University of Zurich[UZH]

Using GPS and accelerometer sensors for human movement analysis

Hoda Allahbakhshi
PhD student
GIScience center, Department of Geography
University of Zurich

Dynamik Gesunden Alterns

MOASIS : Mobility, Activity and Social Interaction Study

MOASIS aims to develop computational models to measure, analyze, and improve health behaviors and health outcomes in the everyday life of aging individuals.

Research objective

To contribute to developing an individualized description of human mobility behavior and patterns.

MOASIS

Physical activity

Physical activity definition: any bodily movement produced by skeletal muscles that results in energy expenditure (Caspersen et al. 1985).

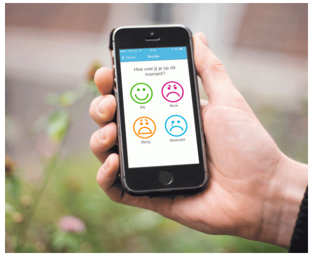
Elements in the built environment, such as streets, land use, the location of green spaces, accessibility to the transport system influence physical activity.

In order to understand the association between physical activity and built environment, it is important to first accurately measure and monitor physical activity.

Four main measures for PA:
FITT: Frequency, Intensity, Time and Type of activity (Cavill et al. 2006)

Methods for studying physical activity

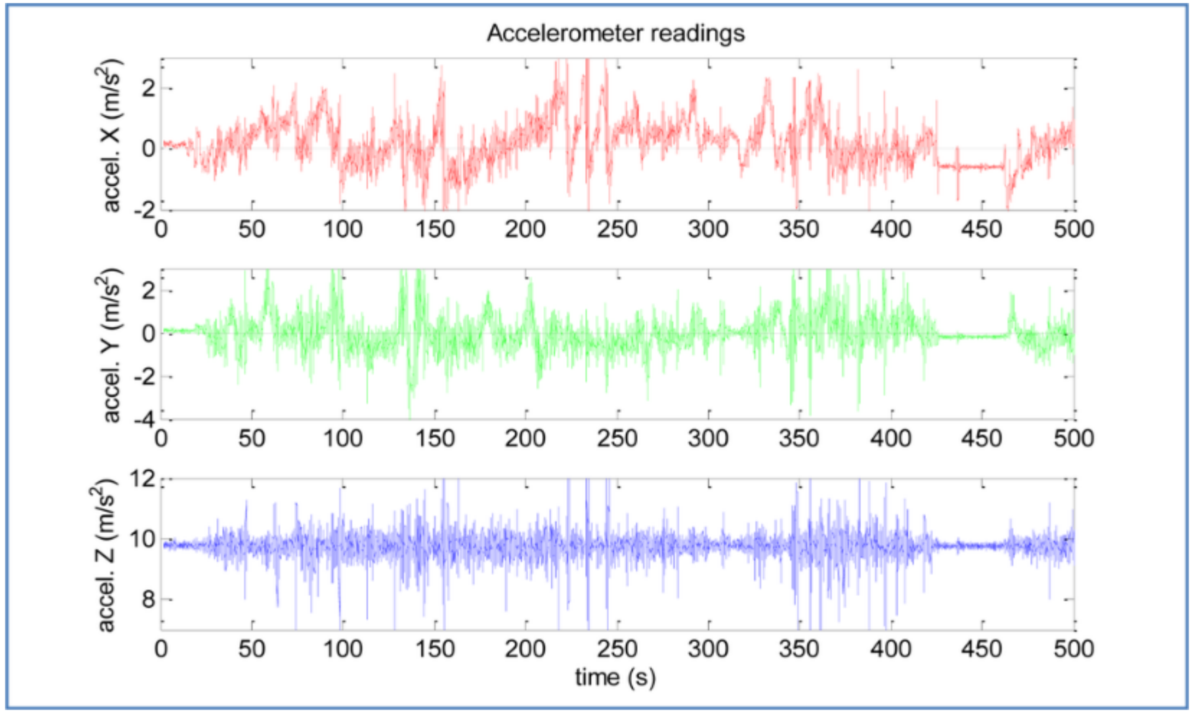
Subjective (e.g. self report)



Objective (e.g. sensor-based)

Three dimensional accelerometer

A 3D accelerometer measures acceleration forces in y, x and z dimensions, and therefore can sense the status of a body's motion or postures.



Martí et al. (2012)

Three dimensional accelerometer

Challenge I: To accurately detect real-life activity types using only a single 3D

- Solution: Complementing accelerometer-based PA measures with additional sensors (e.g. gyroscope, heart rate, pressure, GPS, etc.) or using multiple accelerometer devices

Challenge II: The inability to provide insight about the environment and location where the activity is happening.

- Solution: Combining accelerometer-based PA measures with GPS sensor

The use of GPS sensors in physical Activity applications

- Utilizing GPS spatial coordinates to link PA behavior derived from accelerometer data to the location and relevant spatial data (e.g. land use, walkability, green spaces, neighborhood).

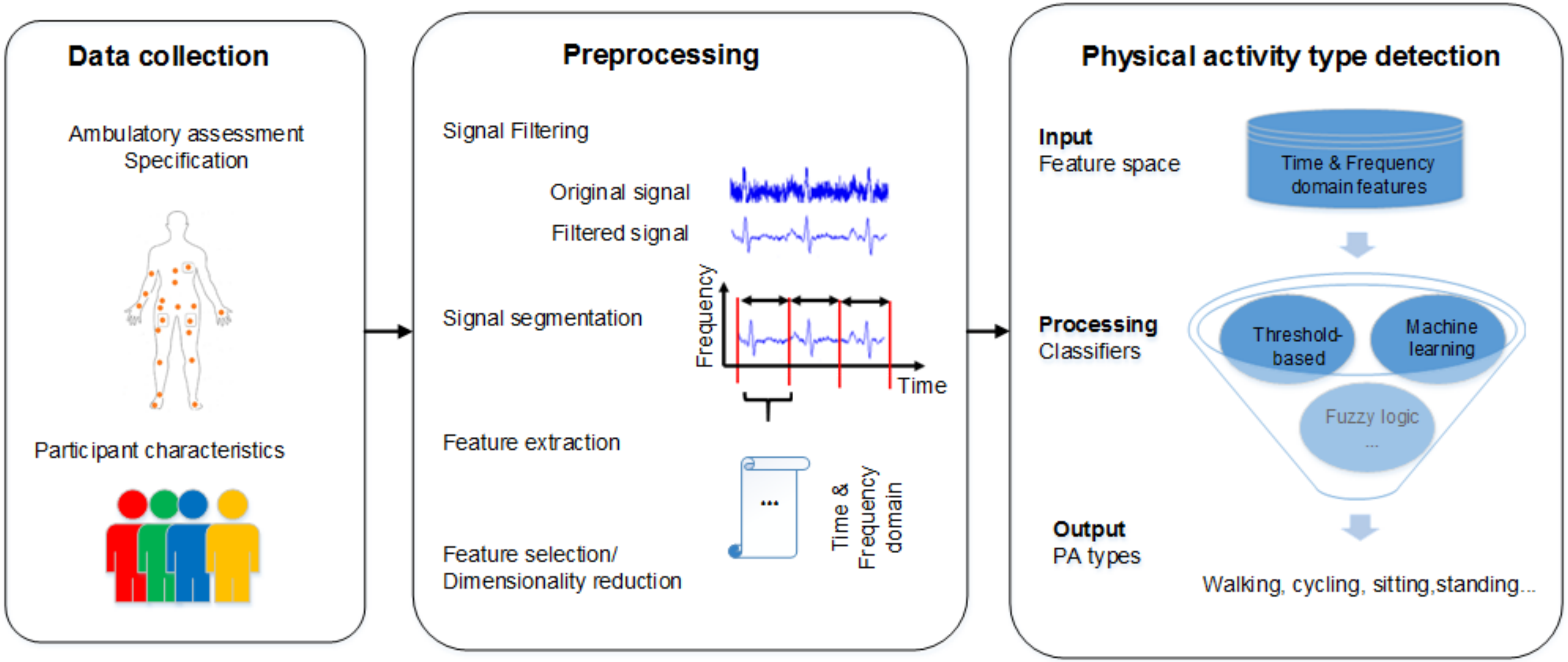
- Applying GPS features such as time, distance, altitude and speed to inform classifiers in PA detection.

Research questions

Q1: To what extent the addition of GPS sensor data to accelerometer data enhances prediction performance in detecting the major posture and motion activity types?

Q2: How does adding GPS data allow the number of sensor devices to be minimized in PA monitoring?

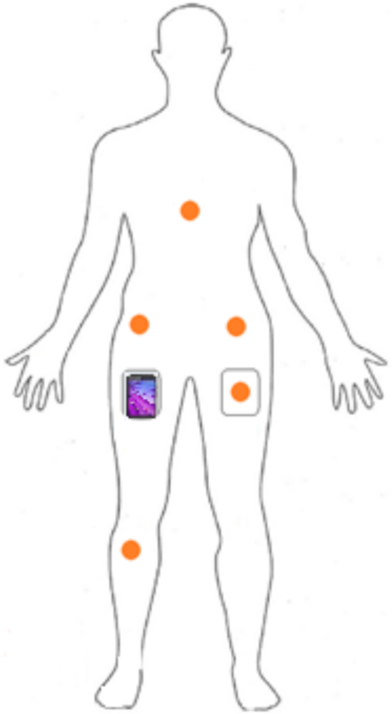
General Workflow for Physical activity type detection



Allahbakhshi, Hoda, et al. "The key factors in physical activity type detection using real-life data: A systematic review." *Frontiers in physiology* 10 (2019): 75.

Devices

Device	Sensors	Sampling rate
uTrail	3D Accelerometer	50 Hz.
	GPS	1 Hz.
Motorola Moto E, 2nd gen	3D Accelerometer	50 Hz.
	GPS	1 Hz.

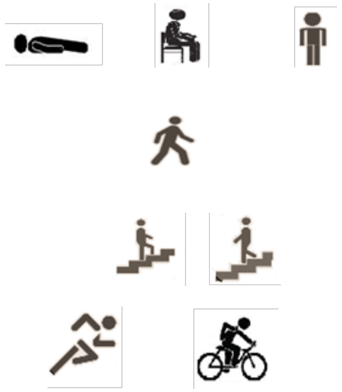


Semi-structured

A protocol to simulate real life: Participants are free to perform required activities in their own way, for example at their comfortable speed or in an outdoor area

Location I: Sport Center

- Lying, sitting, standing
- walking at 3 different speeds,
- walking uphill & downhill,
- walking downstairs &upstairs
- running, cycling



Real-life

Location II: Real-life

Activity	Minimum duration (minute)	Location
Sedentary activities		
Lying	1	Outdoor (e.g. on a bench)
Sitting	1	Outdoor (not in a vehicle)
Standing	1	Outdoor (not in a vehicle)
Non-level walking		
Walking uphill	2	Outdoor
Walking downhill	2	Outdoor
Walking downstairs	2 Floors (8 steps each)	Outdoor
Walking upstairs	2 Floors(8 steps each)	Outdoor
Transport related activities		
Walking, level ground	5	Leisure area (e.g. Park)
	5	Urban area(e.g. Street sidewalk)
Cycling, level ground	5	Leisure area (e.g. Park)
	5	Urban area(e.g. Street bike path)
Running, level ground	1	Leisure area (e.g. Park)
	1	Urban area(e.g. Street sidewalk))

Dataset

Physical Characteristics	Mean (SD)
No. (F/M)	33 (13/20)
Age (year)	29 ± (5.6)
Height (cm)	173 ± (10.05)
Weight (kg)	67 ± (9.8)
BMI (kg.m−2)	22 ± (1.9)

BMI, body mass index;
A **BMI** of 25.0 or more is overweight, while the healthy range is 18.5 to 24.9.

Dataset	Total Acc. Data	Total GPS Data	Acc. Data Per Person	GPS Data Per Person
Semi-structured	61.6 h (11,098,581)	59.6 h (214,628)	1.8 h (336,320.6)	1.8 h (6503.879)
Real-life	99.5 h (17,918,884)	101.5 h (365,631)	3 h (542,996.5)	3 h (11,079.73)
Total	161 h (29,017,465)	161 h (580,259)	4.8 h (879,317.1)	4.8 h (17,583.61)

Methodology

Raw data collection → Preprocessing → Classifier → Activities

Preprocessing:
- Labelling
- Filtering
- Segmentation
- Feature extraction
- Map-matching

Classifier: Random forest

- Sitting
- Standing
- Lying
- Non-level walking
- Walking on level
- Cycling
- Jogging

Feature extraction

Sensor data	**Features**
Accelerometer	Time domain: mean, standard deviation and range of three axes and total acceleration, correlation among three axes, kurtosis, skewness,…
	Frequency domain**:** power spectral density, energy of the signal …
GPS	Speed, elevation difference

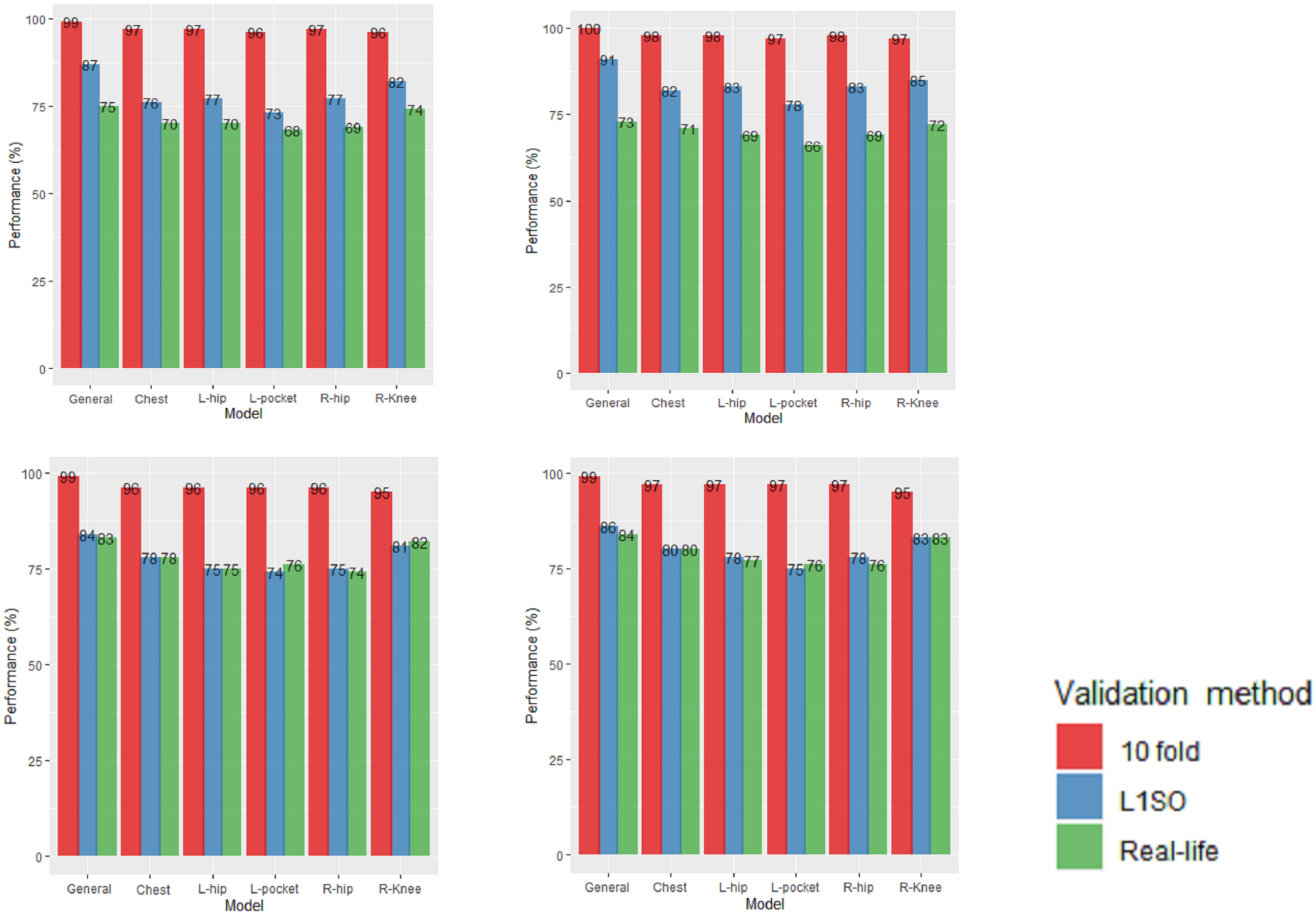
Results

Accelerometer data only

Accelerometer & GPS data

Scenario 1
Training data:
Semi structured dataset

Scenario 2
Training data:
Combined dataset
(Semi structured + real life)



Confusion matrix of a participant (with the highest GPS contribution)

Accelerometer only	Cycle	Lie	N-Walk	Run	Sit	Stand	Walk	**Recall**	**Precision**	**F1**
Cycle	743	0	2	0	0	0	0	100	100	100
Lie	0	185	1	0	1	0	0	99	99	99
N-walk	2	0	800	1	0	0	91	**77**	**89**	**83**
Run	0	0	0	320	0	0	0	99	100	100
Sit	0	1	0	0	170	1	0	99	99	99
Stand	0	1	0	0	0	157	0	99	99	99
Walk	0	0	233	2	0	1	885	**91**	**79**	**84**

Accelerometer & GPS	Cycle	Lie	N-Walk	Run	Sit	Stand	Walk	**Recall**	**Precision**	**F1**
Cycle	738	0	0	0	0	0	0	100	100	100
Lie	0	186	1	0	0	0	0	99	99	99
N-walk	1	0	810	1	0	0	63	**89**	**93**	**91**
Run	0	0	0	318	0	0	1	99	100	99
Sit	0	1	0	0	166	1	0	98	99	99
Stand	0	1	0	0	3	158	0	99	98	98
Walk	1	0	97	2	0	1	1018	**94**	**91**	**93**

Conclusion

- Adding GPS features (speed and elevation difference) to accelerometer data improves classification performance particularly for detecting non-level and level walking.

- The physical activity classification models are strongly transferable on real-life data if combined data are used for training.

- The knee-model provides the minimal device configuration with reliable accuracy for detecting real-life PA types.

- L1SO cross validation is a more realistic evaluation method in physical activity type detection.

Hoda Allahbakhshi

Dr. Lindsey Conrow

sensors

MDPI

Article

Using Accelerometer and GPS Data for Real-Life Physical Activity Type Detection

Hoda Allahbakhshi [1,*], Lindsey Conrow [1,2], Babak Naimi [3] and Robert Weibel [1,2]

[1] Department of Geography, Geographic Information Systems Unit, University of Zurich (UZH), Winterthurerstrasse 190, 8057 Zurich, Switzerland; Lindsey.Conrow@geo.uzh.ch (L.C.); Robert.Weibel@geo.uzh.ch (R.W.)

[2] University Research Priority Program "Dynamics of Healthy Aging", University of Zurich, Andreasstrasse 15, 8050 Zurich, Switzerland

[3] Department of Geosciences and Geography, University of Helsinki, P.O. Box 64, 00014 Helsinki, Finland; Naimi.b@gmail.com

* Correspondence: Hoda.Allahbakhshi@geo.uzh.ch

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Abstract: This paper aims to examine the role of global positioning system (GPS) sensor data in real-life physical activity (PA) type detection. Thirty-three young participants wore devices including GPS and accelerometer sensors on five body positions and performed daily PAs in two protocols, namely semi-structured and real-life. One general random forest (RF) model integrating data from all sensors and five individual RF models using data from each sensor position were trained using semi-structured (Scenario 1) and combined (semi-structured + real-life) data (Scenario 2). The results showed that in general, adding GPS features (speed and elevation difference) to accelerometer data improves classification performance particularly for detecting non-level and level walking. Assessing the transferability of the models on real-life data showed that models from Scenario 2 are strongly transferable, particularly when adding GPS data to the training data. Comparing individual models indicated that knee-models provide comparable classification performance (above 80%) to general models in both scenarios. In conclusion, adding GPS data improves real-life PA type classification performance if combined data are used for training the model. Moreover, the knee-model provides the minimal device configuration with reliable accuracy for detecting real-life PA types.

Keywords: physical activity type; real-life; GPS; GIS

Prof. Robert Weibel

Dr. Babak Naimi

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Thank you