Poster Abstract: A Versatile Annotated Dataset for Multimodal Locomotion Analytics with Mobile Devices

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ABSTRACT

We explain how to obtain a highly versatile and precisely annotated dataset for the multimodal locomotion of mobile users. After presenting the experimental setup, data management challenges and potential applications, we conclude with the best practices for assuring data quality and reducing loss. The dataset currently comprises 7 months of measurements, collected by smartphone's sensors and a body-worn camera, while the 3 participants used 8 different modes of transportation. It comprises 950 GB of sensor data, which corresponds to 750 hours of labelled data. The obtained data will be useful for a wide range of research questions related to activity recognition, and will be made available to the community.

1 INTRODUCTION

In recent years, there have been numerous studies analyzing smartphone sensor data collected during locomotion and motorized transportation. Analyzing such *multimodal* locomotion enables context-aware applications in fields such as: localization, activity recognition and fitness monitoring, smart homes and health-care.

Unfortunately, only few transportation datasets are publicly available, typically, covering only a small set of sensors in highly controlled scenarios, instead of real life situations. For example, Microsoft's GeoLife dataset [1] provides an impressive number of 17621 trajectories of 182 users over three years but the data is not annotated and only contains GPS traces. Wang et al. [2] have collected 12 hours of transportation data in a controlled setting using only accelerometers. Yu et al. [3] collected 8311 hours of transportation data with a single smartphone using only inertial sensors. Consequently, none of these datasets allows to study the influence of the different sensors, effects of sensor placement, and potential benefits of sensor fusion for activity recognition.

To overcome these issues, we designed the University of *Sussex-Huawei Locomotion (SHL)* dataset, which aims to be highly versatile and suitable for a wide range of studies in fields such as transportation recognition, mobility pattern mining, activity recognition, localization, tracking, and sensor fusion. To achieve this versatility, we designed a large-scale data collection setup, and collected 750 hours of labelled data over a period of 7 months. The SHL dataset contains multi-modal locomotion data, which was recorded by 3 participants engaging in 8 different modes of transportation in real-life setting. It was collected by multiple smartphone sensors and body-worn camera, and will be publicly available once it is fully collected and curated[1].

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[1] www.shl-dataset.org

2 DATA COLLECTION SETUP

2.1 Equipment

In order to ensure sensory rich and logistically practical data collection, we used 4 *HUAWEI Mate 9* smartphones [4]. They were placed on body locations where people are used to wearing phones: hand, torso, backpack, and trousers' front pocket. The phones are equipped with a custom data logging application[2][5], which logs 16 sensor modalities: accelerometer, gyroscope, magnetometer, linear acceleration, orientation, gravity, temperature, light sensor, ambient pressure, ambient humidity, location, satellites, cellular networks, WiFi networks, battery level and audio. An example of the GPS data collected for a visit in London is shown in Figure 1.

For each sensor, we measured with the highest respective sample rate as offered by the implementation of the Android services. The Android application synchronizes the phones over a Bluetooth connection, shows status information, and allows the user to annotate the data on the master phone. On this device, the user can choose 8 primary categories: *Still, Walk, Run, Bike, Car, Bus, Train, Subway (Tube)*. Additionally, for some of the categories the user can choose the location (inside or outside) and the posture (stand or sit), which gives 18 combinations in total. These annotations are send to the other phones for consistency.

Additionally, the participants wore a front-facing body camera, which was used to verify label quality during post-processing, and as part of the dataset it will allow vision-based processing, such as object recognition. The camera was set to take pictures every 30 seconds, which is frequent enough to reconstruct the measurement process of the course of the day and is less invasive to the user's privacy than a full recording.

[2] https://github.com/sussexwearlab/DataLogger

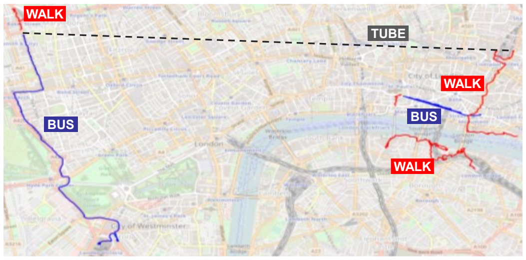

Figure 1. Visualization of the GPS data collected by a user in London, marked with the appropriate activity: bus, walk and tube.

2.2 Data Collection Procedure

Three participants were employed full time, in order to assure the quality of the data and the annotations. They were chosen after an interview during which we explained the data collection process, and examined the participants' motivation and reliability. They also signed a consent form, which was ethically approved by the University of Sussex. To further improve the quality of the data and ensure equal balance between the different activities (which is beneficial for machine learning approaches), we have designed a protocol in which each participant meets with the supervising researcher once a week in order to plan the activities of the following week. For this purposes a spreadsheet was shared online, which contained the activity scenario for each day of the following week. Additionally, we have created a group chat between the research team and each of the participants. This allowed the participants to have real-time support in case of questions, doubts or issues. Once planned, the participants were given the equipment to collect the data and to execute the pre-defined activities. During the data collection, they were asked to fill a diary, which was later used to help them in the annotation process, e.g., to resolve conflicts or recall missing information.

2.3 Data Storage and Annotation

During the data collection, the smartphone and the camera data is stored on the device's SD card. Once a week each user transfers the data to the research team and provides further information. First the user downloads the data on a PC and removes private photos. Second, in order to further improve the quality of the labels, the user performs additional data annotation. For this purpose we have used an in-house annotation tool [6]. The tool loads the sensor data and the time-lapse video, aligns both, and displays them as a time series. This allows the user to verify and correct the time stamps of the labels as well as to add further labels such as: having a *lunch*, *drinking*, having a *social interaction*, *road conditions*, and *traffic conditions*. These additional labels allow a more precise description of the user's day and support a wider scope of research, such as the automatic recognition of eating, or the detection of social interactions. Once the annotation process is finished, the raw and curated data is stored.

At the end of the measurement campaign, we performed a semi-structured interview in order to extract information from the participants about the data collection process. For this purpose, we prepared a questionnaire, which included questions regarding the difficulty to use the equipment, the difficulty to perform different activities, and how to improve the data collection experience. The analysis of the questionnaires should help us to understand the perspective of the measurement subjects and to improve upcoming large-scale measurement campaigns. We assessed data quality throughout the recordings as in Figure 2, which shows how much data is acquired from each sensor modality and allows fast visual identification of data loss, e.g., non-constant data acquisition).

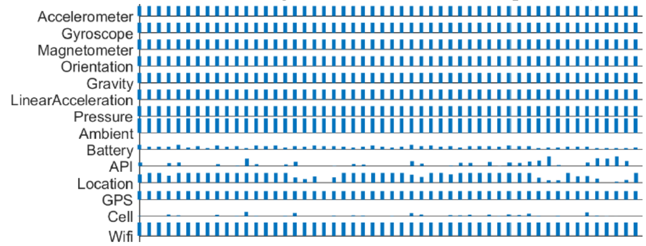

Figure 2. Data collected for 14 sensor modalities, plotted in time intervals of 10 minutes.

3 CONCLUSION

The *SHL* dataset currently contains 750 hours of labelled locomotion data: *Car* (88 h)*, Bus* (107 h)*, Train* (115 h)*, Subway* (89 h), *Walk* (127 h)*, Run* (21 h)*, Bike* (79 h)*,* and *Still* (127 h)*.*

The well-defined data collection procedure (employing participants for data collection, planning activity scenario in advance, the continuous data quality checkup, and the usage of the annotation tool) allowed us to create a versatile and richly annotated dataset.

The large number of included sensors at different body locations, the diverse set of activities in different areas, and the precise annotation, make this dataset a valuable foundation for various research fields, e.g., automatic recognition of transportation modes and activities, detection of social interaction, road conditions detection, traffic conditions detection, localization and sensor fusion. Further applications are expected based on the collection sound recordings and from the camera data, e.g., object and activity recognition. The GPS and WiFi data have valuable applications for indoor localization and can serve as baseline for sensor-based localization.

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