Recognizing kickboard and skateboarding behaviors using wearable activity tracker devices

Julien Tripette[1], Arisa Orihara[1], Nathanael Aubert-Kato[2], Takashi Nakagata[3], Yuji Ohta[1]

[1] Department of Human-Environmental Science, Ochanomizu University, Tokyo, Japan
[2] Department of Computer Science, Ochanomizu University, Tokyo, Japan
[3] Department of Physical Activity Research, National Institutes of Bio-innovation, Nutrition and Health, Osaka, Japan

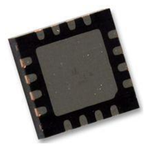
tripette.julien@ocha.ac.jp

Abstract

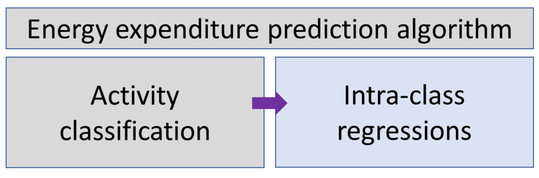
Introduction: Contemporary wearable activity tracker devices and smartphones are able to predict various physical activity parameters. The predictions of daily energy expenditure often rely on data provided by the accelerometer, gyroscope and altimeter sensors. Software that accurately estimates energy expenditure commonly integrates a sequence of 2 algorithmic operations. The first operation consists in allocating data to some activity-specific classes. The second operation consists in intra-class regression procedures to make quantitative estimations of the energy expenditure. Many algorithms have been proposed to classify an ever-increasing number of physical behaviors. Kickboard and skateboarding activities recently became popular among people favoring active commuting. These activities can sometimes make significant contributions to daily energy expenditure. The present study aims at developing a kickboard and skateboarding activity recognition algorithm for wearable activity tracker devices and smartphones. **Methods:** Ten subjects performed the 9 following activities: sitting, standing, walking on a flat surface, walking upstairs, walking down stairs, running, bicycle, kickboard and skateboarding. They wore 2 multi-sensor wearable devices, one at the wrist and one in the trouser back pocket, where activity trackers and smartphones are commonly put. Raw data from the accelerometer, gyroscope and air pressure sensors were collected for each activity during 10 minutes at a sampling rate of 100 Hz. A 10-second sliding window analysis allowed extracting a total 211 data features in both the time and frequency domains. The reduced dataset was split into training and test samples using a subject-wise assignment method. Random forest classifiers were trained to recognize activities. The resulting activity recognition algorithms were evaluated on the test sample. **Results:** Models built with the back pocket sensor data predicted the activities with an average success of 84%. The “kickboard” and “skateboarding” activities had a sensitivity of 73 and 55% respectively with the large majority of the confusion occurring between these two behaviors. Grouping the two activities into one single “push-push-glide” activity class raised the performance to 88%, and the “push-push-glide” class showed a sensitivity of 98%. Models built with the wrist sensor data predicted the activities with a balanced average success of 86%. The “kickboard” and “skateboarding” activities had sensitivities of 95 and 92%, respectively. Models integrating two classification layers to allocate data to a “push-push-glide” activity class before making classifications for “kickboard” and “skateboarding” separately were 100% sensitive to these two behaviors. **Discussion:** Automatic recognition of kickboard and skateboarding activities using data collected by wearable activity tracker is feasible. Integrating this operation to activity tracker software would increase the accuracy of energy expenditure estimations.

Introduction

Activity tracker devices (wrist-worn, waist-worn, research-grade, consumer-grade) or smartphone commonly use accelerometer data to predict daily energy expenditure



Data from the MEMS 3-axis accelerometer



Energy expenditure predictions

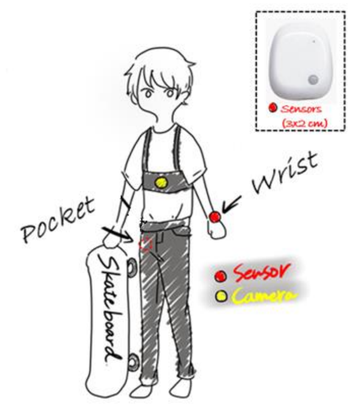
- Data classification may be achieved using activity recognition algorithms
- The more classes, the more activity specific regression equations, the more accurate energy expenditure prediction

Algorithms allowing the recognition of different types of sedentary, locomotive or mixed activities have been presented in many scientific articles. None of them were developed to recognize kick-scooter or skateboarding behaviors. Considering the recent popularity of these devices as means of transportation, the absence of specific regression equation estimating the energy expenditure of these two activities may induce erroneous daily energy expenditure predictions in some people.

→ **The present study aims at developing algorithms able to process activity tracker data in a way that allows to recognizing kick-scooter and skateboard cruising activities.**

Method

N=10	Gender	Age	Level	Stance	Weight
1	woman	12	expert	regular	38
2	woman	26	beginner	goofy	42
3	man	40	expert	regular	83
4	woman	27	expert	regular	45
5	man	22	beginner	regular	54
6	man	22	expert	goofy	65
7	man	13	expert	regular	50
8	man	25	expert	goofy	80
9	man	22	expert	regular	65
10	man	55	beginner	regular	65



- MBIENTLAB MetaMotionS (California, USA)
- accelerometer, gyroscope, pressure sensors (**Matching sensing capabilities of smartphone/activity tracker)**
- Sampling rates
  - Accelerometer sensor: 100Hz
  - Gyroscope sensor: 100Hz
  - Barometer sensor: 0.5Hz
- Raw data = 7-dimension vector
  - Acceleration: 3 axes
  - Angular velocity: 3 axes
  - Air pressure: 1 axis

9 activities is performed for about 10 min:

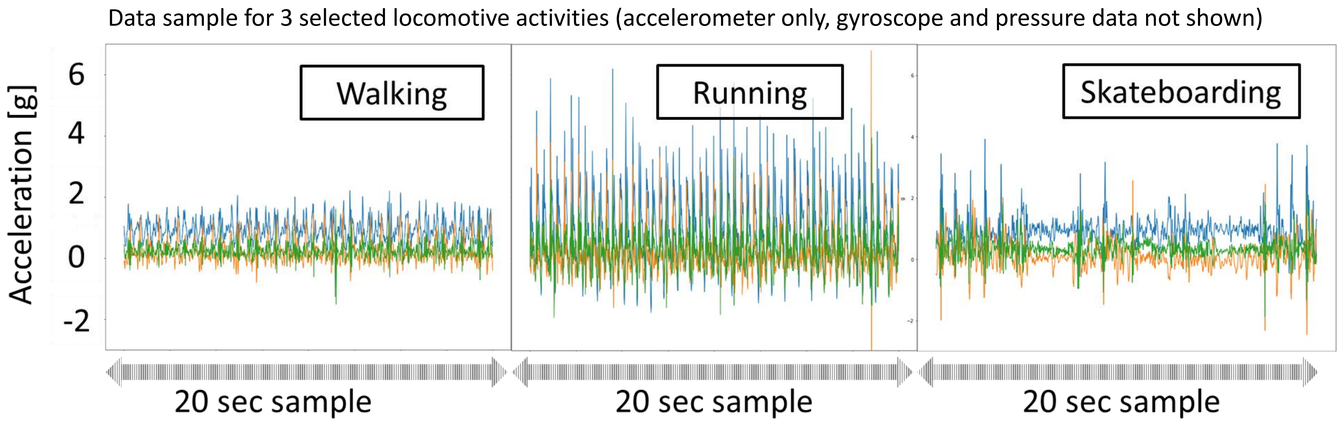
★ Sitting (chatting / watching smartphone)
★ Standing (chatting / watching smartphone)
★ Running (self-paced)
★ Walking
★ Bicycle (utilitarian, self-paced)
★ Climbing stairs (~5 x 2min)
★ Going down-stair (~5 x 2min)
★Skateboard cruising
★kickboard riding

Sedentary activities

Classic locomotive activities

Push-push-glide locomotive activities

Data sample for 3 selected locomotive activities (accelerometer only, gyroscope and pressure data not shown)



Raw data (sample): 100Hz – 7 parameters

	timestamp (+0900)	elapsed (s)	x-axis (g)	y-axis (g)	z-axis (g)	x-axis (deg/s)	y-axis (deg/s)	z-axis (deg/s)	pressure (Pa)
0	2021-11-02T13:54:21.241	157.589	0.947	-0.047	0.429	32.256	13.902	-0.671	NaN
1	2021-11-02T13:54:21.251	157.599	0.882	0.020	0.334	21.159	6.707	-0.915	NaN
2	2021-11-02T13:54:21.260	157.608	0.902	-0.003	0.366	20.610	5.305	0.610	NaN
...	...	...	...	...	...	...	...	...	...
60921	2021-11-02T14:04:34.493	770.841	1.002	0.416	-0.479	60.488	-20.122	-52.012	NaN
60922	2021-11-02T14:04:34.504	770.852	1.095	0.375	0.056	39.512	-6.707	-110.366	NaN
60923	2021-11-02T14:04:34.514	770.862	0.697	0.089	0.315	50.793	-6.341	-157.012	NaN

(5400000, 7)

Feature table: ~5400 data – 211 features

	EnmoTrunc_mean	x_mean	y_mean	z_mean	x_std	y_std	z_std	x_range	y_range	z_range	...	lag_GxAc
0	0.133073	0.905498	-0.093808	0.444770	0.274786	0.167260	0.203635	2.242	1.537	2.169	...	
1	0.158828	0.915922	-0.129329	0.413823	0.324979	0.174654	0.225314	2.370	1.261	1.603	...	
2	0.090285	0.900973	-0.191388	0.424516	0.201682	0.154201	0.140625	2.042	1.323	1.389	...	
...	...	...	...	...	...	...	...	...	...	...	...	...
5324	0.164154	0.858896	0.165359	0.486197	0.297921	0.275169	0.188966	1.614	1.798	1.003	...	
5325	0.165101	0.851217	0.176849	0.485449	0.302394	0.299512	0.192193	1.902	1.834	1.061	...	
5326	0.133439	0.847551	0.169558	0.506423	0.249724	0.235404	0.189994	1.507	1.668	1.222	...	

(5400, 211)

Feature extraction process inspired by: Willetts et al. Scientific Reports (2018)

Random forest classifier

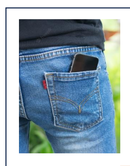
Training-Test split:
- Subject-wise design
- 8 subjects for training – 2 subjects for testing

→45 possible combinations

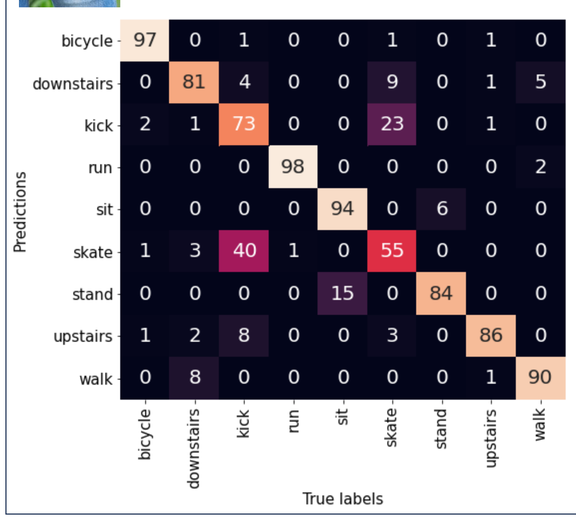
Forest shape:
- 20-tree forests
- No-depth criterion (each leaf is pure)

Procedure:
- 100 runs for each combination
- sklearn.ensemble.RandomForestClassifier

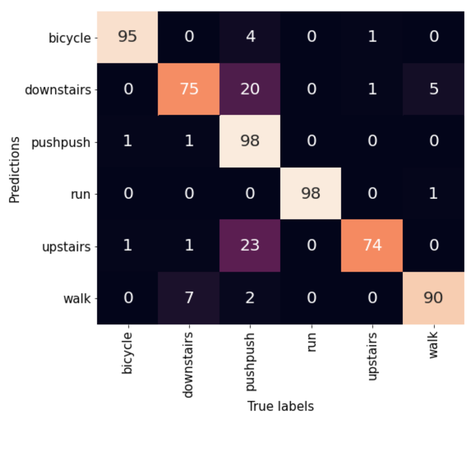
Results



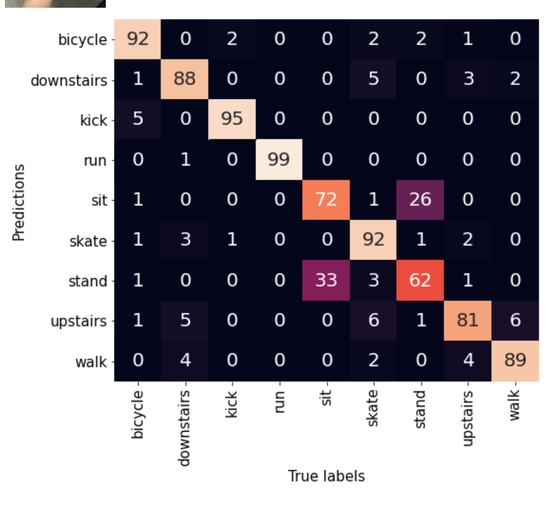
Testing performance: 0.99 (balanced score: 0.84)



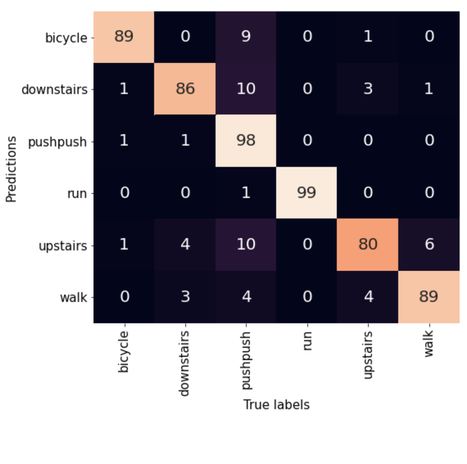
Testing performance: 0.99 (balanced score: 0.88)



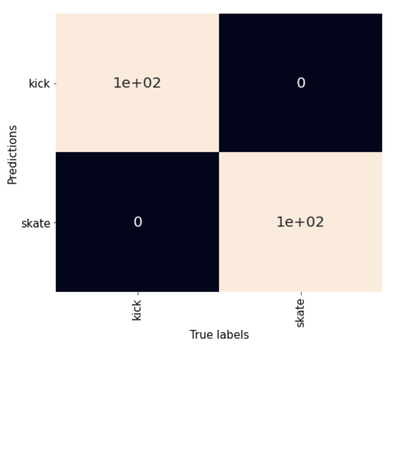
Testing performance: 0.99 (balanced score: 0.86)



Testing performance: 0.92 (balanced score: 0.90)



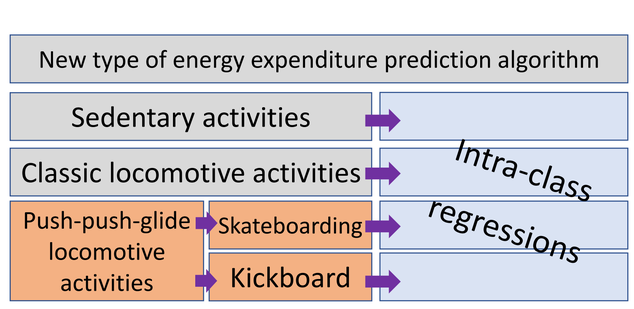
Testing performance: 1.00 (balanced score: 0.99)



Discussion

Automatic recognition of kickboard and skateboarding activities using data collected by wearable activity tracker is feasible. Integrating this operation to activity tracker software would increase the accuracy of energy expenditure estimations.

Data from the MEMS 6-DOF IMU + barometer



More accurate energy expenditure predictions in people using skateboard and kickboard for transportation

21K11335

お茶の水女子大学
Ochanomizu University