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**Article:**

Salis, F., Bertuletti, S., Bonci, T. et al. (2021) A method for gait events detection based on low spatial resolution pressure insoles data. *Journal of Biomechanics*, 127. 110687. ISSN: 0021-9290

<https://doi.org/10.1016/j.jbiomech.2021.110687>

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# A Method for Gait Events Detection based on Low Spatial Resolution Pressure Insoles data

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## Keywords:

gait analysis, wearable sensors, pressure insoles, locomotion, gait events

## Submitting for:

Short communication

## Word Count:

Abstract: 213

Manuscript: 2230

## ABSTRACT

The accurate identification of initial and final foot contacts is a crucial prerequisite for obtaining a reliable estimation of spatio-temporal parameters of gait. Well-accepted gold standard techniques in this field are force platforms and instrumented walkways, which provide a direct measure of the foot-ground reaction forces. Nonetheless, these tools are expensive, non-portable and restrict the analysis to laboratory settings. Instrumented insoles with a reduced number of pressure sensing elements might overcome these limitations, but a suitable method for gait events identification has not been adopted yet. The aim of this paper was to present and validate a method aiming at filling such void, as applied to a system including two insoles with 16 pressure sensing elements (element area = 310 mm<sup>2</sup>), sampling at 100Hz. Gait events were identified exploiting the sensor redundancy and a cluster-based strategy. The method was tested in the laboratory against force platforms on nine healthy subjects for a total of 801 initial and final contacts. Initial and final contacts were detected with low average errors of (about 20 ms and 10 ms, respectively). Similarly, the errors in estimating stance duration and step duration averaged 20 ms and less than 10 ms, respectively. By selecting appropriate thresholds, the method may be easily applied to other pressure insoles featuring similar requirements.

## I. INTRODUCTION

The gait cycle represents the functional element of walking, traditionally identified by the initial contact (IC) of the foot with the ground and the following IC of the same foot (Della Croce et al., 2018; Whittle, 1993). A direct approach to detect these gait events (GEs) is by using force platforms (FPs) and instrumented walkways. These provide a direct measure of forces resulting from the foot-ground interaction, thus representing a gold standard for GEs detection. However, both devices are non-portable, expensive and require an appropriate laboratory environment, therefore constraining the analysis to few strides and/or straight walks (Adkin et al., 2000). Moreover, laboratory analysis only allows for the assessment of walking capacity, which should ideally be complemented with continuous daily living measures of mobility performance to obtain a thorough assessment (World Health Organization, 2007; Rochester et al., 2020). In this perspective, wearable inertial measurement units (IMUs) are the key to enable gait analysis in real-world scenarios as GEs can be identified from the accelerations and angular velocities signals recorded by two units attached to the ankles/feet (Mariani et al., 2012; Trojaniello et al., 2014). However, being the latter an indirect method, processing algorithms performance may be affected by errors, and it should, therefore, be regarded as a silver standard solution.

Foot switches are an effective alternative to estimate GEs and their use has been explored in several studies over the last decades (Agostini et al., 2013; Bae et al., 2011; Hausdorff et al., 1995; Kong et al., 2009; Skelly et al., 2001). The foot switch technology, however, generally includes only two or three sensing elements, which require a proper positioning under the foot. Due its low spatial sensor resolution, the approach does not allow to identify the specific area of the sole-ground contact and, in turn, it may also affect the GEs temporal resolution. This is even more true in case of pathological gait (i.e., pronation, supination, equine gait, foot drop, shuffling children with cerebral palsy), for which few sensors are not sufficient (Smith et al., 2016). Another attractive option is represented by plantar pressure insoles, based on different technologies and sensors configurations (e.g., Tekscan® F-Scan® System; Novel® Pedar® System, etc.). However, these devices are specifically conceived for high-resolution pressure mapping applications and generally include a dense grid of sensors (from 99 to 960 sensing elements) which inevitably lead to higher costs and complexity in terms of data management and reading, but which are not strictly necessary for simple GEs estimations.

In this study we propose an original method for GEs detection, based on the use of instrumented insoles, each including only sixteen force-sensing resistor elements (pressure insoles, PIs). The implemented algorithm exploits the number of sensors by using a cluster-based approach to describe foot-ground contacts in a finer way and avoid missed and extra GEs, providing information about foot positioning. The method was tested against FPs in the laboratory using data collected on healthy subjects.

## II. METHODS

### A. System Description and GEs algorithm

Two plantar PIs (mod. YETI, 221e S.r.l., Padua, Italy; 16 sensing elements; element area = 310 mm<sup>2</sup>; fs = 100 Hz; ground reaction force threshold = 5 N) were used in this study, with a design similar to that adopted by Ciniglio et al. 2021. Each sensing element is constituted by a force sensing resistor, exhibiting a resistance value inversely

94 proportional to the applied force. The output is expressed as voltage (full-scale voltage value  $V_{FS} = 2.8$  V). Each  
95 pressure insole is connected to a central processing unit, which also includes a magneto-IMU (Figure 1) that is not  
96 used for this study. Data is recorded by an ultra-low-power microcontroller and stored in an on-board flash  
97 storage.

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FIGURE 1 ABOUT HERE

The PI signals processing algorithm is described by the following steps (Figure 2):

*(i) Pre-processing.*

PI signals are normalised with respect to  $V_{FS}$ , expressed in normalised units (nu), and then filtered using a 5-points non-linear median filter to have a smoothing effect while enhancing edges (Stork et al., 2003);

*(ii) Detection and selection of instants of rising and falling edges.*

For each of the filtered PI signals  $X_i(t)$ , where  $i=1,\dots,16$  represents the  $i$ -th PI signal, a first derivative approach (Hopkins, 2001) is applied to detect rising and falling edges. Edges are identified from  $\dot{X}_i(t)$  using a peak detection approach (Benocci et al., 2009) with an amplitude threshold defined as  $Th_1 = 5n$ , being  $n$  the signal noise amplitude as computed in static conditions (in this study, we used  $Th_1 = 0.05$  nu). For each PI signal, rising edges are identified as positive peaks  $> Th_1$  and the corresponding time instants are organized in a vector  $t_{RE,i}$ . Similarly, falling edges are identified as negative peaks  $< -Th_1$  and the corresponding time instants are organized in a vector  $t_{FE,i}$ . Rising and falling edges are automatically checked, in terms of time distance and amplitude of the PI signal, to discard false positives. Figure 2a shows an example of detection of a rising edge and a falling edge;

*(iii) Detection and selection of local minima (instants of rising and falling minima).*

The identification of the instants of rising and falling minima is performed by applying to  $X_i(t)$  a threshold  $Th_2 = 0.02$  nu, using rising and falling edges as reference points (Hausdorff et al., 1995). In particular, each rising minima is identified as the first point with  $X_i(t) < Th_2$  preceding the considered rising edge instant, while each falling minima is identified as the first point with  $X_i(t) < Th_2$  after the considered falling edge instant. Rising minima instants and falling minima instants were organised in vectors,  $t_{RM,i}$  and  $t_{FM,i}$  respectively. Figure 2a shows an example of detection of one rising minimum and one falling minimum;

*(iv) Identification of activation/deactivation clusters.*

Once the rising and falling minima instants are detected for all the PI signals, they are organised in chronological order in a unique vector ( $t_{RM}$  and  $t_{FM}$  respectively), also noting the corresponding sensing element number in another vector ( $s_{RM}$  and  $s_{FM}$ ). This step is needed to group the instants of rising/falling minima corresponding to the same foot contact, i.e. the PI sensing elements which activate/deactivate together when the foot hits the ground. An activation cluster is identified imposing that the time distance between consecutive instants of  $t_{RM}$  is lower than  $Th_3 = 0.4s$ . Then, a deactivation cluster includes the instants of  $t_{FM}$  between two consecutive activation clusters. For each cluster, the minima instants and the sensing elements numbers are saved ( $A\_cluster_j / D\_cluster_j$ , where  $j = j$ -th activation/deactivation cluster).

Figure 2b shows an example of one activation cluster and one deactivation cluster.

*(v) Identification of IC/FC (final contact) intervals and definition of IC/FC events.*

A foot-ground contact interval is defined when at least three sensing elements of the PI belonging to the same spatial neighbourhood are consecutively activated and deactivated, i.e. correspond to three consecutive minima belonging to the same cluster ( $A\_cluster$  for ICs and  $D\_cluster$  for FCs). For each PI's sensing element, the neighbourhood consists of those sensing elements which are spatially close to the considered unit (Figure 1) (e.g. for the sensing element no. 12, the neighbourhood includes sensing elements 11, 13, 14, 15, 16; further details are reported in *Appendix B*). In fact, it is reasonable to assume that, when an IC or FC occurs, the sensing elements which refer to the same anatomically functional area of foot sole are activated or deactivated, respectively.

Each IC interval is identified starting from the first rising minima of an activation cluster; while each FC interval is identified starting from the last falling minima of a deactivation cluster.

Finally, each IC is assumed to coincide with the rising minimum instant corresponding to the third sequentially activated sensing elements within the considered IC interval. Likewise, each FC is assumed to coincide with the falling minimum instant corresponding to the third sequentially deactivated sensing elements within the considered FC interval. Figure 2c shows an example of one IC interval and one FC interval.

A workflow of the algorithm can be found in *Appendix A*.

FIGURE 2 ABOUT HERE

149 **B. Experimental setup**

150 The validation experiments involved nine healthy participants (5 females and 4 males; age  $25.4 \pm 1.3$  years, shoe  
151 size  $40.5 \pm 4.1$  EU) and took place at the University of Sassari (Italy). All participants signed an informed consent  
152 approved by the IRB before taking part to the study. PIs were inserted in participants' shoes and central  
153 processing units were clipped over the instep (Figure 3). The only specific requirement for the shoes was to avoid  
154 knee-high boots. Data from two FPs (AMTI, Massachusetts, USA;  $f_s = 1000$  Hz) were acquired through a motion  
155 capture system also including video recordings (Vicon Vue,  $f_s = 50$ Hz). Data from PIs and FPs were synchronized  
156 using an additional central processing unit as external trigger, connected to the motion capture system via cable.  
157 Each participant was asked to walk for six minutes back and forth at comfortable speed, stepping on the FPs as  
158 many times as possible.

159  
160 FIGURE 3 ABOUT HERE  
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162 **C. Data processing**

163 For each subject, a preliminary visual inspection of the "good strides" (entire foot on the FP during stance phase)  
164 was performed using video recordings. Then, FP data were down-sampled to 100 Hz. A pre-processing procedure  
165 was applied for the synchronisation of PIs measurements (started via BLE protocol, v. 4.1) with the FP data, using  
166 the time vector provided by the trigger to interpolate the data.  
167 The GEs detection algorithm results were compared with those obtained from the FPs (ground reaction force  
168 threshold = 25 N) in terms of average root mean square (RMS) error, bias and standard deviation (SD) error  
169 computed over the stances of all participants. An example of IC and FC detection from both PI and FP is shown in  
170 Figure 4.

171  
172 FIGURE 4 ABOUT HERE  
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174 **III. RESULTS**

175 RMS error, bias and SD error obtained from the comparison are reported in Table 1. A total of 801 ICs and 801  
176 FCs were analysed (89 ICs and FCs on average for each participant), while errors on step duration were computed  
177 considering 315 steps in total. Average errors were lower than 10 ms for FCs, 20 ms for ICs, 20 ms for stance  
178 duration, less than 1 ms for step duration.

179  
180 (Table 1)  
181

182 **IV. DISCUSSION**

183 GEs and temporal parameters obtained from the PIs showed a 100% correspondence with those estimated from  
184 the FPs. Low average RMS errors were obtained for stance duration ( $< 20$  ms) and for both IC and FC events, (22  
185 ms and 17 ms, respectively). IC events, as detected by the proposed method were, on average, anticipated with  
186 respect to those detected by the FP (average bias = 21 ms), while FC events were marginally delayed. A bias of 23  
187 ms was obtained for stance duration. Very low values were obtained for the average SD error (7 ms for ICs, 12 ms  
188 for FCs and 7 ms for stance duration). For step duration, both RMS error and SD error were around one sample,  
189 while the average bias was zero.

190 Similar but slightly larger errors were reported by Catalfamo and colleagues (2008) using a F-Scan Mobile Tekscan  
191 pressure insole ( $22 \pm 9$  ms for ICs and  $10 \pm 4$  ms for FCs). However, it should be noted that the proposed algorithm  
192 was successful in obtaining lower errors using a pressure insole with a much smaller number of sensing elements  
193 (16 vs 960) and using a lower sample-frequency (100 Hz vs 200 Hz), with clear advantages in terms of cost and  
194 efficiency.

195 In general, the majority of the methodological studies analysing the performance of different pressure insoles,  
196 focused on gait parameters other than ICs and FCs and reported larger errors (Agarwal et al., 2020; Braun et al.,  
197 2015; Carbonaro et al., 2016; Crea et al., 2014). For instance, the average error reported in Carbonaro et al. (2016)  
198 by comparing a commercial smart shoe including two force sensors (FootMov) against a motion capture system  
199 was  $39 \pm 65$  ms for stance duration. Often, a direct comparison with the results in the literature was not possible

200 due to the lack of a gold standard (Benocci et al., 2009), adoption of manual labelling of the GE detection (Roth  
201 et al., 2018) or different research objectives (i.e., PI signals used only for activity recognition).  
202 The low errors found for both ICs and FCs demonstrated that the combined use of low-cost PI and specific  
203 algorithms for signal processing are a good compromise between more complex solutions, such as high-resolution  
204 pressure mapping technology, and foot-switch systems with a low number of sensors. A notable feature of the  
205 proposed method is that it can be applied to other PIs having a sufficient number of sensing elements. The  
206 minimum sensor number and area would clearly depend on the shoe size of the subjects to analyse (e.g. children),  
207 however, we found that an activated/deactivated area of about 900 mm<sup>2</sup> (area of three sensing unit of the PI)  
208 guaranteed for good results for both male and female adults. Having a sufficiently high number of sensors allows  
209 to describe the foot-ground contact in a comprehensive way and virtually recognise all the possible strategies of  
210 foot-floor contact. Last but not least, the PIs here used can be easily combined with IMUs as part of a multi-sensor  
211 wearable system, which could provide accurate temporal estimates and a for a more extensive gait assessment  
212 also in a free-living context. Further studies will focus on overcoming the limitations of having tested the proposed  
213 method only on healthy subjects and on straight walking.  
214

## 215 **V. ACKNOWLEDGEMENT**

216 The work was supported by the MOBILISE-D (EU H2020, EFPIA, and IMI 2 Joint Undertaking; Grant no. 820820),  
217 the UK EPSRC (K03877X/1 and S032940/1) and the NIHR Sheffield BRC. The study sponsors were not involved in  
218 the study phases, in the writing of the manuscript and in the decision about its submission.

## 219 **VI. CONFLICT OF INTEREST STATEMENT**

220 The authors declare that there are no financial nor personal relationships that can lead to conflicts of interest.  
221

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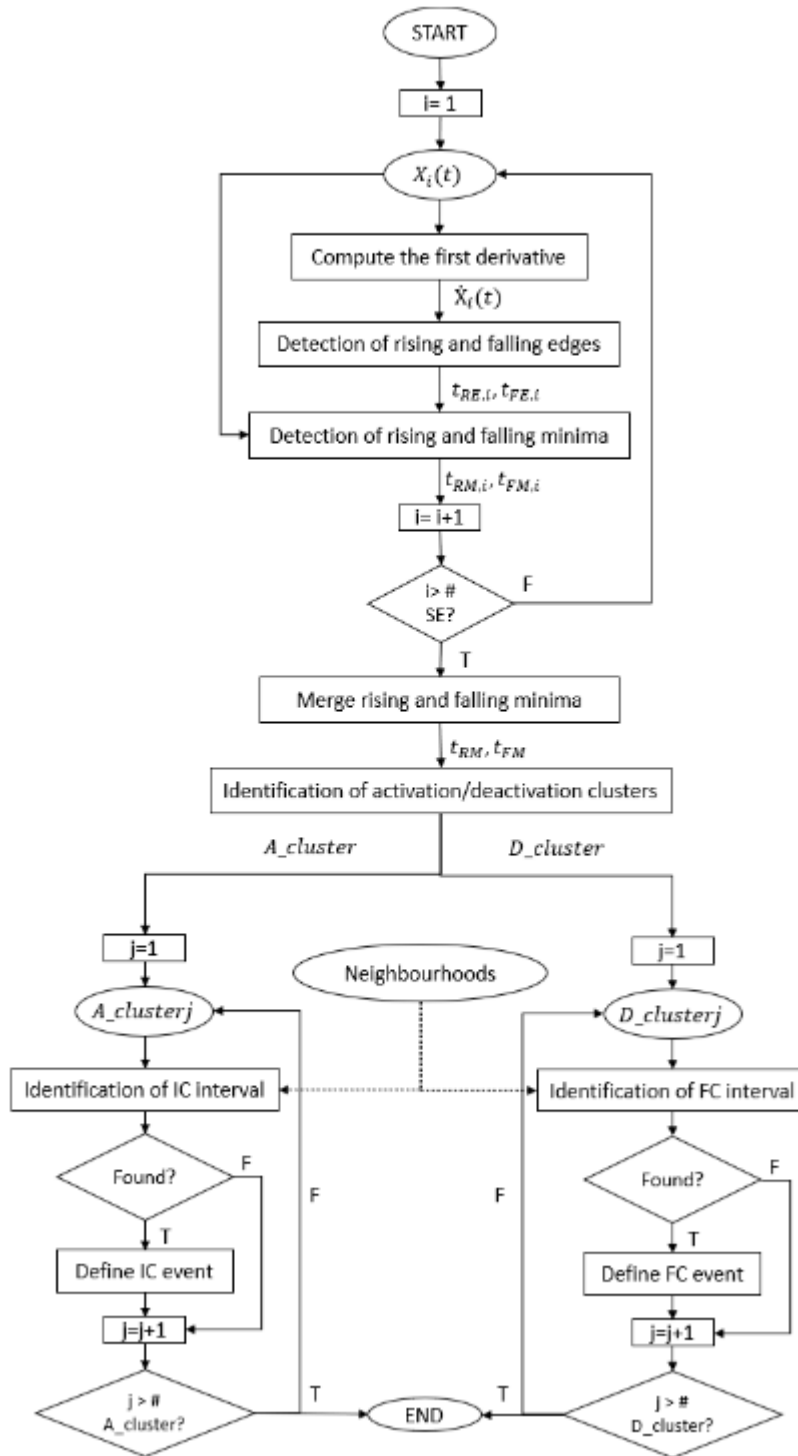


Figure 1. Algorithm workflow

- 284  
 285 Definitions:  
 286  $X_i(t)$  = pre-processed signal from the  $i$ -th sensing element  
 287 #SE = number of sensing elements of the pressure insole  
 288  $\dot{X}_i(t)$  = first derivative of  $Xp_i[n]$   
 289  $t_{RE,i}$  = rising edges instants  
 290  $t_{FE,i}$  = falling edges instants  
 291  $t_{RM,i}$  = rising minima instants  
 292  $t_{FM,i}$  = falling minima instants  
 293  $t_{RE}$  = rising minima instants of all the sensing units

294  $t_{FE}$  = falling minima instants of all the sensing units

295 A\_cluster = activation clusters

296 D\_cluster = deactivation clusters

297

298 Checks on rising and falling edges instants:

299 • Check on temporal distance. This is performed applying a threshold  $Th_d = 0.6$  s. If the distance between  
300 consecutive events is lower than  $Th_d$ , the second event is discarded in case of rising edges, while the  
301 first event is discarded for the falling edges.

302 • Check on the amplitude reached by  $x_i(t)$  after each rising edge instant and before each falling edge  
303 instant. The amplitude reached in the considered window (10 samples after a rising edge instant or 10  
304 samples before a falling edge instant) must be at least 0.3 nu, otherwise the event is discarded.

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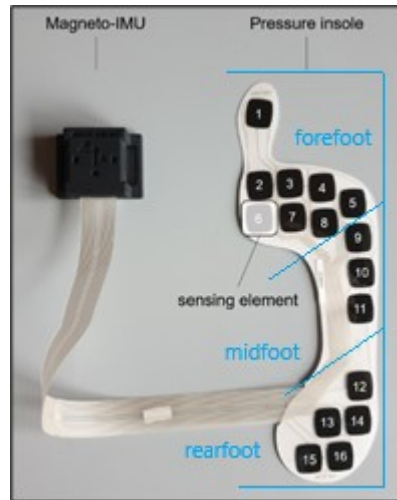
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**APPENDIX B**

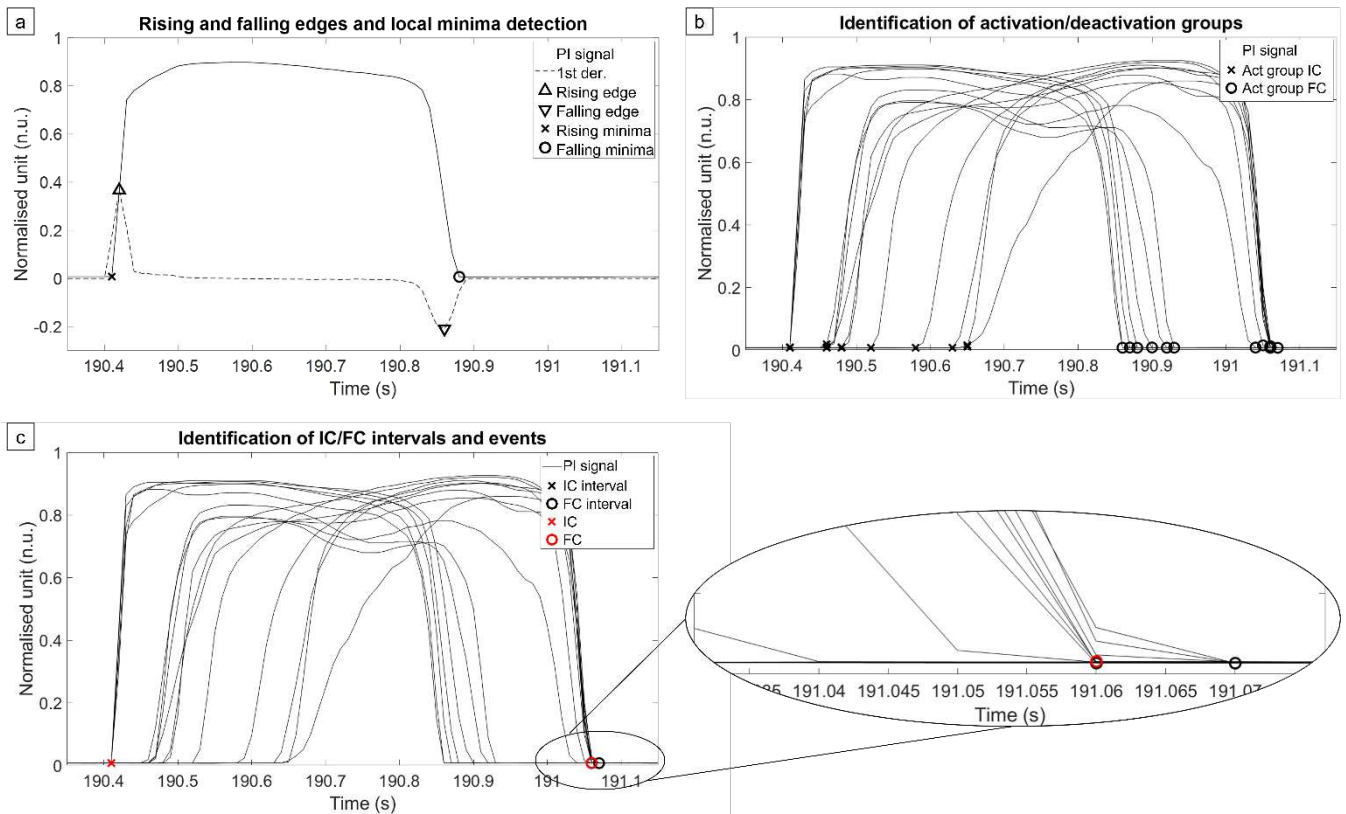
**A. Definition of the neighbourhood for each PI's sensing unit**

The neighbourhood of each sensing element is defined as reported in the following table:

<b>Sensing unit number</b>	<b>Neighbourhood</b>
1	2,3,4,6,7
2	1,3,4,6,7
3	1,2,4,6,7,8,5
4	1,2,3,5,7,8,6,9
5	1,2,3,5,7,8,6,9
6	1,2,3,4,7,8
7	1,2,3,4,5,6,8,9
8	3,4,5,6,7,9,10
9	5,8,4,7,10,11
10	9,11,8,5,12
11	9,10,12,14,13,15,16
12	10,11,13,14,15,16
13	11,12,14,15,16
14	11,12,13,15,16
15	12,13,14,16,11
16	12,13,14,15,11



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 377 Figure 1: Magneto-IMU and pressure insole used for the right foot.  
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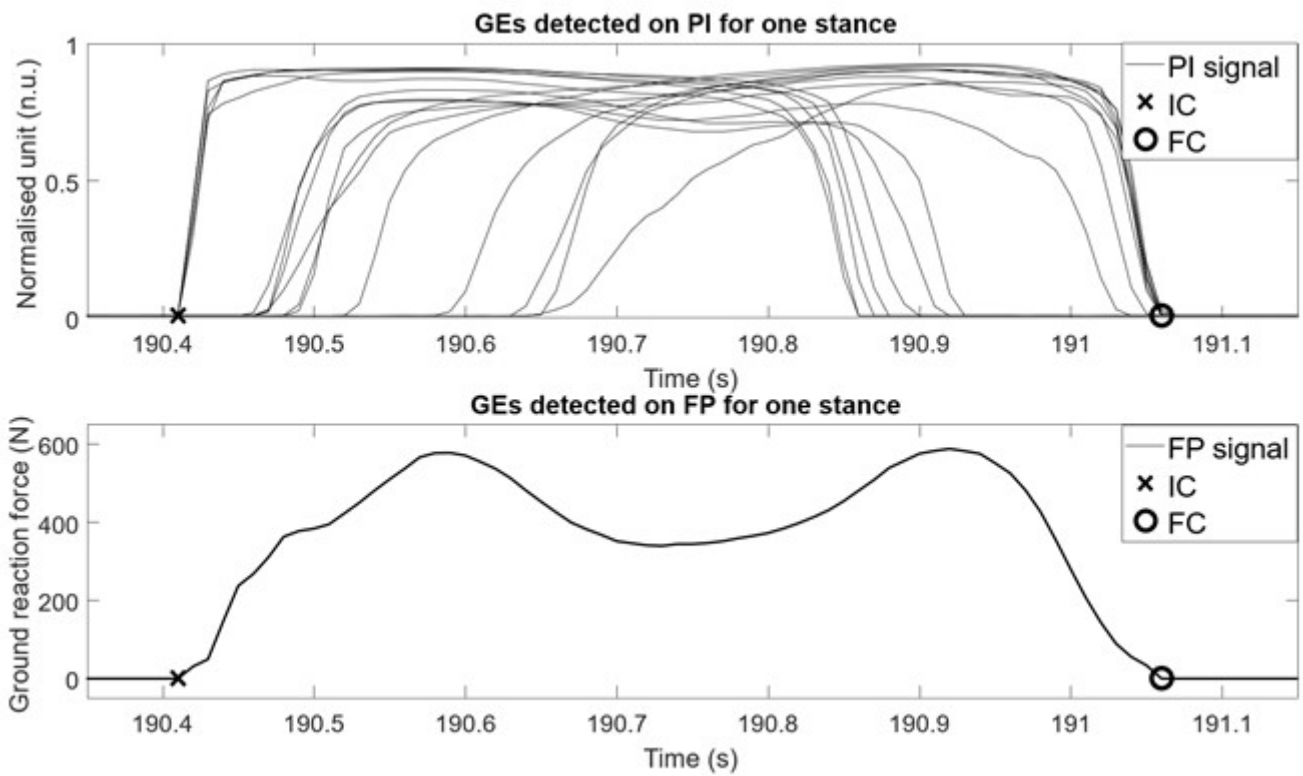


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 381 Figure 2: Principal steps of the algorithm shown for one stance. a) Detection and selection of rising and falling  
 382 edges and local minima (rising and falling minima) for each PI signal; b) Identification of one  
 383 activation/deactivation cluster on PI signals; c) Identification of IC/FC intervals and definition of IC and FC events  
 384 on PI signals.  
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Figure 3: a) PI positioning inside the shoe; b) Clip attached to shoe laces; c) Final sensors positioning with magneto-IMU fixed to the clip.



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Figure 4: Gait events (GEs) detection from both pressure insole (PI) and force plate (FP).

**Table 1: RMS error, bias, and SD error**

Variable	Average RMS Error (ms; frames)	Average Bias (ms; frames)	Average SD Error (ms; frames)
IC	22; 2	-21; -2	7; <1
FC	18; <2	3; <1	12; 1
Stance duration	18; <2	23; 2	7; <1
Step duration	10; 1	0; <1	10; 1

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