7	0.9	0.6	0.6
All trials						
Mean AE (s)	0.13	0.06	0.35	0.21	0.15	0.10
Median AE (s)	0.08	0.03	0.08	0.05	0.06	0.03
% undetected	0.0	0.0	0.6	0.0	0.6	0.3
Subject-independent						
Normal trials						
Mean AE (s)	0.33	0.28	0.57	0.39	0.35	0.29
Median AE (s)	0.22	0.21	0.34	0.31	0.26	0.22
% undetected	0.7	0.7	2.9	2.9	0.7	0.7
Fast trials						
Mean AE (s)	0.34	0.31	0.64	0.60	0.34	0.32
Median AE (s)	0.26	0.24	0.41	0.34	0.24	0.25
% undetected	0.0	0.0	0.6	2.8	0.0	0.6
All trials						
Mean AE (s)	0.33	0.29	0.61	0.34	0.34	0.31
Median AE (s)	0.23	0.19	0.43	0.27	0.24	0.23
% undetected	0.3	0.3	1.6	7.8	0.6	0.3

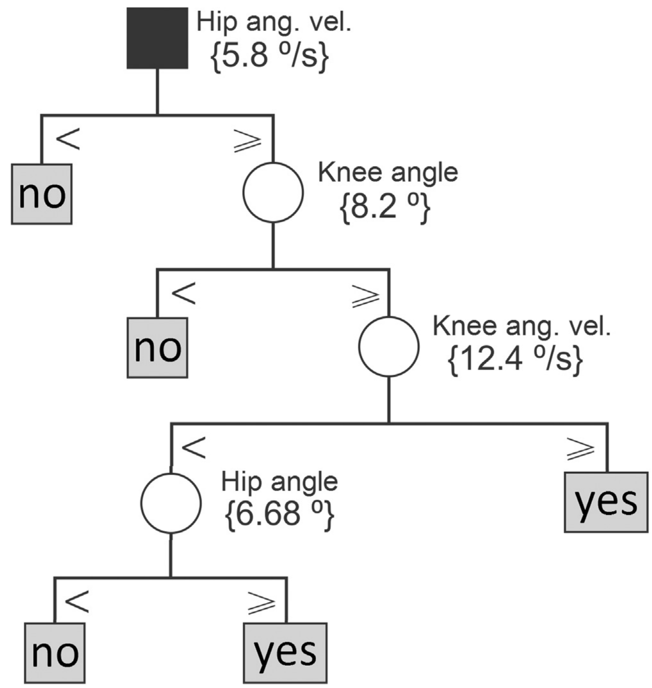

Fig. 4. A classification tree for detection of gait onset using inertial measurement units. The tree was trained on both normal and fast trials from all subjects and thus represents the optimal subject-independent classification tree for inertial measurement units. The joint angles and angular velocities are as defined in Section 2.4. No = onset has not occurred; yes = onset has occurred.

Fig. 5. It was trained using both normal and fast trials with a buffer length of 0.5 s. It initially checks the COP of the stance leg. As the foot is approximately 29 cm in length and COP is measured from the toes (0 cm) to the heel, a very low COP means that the subject is leaning forward and the COP has shifted toward the toes, indicating that the subject will continue walking. If the subject is leaning forward (right half of tree), the tree checks the GRF of the stance foot. A high GRF suggests that the subject is preparing to push off from the stance foot and make another step, so a low value indicates gait termination. If the subject is not leaning forward (left half of tree), the tree checks the standard deviations of the swing leg's joint angles. A lower standard deviation represents a reduced range of motion during the step, indicating gait termination. Further branches reevaluate COP and joint angles to resolve uncertain decisions.

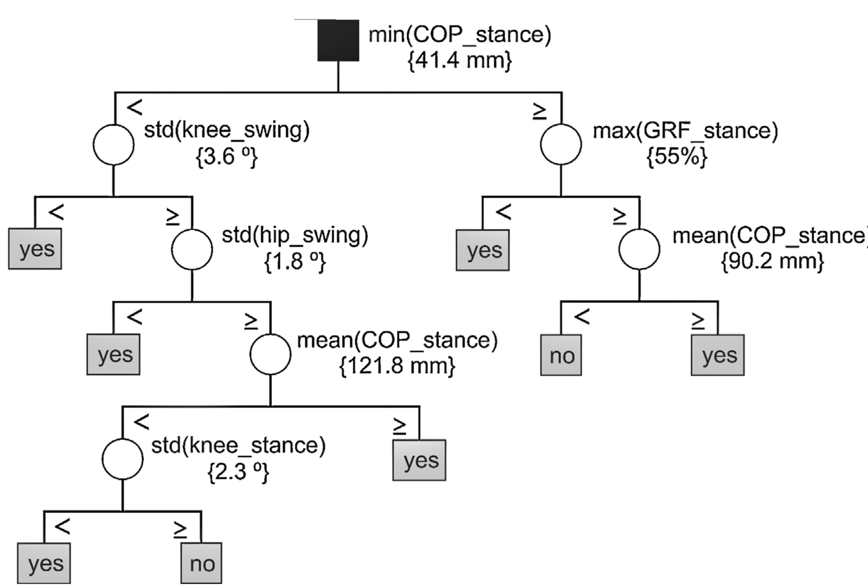

Fig. 5. A classification tree for detection of gait termination using inertial measurement units and insoles. The tree was trained on both normal and fast trials from all subjects with a buffer length of 0.5 s. It represents the optimal subject-independent classification tree when all sensors are available. Features are as defined in Section 2.6. Variables such as knee_swing represent joint angles rather than joint angular velocities (e.g. knee_swing is knee joint angle of the swing leg). Output: no = this is not the last step; yes = this is the last step.

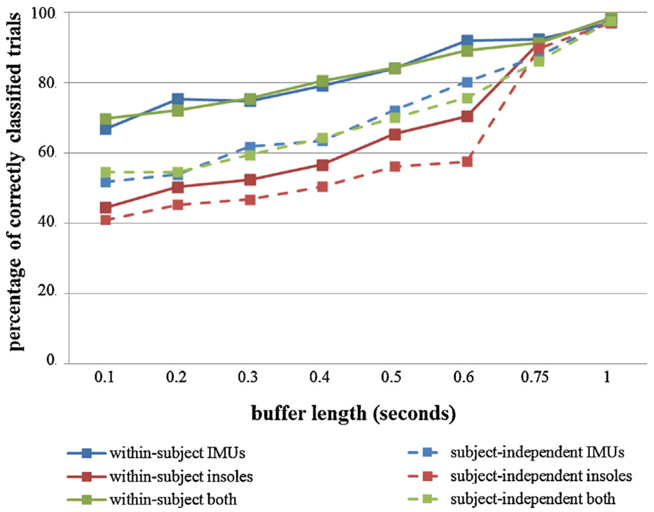

Fig. 6. Percentages of correctly analyzed trials when detecting gait termination. Results are shown for different sensors with within-subject and subject-independent cross-validation. Only normal-speed trials are included.

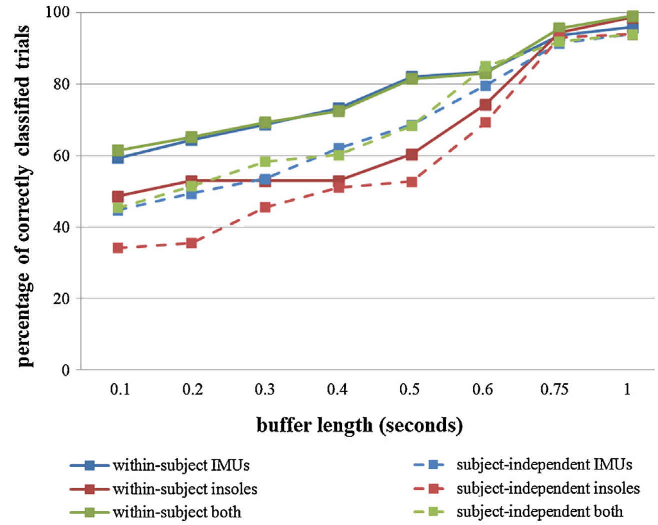

Fig. 8. Percentages of correctly analyzed trials when detecting gait termination. Results are shown for different sensors with within-subject and subject-independent cross-validation. Both normal and fast trials are included.

Figs. 6–8 show results for gait termination detection at different gait speeds.

4. Discussion

4.1. Gait initiation

In within-subject detection, IMUs detect gait onset with a median AE of ∼0.08 s and toe-off with a median AE of under 0.05 s. Insoles yield a similar AE for onset (0.05–0.12 s) and slightly higher AE for toe-off (∼0.06 s). Combining both sensor types gives a slightly lower median AE for onset (∼0.07 s) and similar median AE for toe-off. Less than 3% of events are undetected, suggesting reliable and accurate gait initiation detection in the within-subject case.

Subject-independent validation yields worse results. The median AE when using IMUs, for instance, is over 0.2 s for both events. The percentage of undetected events generally remains below 3%, so gait initiation is nonetheless detected. Still, detection algorithms should be trained for each subject separately if possible.

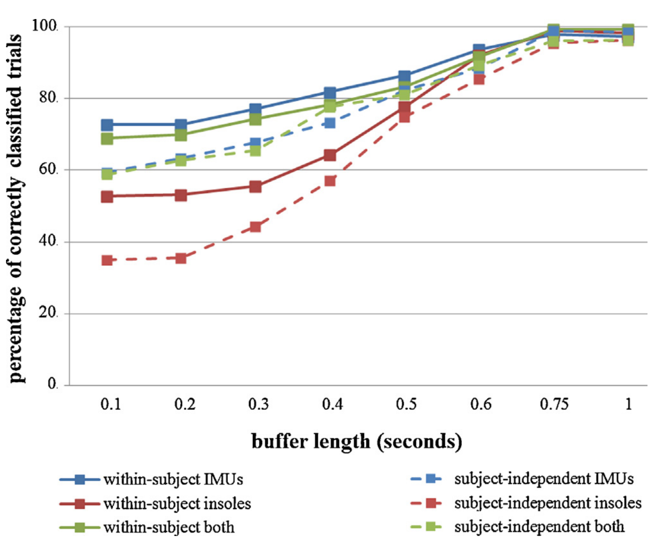

Fig. 7. Percentages of correctly analyzed trials when detecting gait termination. Results are shown for different sensors with within-subject and subject-independent cross-validation. Only fast trials are included.

There are no systematic differences in AE between normal and fast trials. When validating the algorithm with both normal and fast trials, results are similar to using only one speed, suggesting that the algorithm is robust with regard to gait speed. One difference was noted: with only one gait speed, the classification tree primarily selects angular velocities. With both gait speeds included, both angles and angular velocities are selected (seen in Fig. 4).

Interestingly, toe-off is not perfectly detected by the insoles in subject-independent cross-validation. Since they measure GRF, toe-off should be detectable simply as the time when GRF drops to zero. Such a threshold was indeed used by our expert as an initial rough estimate. However, the insole signal also contains noise which can be ignored by the expert but causes problems for an automated detection algorithm. The noise level differed between subjects, which explains why insoles perform better in within-subject cross-validation (where detection can be adapted to each subject's noise level) than in subject-independent cross-validation.

Finally, since our approach uses supervised machine learning, it has three disadvantages. First, onset and toe-off must be manually marked by an expert. This is both time-consuming and potentially inaccurate: the expert may not always mark events correctly, and marked events may not be detectable automatically. For toe-off detection, a simple subject-specific threshold may be sufficient. Second, it is difficult to compare our results to those from expert-based methods: since the expert is considered the 'reference', we cannot say whether our algorithm is better than an expert, but only how well it matches the expert. Third, the detection accuracy may not increase as more sensors are added. This is due to overfitting: as the number of inputs increases, it becomes harder to find optimal classification rules unless the number of observations (trials) also increases. These weaknesses, however, are not a limitation of only our approach, but are inherent in supervised machine learning.

4.2. Gait termination

As seen in Figs. 6–8, the accuracy of gait termination detection strongly depends on the buffer length. This parameter represents the time from the beginning of the step to when the detection algorithm decides whether the step is the final step. Using IMUs and within-subject classification, over 80% of trials can be correctly classified with a buffer shorter than the average step (84.2% with a 0.5 s buffer for normal trials and 81.9% with a 0.4 s buffer for

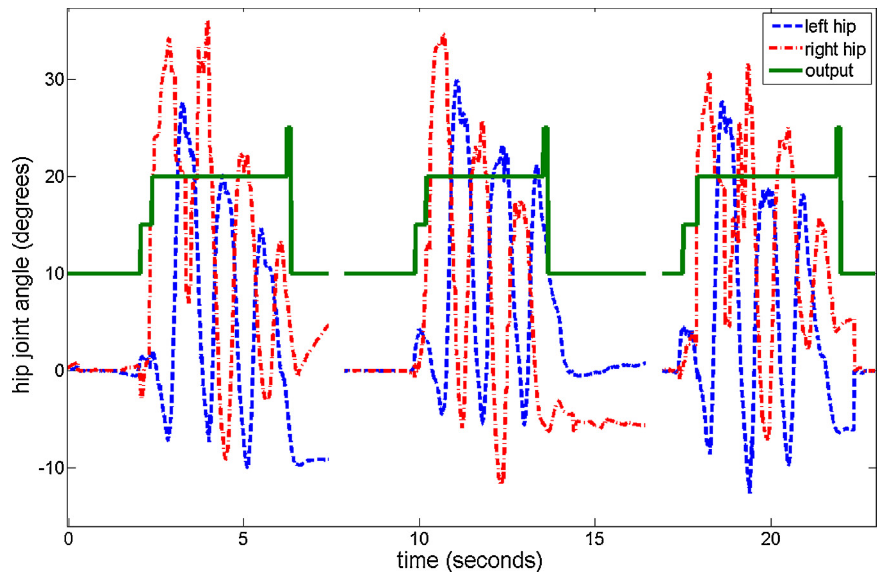

Fig. 9. Preliminary example of real-time gait event detection on three trials from a single subject. The algorithms were trained on the 10 subjects in this paper and tested on a new subject. Dashed lines represent hip joint angles while the solid line represents the output of the detection algorithm. The output is as follows: 10 = before onset, 15 = between onset and toe-off, 20 = after toe-off, 25 = gait termination imminent. Please note that while the three trials occurred consecutively, intervals between trials (when the subject returns to a starting position) are omitted to save space.

fast trials). This means that in over 80% of trials, gait termination can be predicted before the foot hits the ground. Results for the same buffer lengths in subject-independent classification are worse (72.2% for normal trials and 73.4% for fast trials). Nonetheless, even in subject-independent classification, over 80% of trials can be correctly classified with a buffer approximately as long as the average step (80.3% with a 0.6 s buffer for normal trials and 82.3% with a 0.5 s buffer for fast trials).

IMUs yield better results than insoles, which have a relatively low accuracy between approximately 0.1 and 0.5 s. This is caused by the nature of the insoles: since they measure pressure applied to the ground, no data can be obtained for a foot while it is off the ground. Though data is available for the other foot, accuracy increases only for longer buffers where the foot has returned to the ground. Insoles are nonetheless a useful component of gait termination detection, as they are used to accurately segment gait into steps before classification.

A shorter buffer naturally yields worse results, as the detection algorithm has less data with which to decide whether gait termination is about to occur. Nonetheless, as early as 0.1 s after the beginning of the step, IMUs allow approximately 70% correct within-subject classification. 0.1 s after the step begins, the foot is still ascending, which means that detection is possible well before the final step is completed. While 70% is not sufficiently accurate for real-time detection, we see that accuracy increases up to almost 100% for buffer lengths of 1 s. For real-time use in an assistive device, we could foresee an expanded version of the algorithm. Rather than output a result at a specific time (e.g. 0.5 s after beginning of step), the algorithm could constantly calculate the probability of gait termination. It would only act if this probability is sufficiently high (e.g. 90%). While this is not directly feasible with our classification tree, it could be done with probabilistic classifiers such as Bayesian networks.

4.3. *Potential for use*

Our gait initiation detection algorithm detects two events: onset and toe-off. While toe-off could also be detected with a simpler algorithm (threshold on GRF), our algorithm also identifies gait onset, which occurs approximately 0.5 s before toe-off. Such automated onset detection would be useful online if the goal is to respond to a user's action as early as possible. For instance, a powered orthosis could quickly recognize intended gait initiation and activate active assistance. In such cases, false positives would have to be minimized so that assistance would not be erroneously activated. Furthermore, the detection algorithm could be used for offline annotation of large datasets. Manually marking each case of onset is tedious and time-consuming, so an expert could mark a subset of the data and use it to train a detection algorithm.

The gait termination detection algorithm's main advantage is that, in a majority of cases, it can detect gait termination before it has completed. It is thus applicable for rapid online detection. As previously discussed, it could also be expanded to act only if the probability of intended gait termination is sufficiently high. If the subject is using a device to assist gait, the device would then stop providing assistance. In such cases, it would however be necessary to examine whether such assistance would in itself mask the user's intention to stop walking.

The algorithm evaluation in this paper was done offline using cross-validation since this allowed us to perform within-subject validation (train and test on different trials from same subject) and evaluate the effect of parameters such as buffer length. Though it is not the focus of this paper, we have also implemented all algorithms online, during actual gait. Joint angle calculations showed a mean error of less than 5° compared to offline processing [21]. Initiation and termination detection algorithms also achieved similar detection accuracy in online and offline evaluation on three healthy subjects. Since these results are preliminary, we only include an example of gait events detected online in three trials (Fig. 9). Though everything was implemented in Matlab, the algorithms are not computationally intensive and could be implemented on a microcontroller.

The greatest limitation of the approach is that it has not been tested with a target population for assistive devices, such as the elderly or amputees, which may have different gait patterns. Even healthy female subjects, which were not included due to convenience sampling, may already have different gait patterns. Furthermore, the evaluation was performed in a controlled manner, with e.g. gait always beginning from a steady standing posture. In real life, gait initiation might immediately follow a postural transition such as sitting to standing, which may require different detection rules. Of course, this is not only a limitation of our approach; it would also present a significant challenge for other sensors and for expert-defined rules. Nonetheless, a second evaluation with a target population for assistive devices is certainly needed.

5. Conclusions

The approaches described in this paper can be used to detect gait initiation and termination using inertial measurement units and insoles, though not without weaknesses. The gait initiation detection algorithm can be used to detect anticipatory postural adjustments (onset) preceding heel-off while the gait termination detection algorithm can be used to detect whether a step is the final step, though not until the step is already in progress. There is little difference between the two sensor types in gait initiation detection while IMUs are clearly superior for gait termination detection, though insoles are useful for gait segmentation. The algorithms could also be adapted to other sensor types.

The successful evaluation of the system suggests possible implementation in assistive devices such as prostheses or exoskeletons in order to allow rapid response to the wearer's intentions. However, it would then be necessary to evaluate the performance of the system with elderly or disabled persons who may have different gait patterns.

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Competing interests

The authors declare that they have no competing interests.

Ethical approval

The study was approved by the National Medical Ethics Committee of the Republic of Slovenia.

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