Random forest algorithms for recognizing daily life activities using plantar pressure information: A smart-shoe study

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Background: Wearable activity trackers are regarded as a new opportunity to deliver health promotion interventions. The algorithms typically contain two stages: 1) activity classification and 2) quantification of energy expenditures by applying activity-specific regression equations. Although the predictions of traditional activity trackers rely primarily on the processing of accelerometer sensor data, the emergence of smart clothes with multi-sensing capacities could contribute to a more accurate evaluation of daily physical behaviors. This study aims to 1) develop an activity recognition algorithm based on the processing of plantar pressure information provided by a smart-shoe prototype and 2) to determine the optimal hardware and software configurations. **Method:** Seventeen subjects wore a pair of smart-shoe prototypes composed of plantar pressure measurement insoles, and they performed the following nine activities: sitting, standing, walking on a flat surface, walking upstairs, walking downstairs, walking up a slope, running, cycling, and completing office work. The insole featured seven pressure sensors. For each activity, four minutes of plantar pressure data were collected. The plantar pressure data were cut in overlapping windows of different lengths and 167 features were extracted for each window. A random forest model was trained to recognize activity using some selected sensor configurations and different numbers of data features. The resulting activity recognition algorithms were evaluated using data samples specifically directed to validation trials. **Results:** Using all the sensors and all 167 features, the smart shoes predicted the activities with an average success of 89%. "Running" demonstrated the highest percentage of good predictions (100%). "Walking up a slope" was linked with the lowest performance (63%), with the majority of the false positives being "walking on a flat surface" and "walking upstairs." Some 2- and 3-sensor configurations were linked with an

average performance of 87%. A window length of 20 s was found to be optimum.

Conclusion: High-performance human behavior recognition using plantar pressure data only is possible. In the future, smart-shoe devices could contribute to the evaluation of daily physical activities. Minimalist configurations integrating only a small number of sensors and computing a reduced number of selected features could maintain a satisfying performance. Future experiments should also include calorimetric measurements to evaluate the possible contribution of plantar pressure information to predicting energy expenditures.

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Abstract

Background: Wearable activity trackers are regarded as a new opportunity to deliver health promotion interventions. Indeed, while the prediction of active behaviors is currently primarily relying on the processing of accelerometer sensor data, the emergence of smart clothes with multi-sensing capacities is offering new possibilities. Algorithms able to process data from a variety of smart devices and classify daily life activities could therefore be of particular importance to achieve a more accurate evaluation of physical behaviors. This study aims to 1) develop an activity recognition algorithm based on the processing of plantar pressure information provided by a smart-shoe prototype and 2) to determine the optimal hardware and software configurations.

Method: Seventeen subjects wore a pair of smart-shoe prototypes composed of plantar pressure measurement insoles, and they performed the following nine activities: sitting, standing, walking on a flat surface, walking upstairs, walking downstairs, walking up a slope, running, cycling, and completing office work. The insole featured seven pressure sensors. For each activity, at least four minutes of plantar pressure data were collected. The plantar pressure data were cut in overlapping windows of different lengths and 167 features were extracted for each window. Data were split into training and test samples using a subject-wise assignment method. A random forest model was trained to recognize activity. The resulting activity recognition algorithms were evaluated on the test sample. A multi hold-out procedure allowed repeating the operation with 5 different assignments. The analytic conditions were modulated to test 1) different window lengths (1-60 seconds), 2) some selected sensor configurations and 3) different numbers of data features.

Results: A window length of 20 s was found to be optimum and therefore used for the rest of the analysis. Using all the sensors and all 167 features, the smart shoes predicted the activities with an average success of 89%. "Running" demonstrated the highest sensitivity (100%). "Walking up a slope" was linked with the lowest performance (63%), with the majority of the false positives

45 being "walking on a flat surface" and "walking upstairs." Some 2- and 3-sensor configurations
46 were linked with an average success rate of 87%. Reducing the number of features down to 20
47 does not alter significantly the performance of the algorithm.
48 **Conclusion:** High-performance human behavior recognition using plantar pressure data only is
49 possible. In the future, smart-shoe devices could contribute to the evaluation of daily physical
50 activities. Minimalist configurations integrating only a small number of sensors and computing a
51 reduced number of selected features could maintain a satisfying performance. Future experiments
52 must include a more heterogeneous population.
53
Introduction
55 The promotion of an active lifestyle among our populations remains an on-going problem (Barreto,
56 2013). Fortunately, the recent boom in the marketing of activity trackers provides new tools to
57 address this issue. The term "activity tracker" is defined as a category of wearable devices, which
58 aims to provide users with feedback on their physical behaviors, physical fitness, and physical
59 activity. This feedback can be provided through a wide variety of parameters, including "step-
60 count," time spent in activities of selected intensities (sedentary, light, moderate, or vigorous
61 activities), number of floors climbed, and daily energy expenditures (expressed in kilocalories).
62 This type of device has been demonstrated to be effective in supporting active lifestyles and is now
63 widely considered in the development of health promotion policies (Bravata et al., 2007; Bonomi
64 & Westerterp, 2012; Gal et al., 2018, Jennings et al., 2017).
65
66 From a technological perspective, the majority of contemporary activity trackers integrate one
67 MEMS 3-axis accelerometer chip that allows the sensing of the user's body motion. They are
68 typically worn at the hip or wrist and provide feedback on the amount of daily physical activity
69 (Romanzini, Petroski & Reichert, 2012; Kamada et al., 2016). State-of-the-art algorithms directed
70 at evaluating physical behaviors typically feature an activity classification method (Staudenmayer
71 et al., 2009, Ohkawara et al., 2011, Bassett, Rowlands & Trost, 2012). The following are examples
72 of activity classes that are frequently proposed when using the information of one single
73 accelerometer: locomotive vs. non-locomotive vs. mixed activity and sedentary vs. light intensity
74 vs. moderate intensity vs. vigorous intensity activities (Karabulut, Crouter & Bassett, 2005,
75 Oshima et al., 2010). However, latest trackers now feature multi-sensing technologies (e.g.,
76 gyroscope, altimeter, light reflectance, thermal resistor), increasing the amount of available
77 information (e.g., inclination, altitude, heart rate, skin temperature) for physical behavior
78 evaluation, and calling for the development of algorithmic suites able to handle the full wealth of
79 available information (Chen & Bassett, 2005, Park et al., 2011).
80
81 This trend toward multi-sensing evaluation is expected to benefit from current innovations in the
82 field of wearable technologies and smart clothes, which are designed to work in an interconnected
83 network of 5G devices. In such a fast-evolving context, the current methods could rapidly become
84 outdated, and smart clothes able to collect physiological or mechanical information could assume
85 an ever more central role in the evaluation of physical activity (Intille, 2012; Chen et al., 2012;
86 Chen et al., 2016). In the near future, higher-level algorithms will function in the cloud and be
87 capable of collecting available data from a large number of connected devices, and they can select
88 the most relevant information depending on the context to proceed to a continuous and ever more
89 accurate evaluation on physical behaviors. Among these, smart shoes or smart insoles oriented

90   toward the assessment of physical behaviors could be used to evaluate the interaction with the
91   ground and to help refine activity classification.

92

93   Medical insoles capable of measuring plantar pressures have already been commercialized as
94   transportable alternatives to force platforms (Fscan, Tekscan, Inc., USA; ParoTec, Paromed GmbH
95   & Co. KG; PedoSmart). These devices provide a reliable analysis of the center of pressure to assess
96   posture, gait stability, mobility disorders, fall risk, and some other physical considerations.
97   Recently, smart-shoe systems intended for athletes have also been proposed (Nike + Sensor, Nike,
98   Inc., USA; SportProfiler, Digitsol, France; Torin IQ, Altra Running, USA; Mijia, Xiaomi, China).
99   They typically provide feedback on plantar pressure distribution, foot landing type, cadence, and
100 contact duration with the ground, among other measurements. To date, smart-shoe systems aimed
101 at monitoring physical behaviors in daily life have only been presented in the scientific literature
102 (De Pinho André, Diniz & Fuks, 2017; Ngueleu et al., 2019). Devices mentioning a high rate of
103 activity recognition typically have multi-sensing abilities, including accelerometer sensors,
104 gyroscopes, temperature sensors, and GPS antennas, providing a large amount of information to
105 the prediction algorithm. However, the inclusion of several in-shoe sensors would likely induce
106 higher production costs as well as challenges for product designers. Furthermore, the high rates of
107 behavior recognition presented in the literature are at times inherent to the study protocols, which
108 may only include a limited number of activities or focus on specific clinical populations, thus
109 preventing the generalization of the results (De Pinho André, Diniz & Fuks, 2017; Ngueleu et al.,
110 2019).

111

112 Hence, a smart-insole or smart-shoe system that only uses plantar pressure information and that
113 could recognize multiple human daily life activities has yet to be developed. The present research
114 aims to develop efficient and effective activity recognition algorithms for smart-insole devices
115 featuring 1–7 plantar pressure sensors. Nine daily life activities are considered. The smart-insole
116 prototype used in the present study is equipped with the 7-sensor plantar pressure measurement
117 insole, described elsewhere (Saito et al., 2011; Nakajima et al., 2014). The data analysis is
118 conducted using machine learning methods. The identification of the best hardware and software
119 configurations is conducted through a data processing logical frame, which may be re-used by
120 designers willing to develop smart-shoes devices.

121

122

Materials & Methods

7-sensor plantar pressure measurement insole

125 The shoe hygienic insoles, which are 2 mm thick, were equipped with seven force-sensing resistors
126 (FSR400, Interlink Electronics, Inc., CA). The sensors respond to stimulation ranging from 0.2–
127 20 N (8.13–813 kPa), allowing the measurement of human peak plantar pressure (Nandikolla et
128 al., 2017).
129 The sensors were placed on the heel, lateral midfoot, center of the midfoot, lateral forefoot, center
130 of the forefoot, medial forefoot, and big toe (Fig. 1). They were connected to a 12-bit resolution
131 data acquisition unit with a wireless data transmission sampling rate capacity of 100 Hz, allowing
132 real-time recording during normal ambulatory activities. Insoles with a similar configuration have
133 proven to be valid for the evaluation of posture and gait in previous studies (Saito et al., 2011;
134 Nakajima et al., 2014; Anzai et al. 2020). Multiple pairs of the insole in different sizes were
135 available.

136
137 ***Data collection***
138 The experimental protocol was approved by the Ochanomizu University research ethics committee
139 (#2018-01). A total of 17 female subjects signed written consents and participated in the trial (age:
140 26 ± 9 years old, weight: 49 ± 3 kg). All the participants were healthy and did not present mobility
141 disorders. The 7-sensor plantar pressure measurement insoles were inserted in a pair of commercial
142 sneakers (Vans Fable 2, VF Corporation) with stiff and flat midsoles. The insoles and shoes were
143 available from size 22 cm to 27 cm. The participants wore shoes and insoles that best matched
144 their foot size. They performed the following nine activities: sitting, standing, walking on a flat
145 surface, walking upstairs, walking downstairs, walking up a slope, running, cycling, and office
146 work (Table 1). The duration of each activity was approximately 4 min, except "walking on a flat
147 surface" and "running," which was approximately 8 min. The order in which the 9 activities were
148 completed was randomly selected for each subject. Eleven subjects completed the nine activities.
149 During the course of the experiment, certain subjects expressed a desire to shorten their
150 participation mainly owing to upcoming agenda conflicts, discomfort, or tiredness. Two subjects
151 completed eight activities, two subjects completed seven activities, one subject completed six
152 activities, and one subject completed five activities. For each subject, data for "walking on a flat
153 surface", "walking upstairs", "walking downstairs" and "running", respectively, may have been
154 stored in two files. The final dataset consisted of 196 files corresponding to the 140 activities
155 completed by the 17 subjects. Each file contained 14 independent plantar pressure time series
156 (seven sensors for each of the left and right feet).
157
158 ***Data preprocessing***
159 The raw data were converted into Newtons (N) and smoothed using a second-order low-pass
160 Butterworth filter with a cutoff frequency of 5 Hz. For each data file, the time series were cut in
161 windows of 1, 5, 10, 15, 20, 25, 30, 35, 40, 45, 50, 55, and 60 s, with an overlap of 50%.
162
163 ***Feature extraction***
164 For each window, 167 data features were extracted using the information from seven sensors on
165 each foot. The features were extracted from the different types of analysis presented in Table 2.
166
167 The features were grouped into the five following categories:
168 ● *General statistics analysis*: The mean, maximum, standard deviation, and median were
169 calculated for each time series. This category included 56 extracted features.
170 ● *Peak analysis*: The peak number, average and standard deviation (SD) of the interval between
171 peaks, average and SD of the peak magnitudes, and average and SD of the peak widths were
172 calculated for each time series using the SciPy library (Jones et al., 2001). The peak widths
173 were calculated at 30% of the peak height. The default parameters of the library were used for
174 the computation of all other features extracted from the peak analysis. This category included
175 98 extracted features.
176 ● *Gait phase analysis*: The envelope of the signal of the seven sensors was calculated for each
177 foot. For each identified full stance phase, the difference in the force peak yield between the
178 foot contact on the ground (early stance phase) and the foot lift (late stance phase) was
179 calculated and the values averaged over the window. The average duration of the double float
180 phase was also calculated or was set to the null value when such phase does not exist. Two
181 features were extracted in this category.

182   • *Frequency domain analysis*: The signal of the 14 sensors was summed up and a *fast Fourier*
183   *transform* (FFT) was conducted. Preliminary FFT analyses were conducted. The following 5
184   features were extracted from the AC component of the discrete frequency component series
185   (0.05–50 Hz) and included in the final analysis: 1) power density, 2) frequency signal weighted
186   average from 1.67–10 Hz, 3) skewness of the frequency components below 10 Hz, 4) mean of
187   the AC components from 2–10 Hz, and 5) standard deviation of the same segment. Events with
188   a frequency lesser than 2 Hz were assumed to be related to the gait cycle. Gait cycle-related
189   behaviors were expected to be described by the features extracted from the above described
190   *peak analysis*. Moreover, human movements are assumed to not exceed a frequency greater
191   than 10 Hz. Therefore, only the spectral signals at frequencies less than 10 Hz were considered
192   in the present analysis. Five features were extracted in this category.
193   • *Pressure distribution analysis*: The envelope of the signal of sensors 4, 5, 6, and 7, located in
194   the forefoot area (Fig. 1A), was computed. The difference between the mean of this new series
195   of data and the plantar pressures detected by sensor 1 (heel, Fig. 1A) was calculated for the left
196   and right feet. The difference was averaged to express the anterior–posterior distribution of the
197   plantar pressures. The difference between the mean of the plantar pressures detected by sensor
198   6 (head of the first metatarsal) and mean of the plantar pressures detected by sensor 4 (lateral
199   forefoot) were calculated for the left and right feet. The values were averaged to express the
200   medial–lateral distribution of the plantar pressures. Moreover, a Pearson correlation test was
201   used to test the 1) agreement between the envelope of sensor 4, 5, 6, and 7 signals and sensor
202   1 signal and 2) agreement between the signal of sensor 4 and that of sensor 6. These correlation
203   coefficients were calculated for both the left and right feet. Six features were extracted in this
204   category.
205
206 The final number of extracted features depended on the number of sensors included in the
207 processing (cf. paragraphs "Window length," "Number and location of sensors," "Number of
208 features").
209

210 ***Design of activity recognition algorithms***
211 In the present study, the smart-shoe activity prediction algorithms were developed using machine-
212 learning techniques. Data used as input included as many dimensions as the number of features
213 extracted, i.e., 167 when using the information from the seven sensors for each foot. Preliminary
214 processing including different machine-learning methods (e.g., k-means clustering, support vector
215 machine) indicated higher performances for the random forest models (results not provided). The
216 analysis presented in this manuscript focuses on the development of random forest models able to
217 process plantar pressure information for activity recognition. The machine-learning analysis was
218 completed using the Python scikit-learn module (Pedregosa et al., 2011).
219

220 "Forests" were made of 100 decision trees. Each tree in the forest produced an independent
221 prediction (here, an activity), and the mode of the predictions was chosen as the forest decision.
222 Each tree was constructed using a random subset of the dataset, according to the *bagging* method
223 described elsewhere (Breiman, 2001). During the construction process, the nodes were
224 successively split until all data points corresponded to the same activity; that is, until the tree's
225 *gini* impurity score was equal to zero. This configuration enabled each tree in the forest to output
226 one single prediction (also called a pure decision). Highly informative features could appear in
227 several trees and tended to appear in the nodes that were closer to the root of the trees. Conversely,

228 features with poor discriminating capacities appeared in less nodes across the entire forest (Fig. 2
229 and Supplementary Material 1).
230
231 For the training, the data of six subjects (i.e., approximately 33% of the dataset) were used under
232 five different subject-wise assignments (Fig. 3). At the training stage, only the data of the subjects
233 who completed the nine activities were used. A total of 20 training-test runs were performed for
234 each assignment, with each run using different random subsets of the dataset (hereafter called
235 "random states"). For the testing process, the generated random forest modules evaluated the data
236 of the remaining 11 subjects. The results averaged across all five assignments (i.e., across 100
237 forests), were presented as confusion matrices of the predictions vs. actual activities. The results
238 were also presented as mean (minimum, maximum) when summarizing the overall performance
239 across all activities. All the results presented in this manuscript correspond to the outcome of the
240 evaluation of the random forest modules using the test samples only. None of the reported scores
241 are related to the training phases.
242
243 ***Data analysis framework***
244 As illustrated in Figure 4, the analyses are integrated in a 3-stage logical flow.
245 1) The window length analysis aims at identifying the optimum analytic window length.
246 2) The analysis of a pre-selected set of 25 sensor configurations, i.e. configurations using the
247 information of different numbers of sensors and/or the information of sensors placed at
248 different locations, aims at identifying the best hardware combination for each possible number
249 of sensors ranging from 1 to 6 (the 7-sensor configuration only has 1 possible combination).
250 This analysis was conducted using the optimum window length identified in 1).
251 3) A final analysis exploring the contribution of each feature to the forest outputs aims at finding
252 the most efficient number of features to be used for each of the seven best sensor configurations
253 identified in 2). Again, this analysis was conducted using the optimum window length
254 identified in 1).
255 Further details related to each of the three stages are given in the three following subsections.
256
257 ***Stage 1: window length***
258 The described analysis was performed for different window lengths (1, 5, 10, 15, 20, 25, 30, 35,
259 40, 45, 50, 55, and 60 s) using the data of the seven sensors per shoe with each data point having
260 167 dimensions corresponding to the maximal number of data features that were possible to
261 extract. The optimum window length was defined at the point where the slope of the function
262 describing the prediction rate vs. window length began to decrease. This optimum window length
263 was used for all subsequent analysis.
264
265 ***Stage 2: number and location of sensors***
266 The processing was repeated from scratch for different sensor configurations, i.e., different
267 location and/or number of sensors, for the optimal window length only. Twenty-five
268 configurations were selected among the 127 possible combinations of sensors. The selection was
269 performed using subjective criteria: 1) reproduction of a selection of the configurations found in
270 the literature or in the industrial sector of running shoes, 2) selection of combinations allowing the
271 collection of relevant information for the prediction of gait and postural behaviors, and 3) selection
272 of combinations that are believed to miss some pieces of relevant information for the prediction of
273 gait and postural behaviors (Fig. 4). Seventeen configurations were selected with respect to criteria

274   1) and 2). These configurations were expected to perform well. Eight configurations were selected
275   with respect to the criterion 3). These configurations were expected to perform poorly. The number
276   of dimensions of the data points decreased in accordance with the decreased number of sensors.
277   For certain configurations with the same number of sensors, the data points present different
278   numbers of dimensions. Indeed, as indicated in Table 2, some features may need specific sensor
279   locations to be computed. All the tested configurations are noted in Figure 4.
280
281   *Stage 3: number of features*
282   The processing was again repeated from scratch with the best configurations only and for a
283   decreasing number of features, which were removed one-by-one based on their discriminating
284   capacities (Fig. 4). For each sensor configuration, the analysis was performed with the maximum
285   number of available features (similar to what was performed for the previous process, cf. paragraph
286   "Number and location of sensors"). Features were ranked relative to their discriminating
287   capacities, i.e., from the highest to lowest informative feature, across the 100 runs of the analysis
288   (five assignment × 20 random states, cf. "Prediction algorithm: training and test"). The lowest
289   informative feature was removed from the dataset, and a new repetition of training-test runs was
290   performed. The entire process was repeated until only one feature remained. The minimum number
291   of features corresponding to the inflection point for the prediction rate vs. number of the feature
292   was considered to be the optimum number of inputs. A total of 686 combinations of sensor
293   configurations and number of features were tested (i.e. best 1-sensor: 29, best 2-sensor: 54, best 3-
294   sensor: 76, best 4-sensor: 98, best 5-sensor: 120, best 6-sensor: 142, 7-sensor: 167).
295
296

297   # Results
298   The "prediction rates" and "rates of good predictions" presented in the text and figures refer to the
299   accuracy, calculated as follows: correctly predicted sample/total number of samples. When
300   reporting statistical results, the terms "average" and "mean" point to the average accuracy across
301   the 100 forests of one round of evaluations (see Fig. 3). The expressions "best single forest" and
302   "best performer" refer to the one single forest that showed the best accuracy score among the 100
303   forests produced for one round of evaluations. Conversely, the term "worst single forest" points to
304   the one single forest that showed the worst accuracy score among the 100 forests produced for one
305   round of evaluations. Logical links between the 3 stages of the analysis are shown in Fig. 4. The
306   values indicated at the intersections of "true label" and "prediction" in the confusion matrices refer
307   to sensitivity, calculated as follows: true positives/(true positives + false negatives).
308
309   *Stage 1: window length*
310   The average performances of the 7-sensor configuration tested at different window lengths (1, 5,
311   10, 15, 20, 25, 30, 35, 40, 45, 50, 55, and 60 s) are presented in the Fig. 5. The full set of 167
312   features was used for all tests. The best prediction rate was obtained with a 45-s window length:
313   0.90 (min: 0.86, max: 0.91). A 20-s length was associated with an average of 0.89 (min: 0.82, max:
314   0.91). The average prediction rates for window lengths between 20-60 s showed marginal
315   variations within the 0.89-0.90 range. To preserve the highest possible temporal resolution for
316   future applications, 20 s was selected as the optimum length. The rest of the analyses were
317   conducted using a 20-second window length.
318

319   As indicated in Fig. 6, "walking up a slope" could be confused with "walking on a flat surface" or
320   "walking upstairs." Confusions between "walking upstairs" and "walking downstairs" and
321   between "standing" and "office work" were noted to a certain extent depending on the window
322   length.
323
324   ***Stage 2: number and location of sensors***
325   The average performances of a subset of 25 selected sensor configurations are presented in Fig. 7.
326   For each configuration, the analyses were performed using all the available features. The best
327   average prediction rate was 0.89. In addition to the 7-sensor configuration, this rate was observed
328   for the four following configurations:
329   ● 6 sensors, 145 (heel, lateral midfoot, lateral forefoot, medial forefoot, center of the midfoot,
330   center of the forefoot): 0.89 (min: 0.82, max: 0.92)
331   ● 6 sensors, 142, (heel, lateral midfoot, lateral forefoot, big toe, center of the midfoot, center of
332   the forefoot): 0.89 (min: 0.83, max: 0.91)
333   ● 5 sensors, 120 features (heel, lateral midfoot, lateral forefoot, center of the midfoot, and center
334   of the forefoot): 0.89 (min: 0.85, max: 0.92)
335   ● 4 sensors, 98 features (heel, lateral midfoot, lateral forefoot, center of the forefoot): 0.89 (min:
336   0.85, max: 0.92)
337
338   Regarding the best performers, selected forests achieved a prediction rate of 0.92. This result was
339   obtained with a 3-sensor configuration only (heel, lateral midfoot, center of the forefoot). All
340   selected configurations with at least two sensors produced an average rate of good predictions of
341   0.80 or more. All the configurations with at least five sensors produced an average rate of good
342   predictions of 0.85 or more. All the configurations with at least two sensors, which were expected
343   to perform well, produced an average rate of good predictions of 0.87 or more. Certain forests with
344   one sensor located at the center of the forefoot could compute prediction rates as high as 0.86. The
345   mean and maximum rates of good predictions of a larger panel of 67 selected configurations are
346   presented in Supplementary Material 2.
347
348   The confusion matrices presented in Fig. 8 and 9 indicate the sensitivity score of each activity, for
349   the best and worst 1-, 2-, 3-, 4-, 5-, and 6-sensor configurations. Among the best sensor
350   configurations, the decrease in the average prediction rate observed when reducing the number of
351   sensors from two to one might be explained mainly by the higher levels of confusion between
352   "sitting" and "standing" and between "walking downstairs" and "walking upstairs." For example,
353   the best 1-sensor configuration wrongly predicted "walking upstairs" instead of "walking
354   downstairs" in 36% of the cases. Among the worst configurations, the decrease in the average
355   prediction rate observed when reducing the number of sensors from four to three could be
356   explained mainly by a decrease in sensitivity for "cycling" (0.91 and 0.80).
357
358   ***Stage 3: number of features***
359   The changes in performance of the seven selected configurations when decreasing, one-by-one,
360   the number of features used for the prediction are displayed in Fig. 10. For these configurations,
361   the mean rate of good predictions increased from an average 0.46 ± 0.03 when using one feature
362   to 0.87 ± 0.04 when using a set of 20 high performance features. Using 20 features only, all the
363   selected configurations demonstrated a mean rate of good predictions greater than 0.85, with the
364   worst single forest scoring at 0.81 (2-sensor configuration), except for the 1-sensor configuration,

365 which demonstrated a rate of 0.78 (min: 0.72, max: 0.83). The data are presented in Supplementary
366 Material 2. The overall performance remained constant when the predictions were computed with
367 more features. The mean rate of good predictions exhibited an average of 0.87 ± 0.04 when
368 considering computations performed using the maximum number of available features, i.e., 29,
369 54, 76, 98, 120, 142, and 167, respectively, for the selected 1-, 2-, 3-, 4-, 5-, 6-, and 7-sensor
370 configurations.

372 Considering a 20-feature cut-off below which features became increasingly important, 44
373 important features were identified over the 20–140 alternatives enabled by the seven selected
374 configurations (Fig. 11). Seven features systematically ranked among the 20 most important
375 features of the seven selected configurations: average peak interval of the left foot heel sensor
376 (peak analysis), average peak magnitude of the right foot heel sensor (peak analysis), mean of the
377 AC component (frequency domain), number of peaks for the right foot heel sensor (peak analysis),
378 number of peaks for the left foot heel sensor (peak analysis), standard deviation of the left foot
379 heel sensor plantar pressures (general statistics), and standard deviation of the AC component
380 (frequency domain). Among the 44 important features, 24 belong to the "peak analysis" category,
381 16 to the "general statistics" category, 3 to the "frequency domain" category, 1 to the "gait phase"
382 category, and 0 to the "pressure distribution" category. Regarding the 7-sensor configuration only,
383 the features related to the heel and central forefoot were identified five times. No feature directly
384 extracted from the analysis of the big toe pressure ranked among the set of important features.

386 The best 1-sensor configuration (heel sensor) using the single most informative feature
387 demonstrated a mean rate of good predictions of 0.43 (min: 0.41, max: 0.44). Only the "running"
388 and "sitting" activities demonstrated a sensitivity score greater than 50% (Fig. 12). As indicated
389 in Fig. 12, the other selected sensor configurations were associated with sensitivity scores of 82%
390 or more for all activities except "office work," "walking up a slope," and "walking upstairs," when
391 using a limited number (i.e., 9–23) of features. Regarding the 7-sensor configuration specifically,
392 the confusions noted when using the 23 most informative features (Fig. 12) were similar to the
393 ones noted when using the full number of available features (Fig. 6D), except for "walking
394 downstairs," which had a better sensitivity (0.92 vs. 0.84) when using 23 features only. That
395 phenomenon can be explained by the greater difficulty to fit a classifier with a higher number of
396 dimensions. In theory, the same performance should be attainable with more features, at the risk
397 of overfitting the system and decreasing its generality (performance on unknown data) (Lever,
398 Krzywinski & Altman, 2016). Confusion matrices of some selected single forests produced with
399 the best 4-sensor configuration are presented in Fig. 13. A low performance single forest with a
400 relatively high number of features (49 over a maximum of 98 available) was associated with low
401 sensitivity scores for the "office work," "walking downstairs," and "walking up the slope"
402 activities (0.74, 0.61, and 0.56, respectively), consistent with the pattern that has been frequently
403 found on confusion matrices, as displayed in Fig. 6, 8, and 9. Interestingly, the worst single forest
404 among the ones built with 29 features only had the highest sensitivity for the "walking up the
405 slope" activity (0.70). Finally, confusion matrices of the best single forests built with 86 and 22
406 features demonstrated a similar pattern of missed predictions, with "office work" and "walking up
407 the slope" being relatively poorly recognized (<0.85 and <0.65, respectively).

409 ***Supplementary results***

410 A more comprehensive analysis has been conducted considering a larger panel of 67 sensor
411 configurations. Random forest modules were systematically created and tested for each window
412 length candidates (1-60 s) and each possible number of features (maximum to one), without any
413 selection of the best sensor configurations like in the 3-stage data processing flow presented in
414 Fig. 4 (the results of which have been presented in the above three subsections). The machine
415 learning procedure was the same as the one detailed in the method section. Therefore, 75,172
416 additional analyses have been completed, resulting in the computation of 7,517,200 forests.
417 These supplementary analyses were associated with higher prediction scores, highlighting the
418 whole potential of using plantar pressure data for the recognition of physical behaviors. As shown
419 in the Supplementary Material 3, 297 sensor configurations were associated with at least one forest
420 presenting a prediction score of 0.92 or more. Regarding the highest scores, at least 12 forests
421 presented a rate of good predictions of 0.94. The best average scores ranged from 0.54 to 0.91, a
422 scale similar to the one of the results of the 3-stage analysis (Supplementary Material 2). Eighty-
423 seven sensor configurations were associated with average rates of good predictions of 0.90 or
424 more. As shown in Supplementary Material 4B, the best performances observed in these analyses
425 are systematically associated with window lengths of 30 s or longer. Regarding the identification
426 of an optimum analytic window length, the results still points to a period of 20 s (Supplementary
427 Material 4A). The question of the time resolution is discussed later in the manuscript. The results
428 of these supplementary analyses are summarized in Supplementary Material 3 and 4.
429
430

431 **Discussion**
432 In the present study, homemade smart shoes mounted with seven pressure sensors were used to
433 collect plantar pressures during nine daily life activities. From the plantar pressure data, 167
434 features bearing a potential interest for the characterization of gait and posture were extracted.
435 Random forest models using subject-wise training-test assignments were utilized to develop smart-
436 shoe activity recognition algorithms. A 20-s window length was identified as the optimal period
437 for the extraction of the features. Forests could recognize activities at an average rate of good
438 predictions of 0.89, with certain single forests demonstrating a rate as high as 0.92. Reducing the
439 number of sensors to two (heel and lateral forefoot) and selecting 20 high performance features
440 maintained the average rate of good predictions above 0.85.
441

442 *Performances*
443 Smart shoes in their maximal configuration (i.e., 7 sensors per foot and 167 features extracted from
444 the collected plantar pressures) allow random forest modules to recognize activities at a rate of
445 good predictions of 0.89 (min: 0.82, max: 0.91). Each single activity was associated with a
446 sensitivity score of at least 0.87, except "office work" and "walking up a slope," which presented
447 lower scores (0.80 and 0.63, respectively) (Fig. 6B). "Office work" was confused with "standing"
448 in 18% of cases. The latter is not surprising considering the content of the "office work" activity,
449 which includes a considerable number of tasks realized in the standing posture. Numerous subjects
450 consumed a significant amount of time writing and erasing notes on a white table board while
451 performing the "office work"-labelled activity. This could have created this confusion with the
452 "standing" activity. Moreover, poor predictions involving the "walking up a slope" activity being
453 confused with "walking upstairs" or "walking on a flat surface" was a recurrent issue of the present
454 analysis. This type of confusion occurred regardless of the sensor configuration or the number of
455 features used as input. Depending on the field of application, several of the above-mentioned

456 confusions could have marginal or significant consequences on the final evaluation of physical
457 behaviors. Future smart-shoe studies should also consider extracting data features that are more
458 likely to report on slope-related gait alterations.
459
460 Conversely, random forest module outcomes indicated only a small number of confusions for the
461 "cycling," "running," or "sitting" activities. Although "running" and "sitting" are typically well
462 recognized in research protocols that use accelerometer sensors, which remain the current primary
463 hardware choice for activity trackers (Pavey et al., 2017; Trost, Zheng & Wong, 2014; Voicu et
464 al., 2019), the recognition of "sitting" behaviors has actually proven technically challenging in
465 real-life conditions (Kerr et al., 2018). Extrinsic behavioral factors, such as people leaving their
466 tracking device to charge when they are resting or sitting, render the assessment of sedentary
467 behaviors even more difficult. In the present study, smart shoes demonstrated high level of
468 sensitivity for "sitting" (0.96 or more for any of the selected configurations with at least two
469 sensors) and low level of confusion with the other sedentary activity (i.e., "standing," (0.00–0.01),
470 except for some 1- and 2-sensor configurations). Such outcomes should be considered as
471 promising for the monitoring of sedentary behaviors outside the house.
472
473 Finally, differences were noted among the single forests for the performance in each activity. For
474 example, one forest tagged with a low overall performance displayed in Fig. 13 performed
475 surprisingly well for the recognition of the "walking up a slope" activity. However, this enhanced
476 performance would appear to be possible at the expense of an altered sensitivity for other activities.
477 This may reflect the capacity of random forest modules to specialize for one given type of activity.
478 Further analyses, which are beyond the scope of the present report, would be necessary to identify
479 the "ins and outs" of forest specialization and determine if the random forest method could be
480 adapted to the specific case of smart shoes to obtain more homogenous recognition rates across
481 activities. For example, forests with a higher number of trees or hierarchical models assigning data
482 points to sub-classes before proceeding to the final evaluation could be considered for future
483 studies.
484

Comparison with previous studies and originality

486 Several reviews have summarized the outcomes of studies interested in the validity of instrumented
487 insoles developed for activity recognition (De Pinho André, Diniz & Fuks, 2017, Ngueleu et al.,
488 2019). Similar to the observations in the present research, specific studies have reported excellent
489 performances, with rates of good predictions scoring frequently over 0.90. However, they can also
490 be linked with experimental limitations, altering the generalization of the results, such as a small
491 number of tested activities, small number of subjects, special groups of individuals, and training-
492 test procedures completed separately for each subject. Moreover, the majority of these studies have
493 used hardware with multi-sensing capabilities. Hegde et al. (2017) developed the SmartStep
494 system, which featured three pressure sensors, one 3-axis accelerometer, and a gyroscope. The
495 pressure sensors were placed at the heel, first metatarsal head (i.e., equivalent to the medial
496 forefoot), and big toe. They tested the activity recognition capabilities of the SmartStep system for
497 a wide range of daily life activities. Similar to the present report, they observed an average rate of
498 good prediction of approximatively 0.90. They also reported recurrent mis-predictions for
499 "walking downstairs" (0.62), which is frequently confused with "walking on a flat surface" and
500 "walking upstairs" and for "shelving items" (0.61), the description of which resembles the "office
501 work" activity of the present study, and which is frequently confused with "standing." Smart shoe-

502 based activity recognition projects appear to be associated with redundant challenges related to
503 ascending and/or descending locomotive activities and activities combining locomotive and non-
504 locomotive behaviors. Moreover, in another recent study, el Achkar et al. (2016) used a simple
505 decision tree classifier to achieve excellent rates of good predictions for nine activities, including
506 "walking downstairs" (0.98), "walking upstairs" (0.99), and "walking uphill" (0.96). However,
507 their smart-insole system featured a barometer in addition to eight pressure sensors, one 3-axis
508 accelerometer, one 3-axis gyroscope, and one 3-axis magnetometer, which surely helped the
509 assessment of ascending and/or descending locomotive behaviors.
510
511 According to Ngueleu et al. (2019), smart shoe-based activity recognition studies that only use
512 plantar pressure information are limited. Although some of these studies reported acceptable
513 performance, protocols were typically limited to a small number of locomotive behaviors (Zhang
514 et al., 2005; Zhang, Poslad, 2014), small number of subjects, or training-test procedures completed
515 separately for each individual (Sugimoto et al., 2010). Therefore, the present research provides
516 important findings to the relatively small corpus of knowledge on plantar pressure-based activity
517 recognition. Other originalities of the present research include the use of a random forest modeling
518 method to develop different activity classifiers and a comparison of different sensor configurations
519 (number and location) within one single experimental protocol.
520

521 ***Temporal resolution, sensor configuration, number of features, manufacturing, and***
522 ***algorithmic considerations***
523 Although windows of 30 and 45 s were linked with better performances for the recognition of
524 "office work" and "walking up a slope", overall, the performances were consistent across all
525 analyses performed with a window size of 20 s or longer (Fig. 6 B, C, and D). In real-life situations,
526 a short window length reduces the probability of overlapping activities over the span of one
527 analytic period. Therefore, a 20-s length with a 50% overlap between windows was selected as the
528 optimum window length. It allowed computing predictions every 10 s. Considering future
529 applications, this relatively high temporal resolution would allow applying a second statistical
530 algorithmic layer consisting of comparing the prediction of one given window with the ones of its
531 neighbors (Witowski et al., 2014). This would provide the opportunity to have a set of six "instant"
532 predictions to determine the dominant behavior every minute. Further explorations that include
533 free-living experiments are necessary to elaborate further on the issue of temporal resolution.
534
535 One interesting finding of the present study is the marginal alteration of the overall performance
536 obtained with a reduced number of sensors. Although configurations without the heel sensor
537 systematically present lower performances, other configurations that include at least two sensors
538 demonstrate average rates of good predictions of 0.87 or more (Fig. 7). The absence of a heel
539 sensor appears to worsen confusions between ascending and descending activities and between
540 "office work" and "standing" (Fig. 8 and 9). Using one sensor only, the average rates of good
541 predictions declined below 0.80. Furthermore, marginal variations of the overall performance were
542 noted when reducing the number of features down to approximately 20 (Fig. 10). The reduction of
543 the number of features given to the forests was accomplished in a manner that favored the most
544 contributive features. Extracts from the FFT and peak analyses were redundant in the lists of 20
545 important features (Fig. 11). However, this result could also be the mere reflection of the higher
546 number of gait activities included in the present protocol, which all present cyclic plantar pressure
547 patterns. Therefore, future studies should include a more balanced number of locomotive, non-

548   locomotive, and mixed activities to determine whether this trend is confirmed or not. Moreover,
549   no feature extracted directly from the big toe sensor ever scored among the 20 most important
550   features. This location may not be relevant for smart-shoe prototypes aimed at behavior
551   recognition. Although the 167 data features were selected to be as comprehensive as possible and
552   to accommodate the analysis on the reduction of the number of sensors, the list of potentially
553   informative features is not closed. Future studies could propose extracting different features to
554   boost the performance on a similar or different subset of activities. With respect to the above-
555   discussed results, shoe manufacturers willing to develop activity recognition devices should
556   probably consider the opportunity to implement a minimalist sensor configuration instead of the
557   full 7-sensor configuration. They should also consider the relevance of using an exhaustive number
558   of features, whereas a subset of 20 features has been demonstrated to perform equally well. All
559   these considerations will influence shoe design (relative to the location of sensors and other
560   hardware), microprocessor selection (relative to the computational needs), and, ultimately, the
561   financial cost of the device (Eskofier et al., 2017).
562
563   ***Limitations and strengths***
564   Some characteristics of the present protocol could limit the interpretation of the results presented
565   in this report and should be mentioned clearly for the readers. First, the current protocol only
566   includes nine different daily life activities. This number puts the study among smart-shoe protocols
567   testing a large sample of activities (Ngueleu et al. 2019). The challenges related to the recognition
568   of activities that potentially present closed plantar pressure patterns are addressed in an adequate
569   manner. However, a larger number of activities should be studied in the future to reflect more
570   exhaustively physical behaviors of the daily life, e.g., sport activities and a wider panel of activities
571   combining locomotive and non-locomotive behaviors. Second, the experimental design does not
572   include further validation of forest performances in real-life situations. Similarly, no comparison
573   with commercial activity monitors was performed. Future protocols should include a free-living
574   validation to increase the generalization of the results to real-life situations. Third, the present
575   protocol includes a relatively homogenous population. Subjects were all healthy women. To
576   address this potential issue, five different subject-wise training–test assignments were used to
577   develop and test the forests. In addition, a conservative 6-11 training-test assignment ratio has been
578   used to limit the wealth of the available information during the training phase and create more
579   challenging conditions relying on inter-individual differences. However, a more heterogeneous
580   sample of the population must be tested before generalizing further the results of the present study.
581   A more heterogeneous population would indeed provide a more diverse information to the training
582   algorithms, which could also result in increased good prediction scores. Overall, given the
583   homogeneity of the population used in the present study, one should exercise caution when
584   interpreting the results. The best configurations identified in the present study could differ from
585   one population to the other. Designers are therefore encouraged to select a subject sample large
586   enough to be representative of the targeted population and provide the wealthiest possible
587   information to the machine learning algorithms. Finally, the present work does not address the
588   question of a multi-sensing environment. Given that alternative sensing options could already be
589   embedded in other type of devices (e.g., activity trackers, smartphones), one could consider that
590   smart shoes should primarily specialize in the collection of information on the foot–ground
591   interaction. The present protocol allows focusing on the sole performance of plantar pressure-
592   based activity recognition to assess the relevance of including smart shoes in a network of devices
593   dedicated to physical activity evaluation (Chen et al., 2016, Eskofier et al., 2017).

594
595

Conclusions

596 In this work, random forest modules as behavior recognition algorithms for plantar pressure
597 measurement using smart shoes were explored and proved relevant. Indeed, smart shoes mounted
598 with seven pressure sensors and extracting 167 plantar pressure data features could recognize nine
599 different daily life activities with an average of good prediction of 0.89. Interestingly, the results
600 suggest a marginal reduction of performance for configurations downgraded to two, three, four,
601 five, or six sensors and the computation of approximately 20 plantar pressure data features, which
602 could ease the design and manufacturing of smart-shoe products. Future studies are necessary to
603 generalize the present findings to a larger sample of the population and larger number of behaviors.
604 Considering the trend toward the development of wearable devices with 5G capacities, smart shoes
605 could become a crucial element of systems allowing self-monitoring of physical activity, thus
606 having an important role in promoting active and healthy lifestyles.
607
608
609

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610
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613
614

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751

Figure 1

Figure 1. Overview of the smart-shoe prototype and the output.

(A) Pressure sensor location. (B) External view of prototype during experiment with data acquisition system and Bluetooth data transmission unit attached on outside of shoes. (C) Example of raw data time series for the left and right feet at a window of 30 s (activity: walking on a flat surface).

A

1. Heel
2. Lateral midfoot
3. Center of midfoot
4. Lateral forefoot
5. Center of forefoot
6. Medial forefoot
7. Big toe

B

C
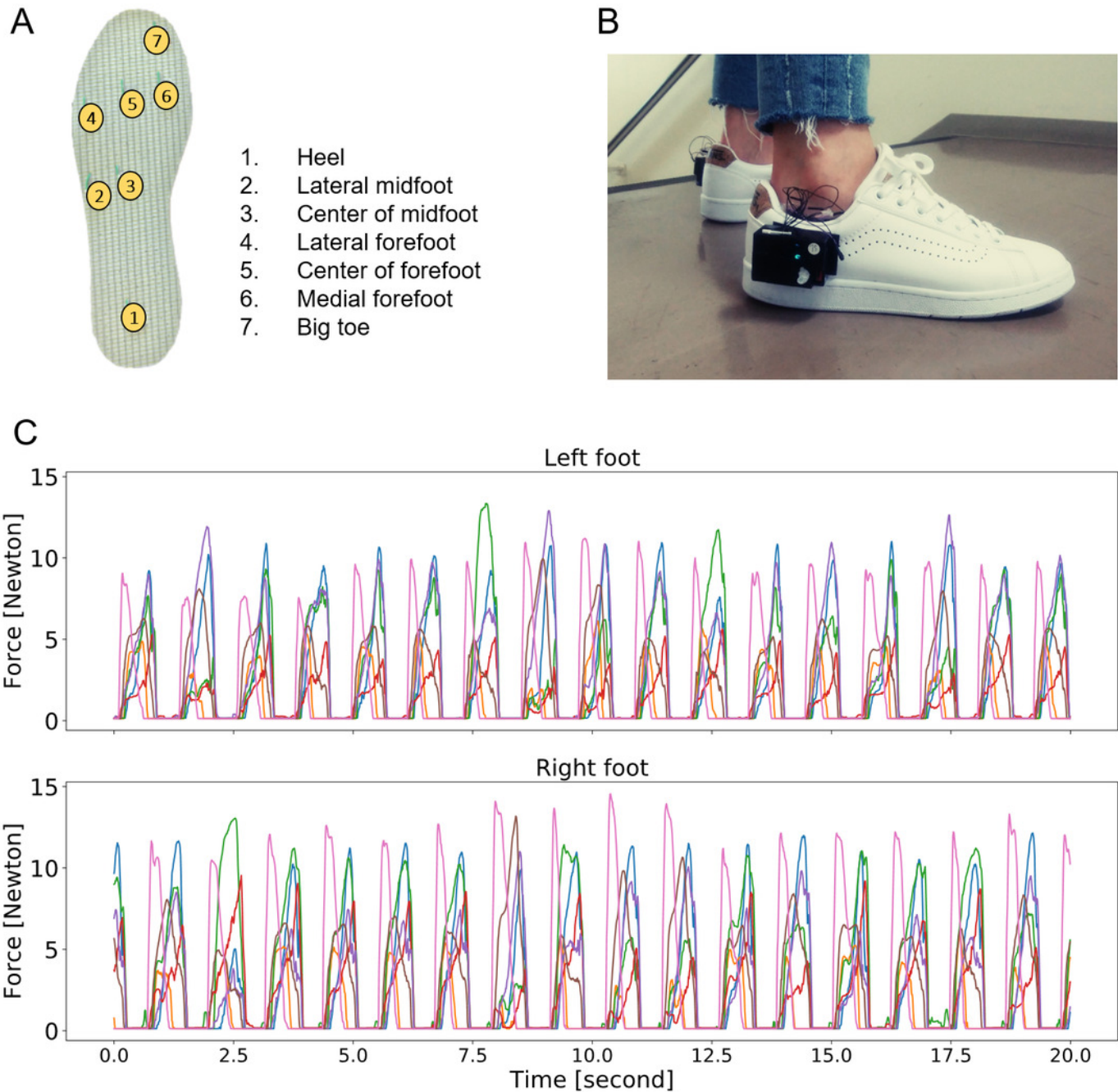
Figure 2

Figure 2. Example of branches for one selected decision tree.

Zoom view on a selected branch of one regression tree of one selected forest. During the training process, the nodes (diamonds) are split until all data points correspond to one activity. At each node, the decision is based on the parameter that best discriminates the sample into two sub-samples. The process is repeated until the generation of a pure offspring, i.e., leaves (rounded corner rectangles) containing the data points of one given activity only. The full tree is available in the Supplementary Material 1 (window length: 20 s, configuration: seven sensors, assignment: 1, run: 1).
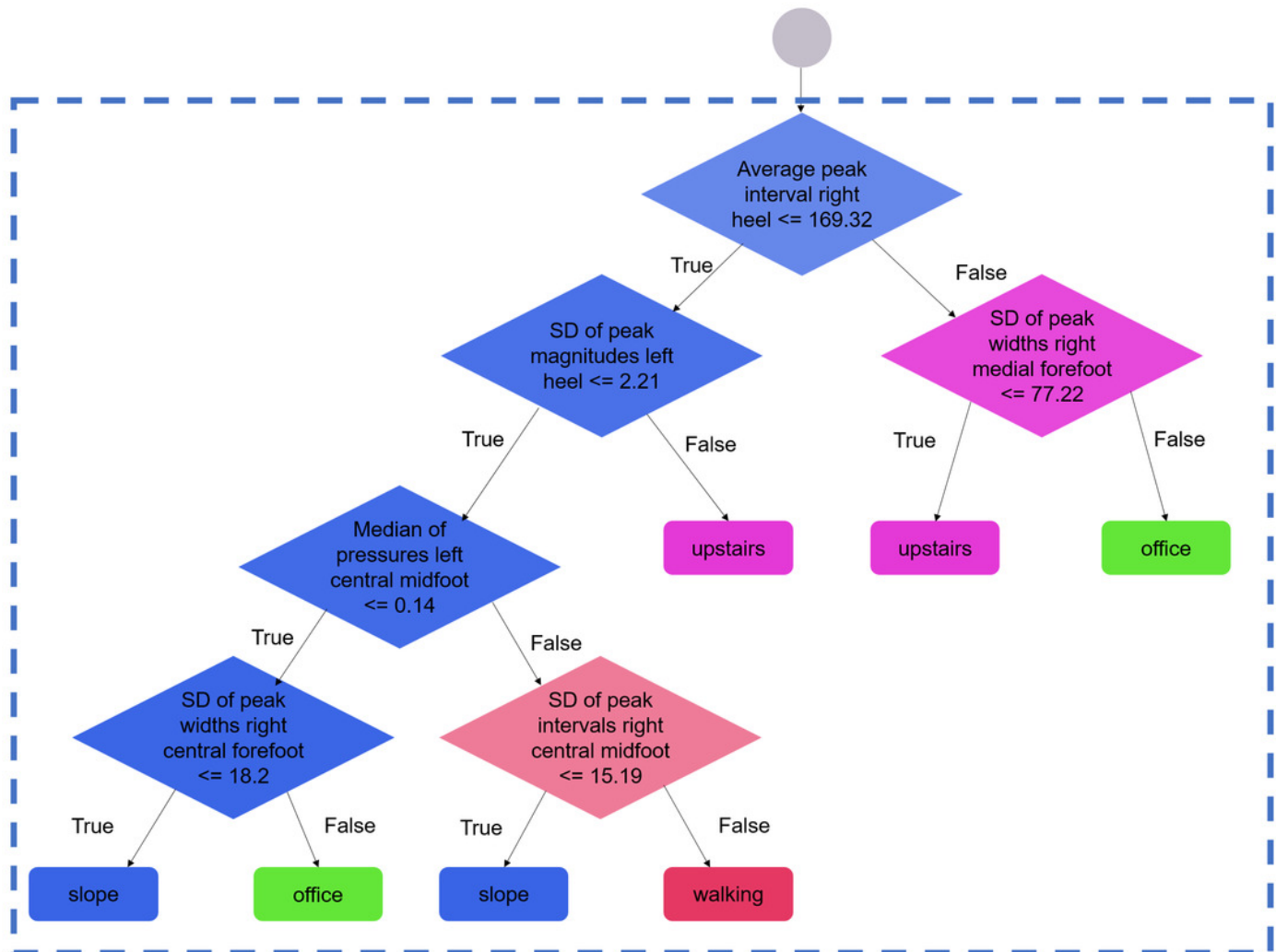
Figure 3

Figure 3. Overview of the machine-learning procedure.

Training-test ratio: 6-11 (subject-wise). Testing method: multi- hold-out (data assigned to 5 different training-test combinations). For each assignment, 20 runs are conducted using different random subsets of the data set (or "random states"). Blue: training samples. Salmon: test samples.
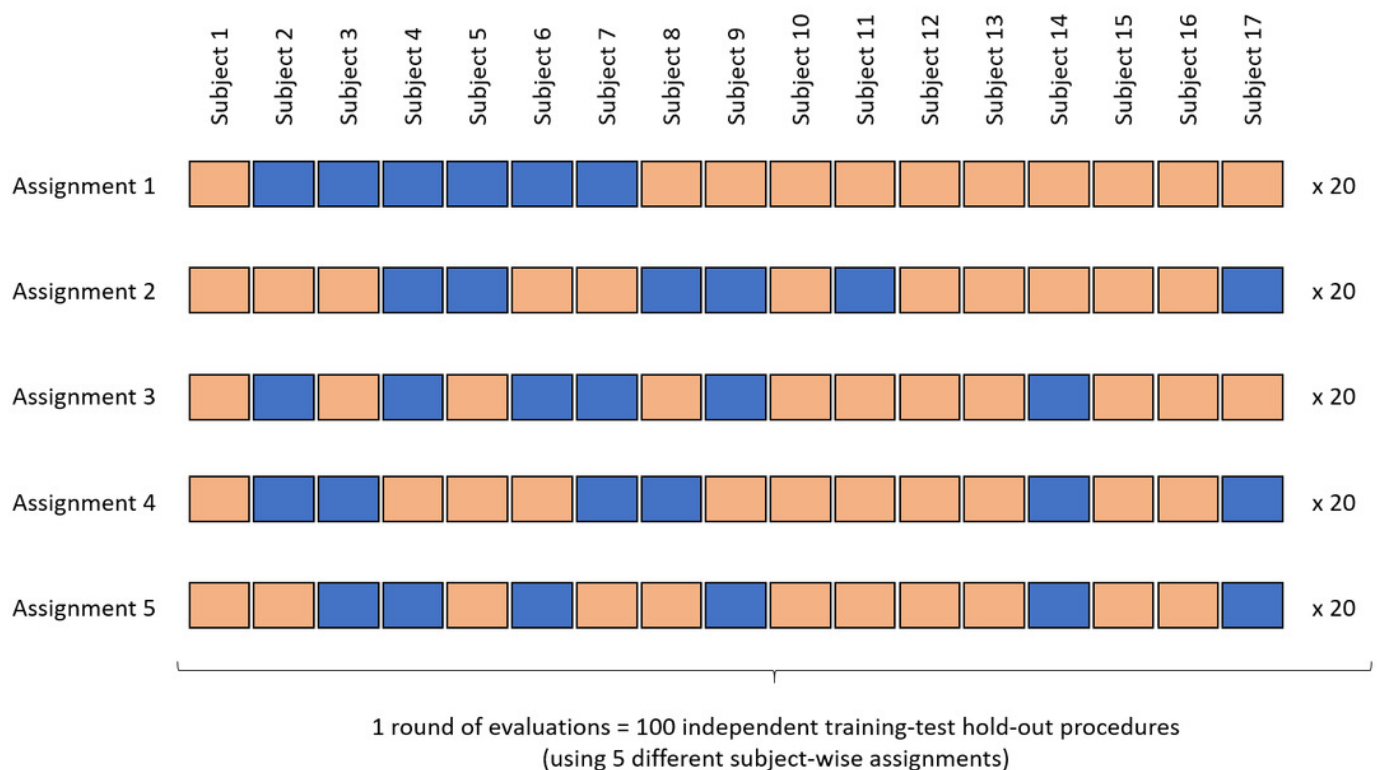
Figure 4

Figure 4. Chart of the 3-stage data processing flow.

Stage 1: "window length". Stage 2: "number and location of sensors". Twenty-five configurations were selected among the 127 possible combinations of sensors (see. "Materials & Methods", "Stage 2: number and location of sensors"). Some of these configurations were expected to perform well (green bars). Some of these configurations were expected to perform poorly (pink bars). Stage 3: "number of features". The orange/dotted connectors indicate the logical links between each stage of the analysis.

Stage 1: "window length"

AIM
→ *Selecting the optimum window length*

METHOD
- *Number of sensor configurations* : 1
  7 sensors

- *Number of features* : 167 (maximum)
- *Number of window lengths*: 13 (1 – 60 seconds)
→ ***Number of analyses: 13***

RESULTS
- *Optimum window size =* ***20 seconds***
→ *The rest of the analysis is performed using window lengths of 20 seconds.*

Detailed results: Fig. 5 and 6

Stage 2: "number and location of sensors"

AIM
→ *Identifying the best sensor combination for each possible number of sensors ranging from 1 to 6.*

METHOD
- *Number of sensor configurations* : 25

1 sensor   2 sensors   3 sensors

4 sensors   5 sensors

6 sensors   7 sensors
Only one possible combination (identical to stage 1)

- *Number of features* : maximum number of features for each sensor configuration (1-sensor: 29/29; 2-sensor: 54/54/54/51 ; 3-sensor: 76/76/76/73; 4-sensor: 98/101/98/101 ; 5-sensor: 120/123/123/123/120/120 ; 6-sensor: 142/145/145/142; 7-sensor: 167)
- *Window length* : 20 seconds only
→ ***Number of analyses: 25***

RESULTS
- *Best sensor configurations (one configuration selected for each number of sensors):*

→ *The rest of the analysis is performed using the above sensor configurations.*

Detailed results: Fig. 7, 8 and 9

Stage 3: "number of features"

AIMS
→ *Identifying the most important features*
→ *Identifying an efficient number of features*

METHOD
- *Number of sensor configurations* : 7
- *Number of features* : maximum → 1

29 (max) ↓ 1 54 (max) ↓ 1 76 (max) ↓ 1

98 (max) ↓ 1 120 (max) ↓ 1 142 (max) ↓ 1

167 (max) ↓ 1   identical to stage 1 and 2

- *Window length* : 20 seconds only
→ ***Number of analyses: 686***

RESULTS
Detailed results: Fig. 10 ,11, 12 and 13

Figure 5

Figure 5. Window length effect on activity recognition rate.

The tests were completed using the full set of 167 features available for a configuration of seven sensors per shoe and for selected window lengths. Pink boxes: 1, 5, 10, and 15 s. Green box: 20 s (considered optimum). Yellow boxes: 25, 30, 35, 40, 45, 50, 55, and 60 s. Red diamonds: mean values.
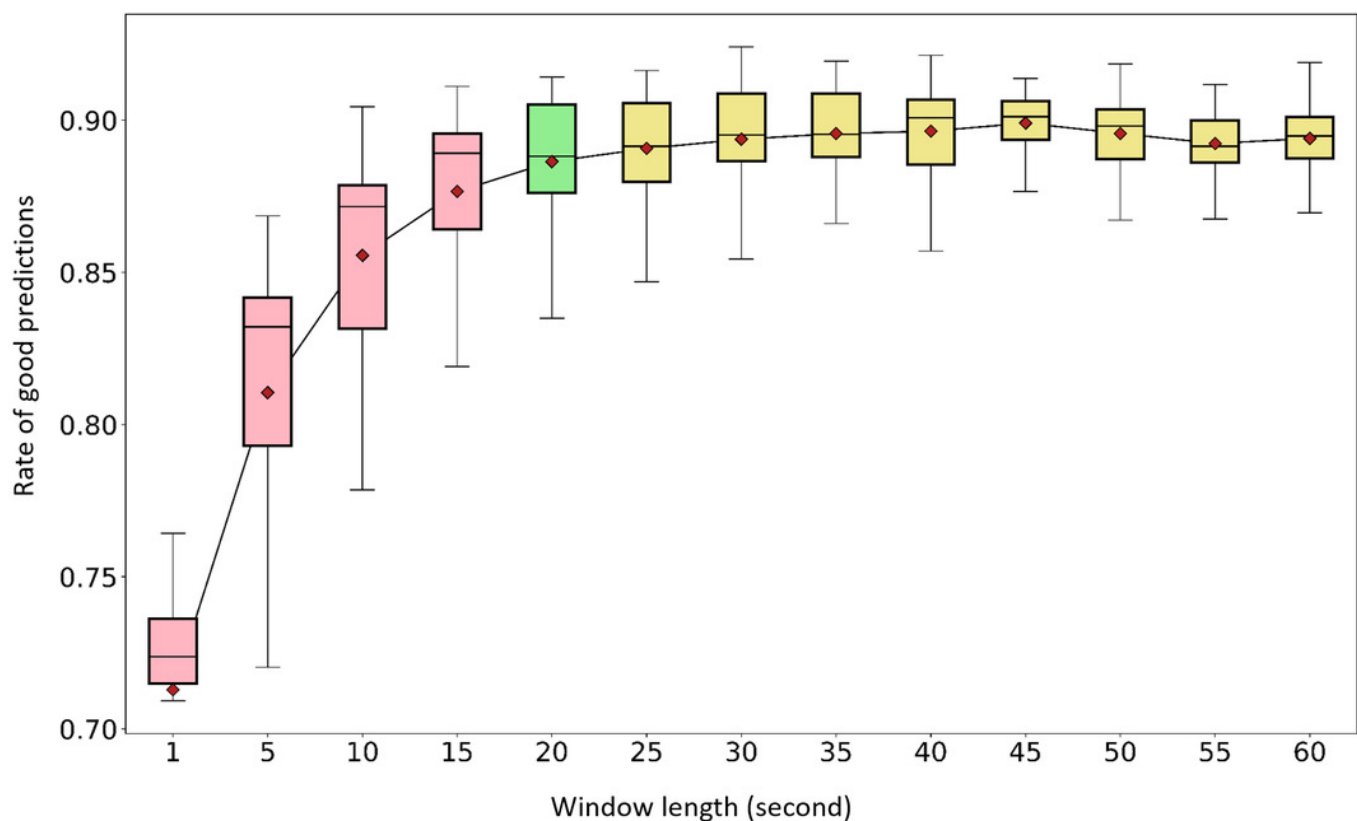
Figure 6

Figure 6. Confusion matrices for four selected window lengths.

Normalized sensitivities are averaged for each activity across the 100 forests. (A) 1-s window length. (B) 20-s. (C) 30-s. (D) 45-s. The tests were completed using the full set of 167 features available for a configuration of seven sensors per shoe.
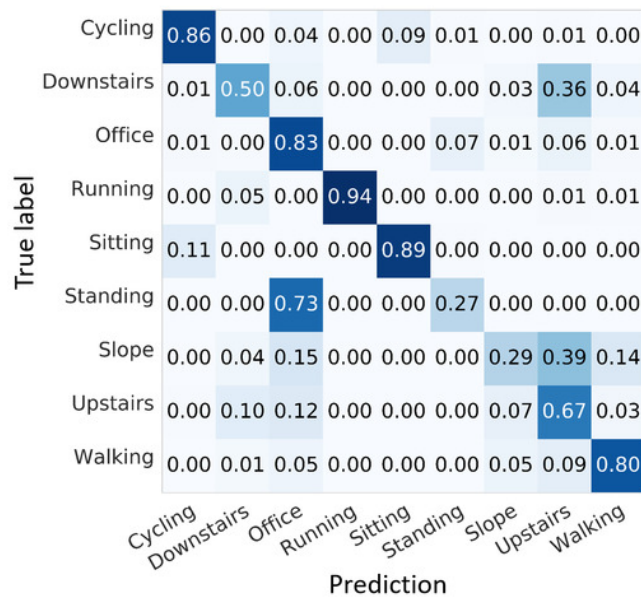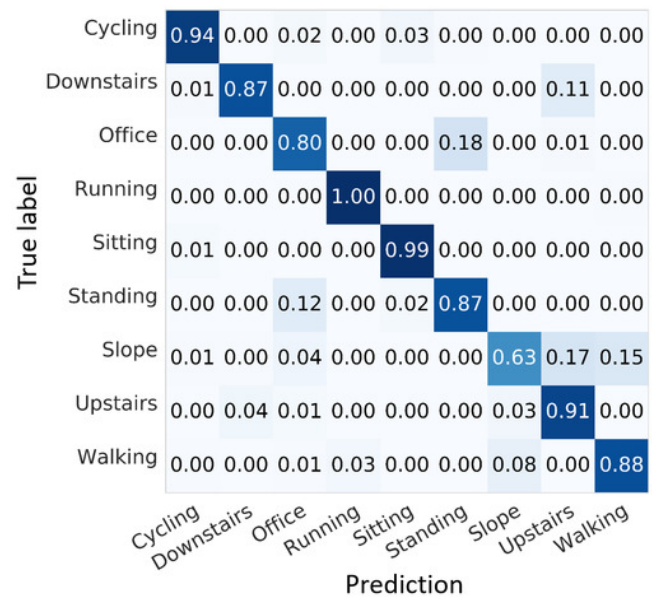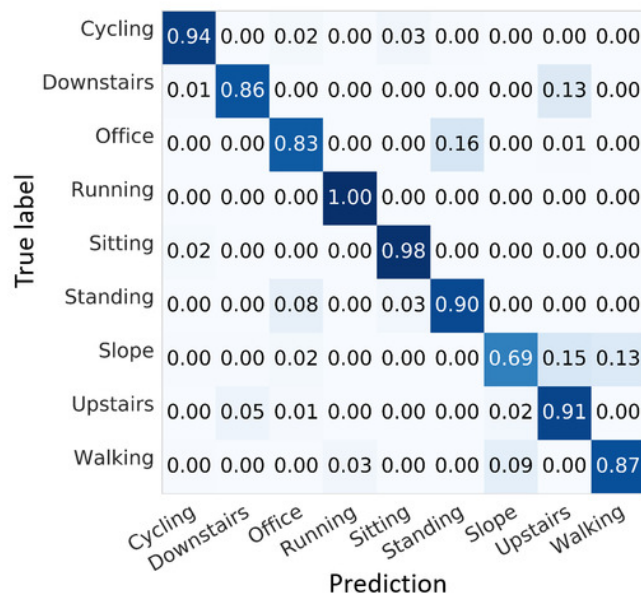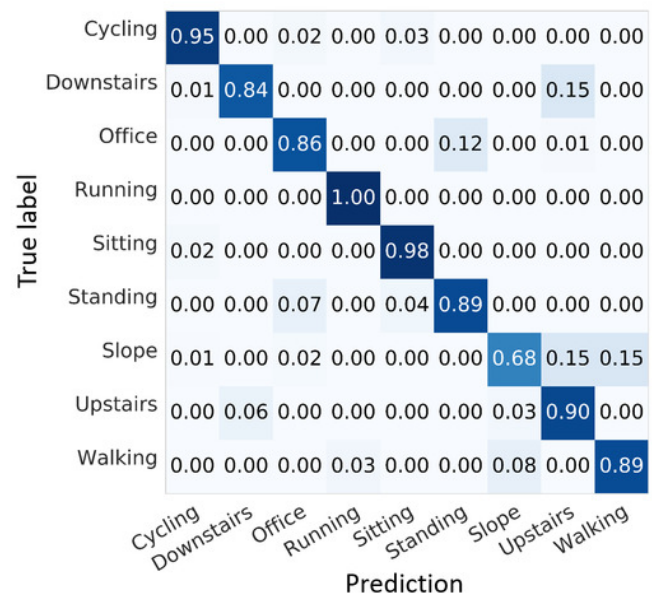
Figure 7

Figure 7. Performance of activity recognition of random forest algorithms for 25 sensor configurations.

The number of features depended on the number and location of the sensors. The number of features from left to right, one sensor: 29, 29; two sensors: 54, 54, 54, 51; three sensors: 76, 76, 76, 73; four sensors: 98, 101, 98, 98; five sensors: 120, 123, 123, 123, 120, 120; six sensors: 142, 145, 145, 142; and seven sensors: 167. Green boxes: sensor configurations that were expected to perform well (positions 1, 2, 3, 4, 7, 8, 11, 12, 13, 15, 16, 17, 18, 21, 22, 23, 25 from left to right). Pink boxes: sensor configurations that were expected to perform poorly (positions 5, 6, 9, 10, 14, 19, 20, 24 from left to right) (cf. Figure 4). Red diamonds: mean values.
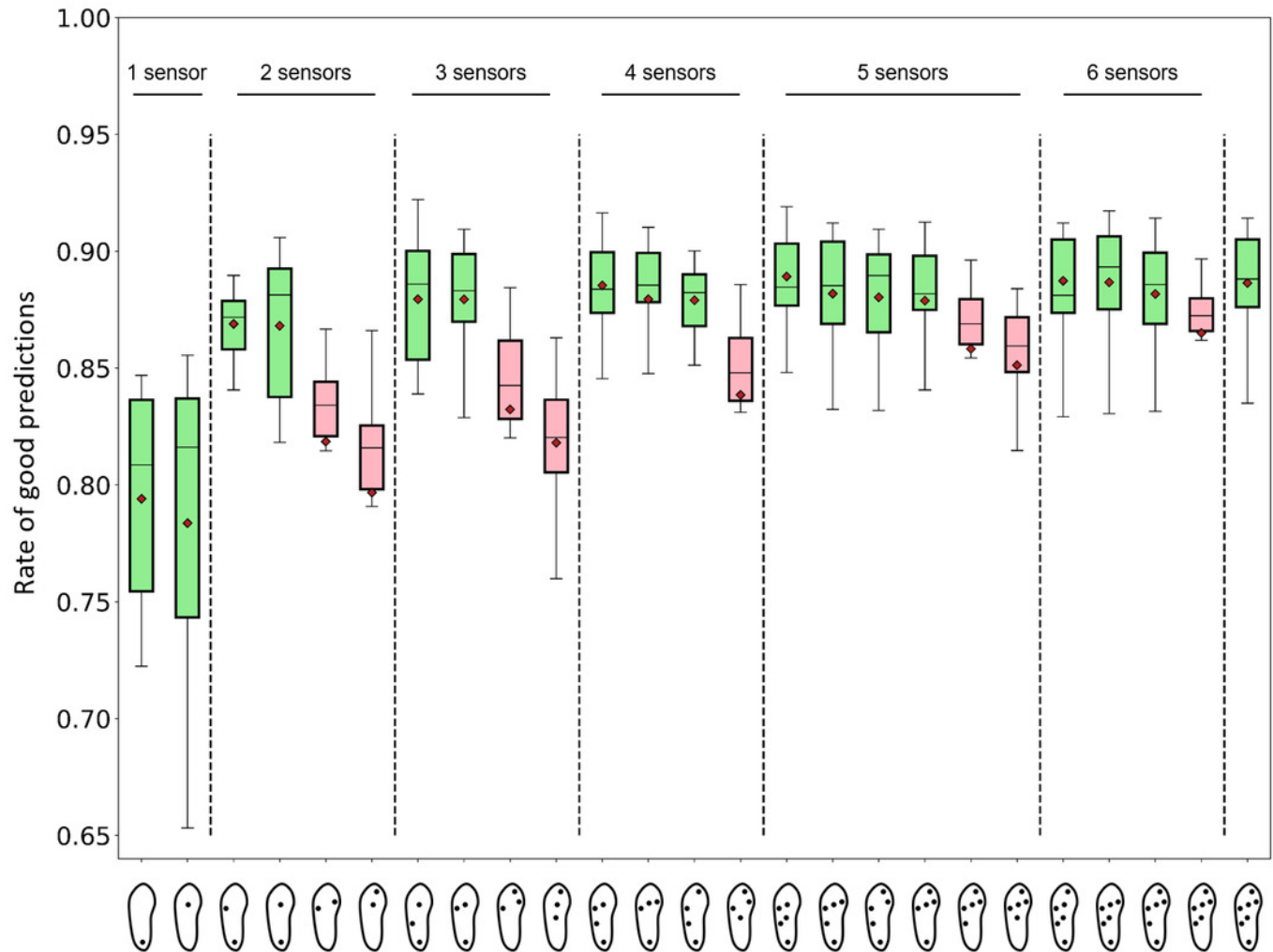
Figure 8

Figure 8. Confusion matrices for the best configuration depending on the number of sensors and using all the available features.

Normalized sensitivities are averaged for each activity across the 100 forests. (A) Best 1-sensor configuration. (B) Best 2-sensor configuration. (C) Best 3-sensor configuration. (D) Best 4-sensor configuration. (E) Best 5-sensor configuration. (F) Best 6-sensor configuration. N: number of features (all features).

A

True label	Cycling	Downstairs	Office	Running	Sitting	Standing	Slope	Upstairs	Walking
Cycling	0.94	0.00	0.02	0.00	0.04	0.00	0.00	0.00	0.00
Downstairs	0.02	0.61	0.00	0.00	0.00	0.00	0.01	0.36	0.00
Office	0.01	0.01	0.78	0.00	0.02	0.16	0.00	0.02	0.00
Running	0.03	0.00	0.00	0.91	0.03	0.00	0.00	0.00	0.03
Sitting	0.12	0.00	0.01	0.00	0.81	0.06	0.00	0.00	0.00
Standing	0.01	0.00	0.11	0.00	0.20	0.68	0.00	0.00	0.00
Slope	0.01	0.03	0.00	0.00	0.00	0.00	0.67	0.16	0.13
Upstairs	0.04	0.23	0.06	0.00	0.00	0.00	0.04	0.63	0.00
Walking	0.00	0.01	0.00	0.03	0.00	0.00	0.11	0.00	0.85

Features
N = 29

Prediction

B

True label	Cycling	Downstairs	Office	Running	Sitting	Standing	Slope	Upstairs	Walking
Cycling	0.91	0.00	0.02	0.00	0.07	0.00	0.00	0.00	0.00
Downstairs	0.01	0.83	0.00	0.00	0.00	0.00	0.00	0.16	0.00
Office	0.00	0.00	0.80	0.00	0.00	0.17	0.00	0.02	0.00
Running	0.00	0.00	0.00	0.99	0.00	0.00	0.00	0.00	0.00
Sitting	0.01	0.00	0.00	0.00	0.96	0.03	0.00	0.00	0.00
Standing	0.00	0.00	0.09	0.00	0.07	0.84	0.00	0.00	0.00
Slope	0.00	0.01	0.00	0.00	0.00	0.00	0.61	0.18	0.19
Upstairs	0.00	0.08	0.03	0.00	0.00	0.00	0.06	0.83	0.00
Walking	0.00	0.01	0.00	0.02	0.00	0.00	0.08	0.00	0.89

Features
N = 54

Prediction

C

True label	Cycling	Downstairs	Office	Running	Sitting	Standing	Slope	Upstairs	Walking
Cycling	0.93	0.00	0.03	0.00	0.03	0.00	0.00	0.00	0.00
Downstairs	0.02	0.87	0.01	0.00	0.00	0.00	0.00	0.10	0.00
Office	0.01	0.00	0.81	0.00	0.00	0.17	0.00	0.01	0.00
Running	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00
Sitting	0.01	0.00	0.00	0.00	0.97	0.01	0.00	0.00	0.00
Standing	0.00	0.00	0.09	0.00	0.03	0.88	0.00	0.00	0.00
Slope	0.01	0.01	0.03	0.00	0.00	0.00	0.62	0.21	0.13
Upstairs	0.02	0.05	0.03	0.00	0.00	0.00	0.02	0.88	0.00
Walking	0.00	0.00	0.01	0.03	0.00	0.00	0.08	0.00	0.87

Features
N = 76

Prediction

D

True label	Cycling	Downstairs	Office	Running	Sitting	Standing	Slope	Upstairs	Walking
Cycling	0.92	0.00	0.02	0.00	0.06	0.00	0.00	0.00	0.00
Downstairs	0.01	0.87	0.00	0.00	0.00	0.00	0.00	0.11	0.00
Office	0.01	0.00	0.81	0.00	0.00	0.17	0.00	0.01	0.00
Running	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00
Sitting	0.02	0.00	0.00	0.00	0.97	0.01	0.00	0.00	0.00
Standing	0.00	0.00	0.09	0.00	0.01	0.90	0.00	0.00	0.00
Slope	0.00	0.01	0.03	0.00	0.00	0.00	0.63	0.20	0.14
Upstairs	0.00	0.06	0.01	0.00	0.00	0.00	0.03	0.90	0.00
Walking	0.00	0.00	0.01	0.03	0.00	0.00	0.08	0.00	0.88

Features
N = 98

Prediction

E

True label	Cycling	Downstairs	Office	Running	Sitting	Standing	Slope	Upstairs	Walking
Cycling	0.93	0.00	0.02	0.00	0.05	0.00	0.00	0.00	0.00
Downstairs	0.00	0.88	0.00	0.00	0.00	0.00	0.00	0.11	0.00
Office	0.00	0.00	0.80	0.00	0.00	0.18	0.00	0.01	0.00
Running	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00
Sitting	0.01	0.00	0.00	0.00	0.98	0.00	0.00	0.00	0.00
Standing	0.00	0.00	0.10	0.00	0.02	0.88	0.00	0.00	0.00
Slope	0.00	0.01	0.02	0.00	0.00	0.00	0.64	0.19	0.14
Upstairs	0.00	0.05	0.01	0.00	0.00	0.00	0.03	0.91	0.00
Walking	0.00	0.00	0.00	0.03	0.00	0.00	0.07	0.00	0.89

Features
N = 120

Prediction

F

True label	Cycling	Downstairs	Office	Running	Sitting	Standing	Slope	Upstairs	Walking
Cycling	0.93	0.00	0.02	0.00	0.04	0.00	0.00	0.00	0.00
Downstairs	0.00	0.89	0.00	0.00	0.00	0.00	0.00	0.11	0.00
Office	0.00	0.00	0.81	0.00	0.00	0.17	0.00	0.01	0.00
Running	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00
Sitting	0.01	0.00	0.00	0.00	0.98	0.01	0.00	0.00	0.00
Standing	0.00	0.00	0.11	0.00	0.02	0.87	0.00	0.00	0.00
Slope	0.00	0.00	0.04	0.00	0.00	0.00	0.61	0.17	0.17
Upstairs	0.00	0.04	0.02	0.00	0.00	0.00	0.04	0.90	0.00
Walking	0.00	0.00	0.00	0.03	0.00	0.00	0.08	0.00	0.89

Features
N = 142

Prediction

Figure 9

Figure 9. Confusion matrices for the worst configuration depending on the number of sensors and using all the available features.

Normalized sensitivities are averaged for each activity across the 100 forests. (A) Worst 1-sensor configuration. (B) Worst 2-sensor configuration. (C) Worst 3-sensor configuration. (D) Worst 4-sensor configuration. (E) Worst 5-sensor configuration. (F) Worst 6-sensor configuration N: number of features (all features). The 1-sensor configuration presented in this figure was initially expected to perform well. It corresponds to the worst 1-sensor configuration among the two selected in this study (cf. Figure 7).
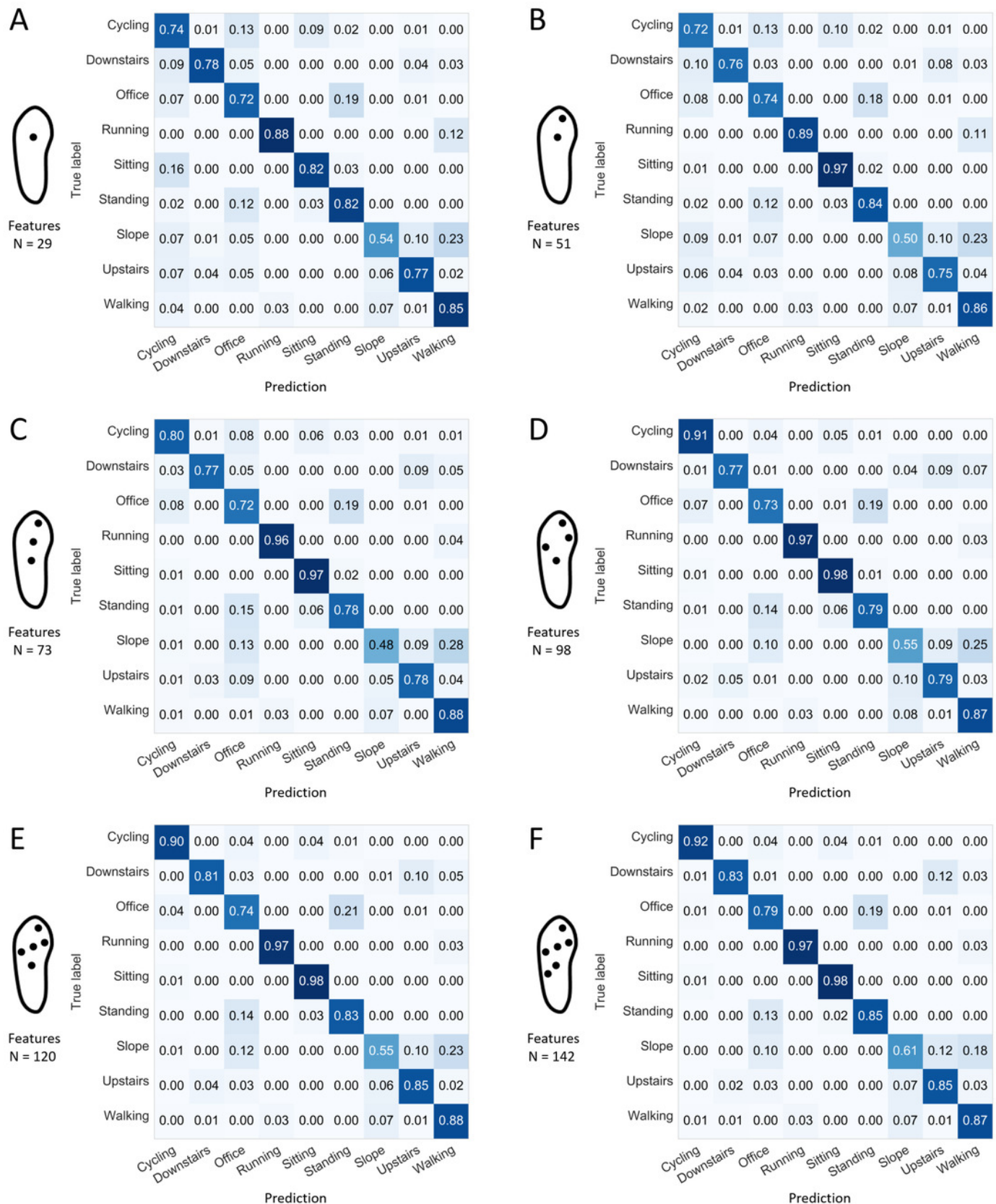
Figure 10

Figure 10. Effect of the number of features on the activity recognition rate.

(A) Results for all identified best 1-, 2-, 3-, 4-, 5-, and 6-sensor configurations (cf. Figure 8) and for the 7-sensor configuration. (B) the 7-sensor configuration. (C) Best 6-sensor configuration. (D) Best 5-sensor configuration. (E) Best 4-sensor configuration. (F) Best 3-sensor configuration. (G) Best 2-sensor configuration. (H) Best 1-sensor configuration.
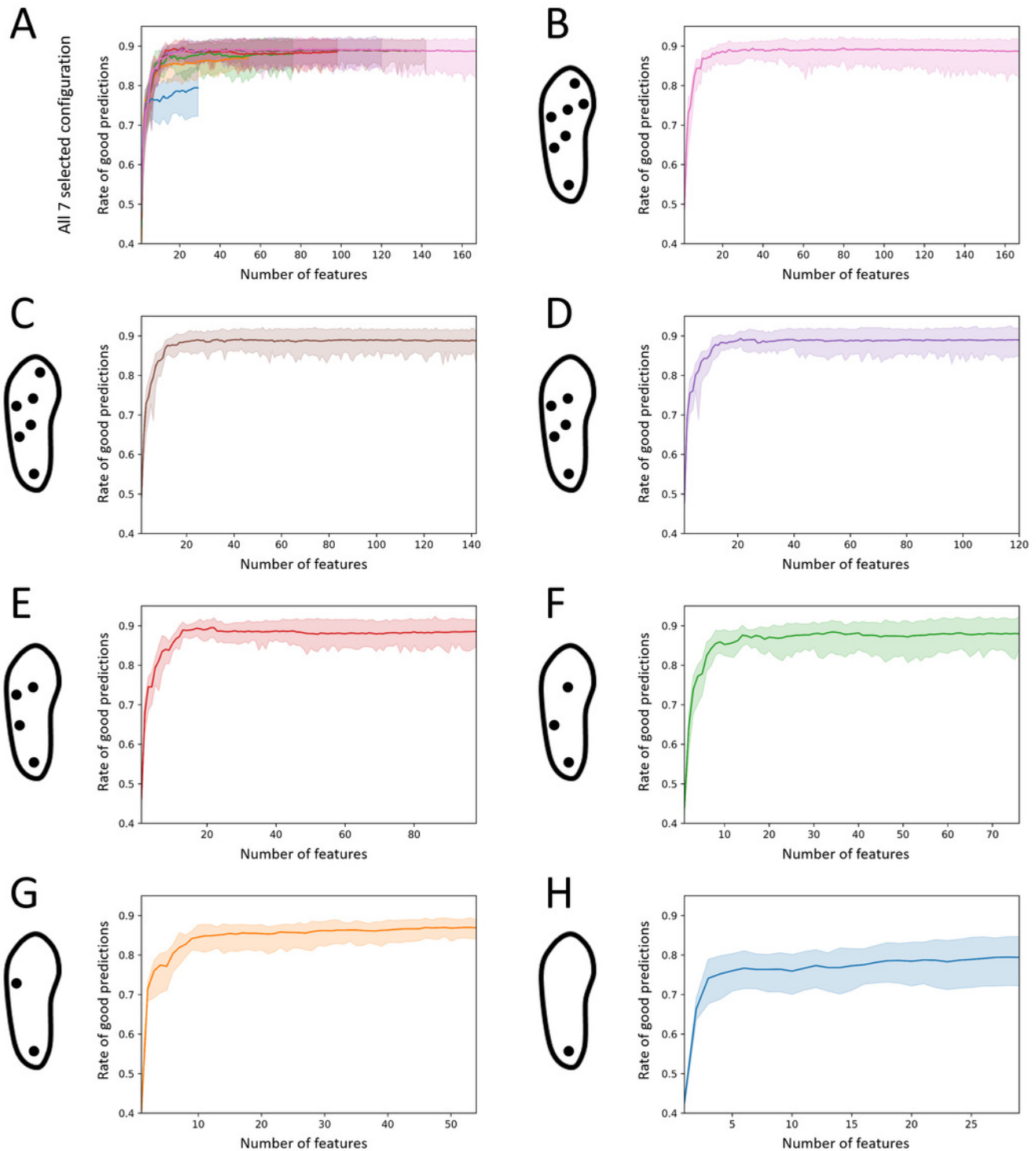
Figure 11

Figure 11. Identification of most important features.

Results are displayed for the previously identified best 1-, 2-, 3-, 4-, 5-, and 6-sensor configurations (cf. Fig 6) and for the 7-sensor configuration. Red: identified as an important feature in all seven selected configurations. White: identified as an important feature in one selected configuration only. FFT: fast Fourier transform; SD: standard deviation.

20th most important feature (top) ↑ ... **Single most important feature** (bottom)

1	2	3	4	5	6	7
median pressure right heel	SD of peak magnitudes right lateral forefoot	SD of peak intervals left central forefoot	SD of pressures left lateral midfoot	mean of pressures right central forefoot	number of peaks right central midfoot	SD of pressures left lateral midfoot
SD of pressures right heel	maximal pressure left heel	SD of pressures right central forefoot	average peak width right lateral midfoot	number of peaks right central midfoot	average peak interval left heel	number of peaks right central forefoot
SD of peak magnitudes left heel	SD of pressures left lateral forefoot	average peak width right lateral midfoot	mean of pressures right central forefoot	number of peaks left lateral midfoot	mean of pressures right central forefoot	SD of pressures left central forefoot
SD of peak widths right heel	average peak width left heel	average peak magnitude right heel	average peak magnitude right heel	average peak magnitude right heel	SD of peak intervals left central forefoot	number of peaks left central forefoot
average peak interval right heel	average peak magnitude right heel	average peak interval left heel	number of peaks right central forefoot	number of peaks right central forefoot	number of peaks right central forefoot	average peak interval left heel
SD of peak widths left heel	average peak interval right heel	mean of pressures right central forefoot	average peak interval left heel	average peak interval left heel	average peak width right lateral midfoot	foot landing vs. lifting forces
FFT power density	mean of pressures left heel	average peak interval right central forefoot	number of peaks left lateral midfoot	foot landing vs. lifting forces	average peak magnitude right heel	maximal pressure right medial forefoot
median pressure left heel	maximal pressure right lateral forefoot	number of peaks right central forefoot	average peak interval right central forefoot	FFT power density	number of peaks left lateral midfoot	number of peaks right heel
average peak magnitude right heel	average peak interval right lateral forefoot	SD of pressures left lateral midfoot	mean of pressures left central forefoot	mean of pressures left central forefoot	mean of pressures left central forefoot	average peak magnitude right heel
average peak width right heel	average peak interval left heel	number of peaks left lateral midfoot	foot landing vs. lifting forces	average peak interval right central forefoot	average peak interval right central forefoot	number of peaks left lateral midfoot
SD of pressures left heel	maximal pressure left lateral forefoot	SD of pressures left central forefoot	number of peaks left central forefoot	number of peaks left lateral forefoot	number of peaks right heel	average peak interval right central forefoot
average peak interval left heel	foot landing vs. lifting forces	number of peaks right heel	number of peaks right heel	number of peaks right heel	number of peaks left lateral forefoot	number of peaks left medial forefoot
maximal pressure left heel	number of peaks right heel	foot landing vs. lifting forces	mean of pressures left lateral forefoot	mean of pressures left lateral forefoot	mean of pressures left lateral forefoot	mean of pressures left lateral forefoot
average peak magnitude left heel	number of peaks left lateral forefoot	number of peaks left central forefoot	number of peaks left lateral forefoot	number of peaks left central forefoot	number of peaks left central forefoot	number of peaks left lateral forefoot
average peak width left heel	mean of pressures left lateral forefoot	mean of pressures left central forefoot	SD of pressures left central forefoot	SD of pressures left central forefoot	SD of pressures left central forefoot	mean of pressures left central forefoot
number of peaks right heel	SD of AC component FFT	SD of AC component FFT	number of peaks left heel	number of peaks left heel	number of peaks left heel	number of peaks left heel
mean of AC component FFT	number of peaks right lateral forefoot	number of peaks left heel	SD of AC component FFT	SD of AC component FFT	mean of AC component FFT	mean of AC component FFT
mean of pressures left heel	SD of pressures left heel	SD of pressures left heel	SD of pressures left heel	SD of pressures left heel	number of peaks right lateral midfoot	number of peaks right lateral midfoot
number of peaks left heel	number of peaks left heel	number of peaks right lateral midfoot	number of peaks right lateral midfoot	number of peaks right lateral midfoot	SD of pressures left heel	SD of pressures left heel
SD of AC component FFT	mean of AC component FFT	mean of AC component FFT	mean of AC component FFT	mean of AC component FFT	SD of AC component FFT	SD of AC component FFT

1	2	3	4	5	6	7

Figure 12

Figure 12. Confusion matrices for four selected configurations using different numbers of features.

Normalized sensitivities are averaged for each activity across the 100 forests. (A) 1-sensor configuration: heel. (B) 3-sensor: heel, lateral midfoot, center of forefoot. (C) 5-sensor: heel, lateral midfoot, center of midfoot, lateral forefoot, center of forefoot. (D) 7-sensor: all. N: number of features.
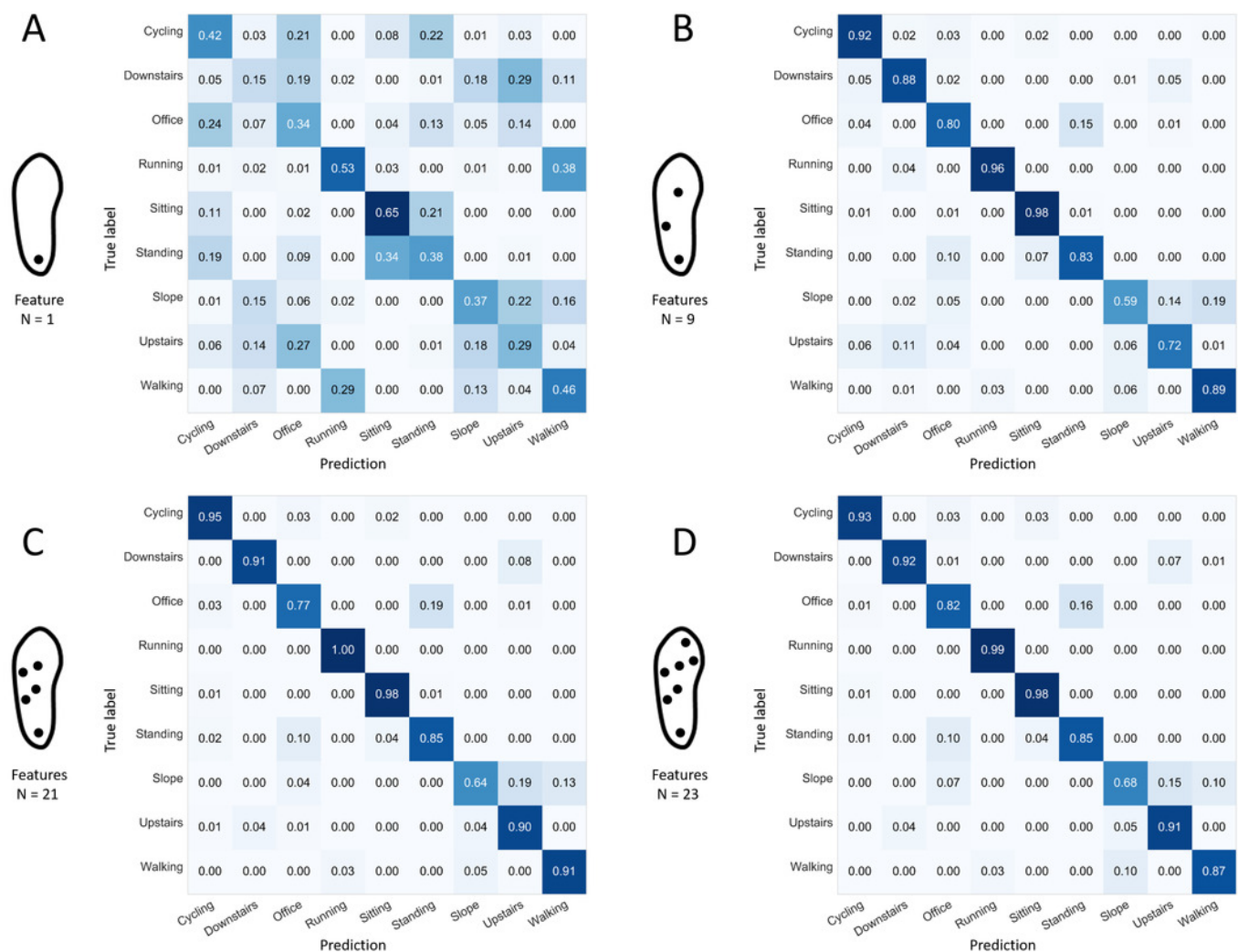
Figure 13

Figure 13. Confusion matrices for selected forests captured from the best 4-sensor configuration.

Values refers to the normalized sensitivity of the selected forest for each activity. (A) One selected bad performer with a relatively low number of used features. (B) One selected good performer with a relatively low number of used features. (C) One selected bad performer with a relatively high number of used features. (D) One selected good performer with a relatively high number of used features. "Best" refers to the results obtained from the forest with the highest prediction rate. "Worst" refers to the results obtained from the forest with the lowest prediction rate. "Performer" here refers to one single forest. N: number of features.
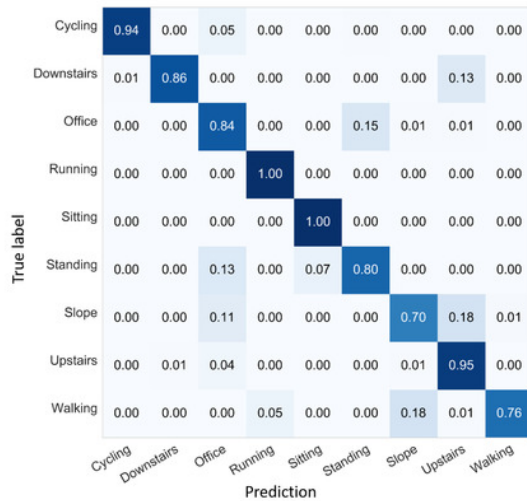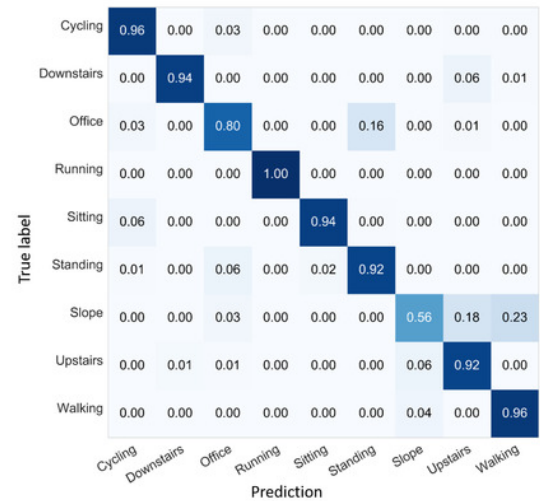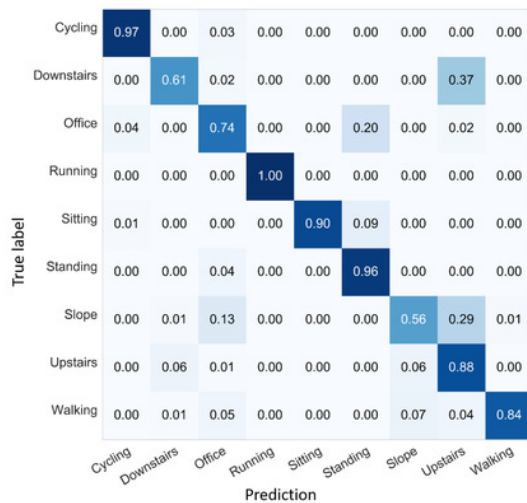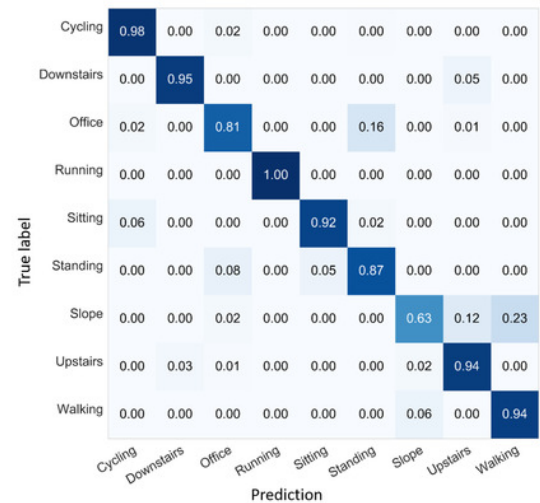
Table 1. Description of activities completed by participants of study.

Activity	Description	Type
Sitting	Chatting and browsing the internet with a smartphone while sitting on an office chair (height: 45cm, all subjects able to touch the ground with their feet when sitting), indoors.	Sedentary
Standing	Chatting and browsing the internet with a smartphone while standing, indoors.	Sedentary
Walking on a flat surface	Walking on a flat hallway in a campus building, indoors; subjects self-arranged what they considered to be slow and moderate pace (4 min each).	Locomotive
Walking upstairs	Climbing stairs, indoors; subjects typically completed between 6 and 14 floors.	Locomotive
Walking downstairs	Going downstairs, indoors; subjects typically completed 14 floors.	Locomotive
Walking up a slope	Walking on a treadmill set at a slope of 10%, indoors.	Locomotive
Running	Running on a treadmill at slow and moderate pace (4 min each), indoors; subjects self-selected what they considered to be slow and moderate pace.	Locomotive
Cycling	Riding a utilitarian bike ("mamachari-type") around the university campus (included turns and changes in pace) at self-selected pace, outdoors.	Locomotive
Office work	Completing several small tasks in a space of approximately 10 m^2, including writing and erasing notes on a white table board, carrying light stationeries or files from one desk to another, cleaning up a desk, opening drawers, indoors; all these tasks involved small amplitude movements and displacements only.	Mixed (sedentary and locomotive)

Table 2. Summary of extracted data features.

SD: standard deviation.

	Type of analysis	Inputs	Number of features extracted
General statistics	Average, maximum, SD, median	Each of the 14 sensors	56
Peak analysis	Peak number, interval between peaks (average, SD), peak magnitude (average, SD), peak width (average, SD)	Each of the 14 sensors	98
Gait phase	Difference between foot landing and foot lift forces	The envelope of the seven sensors of each foot	2
	Double float duration		
Frequency domain	Power density, mean frequency from 1.67–10 Hz, skewness below 10 Hz, AC component from 2–10 Hz (mean and SD)	Sum of all sensors	5
Pressure distribution	Difference between forces on the forefoot and heal (mean of the two feet) and correlation (for each foot)	Heel sensor (#1) vs. envelope sensors located on the forefoot (#4, #5, #6, #7)	6
	Difference between forces on the medial and lateral foot (mean of the two feet) and correlation (for each foot)	Medial forefoot sensor (#6) vs. lateral forefoot sensor (#4)	