

# An Open Labelled Dataset for Mobile Phone Sensing Based Fall Detection

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## ABSTRACT

Fall detection is a classical use case for mobile phone sensing. Nonetheless, no open dataset exists that could be used to train, test and compare fall detection algorithms.

We present a dataset for mobile phone sensing-based fall detection. The dataset contains both accelerometer and gyroscope data. Data were labelled with four types of falls (e.g., “stumbling”) and ten types of non-fall activities (e.g., “sit down”). The dataset was collected with martial artists who simulated falls. We used five different state-of-the-art Android smartphone models worn on the hip in a small bag. Due to the datasets properties of using multiple devices and being labelled with multiple fall- and non-fall categories, we argue that it is suitable to serve as benchmark dataset.<sup>1</sup>

## Keywords

mobile phone sensing; open training dataset; fall detection; accelerometer; gyroscope; martial artists

## 1. INTRODUCTION

Fall detection is one of the classical use cases of mobile phone sensing, most often motivated in relation to assistive technology for elderly people.

For elderly people, falls are indeed a severe risk in terms of losing life quality. The older a person, the higher the risk to fall [3]. Fall detection systems cannot prevent falls but they can help minimize the consequences of a fall, and thus contribute to making elderly people feel safe living independently at home. Smartphones are often looked for to

<sup>1</sup>Note to reviewers: The dataset will be published on [www.figshare.com](http://www.figshare.com) on acceptance of the present paper at a scientific venue, as submitted in this instance to MobiQuitous'15.

provide this kind of assistance. Because of their nature as multi-functional devices, smartphones offer more flexibility in terms of reacting to a detected fall than a simple wristband for example. For instance, a simple voice-based dialogue with the smartphone, could be triggered as first response in order to ensure that indeed a fall has happened and indeed, the elderly person wants to call for help.

Despite such a scenario and argumentation being quite widespread in mobile phone sensing and ambient assisted living [2], every existing work on fall detection uses their own dataset to evaluate their fall detection algorithm.

## 2. DATASET

We created a labelled dataset of accelerometer and gyroscope data. Our goal was to simulate falls in a manner as realistic as possible. To this purpose, we worked together with martial artists, who are able to simulate falls without injuring themselves.

### 2.1 Labels

As labels for falls we selected falls in different directions and different speeds, namely “Stumbling” as a fast forward fall, “Slipping” as a fast backward fall, “Sliding” and “Getting Unconscious” as slow lateral falls.

As labels for non-fall activities (in literature often called “activities of daily life”- ADL) we selected “Walking”, “Stopping”, “Standing”, “Sit Down”, “Sit Down Quickly”, “Get Up”, “Stairs Up”, “Stairs Down”, “Bend Forward” and “Lying on the floor”. Similar labels occur throughout literature on fall detection [1, 4, 5].

### 2.2 Data Collection

The study took place in a gym hall. Falls were performed on the wooden floor, without mattresses.

#### *Simulation of Fall and Non Fall Activities*

We defined eight simulations (sequence of physical activities), seven incorporating a fall and one simulation with merely ADL. The simulations were performed by five martial artists in parallel and each was repeated five times.

Simulations incorporating a fall were performed in two different ways. The first pretends that the fallen person did not

sustain critical injuries and is able to organise help independently. In the second, a long lie period right after the fall simulates an emergency. Getting unconscious was simulated once and treated as an emergency in any case.

### Labelling

An observer manually captured the labels during the simulations with a mobile application running on a tablet device. The observer set a new label whenever the martial artists started with or passed over to an activity.

### Smartphones

We used five Android operated mobile phones, different in model and/or manufacturer for the recording.

## 2.3 Data Structure

The dataset thus contains automatic (accelerometer, gyroscope) and manual (labels) data. Three types of records were created during data collection: acceleration, orientation and label records. These are summarized in Table 1 and described in detail in the subsequent subsections.

Table 1. Acceleration, orientation and label records in dataset.

Record	Timestamp	DeviceID	UserID	Content
Acc.	x	x	x	$A_x, A_y, A_z, A_{xyz}$
Orient.	x	x	x	$\theta_x, \theta_y, \theta_z$
Label	x	-	-	Label, isFallFlag

### Acceleration and Orientation Records

Acceleration and orientation records store sensor data, device name, user name and time stamp of measurement. Sensor data is provided as three dimensional vector.  $(A_x, A_y, A_z)$  from the accelerometer indicating acceleration (in  $m/s^2$ ) along a device axis, not including gravity.  $(\theta_x, \theta_y, \theta_z)$  from gyroscope indicating the rotation (in degrees) around a device axis (azimuth, pitch and roll). Acceleration records additionally contain the total acceleration of the mobile phone  $|A_{xyz}|$ , computed as

$$|A_{xyz}| = \sqrt{|A_x|^2 + |A_y|^2 + |A_z|^2} \quad (1)$$

### Label Records

Records of labelled activities in the dataset store the label of the activity, the timestamp and a flag indicating the type of activity.

## 2.4 Descriptive Statistics

From the recordings we could generate the dataset with 492 records of labelled activities, 159300 records of acceleration and 159300 records of orientation. Table 2 shows the distribution of fall and ADL labels over the dataset. We recorded six hours of falls and four hours of ADL with a sampling frequency set to 5 Hz for both sensors.

## 3. DISCUSSION

The goal of this paper is to present the dataset to the research community. The dataset shall help as baseline to compare fall detection algorithms against each other.

Finally, we point out that this dataset contains accelerometer and gyroscope data from martial artists simulating falls.

Table 2. Distribution of fall and ADL labels

Labelled Activity		Count
Falls	Stumbling	23
	Slipping	21
	Sliding	20
	Get Unconscious	10
	$\Sigma$ Falls	74
ADL	Walking	83
	Stopping	18
	Standing	104
	Sit Down	32
	Sit Down Quickly	12
	Get Up	94
	Stairs Up	10
	Stairs Down	11
	Bend Forward	11
	Lay On the Floor	43
	$\Sigma$ ADL	418
	$\Sigma$ Falls + ADL	492

However, data from real falls by elderly people are not used in our dataset nor in any of the papers known to us. It may turn out that this is not good enough in order to develop reliable fall detection for the elderly people. There is therefore still a need to test fall detection algorithms “for real”, even if it is hard to imagine how this could be done in ethical research study set-ups.

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