Data Acquisition for Smartphone Sensors Based Activity Recognition

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***Abstract* — Activity recognition from smartphone sensors has seen increasing interest in recent years. An effective sensor-based activity recognition system relies on careful training sets that take into consideration large anthropometric variations among users. We present in this paper a data set that was collected from participants with a diverse set of age, height and weight. This data set will present unique opportunities to address robust activity recognition algorithm design.**

***Index Terms*—activity recognition, data collection, smartphone sensors, accelerometers.**

I. Project Description

HUMAN movements are complex in nature even for simple daily activities such as walking and running. For the same type of activity, the styles can be large different among people. This poses great challenge for building successful activity recognition algorithms. The typical approach of using careful training sets usually suffer significant reduction in performance caused by anthropometric variations in real applications. In this work, we acquire a new dataset that contains adequate data with anthropometric variations in gender, weight, height and age.

The sensor type is another significant factor to consider in activity recognition. Many existing datasets use standalone sensors that can be firmly attached to human body [2, 4]. Although these sensors generate relatively reliable and accurate measurements, their application areas are limited. On the contrary, smartphones have been widely available to people and most of them incorporate diverse and powerful sensors including GPS [8], accelerometer, gyroscope and compass. Using these incorporated sensors for activity recognition extends the application areas to fitness monitoring, entertainment [1, 3, 5], elderly care [6, 7] etc. In this project, we adopt the smartphone sensors as the data acquisition device and collect the data from the 3-axis accelerometer and the 3-axis gyroscope. We also use machine learning methods for classification [9-11].

We collected data from 32 subjects. The demographic statistics of these subjects, as listed in Table 1, show that the data covers a wide range of the anthropometric variations. Each subject performs 5 different daily activities – slow walking, fast walking, running, slow biking and fast biking. These activities are performed on a treadmill or biking machine for 75 seconds each under the supervision of a student. The protocol speeds of some activities were reduced if subject felt not comfortable. For the first 3 activities, each was performed twice with the subjects carrying the mobile phone first in their front pocket and then in their back pocket. Biking activities were performed with the mobile phone only in front pocket. As a result, each activity has one label out of 8. An Android APK (Fig. 1) that runs on a Nexus 4 phone was utilized in the data acquisition.

Table 1. Demographic statistics of the participants in the data acquisition

Statistics	Mean	STD	Range
Age	30.5	7.8	20-52
Height (cm)	174.8	9.5	155-191
Weight (kg)	73.9	14.0	42-108

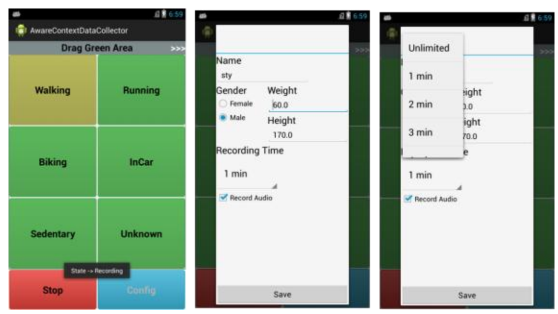

Fig. 1. Data collection APK interface

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