D2.7 Dataset for physical activity recognition using smartphones sensors

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Summary

This document describes our dataset for physical activity recognition. It is collected with ten participants, where each of them performed seven different physical activities while carrying five smartphones on various body positions. For data collection, four smartphone sensors are used: an accelerometer, a linear acceleration sensor, a gyroscope and a magnetometer. This dataset can be used for future studies in many ways such as analyzing the role of various sensors, body positions, and fusion of various sensors. It can also be used to compare various classification methods and dataset features for better activity recognition.

Contents

1 Physical activities dataset

In this chapter, we describe our dataset for seven different physical activities. First, we describe how the dataset was collected. Then we present its structure. Finally, we describe the potential uses of this dataset.

1.1 Data collection protocol

In the data collection experiments, we collected data for seven physical activities, which is publicly available at [1]. These activities are walking, sitting, standing, jogging, biking, walking upstairs, and walking downstairs, which are mainly used in the related studies and they are the basic motion activities in daily life. There were ten participants involved in our data collection experiment who performed each of these activities for 3-4 minutes. All ten participants were male, between the ages of 25 and 30. The experiments were carried out indoors in one of the university buildings, except biking. For walking, and jogging, the department corridor was used. For walking upstairs and downstairs, a 5-floor building with stairs was used. Each of these participants was equipped with five smartphones on five body positions as shown in Fig. 1:

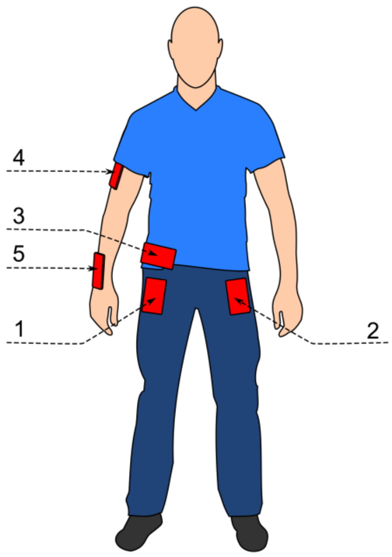

Fig.1. Smartphones on various body positions in data collection process [2].

1. One in their right jean's pocket.
2. One in their left jean's pocket.
3. One on belt position towards the right leg using a belt clipper.
4. One on the right upper arm.
5. One on the right wrist.

The first three positions are commonly used by people carrying smartphones. The fourth position is usually used when activities like jogging are performed. However, we used this position for all activities to see its role on the performance. A smart-watch was simulated with the fifth position as smart-watches are coming into the market these days. For these experiments, we used Samsung Galaxy SII (i9100) smartphones.

The orientation of the smartphones was portrait for the upper arm, wrist, and two pockets, and landscape for the belt position. The data was recorded for all five positions at the same time for each activity and it was collected at a rate of 50 samples per second. This sampling rate (50 samples per second) is enough to recognize human physical activities, as we show in our previous study [3], as well as other relevant studies on activity recognition [6,7,8]. Moreover, in the state of the art, frequencies lower than 50 samples per second have been shown to be sufficient for activity recognition [4, 5]. So this sampling rate can be down sampled in future studies as per needs of the researchers.

For data collection, we adapted our own data collection app from our previous study by adding the linear acceleration sensor. This data collection app is available at [1]. The data was collected for an accelerometer, a gyroscope, a magnetometer, and a linear acceleration sensor. A brief description of these is as follows:

- Accelerometer: It measures acceleration in meter per second squared (m/sec^2) along its all three axis.
- Gyroscope: It measures the angular velocity in radians per second (rad/sec) along its all three axis.
- Magnetometer: It measures the magnetic field in micro tesla (μT) along its all three axis.
- Linear acceleration sensor: It is obtained by removing the gravity component from the accelerometer values. It is also measured in meter per second squared (m/sec^2) along its all three axis.

1.2 Dataset structure

There are ten excel files in our dataset. Each excel file contains data for each participant's seven physical activities for all five positions. We present the dataset in its raw form so that it can be used in various ways in future studies by other researchers.

The following notations are used in these files as excel column headings besides timestamp:

- For accelerometer: Ax = x-axis, Ay = y-axis, Az= Z-aixs
- For linear acceleration sensor: Lx = x-axis, Ly = y axis, Lz= Z-aixs
- For gyroscope: Gx = x-axis, Gy = y-axis, Gz= Z-aixs
- For magnetometer: Mx = x-axis, My = y-axis, Mz= Z-aixs

1.3 Potential uses

This dataset can be used in different ways in future studies. Some of the examples are presented here:

- For comparing various classification algorithms in different experimental setups for physical activity recognition.
- For evaluating the role of different smartphone sensors when they are used alone or in different combinations (sensor fusion).
- For comparing activity recognition performance at different body positions.
- For analyzing position-independence, such that trained classifiers can be used on various body positions without training them on all these positions, thereby giving the user more freedom.

- For comparing generic and personalized training and testing for classification algorithms. We provide each participant data separately so it can be used to train classifiers for individual users, thereby producing a personalized classification scenario.

We used this data for analyzing the role various smartphone sensors in activity recognition. We studied how and when these sensors should be combined for better activity recognition. We extracted various time and frequency domain features for this dataset and then used different classification methods to analyze them. For details on our data features, classifiers, and analysis results, please read our paper [2].

References

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