Human activity recognition with smartphone sensors

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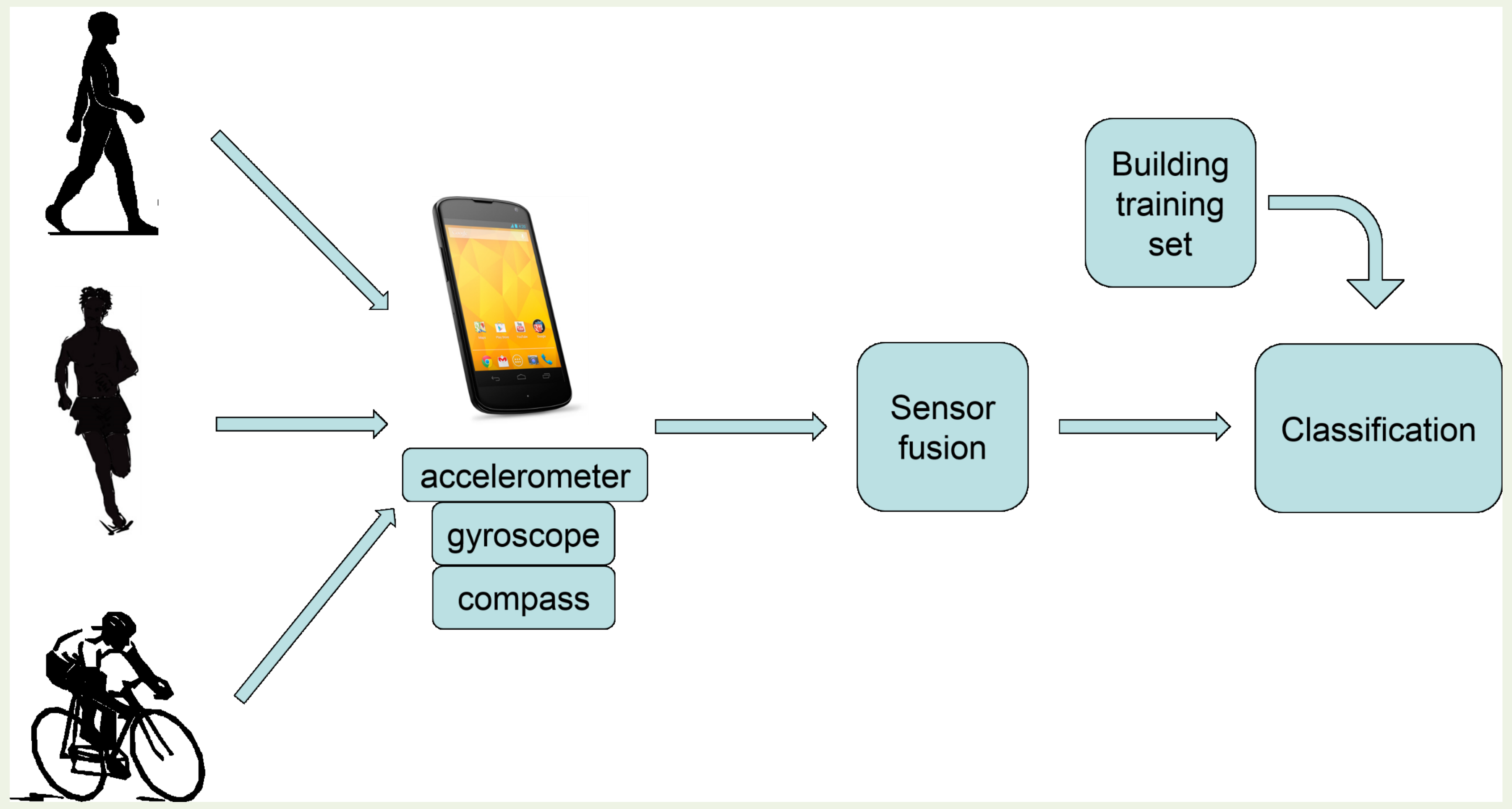
Sensor-based activity recognition

Sensor-based activity recognition integrate data mining, machine learning techniques with the sensor network area. Newer smartphone provides sufficient sensor integration and calculation power, making it the perfect device for continuous activity data recording in everyday life.

Applications include:

- Personal fitness
- Healthcare
- Elderly care
- Entertainment etc.



Data acquisition

- The sensor data is collected using an APK from Intel on an Android phone (Nexus 4).
- Each activity is performed with 10 seconds stationary period at beginning and end.
- In order to control the acquisition environment, all activities are performed on the constraint of treadmill or bicycle machine.

Main Challenges in activity recognition

- ***Challenge One*** : Intra-class variability. Although shared with general pattern recognition problem, this variability is more dominant in activity recognition. Some factors to consider are:

i. The variability of individuals with respect to gender, height, weight, body frame, etc.

ii. Activity styles may be on different dynamic scales for the same individual depending on the his/her body condition and/or emotion.

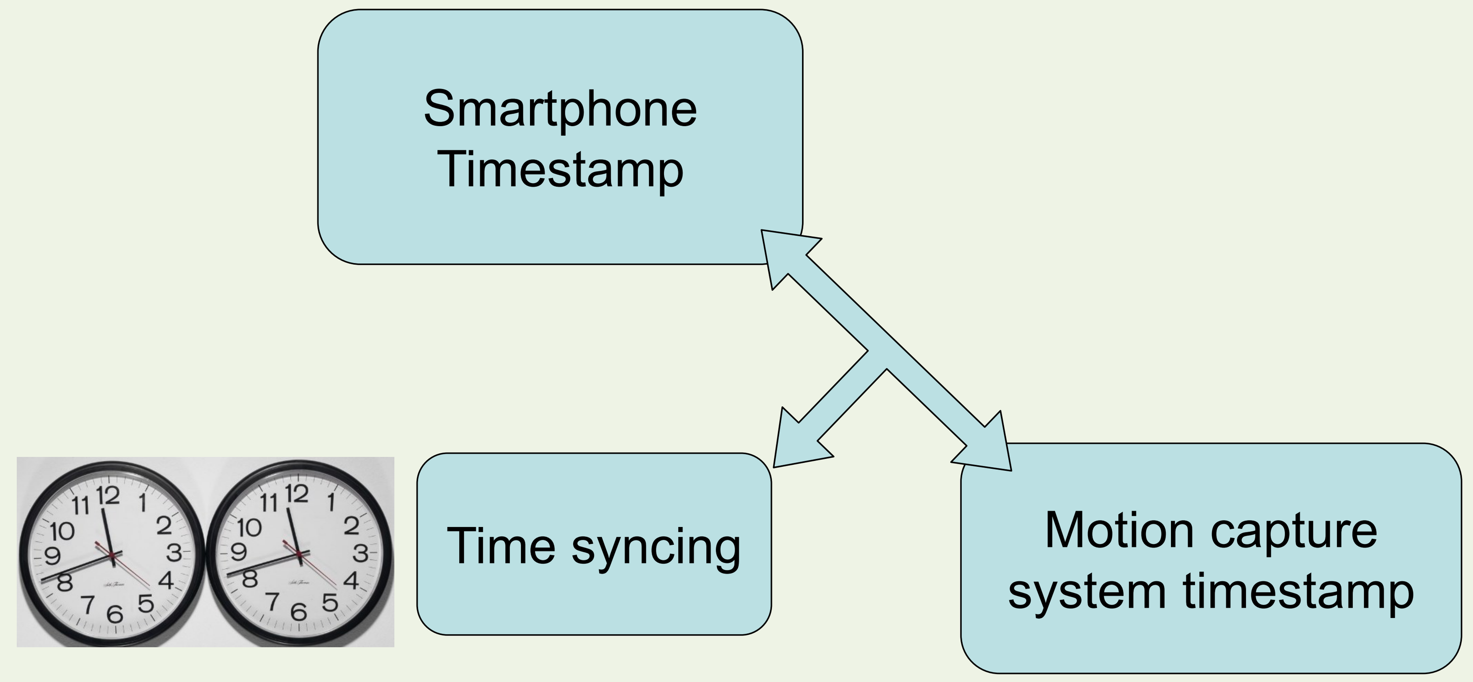
✓ We tried to address this issue by selecting a diverse group of participants. Also we let the participants perform activities with smartphone in different locations (front/back pockets) and at different speeds (Table 1). Data of 32 individuals have been collected to be interpreted as the training set.

Activity	Location	Speed	Duration
Slow walking	Back pocket	2.0 MPH	75 sec
	Front pocket	2.0 MPH	75 sec
Fast walking	Back pocket	3.8 MPH	75 sec
	Front pocket	3.8 MPH	75 sec
Running	Back pocket	4.4 MPH	75 sec
	Front pocket	4.4 MPH	75 sec
Biking	Front pocket	8~10 MPH	75 sec
	Front pocket	14~16 MPH	75 sec
Transition: Walking – Running – Walking	Back pocket	2.6 – 4.4 – 2.6 MPH	1 min – 1 min – 1 min
	Front pocket	2.6 – 4.4 – 2.6 MPH	1 min – 1 min – 1 min

Table 1. Detail information on the physical activity data collection

- ***Challenge Two*** : Exact transition between activities is not well defined. Accurately deciding the transition time is crucial for recognition. The accurate data labels are also lacking for classification.

✓ To solve this problem, we utilize the motion capture system to provide ground truth labelling since camera data could be much easier to interpret.



Activity transition

- Attach reflective markers on the smartphone. Motion capture system can then provide coordinate information of the markers during the activity recording.
- These coordinates data can be interpreted as the ground truth labelling of activity transition.
- The key issue we are solving now is the time syncing between mocap and the smartphone. A newer version of the mocap system will provide the absolute time, which can be used to sync the phone time.

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