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Data Article

Activities of daily living with motion: A dataset with accelerometer, magnetometer and gyroscope data from mobile devices

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ABSTRACT

The dataset presented in this paper is related to the performance of five Activities of Daily Living (ADL) with motion, such as walking, running, standing, walking upstairs, and walking downstairs. These activities were performed with a mobile device in a waistband, containing the data acquired from accelerometer, magnetometer, and gyroscope sensors. These data include the motion data, which allow the characterization of the different types of movement. The data acquisition was performed in open environments by 25 individuals (15 man, and 10 woman) in the Covilhã, and Fundão municipalities (Portugal). The data related to the different sensors was acquired with a sampling rate of 100 Hz by the accelerometer, 50 Hz by the magnetometer, and 100 Hz by the gyroscope sensors. It includes the captures related to a minimum of 2000 captures for each ADL, which corresponds to 2.8 h (approximately) for each ADL. In total, this dataset includes 13.9 h (approximately) of captures. These data can be reused for the implementation of data processing techniques, and artificial intelligence methods.

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Specifications Table

Subject	Electrical and Electronic Engineering Biomedical Engineering Health
Specific subject area	Activities of Daily Living Sensors Mobile Devices
Type of data	Table
How data were acquired	The data from accelerometer, magnetometer, and gyroscope sensors were acquired with a mobile application installed in a BQ Aquaris 5.7 smartphone [1], which it has a Quad Core CPU and 16 GB of internal memory. The smartphone was placed in a waistband during the performance of the different activities. During the data collection, the user performs only the daily activities of interest, so no there is no data collection during other activities. Therefore, the acquired data is reliable and without such noise (e.g., no data collection during driving in vehicles, sleeping, etc.).
Data format	Raw text files
Parameters for data collection	The selected individuals placed the smartphone in a waistband. Also, they previously selected, in the mobile application, the activity that they will perform for the labelling of the dataset. The different actions in the mobile application were previously explained to the intervenient before the start of the data acquisition.
Description of data collection	After the selection of the activity that the user will perform, he/she put the smartphone in a waistband. During the data collection, the three sensors (*i.e.,* accelerometer, magnetometer, and gyroscope sensors) collected the data at the same time, and the mobile application store it in text files for further analysis. The accelerometer, magnetometer, and gyroscope sensors are tri-axial sensors with the variables X, Y, and Z. The accelerometer has the model LIS3DHTR with a range between 0 and 32 m/s^2, a resolution of 0.004, and a power of 0.13 mA. Next, the magnetometer or Magnetic Field sensor has a model of AKM8963C with a range between 0 and 600 m/s^2, a resolution of 0.002, and a power of 0.25 mA. Finally, the gyroscope sensor was corrected by Google Inc, and it has a range between 0 and 34.91 m/s^2, a resolution of 0.011, and a power of 6.48 mA.
Data source location	Primary data sources: City/Town/Region: Covilhã Country: Portugal Latitude and longitude (and GPS coordinates, if possible) for collected samples/data: 40° 16' 50.037" N 7° 30' 15.555" W City/Town/Region: Fundão Country: Portugal Latitude and longitude (and GPS coordinates, if possible) for collected samples/data: 40° 7' 30.129" N 7° 30' 39.966" W
Data accessibility	Repository name: Raw dataset with accelerometer, gyroscope and magnetometer data for activities with motion Data identification number: 10.17632/xknhpz5t96.2 Direct URL to data: http://dx.doi.org/10.17632/xknhpz5t96.2
Related research article	I.M. Pires, N.M. Garcia, N. Pombo, F. Flórez-Revuelta, S. Spinsante, M.C. Teixeira, Identification of Activities of Daily Living through Data Fusion on Motion and Magnetic Sensors embedded on Mobile Devices, Pervasive and Mobile Computing, Elsevier, 47, pp. 78-93 https://doi.org/10.1016/j.pmcj.2018.05.005 I.M. Pires, G. Marques, N.M. Garcia, F. Flórez-Revuelta, M.C. Teixeira, E. Zdravevski, S. Spinsante, M. Coimbra, Pattern Recognition Techniques for the Identification of Activities of Daily Living Using a Mobile Device Accelerometer, Electronics 2020, 9, 509 https://doi.org/10.3390/electronics9030509

Value of the Data

- This dataset is important for the definition of patterns for the different activities [2–4], allowing the development of technological methods to support these activities;

- These data may allow the development of methods that allows to prevent the sedentarism, stimulate the physical activity, and monitor people with special needs, which it is commonly verified in young people [5–7].
- As these data can be corrected anywhere at anytime with a common smartphone, the data is useful for the development of low-cost solutions to support the different activities with its identification and monitoring, allowing to the creation of a personal digital life coach [8–11].
- It allows the reliable monitoring of people with special needs, including elderly people, and people with some healthcare problems with a simple mobile application or other commonly available devices to prevent some warning situations, alerting the responsible people to act in time [12,13].
- The use of artificial intelligence help in the support and it needs a large amount of data to implement reliable methods [14–16].
- Different methods may be tested with this labelled dataset to the implementation of intelligent methods with mobile technologies used daily [17–20].

1. Data Description

This paper presents a dataset with the data acquired during the performance of five ADL, including walking, running, standing, walking upstairs, and walking downstairs. The data acquisition process was performed with a smartphone named BQ Aquaris 5.7 placed in a waistband.

The dataset contains five main folders, *i.e.*, one folder for each ADL, and each folder contains more than 2000 numbered folders with the files related to the data acquired from the sensors embedded in the off-the-shelf mobile device. Thus, three files named as “accelerometer.txt”, “magnetometer.txt”, and “gyroscope.txt” ae available in each subfolder of this dataset. The dataset contains around 10,000 files related to the accelerometer sensor, around 10,000 files related to the magnetometer sensor, and around 10,000 files related to the gyroscope sensor. The data acquired from the different sensors are collected in m/s^2.

The files related to the accelerometer sensor includes the following columns:

- First column: Timestamp of each data acquired in milliseconds (ms).
- Second column: Value of the *x*-axis of the accelerometer (m/s^2).
- Third column: Value of the *y*-axis of the accelerometer (m/s^2).
- Fourth column: Value of the *z*-axis of the accelerometer (m/s^2).

Next, the files related to the magnetometer sensor includes the following columns:

- First column: Timestamp of each data acquired (ms).
- Second column: Value of the *x*-axis of the magnetometer (m/s^2).
- Third column: Value of the *y*-axis of the magnetometer (m/s^2).
- Fourth column: Value of the *z*-axis of the magnetometer (m/s^2).

Finally, the files related to the gyroscope sensor includes the following columns:

- First column: Timestamp of each data acquired (ms).
- Second column: Value of the *x*-axis of the magnetometer (m/s^2);
- Third column: Value of the *y*-axis of the magnetometer (m/s^2).
- Fourth column: Value of the *z*-axis of the magnetometer (m/s^2).

As example, the charts related to walking downstairs are shown in Figs. 1 to 3. The different movements can be identified as well as the performance of steps during the execution of the activity.

The analysis of the data corresponds to the fusion of different sensors data in three groups. These are:

- Accelerometer.
- Accelerometer, and Magnetometer.
- Accelerometer, Magnetometer, and Gyroscope.

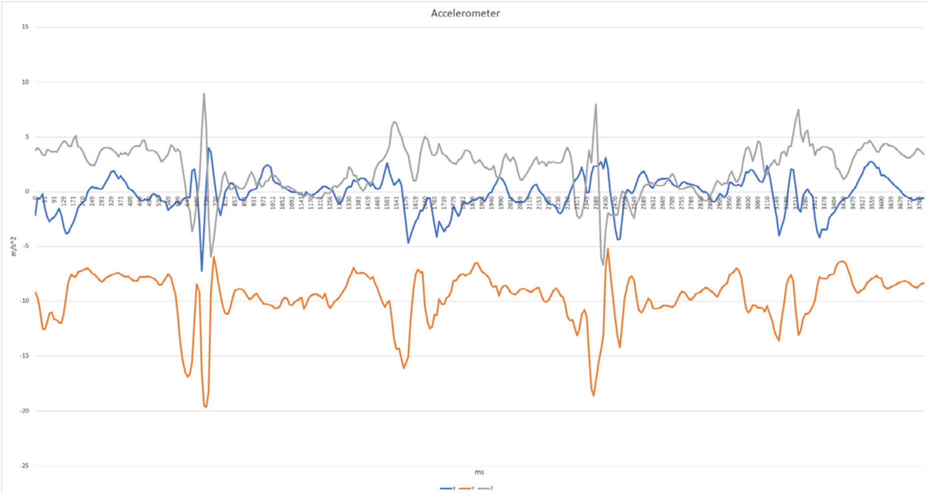

Fig. 1. Example of accelerometer data related to walking downstairs.

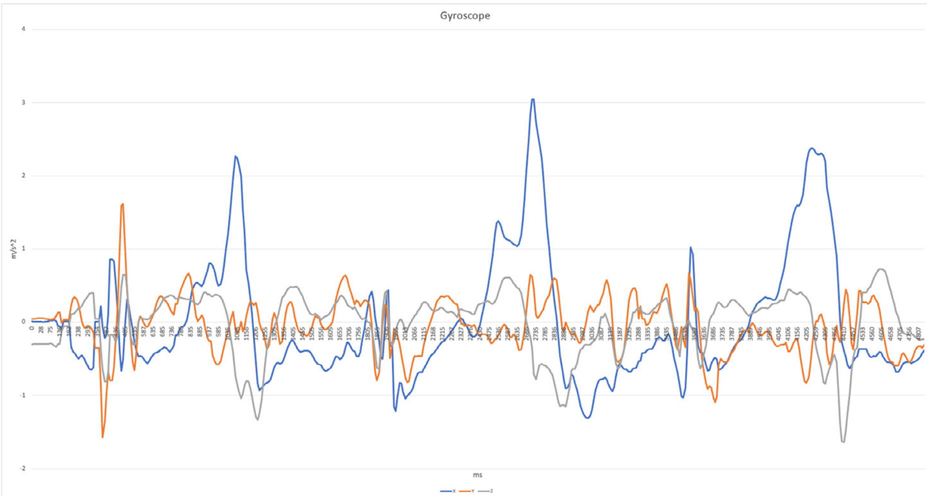

Fig. 2. Example of gyroscope data related to walking downstairs.

For the different analysis, the Euclidean norm was calculated for each point in the different files. Based on the data acquired from the different ADL, there are two types of features analysed from the data acquired by the different sensors. Thus, the measured features are forked in features related to maximum peaks, and features related to raw data. The features related to maximum peaks are:

- Average distance between five highest peaks: The maximum peaks were calculated, storing the timestamps of them. Next, the time between the five highest peaks were calculated.
- Average of maximum peaks: The mean of all maximum peaks was calculated.
- Standard deviation of maximum peaks: The standard deviation of all maximum peaks was calculated.
- Variance of maximum peaks: The variance of all maximum peaks was calculated.
- Median of maximum peaks: The median of all maximum peaks was calculated.

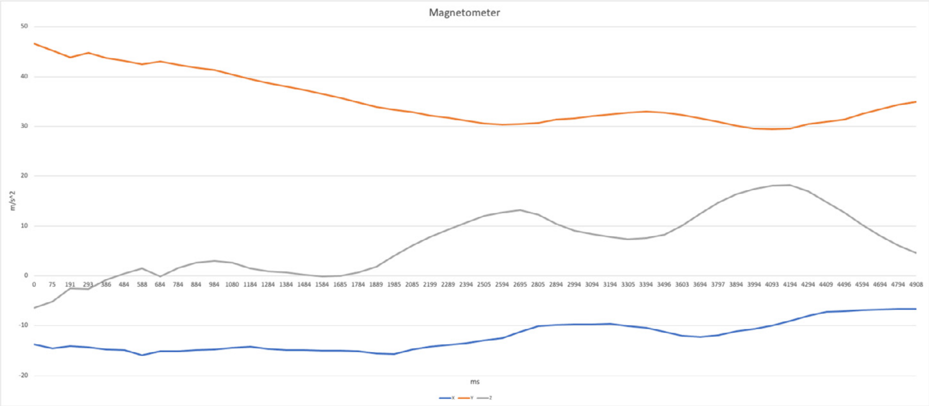

Fig. 3. Example of magnetometer data related to walking downstairs.

Next, the features related to raw data are:

- Average of raw data: The mean of values of the raw data was calculated.
- Standard deviation of raw data: The standard deviation of values of the raw data was calculated.
- Maximum of raw data: The maximum value of the raw data was calculated.
- Minimum of raw data: The minimum value of the raw data was calculated.
- Variance of raw data: The variance of values of the raw data was calculated.
- Median of raw data: The median of values of the raw data was calculated.

Table 1 presents the average of the different parameters of all accelerometer samples of the data acquisition related to each ADL.

Table 2 presents the average of the different parameters calculated after the fusion of the accelerometer and magnetometer samples of the data acquisition related to each ADL.

Table 3 presents the average of the different parameters calculated after the fusion of the accelerometer, magnetometer, and gyroscope samples of the data acquisition related to each ADL.

Table 1
Average of the parameters calculated for each ADL with the accelerometer sensor.

Parameters	Walking	Running	Standing	Walking Upstairs	Walking Downstairs
Average distance between five highest peaks	480.05	400.56	506.97	342.06	11.83
Average of maximum peaks	13.52	18.97	9.71	11.21	2.73
Standard deviation of maximum peaks	2.39	2.69	0.01	1.95	8.50
Variance of maximum peaks	6.41	10.40	0.01	4.30	11.35
Median of maximum peaks	13.64	19.57	9.71	10.98	9.92
Average of raw data	10.39	11.20	9.68	9.90	2.41
Standard deviation of raw data	2.75	5.67	0.02	1.81	17.07
Maximum of raw data	17.35	21.96	9.74	15.09	5.22
Minimum of raw data	4.21	1.49	9.63	5.80	6.69
Variance of raw data	8.39	33.59	0.00	3.74	10.20
Median of raw data	11.64	14.98	9.69	10.22	11.83

Table 2
Average of the parameters calculated for each ADL with the accelerometer, and magnetometer sensors.

Sensor	Parameters	Walking	Running	Standing	Walking Upstairs	Walking Downstairs
Accelerometer	Average distance between five highest peaks	476.60	398.53	506.14	332.32	312.81
	Average of maximum peaks	13.51	18.95	9.71	11.20	11.85
	Standard deviation of maximum peaks	2.40	2.71	0.01	1.96	2.73
	Variance of maximum peaks	6.50	10.57	0.01	4.37	8.55
	Median of maximum peaks	13.62	19.57	9.71	10.97	11.38
	Average of raw data	2.76	5.69	0.02	1.80	2.42
	Standard deviation of raw data	17.58	22.42	9.74	15.15	17.16
	Maximum of raw data	10.40	11.23	9.68	9.92	9.93
	Minimum of raw data	4.39	1.50	9.63	6.14	5.46
	Variance of raw data	8.45	33.85	0.00	3.77	6.77
	Median of raw data	11.57	14.86	9.69	10.22	10.19
Magnetometer	Average distance between five highest peaks	341.24	130.34	136.80	191.59	176.94
	Average of maximum peaks	43.21	40.80	42.44	41.34	42.63
	Standard deviation of maximum peaks	2.18	2.71	0.28	2.99	2.90
	Variance of maximum peaks	12.11	14.74	0.10	22.76	17.71
	Median of maximum peaks	43.28	40.91	42.46	41.31	42.84
	Average of raw data	2.19	2.71	0.28	3.02	2.93
	Standard deviation of raw data	43.07	40.79	42.44	41.30	42.59
	Maximum of raw data	46.83	45.13	42.89	46.88	47.63
	Minimum of raw data	39.08	36.24	41.85	36.05	36.94
	Variance of raw data	12.01	14.74	0.10	23.73	18.60
	Median of raw data	43.16	40.85	42.45	41.23	42.76

2. Experimental Design, Materials and Methods

The smartphone acquired samples with 5 seconds of data collected from the different sensors, *i.e.*, accelerometer, magnetometer, and gyroscope. The data were collected with a smartphone in a smartphone in a waistband horizontally positioned.

The instrumentation of the different individuals is simple to increase the acceptance of the presented methodology of data acquisition, and further mobile applications developed.

2.1. Participants

A total of 25 individuals with different types of diseases aged between 16 and 60 years old were selected for participation in the data acquisition. Regarding the lifestyles of the different participants, 10 individuals are mainly active, and the others 15 individuals are mainly sedentary. The data acquisition was performed in different environments, such as hall, street, and other places.

(1) Age = 33.5200 ± 13.5250 years old

2.2. Procedure

The different sensors data were recorded during the voluntary performance of the different ADL with the smartphone placed on a waistband.

Table 3
Average of the parameters calculated for each ADL with the accelerometer, magnetometer, and gyroscope sensors.

Sensor	Parameters	Walking	Running	Standing	Walking Upstairs	Walking Downstairs
Accelerometer	Average distance between five highest peaks	476.60	398.53	506.14	332.20	313.67
	Average of maximum peaks	13.51	18.95	9.71	11.20	11.86
	Standard deviation of maximum peaks	2.40	2.71	0.01	1.96	2.73
	Variance of maximum peaks	6.50	10.57	0.01	4.37	8.55
	Median of maximum peaks	13.62	19.57	9.71	10.97	11.39
	Average of raw data	2.76	5.69	0.02	1.80	2.42
	Standard deviation of raw data	17.58	22.42	9.74	15.15	17.15
	Maximum of raw data	10.40	11.23	9.68	9.92	9.94
	Minimum of raw data	4.39	1.50	9.63	6.14	5.46
	Variance of raw data	8.45	33.85	0.00	3.77	6.77
	Median of raw data	11.57	14.86	9.69	10.22	10.20
Magnetometer	Average distance between five highest peaks	341.24	130.34	136.80	191.63	177.26
	Average of maximum peaks	43.21	40.80	42.44	41.34	42.62
	Standard deviation of maximum peaks	2.18	2.71	0.28	2.99	2.90
	Variance of maximum peaks	12.11	14.74	0.10	22.77	17.70
	Median of maximum peaks	43.28	40.91	42.46	41.31	42.83
	Average of raw data	2.19	2.71	0.28	3.02	2.93
	Standard deviation of raw data	43.07	40.79	42.44	41.30	42.58
	Maximum of raw data	46.83	45.13	42.89	46.88	47.62
	Minimum of raw data	39.08	36.24	41.85	36.05	36.93
	Variance of raw data	12.01	14.74	0.10	23.74	18.60
	Median of raw data	43.16	40.85	42.45	41.24	42.75
Gyroscope	Average distance between five highest peaks	539.48	442.54	468.05	320.02	351.75
	Average of maximum peaks	3.83	4.00	0.03	1.72	1.61
	Standard deviation of maximum peaks	1.97	0.76	0.02	1.05	1.08
	Variance of maximum peaks	9.36	0.76	0.00	2.80	3.11
	Median of maximum peaks	3.59	4.14	0.02	1.57	1.40
	Average of raw data	1.78	1.15	0.01	1.47	1.43
	Standard deviation of raw data	2.36	2.36	0.02	1.41	1.18
	Maximum of raw data	9.08	5.82	0.10	16.32	15.36
	Minimum of raw data	0.14	0.27	0.01	0.17	0.12
	Variance of raw data	6.60	1.46	0.01	3.71	3.88
	Median of raw data	2.58	3.08	0.02	1.31	1.11

Initially, the individuals were instrumented as presented in Fig. 4. Then, the individual start the execution of the different ADL.

The main idea is the easy instrumentation for the collection of data elated to the different activities, such as walking, walking upstairs, walking downstairs, running, and standing. The rules for the instrumentation and data acquisition are easy to understand. These are:

(1) Instrument the individual with a waistband.
(2) Put the smartphone in a waistband in the horizontal orientation.
(3) Open the mobile application to acquire the different sensors' data.
(4) Press the button to start the data acquisition.
(5) The individual starts the performance of the activity.

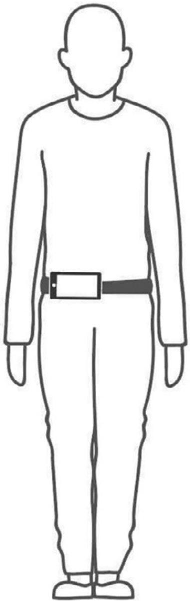

Fig. 4. Instrumentation of the different individuals.

(6) The data acquisition starts after 10 s.
(7) The data acquisition has a duration of 5 s.
(8) The data acquisition stops for 5 min.
(9) The flow returns to the point 7, and it repeats continuously.

Ethics Statement

The participants signed an ethical agreement to allow us to share the results of the tests in an anonymous form. The agreement also provided the participants' informed consent considering the risks and the objective of the study. Ethics Committee from Universidade da Beira Interior approved the study with the number CE-UBI-Pj-2020-035.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships which have, or could be perceived to have, influenced the work reported in this article.

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