Real-time cross-step detection using center-of-pressure based algorithm

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Method Article

Keywords: Gait event detection, Center of pressure, Cross-step, Real-time algorithm, Treadmill walking, Balance assessment, Instrumented treadmill, Perturbation-based balance training, Biofeedback

Posted Date: August 16th, 2023

DOI: https://doi.org/10.21203/rs.3.rs-3245720/v1

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Abstract

Background

Gait event detection is crucial for assessment, evaluation and provision of biofeedback of during rehabilitation of walking. Existing online gait event detection algorithms mostly rely on add-on sensors, limiting their practicality. Instrumented treadmills offer a promising alternative by utilizing the Center of Pressure (CoP) signal for real-time gait event detection. However, current methods have limitations, particularly in detecting cross-step events during perturbed walking conditions.

Methods

We present and validate a real-time CoP-based algorithm to detect gait events and cross-steps, which combines thresholding and logic techniques. The algorithm was evaluated on CoP datasets from healthy participants, stroke survivors, and unilateral amputees that underwent perturbation-based balance assessments, encompassing different walking speeds. Real-time detected gait events were compared to offline identified counterparts in order to present related temporal delays and success rate.

Results

The proposed algorithm demonstrated high accuracy in detecting gait events during native gait, as well as cross-step events during perturbed walking conditions. It successfully recognized the majority of cross-steps, with a detection success rate of 94%. However, some misclassifications or missed events occurred, mainly due to the complexity of cross-step events. Temporal delays for heel-strikes during native gait and cross-step events averaged at 78 ms and 64 ms respectively, while toe-off delays were 126 ms and 111 ms respectively.

Conclusion

The proposed algorithm represents an advancement in gait event detection on instrumented treadmills. By leveraging the CoP signal, it successfully identifies gait events and cross-steps in real-time, providing valuable insights into human locomotion. The algorithm's ability to accommodate diverse CoP patterns enhance its applicability to a wide range of individuals and gait characteristics. The algorithm's performance was consistent across different populations, suggesting its potential for diverse clinical and research settings, particularly in the domains of gait analysis and rehabilitation practices.

INTRODUCTION

Gait analysis plays a crucial role in understanding human locomotion and assessing the effectiveness of rehabilitation therapies [1–3]. Accurate and reliable real-time detection of gait events, such as heel strikes...
(HS) and toe-offs (TO), is essential for monitoring various gait parameters as well as for provision of real-time biofeedback during training of walking. Conventionally, online gait event detection algorithms rely on various sensors (Inertial Measurement Units – IMU, pressure insoles, angular sensors or optical tracking systems) attached to the lower limbs or body to capture the kinematics of movement [4–7]. However, these methods can be often burdensome for participants, have potential issues with the synchronization and often limit the practicality of the procedure setup, especially for everyday use in clinical environment [8].

In recent years, instrumented treadmills such as single or split-belt treadmill variations have gained popularity as a valuable tool for gait analysis and training that are equipped with force transducers to measure the Center of Pressure (CoP) during walking [9–12]. Here, the CoP represents the point where the vertical ground reaction force is applied and can provide valuable insights into gait dynamics [13–16]. Leveraging the CoP signal, researchers have also developed real-time algorithms for detecting gait events and gait subphases without the need for additional human add-on sensors [14, 17–19]. Additionally, force signals from the instrumented split-belt treadmills have been used by the researchers to employ a thresholding method based on force data for detecting gait events [20, 21].

Two related studies have examined the CoP-based algorithm, one involving healthy participants and the other focusing on subjects with amputations [14, 22]. In the both studies, participants performed their native gait, revealing asymmetrical butterfly-shaped CoP signals assessed in people with amputations [22] as opposed to the unimpaired gait in healthy subjects [14]. The acquired signals were analyzed to assess specific gait characteristics such as step length, width, time, and durations of double and single support. However, these studies did not include analysis and evaluation of perturbed walking conditions.

One particular challenge for real-time gait event detection algorithms is accurate identification of stepping responses during perturbation-based balance training (PBT). PBT has emerged as a valuable approach for improving balance control and reducing the risk of falls in elderly and neurologically impaired [23–25]. During PBT, individuals experience controlled perturbations that challenge their stability, leading to different reactive balance strategies. These strategies involve adjustments in step length and width to regain dynamic stability. Among these adjustments, cross-steps have been identified as reactive balance responses following outward perturbations, where individuals cross their legs during the gait cycle to stabilize the body and restore equilibrium [26–28]. Therefore, accurately detecting cross-steps poses a significant challenge to traditional algorithms, as cross-steps disrupt the expected "butterfly-shaped" pattern of CoP movement following externally or internally elicited perturbation [26, 27]. While these studies have explored gait abnormalities caused by pathology or varying step widths and lengths, the specific scenario of crossing legs during walking has not been thoroughly investigated. Consequently, there is a gap in contemporary methods that can reliably examine cross-step events. Currently, the lack of real-time algorithms capable of detecting and quantifying cross-steps without the need for wearable sensors is a notable limitation hindering the use of real-time biofeedback during gait training.
The aim of this study was to develop a real-time algorithm that utilizes the CoP signal from a single-belt instrumented treadmill to accurately detect heel-strike and toe-off events during both native and perturbed gait, specifically addressing cross-step events. We conducted extensive experiments to evaluate the algorithm's reliability and accuracy on diverse populations, including healthy participants, subjects with unilateral transtibial amputations, and individuals after stroke, across different walking speeds.

**METHODS**

**Participants**

This study utilized data from our previous measurements, involving a total of forty-four participants. These participants represent three groups: thirteen stroke survivors (2 females, 5 with left-sided hemiparesis in subacute phase, age range 20–67 years, mean 48 ± 8.7; height 178 ± 8 cm; body mass 79 ± 11 kg), ten subjects with transtibial amputation (2 females, 5 with left-sided amputation, age range 28–63 years, mean 50 ± 10; height 176 ± 11 cm; body mass 87 ± 18 kg) and twenty-one healthy adults (3 females, age range 21–61 years, mean 36 ± 11; height 179 ± 6 cm; body mass 77 ± 9 kg) without any known neurological, muscular or orthopaedic problems. The inclusion criteria for the stroke survivors and subjects with transtibial amputation required them to be independent in ambulation (with a functional ambulation category FAC of at least 5), capable to walk independently or under supervision without the use of walking aids, and able to follow instructions. There were no specific inclusion criteria for healthy adults. The study received approval from the Slovenian national ethics committee and all participants provided written informed consent.

**Procedures and measurements**

The CoP data was obtained during our previous studies, assessing dynamic balancing responses, in which participants experienced perturbing force impulses applied to the pelvis while walking on an instrumented treadmill [3, 16, 27, 29]. The perturbing force impulses, directed mediolaterally, provoke reactive balance responses that often led to cross-stepping behaviour following the onset of the perturbation. CoP signals were obtained through four precise force transducers (K3D120, ME Systeme GmbH) placed underneath treadmill and equipped with measuring amplifiers (measuring amplifiers GSV-1A4, ME Systeme GmbH). The perturbing force impulses were triggered when participant entered left or right stance phase (i.e. at left or right heel strike). Each participant started gait balance assessment with an introductory session in order to familiarize with the treadmill walking as well as with the perturbation amplitudes. Our database consisted of three datasets, each associated with a different walking speed: 1) sessions with healthy participants walking at speeds of 0.4 m/s, 0.6 m/s, and 0.8 m/s consecutively; 2) sessions with stroke participants walking at a speed of 0.4 m/s; and 3) sessions with subjects with transtibial amputation walking at a speed of 0.5 m/s. To establish their natural gait pattern, each participant walked for 2–3 minutes without any perturbations, followed by an approximately 7–10 minutes assessment during which force impulses were randomly applied to either the left or right side of the pelvis every 8 seconds on average.
Data processing

The algorithm script was written and evaluated in the post hoc simulation using Matlab R2021a (The MathWorks, Inc.). Initially, CoP signals from both the native gait and perturbed gait of each participant were sampled at a frequency of 200 Hz. Subsequently, CoP signals from both walking conditions were processed using the algorithm (described in the subsequent subsection below) simulation. The simulation outputs consisted of the identification of gait events including left and right heel strikes, left and right toe offs and cross-step events. The native gait contained approximately 20 to 60 gait cycles, while for the perturbed gait we specifically focused on collecting cross-step performances, which encompassed eight consecutive gait events starting from the heel strike event. Moreover, the CoP_{AP} signal was subjected to offline manual analysis to precisely determine the locations of each gait event. Specifically, the peaks of the CoP_{AP} signal were identified, with positive peaks indicating toe off events (aligned with the walking direction), while negative peaks represented heel strikes [18]. Consequently, by comparing the offline identified gait events with the real-time counterparts obtained from the algorithm's output, we calculated the time delay to assess the algorithm's temporal accuracy in detecting gait events. Histograms were generated to illustrate the delays of the gait events for each walking speed and participant group individually, with the average and standard deviation of the calculated delays provided. The primary outcome of this study was the algorithm's success rate (\%) of detecting cross-step events. The success rate (\%) for each participant was defined as the ratio between successfully recognized cross-steps and the total number of cross-steps performed at each walking speed. In the case of the natural gait, the success rate (\%) was determined based on both successfully and unsuccessfully detected gait events.

Algorithm description

The operational overview of the algorithm is shown in Fig. 1. The algorithm was designed to detect gait events in real-time relies exclusively on the CoP signal and comprises two main components: adaptive relay-like functions and logic for determining gait events. Two adaptive relay-like functions, one for CoP_{ML} and the other for CoP_{AP} axis, monitor the limits of the CoP signal during each gait phase (LeftSingleSupport, DoubleSupportToRight, RightSingleSupport and DoubleSupportToLeft). Thereafter, they dynamically adjust the upper T\_U and lower T\_L thresholds for either the mediolateral or anteroposterior axis, according to the rules outlined in equations (1) and (2), where the parameter Ratio_{ML,AP} defines threshold position between UpperLimit_{ML,AP} and LowerLimit_{ML,AP}. Both thresholds T\_U and T\_L are also limited between minimal T_{min} and maximal value T_{max} as shown in Eq. (3). By utilizing Eq. (4), the threshold Threshold_{ML,AP} then selects the appropriate threshold (T\_U or T\_L) based on the ongoing function state: RightSide or LeftSide in the mediolateral direction, and FrontSide or RearSide in the anteroposterior direction.

\[
T\_U = UpperLimit_{ML,AP} - Ratio_{ML,AP} \left( UpperLimit_{ML,AP} - LowerLimit_{ML,AP} \right)
\]
\[ T_L = \text{LowerLimit}_{ML,AP} + \text{Ratio}_{ML,AP} \left( \text{UpperLimit}_{ML,AP} - \text{LowerLimit}_{ML,AP} \right) \]

\[
T_U, L = \begin{cases} 
T_{\text{min}} & \text{if } T_{U,L} \leq T_{\text{min}} \\
T_{U,L} & \text{if } T_{\text{min}} < T_{U,L} < T_{\text{max}} \\
T_{\text{max}} & \text{if } T_{U,L} \geq T_{\text{max}} 
\end{cases}
\]

\[
\text{Threshold}_{ML,AP} = \begin{cases} 
T_U & \text{if } \text{RightSide or FrontSide} \\
T_L & \text{if } \text{LeftSide or RearSide}
\end{cases}
\]

Upon the CoP crossing either Threshold\textsubscript{ML} or Threshold\textsubscript{AP}, the adaptive relay-like functions switch sides and provide output to identify potential operational sides: Side\textsubscript{ML} (RightSide or LeftSide) and Side\textsubscript{AP} (FrontSide or RearSide). An example of adaptive relay-like function is shown in Fig. 2. The logic component of the algorithm then monitors the crossings of the thresholds and provide gait events at the corresponding instances of threshold crossings. Essentially, if both the CoP\textsubscript{ML} and CoP\textsubscript{AP} cross their respective thresholds during the same gait phase, the algorithm recognizes it as a normal gait, also allowing for asymmetric CoP patterns resembling a “butterfly” shape. However, if CoP crosses threshold in AP axis twice consecutively, without any threshold crossing in the ML axis, the algorithm identifies it as a cross-step event. In such cases, the gait events are determined based on the crossings of the Threshold\textsubscript{AP}. The algorithm terminates the cross-step state when the CoP\textsubscript{ML} crosses Threshold\textsubscript{ML} again.

The parameters of the algorithm were configured as follows: Ratio\textsubscript{ML} and Ratio\textsubscript{AP} were both assigned a value of 0.2. For the AP direction, T\textsubscript{min} and T\textsubscript{max} were both set to 0.04 m, while for the ML direction, T\textsubscript{min} and T\textsubscript{max} were set to 0.05 m and 0.00 m, respectively. The algorithm parameters were chosen based on our prior experience from previous experiments where the algorithm was utilized, acquired through the iterative experimentation and refinement to ensure optimal performance of the algorithm. These parameters were consistent across all simulations conducted on CoP datasets in the present study.

FIGURE 1 HERE

FIGURE 2 HERE

**Statistical analysis**

A repeated measures analysis of variance (ANOVA) was employed to assess the potential relationship between the success rate of cross-step detection by the algorithm and various walking speeds. This analysis incorporated data from a group of 12 healthy participants, examining walking speeds of 0.4 m/s, 0.6 m/s, and 0.8 m/s. To investigate the impact of pathology on the algorithm's cross-step detection...
success rate, a one-way ANOVA was utilized. Specifically, the analysis compared the cross-step detection success rates of the algorithm for three groups: a healthy group walking at 0.4 m/s, a stroke group walking at 0.4 m/s, and an amputee group walking at 0.5 m/s. The statistical significance level was set at 5%.

RESULTS

Figure 3 illustrates the typical pattern of cross-step performance in comparison to the native gait pattern. In the native gait, the CoP exhibits a distinctive a butterfly-like shape, conversely, in the cross-step gait the CoP deviates from the butterfly shape, either deflecting to the left (as depicted in Fig. 3) or to the right side of the butterfly. It is shown that the accurate heal strikes (indicated by solid circle markers) occur at the both bottom extremes of the CoP butterfly and toe offs occur at the both top extremes (indicated by solid square markers). On the other hand, gait events detected in real-time using the algorithm (blank circle and square markers) exhibits a temporal delay in relation to the actual occurrences of gait events.

FIGURE 3 HERE

A total of 2253 cross-steps were observed in CoP data of all 44 participants. Among these, the proposed algorithm successfully recognized 2120 cross-steps, indicating that all gait events during cross-step performances were accurately detected and ordered without any omissions. However, there were 133 cross-steps classified as failures, where at least one gait event within the cross-step period was recognized incorrectly (e.g. left heel strike instead of right heel strike) or missed entirely, even if the other gait events were recognized correctly.

Table 1 represents the simulation results of walking for three different speeds (0.4, 0.6, and 0.8 m/s) in the healthy group, walking at 0.4 m/s in the stroke group, and walking at 0.5 m/s in the amputee group. Simulation results contain calculated delays between true and real-time detected gait events of native gait and cross-step gait, along with the corresponding success rates for native and cross-step gait. These results are also visualized as histograms in Figs. 4 and 5, showing the normalized frequency distributions of specific gait event delays. The first row of the histograms represents the combined delays of heel strikes (combined left and right), while the subsequent row displays histograms for toe off delays (combined left and right). Each participant's group is presented separately in these histograms.
### Table 1
Detection time delays and the algorithm’s success rate across groups

<table>
<thead>
<tr>
<th>Group</th>
<th>Walking speed (m/s)</th>
<th>No. of subjects</th>
<th>NATIVE GAIT</th>
<th>CROSS-STEPS</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td>HS delay (ms)</td>
<td>TO delay (ms)</td>
</tr>
<tr>
<td>Healthy</td>
<td>0.4</td>
<td>21</td>
<td>94 (36)</td>
<td>158 (41)</td>
</tr>
<tr>
<td></td>
<td>0.6</td>
<td>12</td>
<td>73 (20)</td>
<td>98 (24)</td>
</tr>
<tr>
<td></td>
<td>0.8</td>
<td>12</td>
<td>61 (16)</td>
<td>76 (24)</td>
</tr>
<tr>
<td>Stroke</td>
<td>0.4</td>
<td>13</td>
<td>86 (32)</td>
<td>158 (43)</td>
</tr>
<tr>
<td>Amputee</td>
<td>0.5</td>
<td>10</td>
<td>68 (31)</td>
<td>113 (27)</td>
</tr>
<tr>
<td>Overall M (STD)</td>
<td></td>
<td></td>
<td>78 (32)</td>
<td>126 (47)</td>
</tr>
</tbody>
</table>

HS – heel strike, TO – toe off, M (STD) – mean (standard deviation)

Table 1 HERE

Figure 4 illustrates the delays of gait events under native walking conditions for all three groups, while Fig. 5 demonstrates the delays of gait events during cross-step periods. Each histogram includes the mean value and standard deviation of the corresponding gait event delay. On average, the delay for heel strikes during native gait was 78 ms (standard deviation 32 ms), while during cross-step events, it decreased to 64 ms (standard deviation 28 ms). In contrast, toe off delays exhibited higher average values of 126 ms (standard deviation 47 ms) during native gait and 111 ms (standard deviation 47 ms) during cross-step events. The simulation of the algorithm conducted on native gait data successfully detected all gait events, which show 100% success rate. The success rate of identifying cross-step events and therefore all gait events in their proper sequence, reached 94% (standard deviation 11%).

A repeated measures ANOVA conducted on a sample of 12 healthy participants show statistically significant difference in the algorithm’s cross-step detection success rate score across different walking speeds ($F(2, 11) = 5.95, p = 0.0086$). A one-way ANOVA revealed that there was no statistically significant difference in the algorithm’s cross-step detection success rate among different pathologies — stroke, amputee and a healthy group ($F(2, 41) = 2.08, p = 0.1374$).

FIGURE 4 HERE
DISCUSSION

In this study we presented and validated a real-time gait event detection algorithm that utilizes CoP signal from the single-belt instrumented treadmill. By focusing on the CoP signal, the proposed algorithm eliminates the need for additional sensors attached to the participant’s lower extremities or body, simplifying the setup process for the everyday rehabilitation therapy. The algorithm was designed to overcome the limitations of current CoP-based gait event detection methods, which may not identify cross-step events. The results of the study demonstrated the effectiveness and reliability of the proposed algorithm in accurately detecting cross-step events, as well as other gait events during native gait. Validation was performed on different datasets assessed during native and perturbed walking requiring cross-steps in healthy and impaired populations.

The distinctive pattern of cross-step performance, characterized by a deviation from the butterfly-shaped CoP movement observed in the native gait, formed the basis for developing the algorithm. The algorithm was successful when recognizing gait events during native walking patterns of all participants. Furthermore, it successfully recognized the majority of cross-steps, with a high average accuracy rate of 94%. However, there were some cases where gait events within the cross-step period were misclassified or missed entirely, resulting in a failure rate of approximately 6%. These misclassifications could be attributed to the complexity of individual cross-step events, which disrupted the CoP pattern and posed a challenge to the algorithm. It is important to note that in instances of misclassifications, the algorithm continues its operation without interruption. Rather, it simply overlooks the occurrence of a gait event and awaits the subsequent one, thereby demonstrating high level of robustness, which is needed particularly when utilized in real-time biofeedback provision during gait training.

The delays in detecting gait events were analyzed for both native gait and cross-step events. The algorithm exhibited a temporal delay in detecting gait events compared to their actual occurrences, which is a common characteristic of real-time gait event detection algorithms [6, 7, 22, 30]. The delays related to heel strikes during native gait were smaller than during cross-step events, suggesting that the algorithm could effectively capture the distinct features of cross-step events. However, the delays for toe-off events were bigger during both native gait and cross-step events, which is a result of the algorithm’s parameter selection.

The algorithm has variety of parameters that implicitly define the accuracy and reliability of detecting gait events and cross-steps. Here, if the CoP is very fluctuant due to various possible reasons: variable pathological gait as also reported in [10], precision and resolution of the force plates and the CoP filtering [31]; the parameters in the proposed algorithm such as threshold ratio need to be appropriate not to false detect a local extrema of the CoP. There are also low-pass filters embedded in the measuring amplifiers or additionally added in the data acquisition software in order to cut away higher degree of oscillations of the CoP; however, real-time filtering on the other hand introduces time delay into the system by itself.
Similar issue was reported in [22], where more conservative CoP peak detection sensitivity introduces temporal delay of 0.1 s between true CoP peak occurrence and the online detected one.

The algorithm's performance was evaluated on different populations, including healthy participants, subjects with unilateral transtibial amputation, and individuals after stroke. The results demonstrated that the algorithm was effective across these populations, with no significant difference in the cross-step detection success rate among different pathologies. This finding suggests that the algorithm can be applied in diverse clinical and research settings, making it a potentially valuable tool for gait analysis and training in clinical rehabilitation.

**Limitations**

The present study on the proposed real-time CoP-based algorithm that detects gait events and cross-steps has several limitations. To ensure successful operation of the algorithm, at least one of the CoP (ML or AP) signals must exhibit deterministic behaviour, clearly displaying signal peaks. In cases where the CoP signals are non-deterministic and the CoP oscillates unpredictably during stepping, the algorithm's functioning may be compromised. However, once a predictable CoP pattern is established, the algorithm is designed to persistently operate. Additionally, if the CoP signal lacks clear expression, causing the algorithm to fail in detecting gait events, those events will be skipped until the CoP pattern becomes sufficiently evident. This limitation highlights the dependency of the algorithm's performance on the clarity of the CoP signal, indicating that it may not accurately capture all gait events in situations where the CoP expression is indistinct. Another limitation of this study is related to the dataset used for algorithm evaluation. We included a variety of gait measurements from our database, where participants performed cross-steps during studies on dynamic balance responses following perturbations. Here, the datasets across different groups included varying walking speeds and perturbation amplitudes ranging from 5–15% of body weight. This variability in the dataset made it challenging to conduct direct statistical analyses. However, the diversity in the datasets proves beneficial for the analysis of the algorithm itself, as it exposes the algorithm to a wider range of CoP behaviours and allows for a comprehensive evaluation.

**CONCLUSION**

In conclusion, the proposed algorithm for detecting gait events and cross-steps demonstrates great potential for various applications in the field of biofeedback training and virtual reality. By effectively identifying gait events and cross-steps, the algorithm enables perturbation triggering and ensures the safety of individuals by detecting also cross-steps. Moreover, the algorithm's adaptive relay-like function opens up possibilities for triggering or monitoring other biomechanical signals, extending its utility beyond gait analysis. An additional strength of the algorithm is its resilience to signal drifting, allowing for accurate and reliable detection over extended periods. Additionally, its ability to accommodate diverse CoP patterns enhances its applicability to a wide range of individuals and their gait characteristics.
Overall, the proposed algorithm represents a significant advancement in gait event detection during walking on instrumented treadmills. By leveraging the CoP signal, this real-time algorithm provides a valuable tool for accurately identifying cross-step events, offering valuable insights into human locomotion. These findings have far-reaching implications for gait analysis and rehabilitation techniques, promising to enhance patient care and treatment outcomes without the need of add-on sensors. Further research can focus on refining the algorithm and validating its performance in real-world scenarios to facilitate its widespread utilization.

**Abbreviations**

CoP  
center of pressure  
PBT  
perturbation-based balance training  
HS  
heel strike  
TO  
toe off  
ML  
mediolateral  
AP  
anteroposterior

**Declarations**

**Funding**

This research was partially supported by the Slovenian Research Agency under research project number J2-8172 and research program number P2-0228.

**Acknowledgements**

Not applicable.

**Authors’ contributions**

MZ initiated the study and contributed to the signal processing, data analysis and prepared the manuscript. MZ and ZM contributed to the concept and interpretation of the experimental results. Both authors revised the manuscript and approved the final version.

**Consent for publication**
All authors have approved this manuscript for publication. This manuscript has not previously been published and is not pending publication elsewhere.

**Availability of data**

The data used in this study may be available by the corresponding author upon a reasonable request to any qualified researcher.

**Conflict of interest**

The authors declare that they have no competing interests.

**Ethics approval and participation consent**

The data were collected in the previous study, which was approved by the Republic of Slovenia National Ethics Committee, decision number 80/03/15. All participants gave written informed consent.

**References**


Figures
Figure 1

The algorithm for real-time gait event and cross-step detection operates by employing a thresholding technique applied to the Center of Pressure (CoP) signal.

Figure 2

Adaptive relay-like function used in the algorithm, where the threshold adapts based on the upper and lower limits of the CoP. The function alters its state (sides) whenever CoP crosses the threshold, which is seen at the switch points.
Figure 3

An illustration of the a) native gait and b) cross-step gait by showing consecutive steps and CoP pattern, and the c) time-dependent graphs of CoP, where markers represent gait events (toe offs, heel strikes) gathered manually offline (solid markers) and by the proposed algorithm (blank markers).

Figure 4
Normalized frequency distribution of heel strike and toe off detection delays across participant groups and walking speeds during native gait. The mean values accompanied by the corresponding standard deviation are denoted as M (STD).

Figure 5

Normalized frequency distribution of heel strike and toe off detection delays across participant groups and walking speeds during cross-step events. The mean values accompanied by the corresponding standard deviation are denoted as M (STD).