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Influence of EMG-signal processing and experimental set-up on prediction of gait events by neural network

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1           **Influence of EMG-signal processing and experimental set-up on**  
2                           **prediction of gait events by neural network**

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26 **Abstract**

27 Machine-learning approaches are satisfactorily implemented for classifying and assessing  
28 gait events from only surface electromyographic (sEMG) signals during walking.  
29 However, it is acknowledged that the choice of sEMG-processing type may affect the  
30 reliability of methodologies based on it. Analogously, the number of sEMG signals  
31 involved in machine-learning procedure could influence the classification process. Aim  
32 of this study is to quantify the impact of different EMG-signal-processing specifications  
33 and/or different complexity of the experimental sEMG-protocol (different number of  
34 sEMG-sensors) on the performance of a neural-network-based approach for binary  
35 classifying gait phases and predicting gait-event timing. To this purpose, sEMG signals  
36 are collected from eight leg-muscles in about 10.000 strides from 23 healthy adults during  
37 walking and then fed to a multi-layer perceptron model. Four different signal-processing  
38 approaches are tested and five experimental set-ups (from four to one sEMG sensors per  
39 leg) are compared. Results indicate that both the choice of sEMG processing and the  
40 reduction of sEMG-protocol complexity actually affect classification/prediction  
41 performances. Moreover, the study succeeds in the double goal of identifying the linear  
42 envelope as the sEMG-processing type which reaches the best neural-network  
43 performance (classification accuracy of  $93.4\pm 2.3\%$ ; mean absolute error  $21.6\pm 7.0$  and  
44  $38.1\pm 15.2$  ms for heel-strike/toe-off prediction, respectively) and providing a  
45 quantification of the progressive deterioration of classification/prediction performances  
46 with the reduction of the number of sensors used (from  $93.4\pm 2.3\%$  to  $79.9\pm 6.1\%$  for  
47 classification accuracy). These findings could be very useful for clinics to the aim of  
48 choosing the most suitable approach balancing technical performances, patient comfort,  
49 and clinical needs.

50

## 51 **1. Introduction**

52 Each single gait cycle of human walking is composed of two main phases: the stance  
53 phase, from the beginning to around 60% of gait cycle; the swing phase, from 60% to the  
54 end of gait cycle [1]. The stance phase denotes the whole time interval when the reference  
55 foot is touching the ground. The swing phase quantifies the period when the foot is no  
56 longer on the ground and swings in the air for leg advancement. Crucial for quantification  
57 of gait phases duration are the transition events between the two phases: toe-off (TO,  
58 from stance to swing) and heel-strike (HS, from swing to stance). The assessment of these  
59 temporal parameters is one of the typical tasks of gait analysis [2,3].

60 In the recent years, artificial-intelligence techniques have been proposed for the  
61 classification of stance vs. swing and for the assessment of temporal gait events [4,5].  
62 Particularly valuable are those methodologies where machine and deep learning are  
63 implemented with the aim of limiting the number of sensors involved in the experimental  
64 set-up, such as electromyography-based approaches [6-12]. These studies are designed  
65 to classify gait phases and predict gait events from only surface electromyographic signals  
66 (sEMG), avoiding the requirement of directly measuring temporal data by means of  
67 additional systems or sensors (foot-switch sensors, IMUs, pressure mats, stereo-  
68 photogrammetry). This would allow to reduce burden for patient, simplify clinical  
69 protocols, and make test faster, specifically in the evaluation of neuromuscular diseases  
70 or for walking-aid devices where the acquisition of myoelectric signals is largely advised  
71 [13,14]. The advantage would be even greater if it could be possible not only limiting the  
72 number of sensors for temporal-data measurement, but also decreasing the number of  
73 sEMG probes themselves. Obviously, reducing the number of sEMG sensors means  
74 having fewer signals to be processed by the neural network. This is expected to lead to a  
75 deterioration of classification performances. To our knowledge, a reliable analysis of the

76 effect on classification/prediction performance of the reduction of sEMG signals involved  
77 in feeding the neural network is not yet available in literature.

78 Furthermore, the problem of gait-phase classification with neural-network-based  
79 interpretation of only electromyographic signals has been typically faced extracting  
80 explicit features from sEMG signal and then using them as input to the machine learning  
81 stages [6-10]. The present group of researchers recently experimented a different strategy  
82 [11,12], consisting in the application of neural networks to learn hidden features from a  
83 processed sEMG signal. This strategy seems to improve the classification performances  
84 [11], but at the same time it introduces the need of identifying the most suitable sEMG-  
85 processing type. Recent studies, indeed, indicate that the choice of processing type and  
86 processing-parameter value could be very subjective [15], could influence the reliability  
87 of methodologies implemented to assess muscle activity [16], and could also affect the  
88 estimation of gait events (HS and TO) [17]. Thus, the choice of the sEMG processing is  
89 still an open issue.

90 The aim of the present study is to quantify the impact of different complexity of the  
91 experimental sEMG-protocol (i. e. different number of sEMG sensors) and/or different  
92 EMG-signal-processing specifications on the performance of a neural-network-based  
93 approach for the binary classification of gait phases and prediction of gait-event (HS and  
94 TO) timing. This aim is pursued, attempting to provide the following main contributions:

- 95 1) identifying which one of the following widely-used approaches to process EMG  
96 signals allows to achieve the best classification/prediction performances: a) band-  
97 pass filtered signal; b) full-wave rectified signal; c) linear envelope of the signal;  
98 and d) root mean square signal. Details of these sEMG-signal processing are  
99 reported in Section 3.3;

- 100 2) testing the sensitivity of the performances to different values of envelope cut-off-  
101 frequency. Values of 5, 10, 15, and 20 Hz were adopted, considering that envelope  
102 cut-off frequency typically ranges from 3 Hz to 25 Hz [15].
- 103 3) quantifying the conceivable decrease of classification/prediction performance  
104 with the reduction of the number of sEMG signals involved in feeding the neural  
105 network. Five experimental set-ups are considered to this purpose, including: 1)  
106 sensors positioned on the proximal and distal leg (medial hamstrings, MH, vastus  
107 lateralis, VL, tibialis anterior, TA, and gastrocnemius lateralis, GL, full set-up); 2)  
108 only sensors positioned on the proximal leg (MH and VL, proximal leg set-up);  
109 3) only sensors positioned on the distal leg (TA and GL, distal leg set-up); 4) only  
110 sensors positioned on tibialis-anterior muscle (TA set-up); and 5) only sensors  
111 positioned on gastrocnemius-lateralis muscle (GL set-up).

112 The manuscript is organized as follows: Section 2 provides a brief review of the related  
113 works. Section 3 introduces the dataset, illustrates the acquisition and the pre-processing  
114 of the signals, describes the procedure of gait-phase classification and gait-event  
115 prediction by machine-learning approach, and presents the statistical tests. Section 4  
116 reports the experimental results that are then discussed in Section 5. Both results and  
117 discussion sections are split in two sub-sections about signal pre-processing and reduction  
118 of experimental set-up, respectively. Eventually, Section 6 ends the study and provides  
119 insights for further research developments.

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124

## 125 **2. Related Works**

126 A relatively small number of works in literature address gait-phase classification  
127 from EMG signals only. In [6] a set of time-domain features, namely mean absolute value  
128 (MAV), waveform length (WL), zero crossing (ZC), and slope sign changes (SSC) were  
129 extracted from EMG signal and hidden Markov models were used to classify stance and  
130 swing phases. Evaluation on treadmill walking of a single subject reported a maximum  
131 accuracy of 91.1%. Monitored muscles are Vastus Medialis, Semitendinosus, Adductors,  
132 and Tensor Fascia Latae. A novel bilateral EMG feature, called weighted signal  
133 difference (WSD), was introduced in [9] and used to train a support vector classifier  
134 (SVC). Intra-subject evaluation is performed on two subjects walking on a treadmill at  
135 different speed, reporting a best accuracy of 96%. Monitored muscles were Soleus,  
136 Tibialis Anterior, Gastrocnemius Lateralis, Vastus Lateralis, Rectus Femoris and Gluteus  
137 Maximus. In [7] a control system for a foot-knee exoskeleton based on the processing of  
138 eight EMG signals is proposed. Four time-domain features (MAV, WL, Variance and  
139 SGC) were extracted and Bayesian Information Criteria (BIC) was used to predict 8  
140 distinct gait events. Evaluation on one healthy subject revealed low repeatability of the  
141 method, with a 30% drop in accuracy testing on different gait cycles. Monitored muscles  
142 were Quadriceps, Hamstring, Gastrocnemius and Tibialis Anterior. In [8] and [10] a set  
143 of temporal features, namely root mean square (RMS), standard deviation (SD), MAV,  
144 WL, and integrated EMG (IEMG), were fed to a single layer neural networks to detect  
145 TO and HS on a population of 8 healthy adults. The study targets inter-subject prediction  
146 by testing the network on one unlearned subject (not used in training), however no cross  
147 validation is performed and the test is performed on a 5-second walk only. No indication  
148 is provided regarding accuracy of prediction and a mean average error of 35 ms and 49

149 ms is reported for HS and TO prediction respectively. Monitored muscles were Tibialis  
150 Anterior (TA) and Medial Gastrocnemius (mGas).

151 All the works mentioned above were based on explicit features extraction and used  
152 different sets of features as input to the machine learning stage. Recently, a different  
153 approach was introduced [11,12], where the original sEMG signal is first pre-processed,  
154 in order to obtain a smoothed and cleaner signal, and then neural networks were used to  
155 learn hidden features, classifying the two main gait phases and successively individuate  
156 the TO and HS events as the transitions between different phases. The sEMG signals  
157 acquired during level ground walking from eight lower-limb muscles, tibialis anterior  
158 (TA), gastrocnemius lateralis (GL), medial hamstrings (MH), and vastus lateralis (VL) of  
159 each leg, in more than 10.000 strides from 23 healthy adult subjects were involved [11].  
160 As far as we know, this work is still reporting the best performances in HS and TO  
161 prediction (mean absolute error of  $21.6 \pm 7.0$  ms and  $38.1 \pm 15.2$  ms, respectively and F1-  
162 score  $\approx 99\%$ ) among the mentioned sEMG-based studies. These promising results were  
163 achieved by feeding the classifier with the envelope of EMG signal, computed as follows  
164 [11]: sEMG signal was band-pass filtered (linear-phase FIR filter, cut-off frequency: 20  
165 - 450 Hz), then full-wave rectified, and eventually the envelope was extracted (second-  
166 order Butterworth low-pass filter, cut-off frequency: 5 Hz). Such a pre-processing  
167 pipeline was designed following the indications provided by previous acknowledged  
168 studies [18,19].

169

### 170 **3. Materials and Methods**

#### 171 **3.1 Participants**

172 Twenty-three able-bodied adults were involved in the experimental procedure.  
173 Volunteer data, reported as mean value  $\pm$ SD, are the following: height =  $173 \pm 10$  cm;



174 mass =  $63.3 \pm 12.4$  kg; age =  $23.8 \pm 1.9$  years; and female/male ratio = 12/11. Subjects  
175 with articular pain, with disorder of the nervous system, in obese or overweight condition  
176 (body mass index > 25), and with history of orthopaedic surgery that may affect walking  
177 performances were exempted from the study. The research presented here was undertaken  
178 following the ethical principles of Helsinki Declaration and was approved by local ethical  
179 committee.

180

### 181 **3.2 Signal acquisition**

182 The multichannel recording system Step32 (Medical Technology, Italy, Version PCI-  
183 32 ch2.0.1. DV) was employed for signal acquisition (resolution: 12 bits; sampling rate:  
184 2 kHz). Three foot-switches were placed under the heel, the first and the fifth metatarsal  
185 heads of both subject's feet, for acquiring foot-floor-contact signal. Four sEMG sensors  
186 were applied over vastus lateralis (VL), medial hamstrings (MH), tibialis anterior (TA),  
187 and gastrocnemius lateralis (GL) of both legs, complying with recommendations  
188 suggested by SENIAM standards [19]. After that, subject walked barefoot approximately  
189 5 minutes on an eight-shaped path at her/his own pace. Experiments were performed in  
190 Motion Analysis Laboratory of the Università Politecnica delle Marche, Ancona, Italy.  
191 Characteristics of sEMG single-differential probes are: material = Ag/Ag-Cl disks; gain  
192 = 1000, filtering = high-pass filter with cut-off frequency of 10 Hz; input impedance >  
193  $1.5\text{G}\Omega$ ; Common-Mode Rejection Ratio > 126 dB; input referred noise  $\leq 1 \mu\text{Vrms}$ ; and  
194 manufacturer = Medical Technology, Italy. sEMG probes with fixed geometry have size  
195 of  $7 \times 27 \times 19$  mm; electrode diameter of 4 mm; and inter-electrode distance of 8 mm).  
196 sEMG probes with variable geometry have a minimum inter-electrode distance of 12 mm.  
197 Characteristics of foot-switches are: size =  $11 \text{ mm} \times 11 \text{ mm} \times 0.5 \text{ mm}$  and activation  
198 force = 3 N. Additional information about signal acquisition could be obtained in [20].

### 199 3.3 Signal pre-processing

200 Foot-switch signals were processed for recognizing gait cycles and stance/swing  
201 phases [21]. To test the effect of signal filtering on classification performance, sEMG  
202 signal were pre-processed with four different approaches.

203  
204 *Band-pass filtered signal (BPFS)*: sEMG signals were band-pass filtered (linear-phase  
205 FIR filter, cut-off frequency: 20 - 450 Hz) for taking out high frequency noise and motion  
206 artefacts.

207  
208 *Full-wave Rectified signal (FWRS)*: sEMG signals were band-pass filtered (linear-phase  
209 FIR filter, cut-off frequency: 20 - 450 Hz). Then, a full-wave rectification was achieved,  
210 taking the absolute value of the signal.

211  
212 *Linear envelope of the signal (LE)*: sEMG signals were band-pass filtered (linear-phase  
213 FIR filter, cut-off frequency: 20 - 450 Hz) and full-wave rectified. Then, envelope of the  
214 signal was extracted (second-order Butterworth low-pass filter). Four different values of  
215 cut-off frequency were tested: 5, 10, 15, and 20 Hz. These four different processing of  
216 the envelope have been referred to as  $LE_5$ ,  $LE_{10}$ ,  $LE_{15}$ , and  $LE_{20}$ , respectively.

217  
218 *Root mean square signal (RMSS)*: sEMG signals were band-pass filtered (linear-phase  
219 FIR filter, cut-off frequency: 20 - 450 Hz). Then, a sliding window of length  $N$  scans the  
220 signal sample by sample.  $RMSV$  computed in the first window is the first sample of the  
221 Root mean square signal.  $RMSV$  computed in the second window is the second sample of  
222 the Root mean square signal and so on.  $RMSV$  is computed as in the following formula:

223

$$224 \quad RMSV = \sqrt{\frac{1}{N} \sum_{k=1}^N |x_k|^2} \quad (1)$$

225

226 where  $N$  is number of samples,  $x_k$  is the  $k$ -sample. Two different values of sliding-window  
227 duration were tested: 100 samples ( $RMSS_{100}$ ) and 500 samples ( $RMSS_{500}$ ). After every  
228 kind of filtering, sEMG signals were min-max normalized within each subject and for  
229 each muscle, thus mapping the values in the  $[0-1]$  interval. All the pre-processing  
230 operations were implemented using Matlab relying on standard functions provided by the  
231 Signal Processing Toolbox<sup>1</sup>.

232

### 233 **3.4 Data preparation**

234 Each sEMG signal was separated into 20-sample windows, matching 10 milliseconds  
235 (ms). A chronological sequence of vectors made up of  $20 \times n$  samples was composed,  
236 where each vector included  $n$  synchronized 20-sample windows from sEMG signals of  $n$   
237 muscles ( $n/2$  for each leg). In details, the first sample of the first vector of the sequence  
238 was the first sample of the sEMG signal from the muscle 1 (TA, right leg), the second  
239 sample of the first vector was the first sample of the EMG signal from the muscle 2 (GL,  
240 right leg), and so on up to the muscle  $n$ . After that, each vector was given a specific label  
241 of 0 (or 1), when all basographic-signal samples assume a value of 0 (or 1). Vectors  
242 containing transitions between phases were not included in the training set.

243 The classifier was then trained following the leave-one-out cross validation  
244 procedure: 22 out of 23 subjects were involved in training the classifier (Learned subjects,  
245 LS); the remaining subject was employed to test the classification output (Unlearned  
246 subject, US). LS were further separated into two subsets: training set containing the first  
247 90% of each subject signal (LS-train); testing set including the remaining 10% (LS-test).

---

<sup>1</sup> <https://it.mathworks.com/products/signal.html>

248 In details, the classifier was fed with the vectors extracted from LS-train. The vectors  
249 from US and LS-test were employed for testing the classifier performances in unseen  
250 subject and in unseen samples of learned subjects, respectively. In this stage, foot-switch  
251 signal was the ground truth. This process has been repeated twenty-three times, each time  
252 employing a different subject as US.

253

### 254 **3.5 The neural network**

255 A Multi Layer Perceptron (MLP) classifier was used in the present study. The MLP  
256 architecture is characterized by:

- 257 • 3 hidden layers of 512, 256 and 128 neurons, respectively;
- 258 • a one-dimensional binary output, provided by applying a 0.5 threshold to a  
259 sigmoid activation;
- 260 • a rectified linear units (ReLU) between each couple of consecutive hidden  
261 layers to supply non-linearity;
- 262 • a stochastic gradient descent optimization algorithm with binary cross  
263 entropy loss function.

264 The specific architecture was chosen among others, with different numbers of layers,  
265 tested in [11], as it provided the best classification accuracy. In training the network, 10%  
266 of the training dataset was used as validation set. At each training epoch, accuracy on the  
267 validation set is measured and training was stopped when the validation accuracy did not  
268 increase in 10 consecutive epochs. Then, the trained network weights, corresponding to  
269 the best validation accuracy, were used to evaluate the model on the LS-test and US sets.

270 The neural network and the corresponding training and testing code were implemented in  
271 Python using the Pytorch deep learning framework<sup>2</sup> and the Scikit-Learn python library<sup>3</sup>.

272

### 273 **3.6 Gait-event identification**

274 The binary output of the classifier has been chronologically arranged to provide the  
275 predicted foot-floor-contact signal, as a vector made up of sequences of 0 (stance phase)  
276 alternating with sequences of 1 (swing phase). While signal windows containing  
277 transitions were discarded in the training phase, all of them were fed as input to the  
278 classifier, in order to predict the foot-floor-contact signal. It is acknowledged that stance  
279 and swing are typically lasting around 60% and 40% of gait cycle, during able-bodied  
280 walking [1]. Accordingly, the sample sequences shorter than 500 samples (< 25% of gait  
281 cycle) were removed to clean out the predicted signal. Afterward, stance-to-swing (toe  
282 off, TO) and swing-to-stance (heel strike, HS) transitions have been assessed in the  
283 cleaned signal. TO was identified as the sample when the value switched from 0 to 1.  
284 Similarly, HS was identified as the sample when the value switched from 1 to 0.  
285 Prediction performances were quantified in terms of precision, recall, and F1-score.  
286 Precision is computed as:

$$287 \quad \textit{Precision} = \frac{TP}{TP + FP} \quad (2)$$

288

289 where *TP* is true positive and *FP* is false positive. Recall is computed as:

290

---

<sup>2</sup> <https://pytorch.org/>

<sup>3</sup> <https://scikit-learn.org/stable/>

291 
$$Recall = \frac{TP}{TP + FN} \quad (3)$$

292

293 where  $FN$  is false negative. F1-score is computed as:

294

295 
$$F1 - score = 2 \cdot \frac{Precision \cdot Recall}{Precision + Recall} \quad (4)$$

296

297 Predicted HS or TO at time  $t_p$  were acknowledged as true positives ( $TP$ ) if an event of the  
298 same type occurs in ground-truth signal at time  $t_g$  such that  $|t_g - t_p| < T$ .  $T$  is a time  
299 tolerance, set to 600 samples. Otherwise, the predicted event was acknowledged as a false  
300 positive ( $FP$ ). For all  $TP$ , mean absolute error (MAE) has been computed, as the mean  
301 time distance between the predicted event and the corresponding event in ground-truth  
302 signal.

303

### 304 **3.7 Statistics**

305 Shapiro-Wilk test was used to evaluate the hypothesis that each data vector had a  
306 normal distribution. Comparison between two normally distributed samples was  
307 performed with two-tailed, non-paired Student's t-test. Two-sample Kolmogorov-  
308 Smirnov test was used to compare not normally distributed samples. Statistical  
309 significance was set at 5%.

310

311

312

313

## 314 4. Results

### 315 4.1 Signal pre-processing

316 Average classification accuracies as result of different pre-processing of the signal  
317 are reported in Table 1, for Learned-test set (LS-test) and Unlearned set (US). Linear  
318 envelope (*LE*) of the signal is evaluated considering four different values of cut-off  
319 frequency: 5, 10, 15, and 20 Hz.

320

321 **Table 1.** Mean classification accuracy as result of  
322 different pre-processing of the signal.

Mean classification accuracy (%)		
	LS-test	US
<i>LE<sub>5</sub></i>	94.8 ± 0.2	93.4 ± 2.3
<i>LE<sub>10</sub></i>	93.8 ± 0.3	93.1 ± 2.4
<i>LE<sub>15</sub></i>	93.2 ± 0.3	91.4 ± 2.4
<i>LE<sub>20</sub></i>	92.4 ± 0.4	90.3 ± 3.3
<i>RMSS<sub>100</sub></i>	92.3 ± 0.5	90.1 ± 2.9
<i>RMSS<sub>500</sub></i>	93.0 ± 0.4	91.0 ± 3.7
<i>FWRS</i>	88.8 ± 0.2	88.0 ± 2.9
<i>BPFS</i>	86.5 ± 0.6	84.0 ± 3.7

323

324

325 Classification results highlight that accuracy is decreasing with increasing cut-off  
326 frequency in both LS-test (from 94.8% to 92.4%) and US (from 93.4% to 90.3%). In a  
327 similar way, SD is increasing with increasing cut-off frequency (from 0.2 to 0.4 in LS-  
328 test; from 2.3 to 3.3 in US). Comparison between Root mean square signals (*RMSS*)  
329 computed with two different values of sliding-window duration shows slightly better  
330 accuracy for *RMSS<sub>500</sub>* for both LS-test and US. All *LE* and *RMSS* approaches report a  
331 mean classification accuracy > 92% in LS-test and > 90% in US. Otherwise, *FWRS* and

332 *BPFS* approaches remain definitely  $< 90\%$ , in particular for US. Overall, best mean  
 333 accuracy (and SD) is provided by  $LE_5$  in both LS-test and US.

334

335 **Table 2.** MAE (mean absolute error), precision, recall, and F1-score as result  
 336 of different pre-processing of the signal for Heel Strike (HS) and Toe Off  
 337 (TO) prediction in US.

Mean prediction performances				
Heel Strike (HS)	MAE (ms)	Precision (%)	Recall (%)	F1-score (%)
$LE_5$	$21.6 \pm 7.0$	$99.7 \pm 0.6$	$98.5 \pm 3.0$	$99.0 \pm 1.7$
$LE_{10}$	$26.7 \pm 9.8$	$99.6 \pm 0.7$	$98.8 \pm 1.6$	$99.2 \pm 1.1$
$LE_{15}$	$27.4 \pm 11.7$	$99.5 \pm 0.6$	$98.7 \pm 1.3$	$99.1 \pm 0.9$
$LE_{20}$	$35.1 \pm 26.5$	$98.9 \pm 2.5$	$98.1 \pm 3.3$	$98.5 \pm 2.8$
$RMSS_{100}$	$28.1 \pm 9.6$	$99.2 \pm 1.2$	$98.0 \pm 3.0$	$98.6 \pm 1.9$
$RMSS_{500}$	$33.9 \pm 14.3$	$98.7 \pm 2.2$	$98.1 \pm 2.6$	$98.4 \pm 2.3$
$FWRS$	$47.3 \pm 24.9$	$99.2 \pm 1.0$	$98.4 \pm 1.8$	$98.9 \pm 1.4$
$BPFS$	$77.4 \pm 40.4$	$95.6 \pm 5.9$	$90.4 \pm 13.0$	$92.6 \pm 9.7$
Toe Off (TO)	MAE (ms)	Precision (%)	Recall (%)	F1-score (%)
$LE_5$	$38.1 \pm 15.2$	$99.1 \pm 1.5$	$97.9 \pm 3.6$	$98.4 \pm 2.4$
$LE_{10}$	$46.0 \pm 22.6$	$98.7 \pm 2.3$	$97.9 \pm 2.9$	$98.3 \pm 2.5$
$LE_{15}$	$47.9 \pm 19.3$	$98.4 \pm 2.3$	$97.6 \pm 2.7$	$98.0 \pm 2.4$
$LE_{20}$	$58.2 \pm 26.4$	$98.5 \pm 2.1$	$97.6 \pm 2.8$	$98.0 \pm 2.4$
$RMSS_{100}$	$58.3 \pm 22.3$	$98.6 \pm 1.9$	$97.4 \pm 3.6$	$97.9 \pm 2.7$
$RMSS_{500}$	$54.1 \pm 29.5$	$97.8 \pm 3.2$	$97.1 \pm 3.6$	$97.5 \pm 3.4$
$FWRS$	$58.8 \pm 29.9$	$97.3 \pm 5.0$	$96.5 \pm 5.3$	$96.9 \pm 5.1$
$BPFS$	$67.7 \pm 25.6$	$97.6 \pm 3.1$	$92.2 \pm 11.4$	$94.5 \pm 7.8$

338

339

340



341 Performances in assessing HS and TO events in US are reported in Table 2, in terms  
342 of MAE, precision, recall, and F1-score.  $LE_5$  provides the best MAE in HS and TO  
343 identification in US, in terms of both mean and SD ( $21.6 \pm 7.0$  ms and  $38.1 \pm 15.2$  ms,  
344 respectively). Even  $LE_{10}$ ,  $LE_{15}$ , and  $RMSS_{100}$  are able to keep HS-MAE value  $< 30$  ms,  
345 but they fail in keeping TO-MAE value  $< 40$  ms. All  $LE$  and  $RMSS$  approaches are able  
346 to maintain precision, recall and F1-score  $> 98\%$  for HS and  $> 97\%$  for TO.  $FWRS$  and  
347  $BPFS$  approaches supply the worst performances. Average performances in every subject  
348 are reported in supplementary material 1-8.

349 All experiments run on a machine equipped with a 2,6 GHz Intel Core i7 processor,  
350 16 GB RAM. The best performing signal pre-processing pipeline ( $LE_5$ ) required  
351 approximately 70 milliseconds in average to process a 1-second signal. It then took  
352 around 0.2 milliseconds for the neural network to process and predict gait events for a  
353 single pre-processed signal window (20 samples). In conclusion, the total processing time  
354 sums up to 90 milliseconds to predict TO and HS events for a 1 second walk. In the  
355 present experiments, the network training time over 22 training subjects (one single fold)  
356 ranges from approximately 30 minutes, when the simpler experimental protocol is  
357 adopted (a single EMG signal per leg, two in total) to approximately 60 minutes, when  
358 all the four EMG signals per leg (eight in total) are used. However, we also note that the  
359 network training has to be done only once, then the trained network can be applied as-is  
360 to predict TO and HS in unseen subjects.

361

## 362 **4.2 Reduction of experimental set-up**

363 Since it turned out to be the best-performing processing technique,  $LE_5$  has been used  
364 to perform the analysis of the reduction of experimental set-up. Average classification  
365 accuracies as a result of different experimental set-ups are reported in Table 3, for

366 Learned-test set (LS-test) and Unlearned set (US). The full protocol (reference) provides  
367 the best classification accuracy ( $94.8 \pm 0.2\%$  for LS-test and  $93.4 \pm 2.3\%$  for US). In the  
368 distal-leg approach, a significant ( $p < 0.05$ ) decrease of 2 percentage points of  
369 classification accuracy is detected for both LS-test and US, compared to the reference.  
370 However, accuracy is still widely  $> 90\%$ . The gap from the reference further increases ( $p$   
371  $< 0.05$ ), considering the single muscles (GL and TA) and the proximal-leg approach  
372 (Table 3). Performances in assessing HS and TO events in US are reported in Table 4, in  
373 terms of MAE, precision, recall, and F1-score. The full protocol supplies the best MAE  
374 in HS and TO identification in US, in terms of both mean and SD ( $21.6 \pm 7.0$  ms and  $38.1$   
375  $\pm 15.2$  ms, respectively) and the best F1-score ( $99.0 \pm 1.7\%$  and  $98.4 \pm 2.4\%$ ). A  
376 significant worsening in HS-MAE ( $\approx + 10$  ms,  $p < 0.05$ ) is detected in prediction of distal-  
377 leg and GL approaches.

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**Table 3.** Mean classification accuracy as result of different experimental set-ups

Mean classification accuracy (%)		
	LS-test	US
<b>Full</b>	$94.8 \pm 0.2$	$93.4 \pm 2.3$
<b>Proximal leg</b>	$84.6 \pm 0.9$	$79.9 \pm 6.1$
<b>Distal leg</b>	$92.6 \pm 0.3$	$91.4 \pm 2.6$
<b>GL</b>	$88.4 \pm 0.5$	$89.1 \pm 3.6$
<b>TA</b>	$86.9 \pm 0.4$	$84.6 \pm 6.9$

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**Table 4.** MAE (mean absolute error), precision, recall, and F1-score as result of different experimental set-ups for Heel Strike (HS) and Toe Off (TO) prediction in US.

Mean prediction performances				
Heel Strike (HS)	MAE (ms)	Precision (%)	Recall (%)	F1-score (%)
Full	21.6 ± 7.0	99.7 ± 0.6	98.5 ± 3.0	99.0 ± 1.7
Proximal leg	52.9 ± 23.8	96.3 ± 5.0	90.0 ± 9.3	92.8 ± 6.5
Distal leg	33.2 ± 13.1	99.5 ± 0.7	97.3 ± 4.6	98.3 ± 2.7
GL	33.0 ± 12.0	99.7 ± 0.4	96.5 ± 6.7	98.0 ± 4.1
TA	53.6 ± 38.4	95.5 ± 6.1	83.8 ± 15.1	88.7 ± 10.9

Toe Off (TO)	MAE (ms)	Precision (%)	Recall (%)	F1-score (%)
Full	38.1 ± 15.2	99.1 ± 1.5	97.9 ± 3.6	98.4 ± 2.4
Proximal leg	71.2 ± 24.4	92.3 ± 11.0	86.1 ± 11.9	88.9 ± 10.7
Distal leg	45.1 ± 18.7	98.6 ± 2.0	96.4 ± 5.0	97.5 ± 3.3
GL	64.6 ± 25.8	98.9 ± 1.5	95.7 ± 6.7	97.1 ± 4.1
TA	49.0 ± 16.6	95.7 ± 5.7	83.9 ± 15.5	88.8 ± 11.1

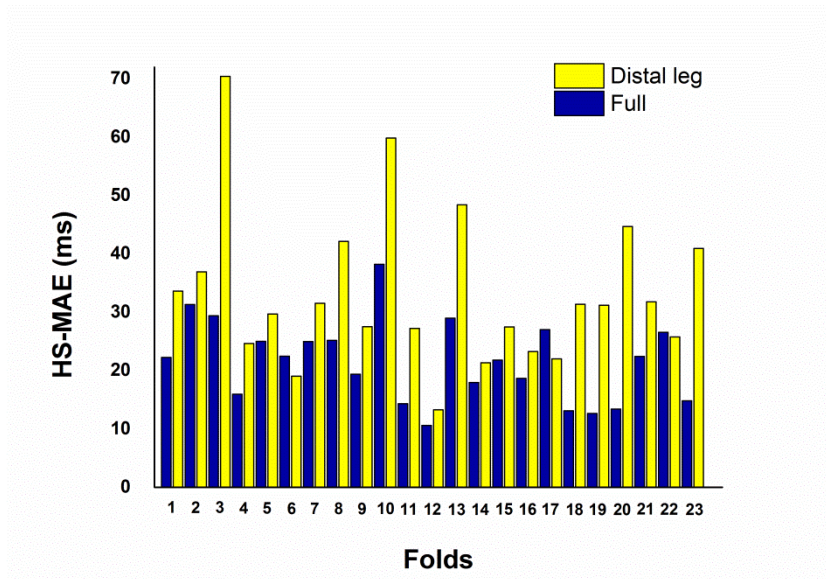
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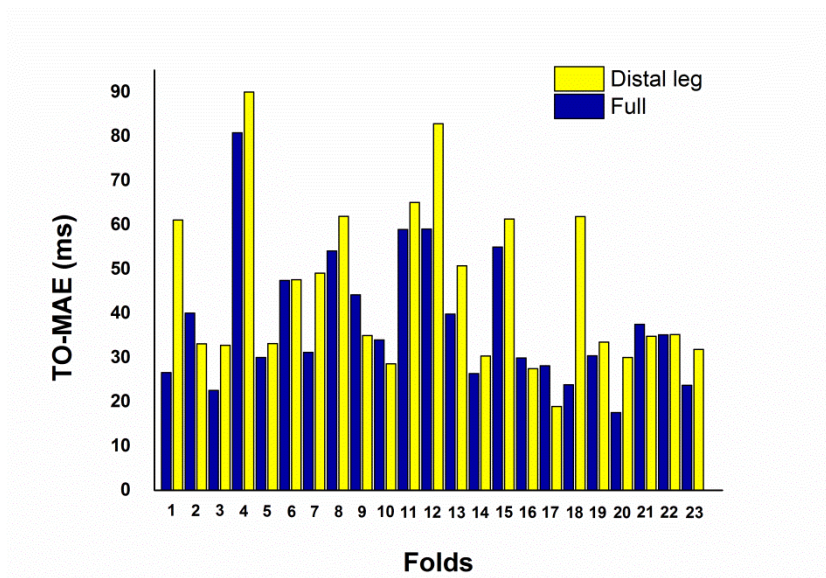
396 A further increase of MAE ( $\approx + 20$  ms,  $p < 0.05$ ) and decrease of F1-score (from 6%  
397 to 10%) were predicted by the other two approaches. TO-MAE worsens in prediction of  
398 distal-leg and TA approaches ( $\approx 7$  and 11 ms, respectively), even if not significantly ( $p >$   
399 0.05). A concomitant decrease of F1-score is detected ( $\approx -1\%$ ). Further remarkable  
400 worsening of both parameters was reported for the other two approaches. Figure 1 shows  
401 a direct comparison between the accuracy provided by distal-leg (yellow bars) vs.  
402 reference set-up (full, blue bars) in each fold. Average performances in every subject are  
403 reported in supplementary material 9-12.

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408 **Fig. 1.** Direct comparison of MAE provided in each fold by full set-up  
 409 (dark blue bars) vs. distal-leg set-up (yellow bars) for HS (upper  
 410 panel) and TO (lower panel) predictions.  
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414 **5. Discussion**

415 The present group of researchers recently proposed a neural-network-based  
 416 approach for classifying stance vs. swing and assessing temporal gait events from  
 417 electromyographic signals [11]. A twofold objective is pursued in the present study, i.e.

418 to test the influence on the performance of the above-mentioned approach of: 1) different  
419 pre-processing of sEMG signal; 2) reduction of the number of sEMG probes included in  
420 the experimental set-up. The approach described in [11] was chosen as reference model,  
421 because to our knowledge it is still outperforming all similar studies in terms of HS and  
422 TO prediction [6-10]. Foot-switch signal was adopted as the ground truth, since it  
423 represents the gold standard in gait segmentation [21-23].

424

### 425 **5.1 Signal pre-processing**

426 The first step was to test if the change of low-pass cut-off frequency for extracting  
427 the envelope could affect classification and/or prediction performances. Average results  
428 show that classification accuracy (Table 1) and prediction MAE (Table 2) gradually  
429 worsen with concomitantly increasing cut-off-frequency value (starting from the  
430 reference value of 5 Hz), in terms of both mean value and SD. These results clearly show  
431 that the performances of the classifier are affected by the choice of the cut-off-frequency  
432 and 5 Hz is the best value for the goal we set. This suggests that when the envelope of  
433 sEMG signal is used, the cut-off-frequency value should be carefully evaluated in relation  
434 to the adopted methodology and pursued aim, in order to avoid estimation bias, as shown  
435 for co-contraction assessment in [16].

436 The second step was to compare the performances of the classifier after feeding the  
437 neural network with sEMG signal filtered in different ways. The simplest filter analyzed  
438 is *BPFS*, because it is necessary for removing low-frequency motion artefacts and high-  
439 frequency noise from the signal. This approach returns the worst mean and single-subject  
440 (see supplementary material 8) classification accuracy among the approaches considered  
441 in the present study, especially for the unseen subjects (mean  $\pm$  SD = 84.0  $\pm$  3.7%, Table  
442 1). The worst performances are provided also in the assessment of gait events (Table 2).

443 *BPFS* is the only approach not performing the rectification of the signal. Thus, these  
444 findings indicate that the full-wave rectification is strongly recommended in processing  
445 the signal to feed the neural network. However, the full-wave rectification alone does not  
446 seem to be enough. *FWRS* approach truly improves *BPFS* one, but accuracy is still < 90%.  
447 Moreover, the performances are far from the ones provided by more refined processing  
448 approaches, such as *LE* and *RMSS* (Table 1 and 2). All *LE* and *RMSS* approaches, indeed,  
449 report a mean classification accuracy > 90% (Table 1) and keep mean precision, recall  
450 and F1-score > 98% for HS and > 97% for TO (Table 2). Furthermore, the best performing  
451 *LE* approach (*LE*<sub>5</sub>) outperforms also the *RMSS* approaches, above all in terms of average  
452 classification accuracy ( $\approx 95\%$  in learned subjects and  $> 93\%$  in unseen subjects), HS-  
453 MAE ( $21.6 \pm 7.0$  ms vs.  $28.1 \pm 9.6$  ms provided by the best performing *RMSS* approach),  
454 and TO-MAE ( $38.1 \pm 15.2$  ms vs.  $54.1 \pm 29.5$  ms). About *RMSS*, the different durations  
455 of sliding-window do not seem to influence the classifier performance.

456 In the end, present results confirm that the choice of the sEMG processing actually  
457 affects the classification/prediction performances, as expected [15-17]. Moreover, the  
458 present study succeeds in identifying the linear envelope (cut-off frequency 5 Hz) as the  
459 sEMG-processing type which provides the best performance of the neural network in  
460 terms of both classification accuracy and gait-event-prediction, among the four widely-  
461 used approaches analyzed in the present study. This methodological finding, reported  
462 here for the first time, is very useful information for improving the precision of the clinical  
463 test by means of the most adequate processing of the signal. It seems especially valuable  
464 for those clinical conditions (such as neurological disorders) where elevated precision of  
465 predictions is fundamental to properly identify subject recovery during follow-up.

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## 468 **5.2 Reduction of experimental set-up**

469 Since  $LE_5$  is resulted being the best-performing approach for the sEMG-signal  
470 processing, it was used to run the analysis of the reduction of experimental set-up, i.e. the  
471 number of sEMG probes. Besides the full protocol [11], four reduced experimental set-  
472 ups are considered in the present paper, in order to test the influence of protocol  
473 simplification on classification/prediction performances. The first step was to test if the  
474 reduction from four to two sEMG sensors per leg could provide classification/prediction  
475 results consistent with those provided by the full set-up. Two attempts were made, using  
476 signals from a couple of sensors applied to the same leg segment (proximal or distal), one  
477 in the front and one in the back. Table 3 shows as mean classification accuracy provided  
478 by the proximal-leg set-up clearly deteriorates compared to the full set-up, falling below  
479 85% in learned subjects and below 80% in unseen ones. This is also more evident by  
480 analysing each single subject, as reported in supplementary material 9. The proximal-leg-  
481 based reduction of the number of sensors strongly affects also MAE, precision, recall,  
482 and F1-score, especially in TO prediction (MAE =  $71.2 \pm 24.4$  ms and F1-score < 90%,  
483 Table 4). The matter is different for the distal-leg set-up. Although a decrease of mean  
484 classification accuracy is still detected, it amounts to only 2 percentage points in both  
485 learned ( $92.6 \pm 0.3\%$ ) and unseen subjects ( $91.4 \pm 2.6\%$ ). Moreover, precision, recall, and  
486 F1-score remain practically unaltered. The mean increase of MAE compared to the full  
487 set-up (+ 11.6 ms for HS; + 7.0 ms for TO, Table 4) is the price to pay for using only two  
488 probes per leg. For allowing a more detailed evaluation, MAEs provided by the two set-  
489 ups in each single subject are compared in Fig. 1. These findings show as the distal-leg  
490 set-up clearly outperforms the proximal-leg one in terms of all performance parameters.  
491 To our knowledge, only Nazmi at al. [10] provided neural-network prediction of gait  
492 events using only two sEMG probes per leg on distal-leg muscles (tibialis anterior and

493 gastrocnemius medialis). They achieved, for unseen subjects, a mean classification  
494 accuracy of 77% and MAE of 35 ms and 49 ms in assessing HS and TO, respectively.  
495 Compared to those, the present distal-leg-set-up results appear promising, considering  
496 also that in present study F1-score is around 98%, while in [10] this information is not  
497 reported. It is worth mentioning that in [10] HS and TO predictions are computed in only  
498 5 seconds of a single subject, whereas in the present study an extensive evaluation is  
499 performed, predicting HS and TO in a 5-minute walking of 23 different subjects (with  
500 leave-one-out cross validation).

501 The second step was to test the effect of a further reduction to a single muscle of  
502 experimental set-up. Considering the promising results achieved, two further attempts  
503 were made, using signals from one sensor applied to a single muscle, in the front (TA) or  
504 in the back (GL) of the distal leg. The results shown in Table 3 highlight that phase  
505 classification based on a single sEMG signal leads to a deterioration of mean accuracy,  
506 compared to both full and distal-leg set-ups. This is true for both TA (- 8% in learned and  
507 - 7% in unseen subjects, compared to the full protocol) and GL set-ups (- 6% in learned  
508 and - 4% in unseen subjects), although GL set-up achieves better accuracy, getting close  
509 to 90% in unseen subjects. However, classification accuracies are still better than the ones  
510 provided by the proximal-leg set-up and in [10]. TA and GL set-ups work differently in  
511 HS and TO prediction. Compared to full set-up, mean precision, recall, and F1-score  
512 remain practically unaltered for GL set-up. Prediction of TA set-up is instead affected by  
513 a strong decrease of mean recall value (-14% and -12% compared to full and GL set-ups,  
514 respectively). This means that a high number of false positive detection of HS and TO  
515 affects the prediction. Consequently, a concomitant deterioration of F1 score is observed  
516 (-10% and -9% compared to full and GL set-ups, respectively). HS prediction provided  
517 by GL set-up presents a mean increase of MAE compared to the full set-up, but achieves



518 the same value provided by distal-leg set-up ( $33.0 \pm 12.0$  ms vs.  $33.2 \pm 13.1$  ms).  
519 Furthermore, mean HS-MAE is still comparable with the one reported in [10], using two  
520 distal-leg muscles. TA set-up reports a significant growth of mean HS-MAE compared  
521 to full (+33 ms), distal-leg (+20 ms), and GL (+20 ms) set-ups. These findings seem to  
522 indicate that between GL and TA signals, only GL-signal plays a fundamental role in  
523 prediction of heel strike. TO prediction is less accurate in GL-set-up (+26 ms and +19  
524 ms of mean MAE compared to full and distal-leg set-ups, respectively). Larger MAEs in  
525 TO prediction were foreseen, since it was explained that it is more challenging to assess  
526 TO than HS [10,24]. On average, TO-MAE is lower for TA set-up ( $49.0 \pm 16.6\%$ ,  
527 comparable with distal-leg set up). However, as already mentioned, it is associate to low  
528 performances in terms of classification accuracy ( $84.6 \pm 6.9\%$ ), recall ( $83.9 \pm 15.5\%$ ),  
529 and F1-score ( $88.8 \pm 11.1\%$ ). Thus, in our opinion TA-set-up-based prediction should be  
530 considered not reliable and the desirable simplification of experimental set-up (one single  
531 sensor) should involve only the GL set-up. In this case, this simplification would be paid  
532 with a deterioration of TO (not HS) prediction. This could be a good compromise for  
533 tasks such as stride recognition, stride-time computation, identification of toe walking,  
534 and so on, where only HS event is involved.

535 In the end, present findings indicate that the reduction of the complexity of the  
536 experimental sEMG-protocol (i. e. decreased number of sEMG sensors) affects the  
537 performances especially in terms of gait-event-prediction parameters, as expected [10].  
538 Moreover, the present study succeeds in the goal of providing for the first time a  
539 quantification of the progressive deterioration of classification/prediction performances  
540 with the reduction of the number of sensors used. This could be very useful in clinics to  
541 the aim of choosing the most suitable approach, balancing technical performances, patient  
542 comfort, and clinical needs. Since a simplification of experimental set-up is always

543 desirable, the present study proposes the distal set-up (consisting of two sensors over TA  
544 and GL per leg) as a suitable alternative to the full protocol in those circumstances where  
545 limiting time consumption and patient discomfort is a primary issue. The price to pay for  
546 this simplification is essentially a worsening of HS and TO prediction (about 10 ms, on  
547 average). A further reduction of experimental set-up to a single muscle seems to be  
548 feasible without a further deterioration of performances only if GL is chosen as the  
549 reference muscle and for computation where only heel-strike events are involved.

550

551

## 552 **6. Conclusions**

553 The present study shows that both the sEMG-processing type and the reduction of  
554 sEMG-protocol complexity actually affect the performances of neural-network-based  
555 classification of gait phases and assessment of temporal gait events. A further novel  
556 contribution is to provide also a reliable quantification of this performance deterioration.  
557 The quantitative knowledge of the consequences of the reduction of the number of sensors  
558 in terms of classification/prediction accuracy could be very useful in clinics to drive the  
559 choice of the most suitable experimental set-up for gait analysis, able to balance the need  
560 of handling patient comfort and limiting time consumption with the necessity of  
561 maintaining an elevated precision of test results. Higher precision in gait event prediction  
562 is increasingly requested in clinics, especially in those pathologies where one of the gait  
563 phases could be strongly reduced (neurological disorders). The present study provides  
564 also the information about the most suitable sEMG-processing type (linear envelope with  
565 a cut-off frequency = 5 Hz) to satisfy this necessity.

566 Four acknowledged and widely-used approaches to process EMG signals were  
567 included in the present comparative analysis. Future development could be designed to

568 involve more advanced signal-processing techniques in frequency or time/frequency  
569 domain, such as Fourier transform or wavelet transform. Moreover, the potential  
570 influence of gait velocity could be also taken into account. This would be an intriguing  
571 further direction, as EMG envelopes show adaptations to different gait velocities.

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