Human Activity Recognition via Smartphone Accelerometry

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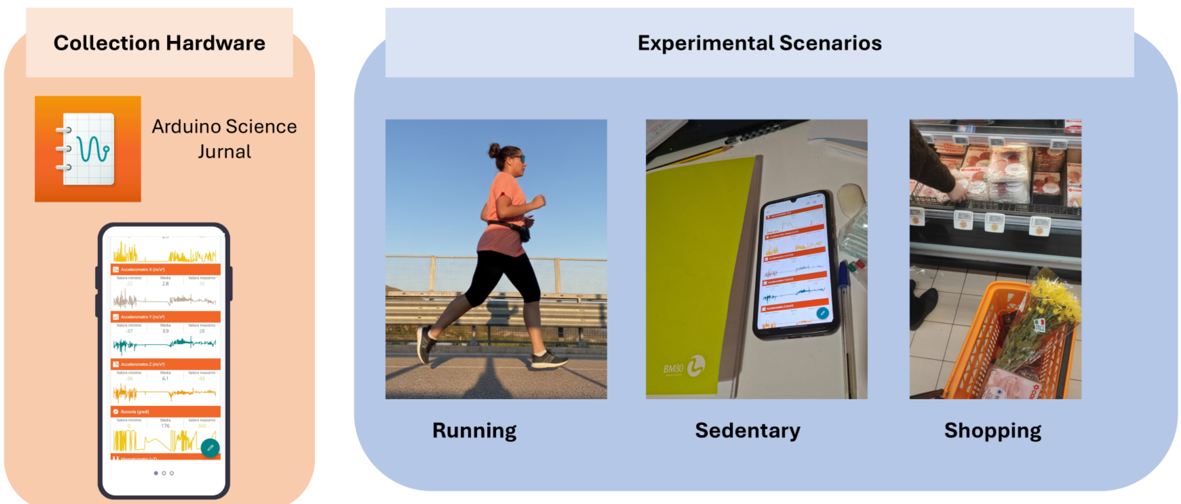

Figure 1. Experimental Protocol and Data Acquisition

1. Data Acquisition Platform and Experimental Protocol

The dataset was generated using the **Arduino Science Journal** application, leveraging the high-frequency inertial sensors (triaxial accelerometer) embedded within a standard smartphone device. Data collection was performed during a single, continuous session lasting 100 minutes and 21 seconds. The experiment was designed to capture three distinct phases of activity.

2. Experimental Protocol

The study involved the recording of **112275 samples**, representing three distinct levels of ambulatory intensity:

1. **Phase 1: High Activity (Running)** In which the subject performed a sustained running activity. This phase exhibits the highest variance and amplitude in the accelerometer and motion sensor data. These spikes are attributed to the mechanical impact and rapid body displacement associated with a running gait.
2. **Phase 2: Low Activity (Sedentary/Baseline)** Although the device was primarily positioned on a stable horizontal surface, the subject sporadically interacted with it to monitor the status of the ongoing experiment.
3. **Phase 3: Moderate Activity (Walking/Errands)** The subject performed daily errands, specifically walking through a supermarket to pick up groceries. This phase shows moderate variance. The morphological profile is clearly distinguishable from the high-intensity running phase and the low-intensity sedentary activity. In Figure 1, we have represented the experimental protocol followed during the data collection process

3. Data Description

The dataset consists of multiple, unsynchronized sensor streams. Each stream provides a Unix epoch timestamp (in milliseconds) that serves as the primary temporal reference for subsequent signal alignment.

Environmental context is captured by the **AmbientLightSensor**, which measures light levels in Lux. As evidenced in Figure 6, this metric is essential for identifying the device's surroundings and usage patterns: the high light intensity indicates when the phone was held in hand during a run or placed on a bright table, while a drop to near-zero Lux confirms when the device was placed in a pocket during grocery shopping.

Movement data is recorded through two primary methods. The **LinearAccelerometerSensor** tracks acceleration forces along three physical axes while excluding gravity, making it the most direct indicator of dynamic, user-generated motion. In contrast, the **AccX, AccY, and AccZ** parameters provide raw accelerometer readings in m/s^2 that include the constant force of gravity, which remains at approximately $9.81\,m/s^2$ on the vertical axis during periods of rest.

Directional orientation is handled by the **CompassSensor** and the **MagneticRotationSensor**. The former measures the device's heading relative to magnetic north in degrees, while the latter utilizes a fusion of magnetometer and accelerometer data to provide a more stable and accurate estimate of the device's rotation in space.

While we keep the full sensor suite synchronized to maintain a complete experimental record, we primarily target the linear accelerometer sensor data. Specifically, because the smartphone's orientation can shift unpredictably during physical movement.

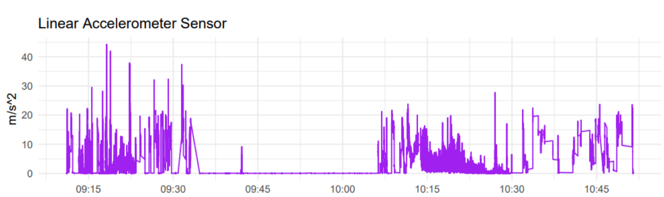

Figure 2. Linear Accelerometer Sensor readings. The spikes correspond to running, while the flatline indicates the device was stationary.

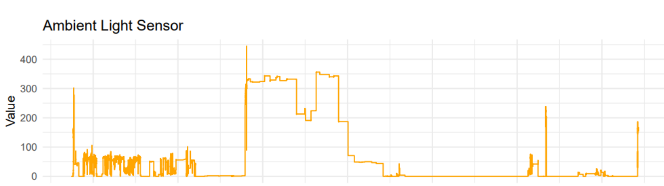

Figure 3. Ambient Light Sensor readings over time. The graph highlights transitions between different environments

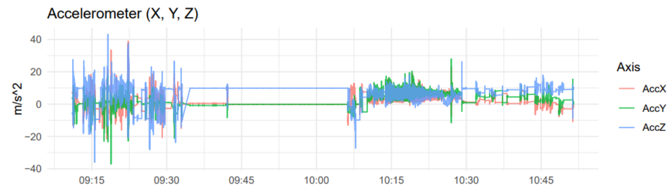

Figure 4. AccX, AccY, and AccZ Accelerometer

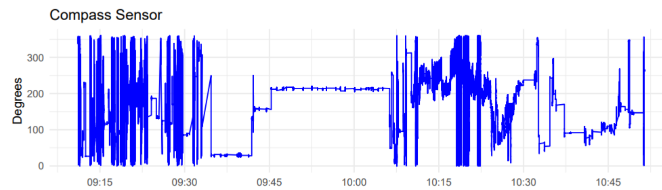

Figure 5. Compass Sensor

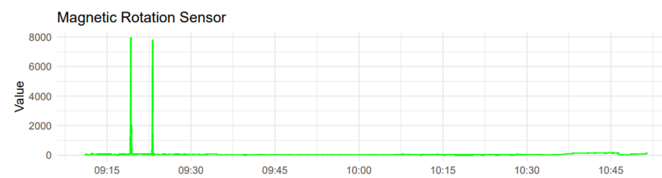

Figure 6. Magnetic Rotation Sensor