웨어러블 센서를 이용한 사건인지 기반 일상 활동 예측

Event Cognition-based Daily Activity Prediction From Wearable Sensors

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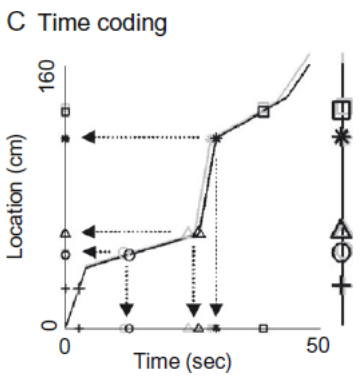
Event Cognition

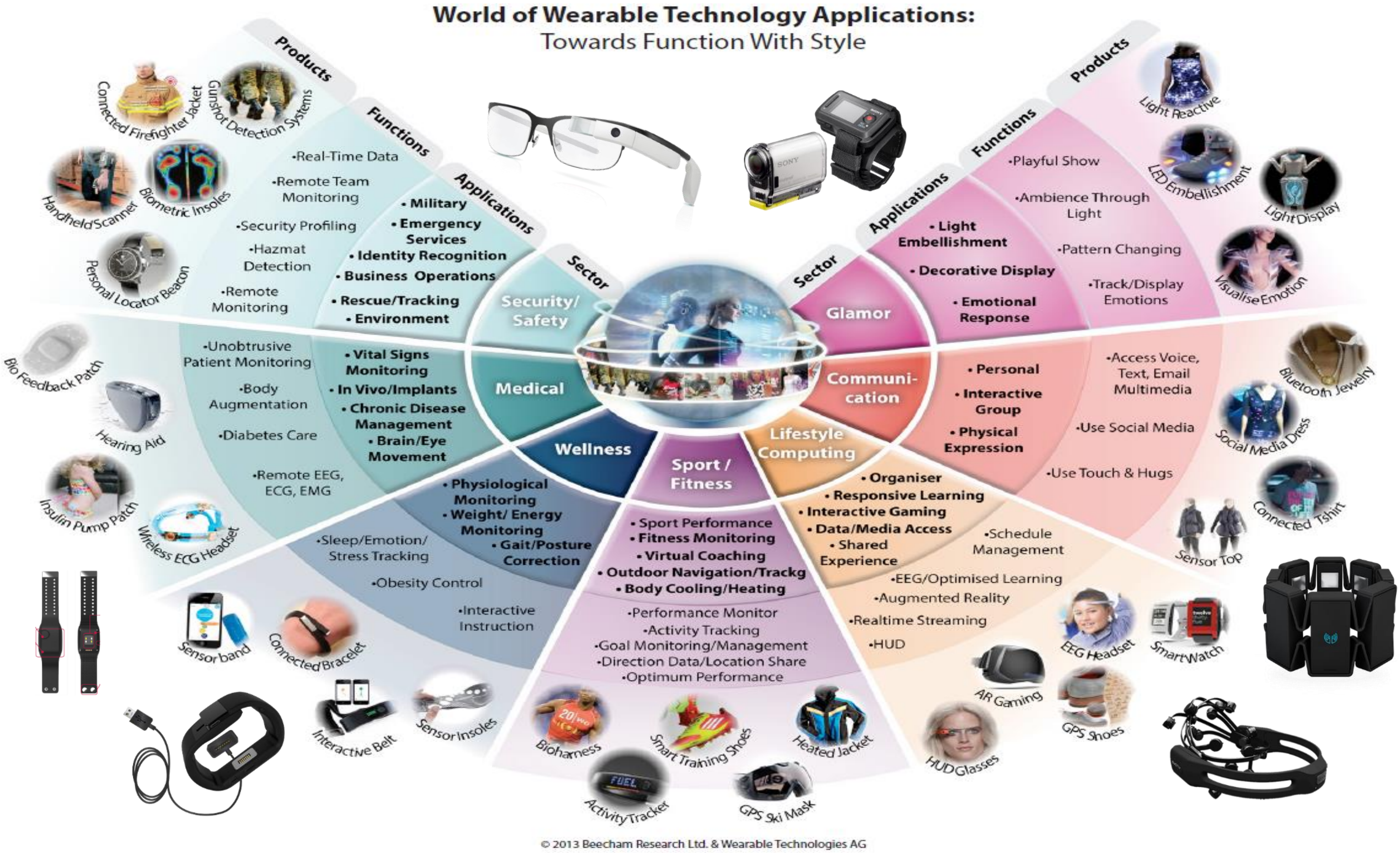
- **When is it?**
  - **Physical timestamp: 8:31 AM, 5:20 PM**
  - **Discrete time zone (or z/o): wake time, breakfast time, morning, night**
  - **Temporal constraints → Pulses & Steps (Ellis, 1988)**



Hasselmo (2009)

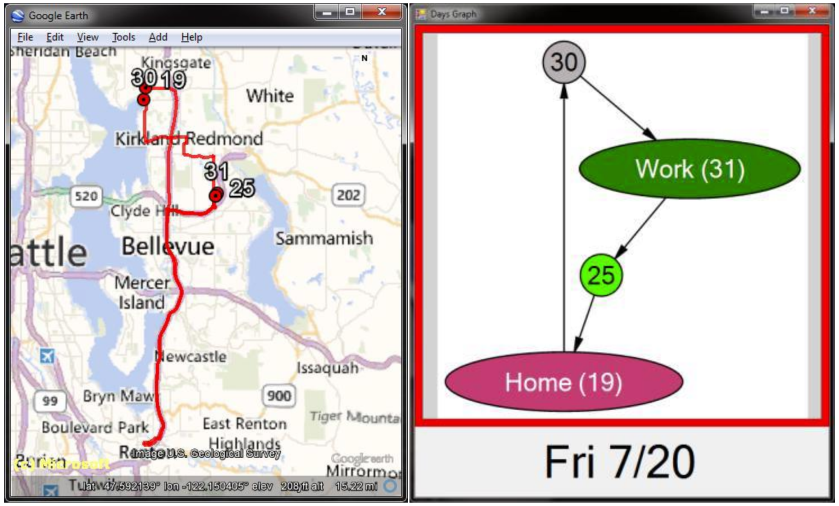
- **Where am I?**
  - **Physical coordinates: GPS, ZigBee, odometer, etc.**
  - **Logical place information (z/o): home, street, on the bus**
    ***can be hierarchical: Office #417 < Building #138 < SNU < Seoul < Korea;**
    Sofa < Living room < Home
- **What am I doing now?**
  - **Action: stand up, sit down, walking, running → related to physical body movements**
  - **Activity (z/o): eating, sleeping*, working, talking, etc.**
    ***can be also hierarchical and there could be OBJECTS handled or PEOPLE being together.**
- **Why?**
  - **Intention, Goal, …**

Wearable Devices

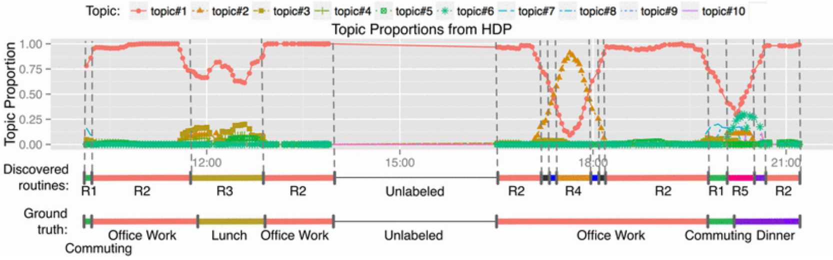


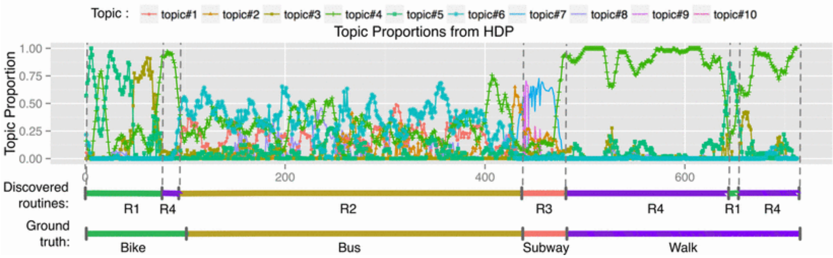
Related Works (1/2)

- **Day similarity from GPS traces**
  - Biagioni & Krumm (2013)
  - Assessing the similarity of a person's days based on location traces recorded from GPS
  - Sum of pairs distance w/DTW and the distance sensitive edit distance w/DTW, worked best at matching human assessments of day similarity



- **Automatic routine discovery**
  - Sun et al. (2014)
  - Nonparametric discovery of human routines from sensor data.
  - Vocabulary extraction ← DPGMM
  - Latent routine discovery ← HDP

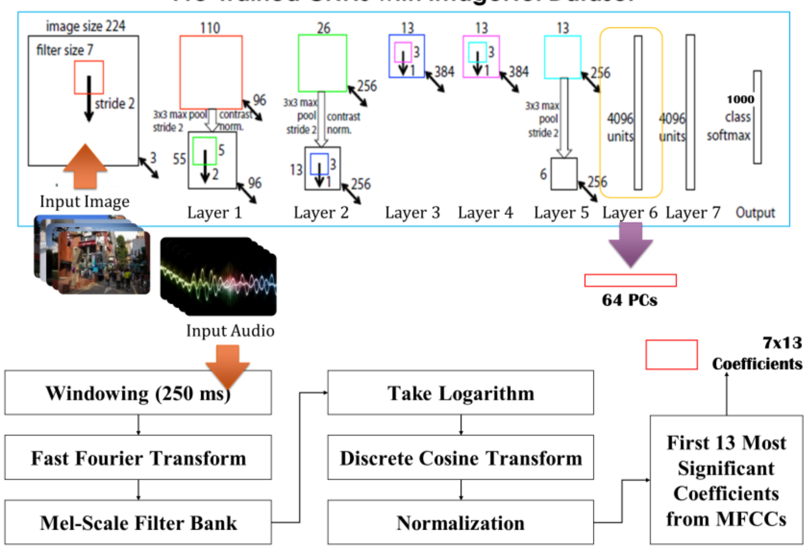




Related Works (2/2)

- **Multimodal activity recognition**
  - Lee et al. (2015)
  - Activity recognition by learning lifelogs from wearable sensors
  - Visual features ← CNN, PCA
  - Auditory features ← MFCC coefficients
  - Classification by using KNN

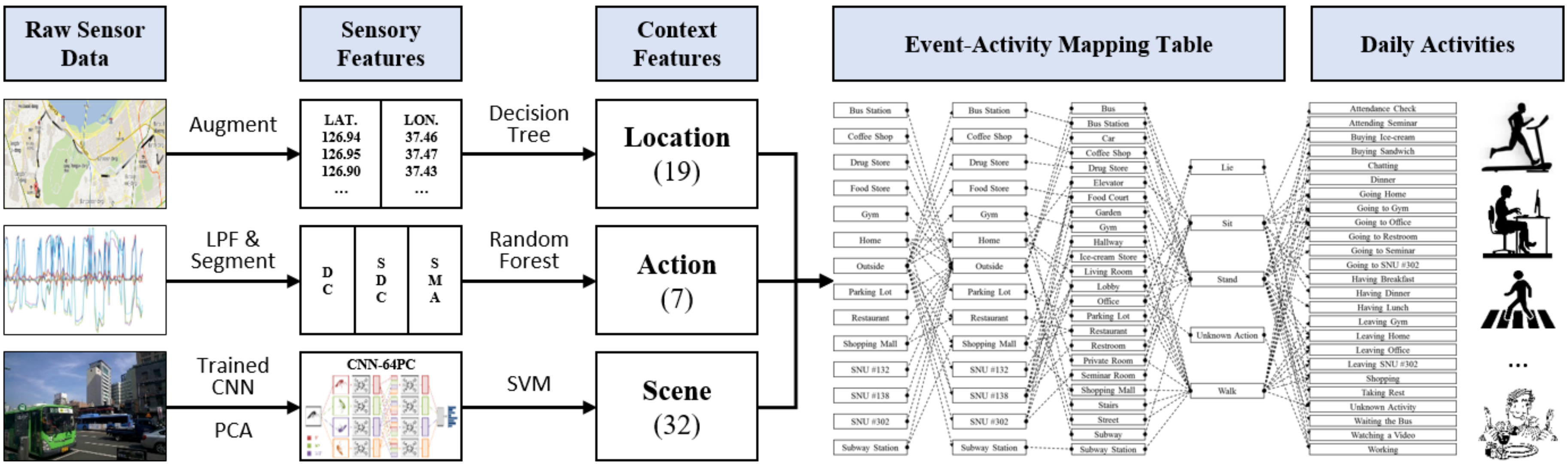
- **Egocentric activity prediction**
  - Castro et al. (2015)
  - Predicting daily activities from egocentric images using deep learning
  - CNN late fusion ensemble (RDF, KNN)
  - Image pixel + Metadata + Histogram



W: Working F: Family Tv: Television M: Meeting
R: Reading H: Hygiene Dr: Driving Do: Dogs C: Cooking

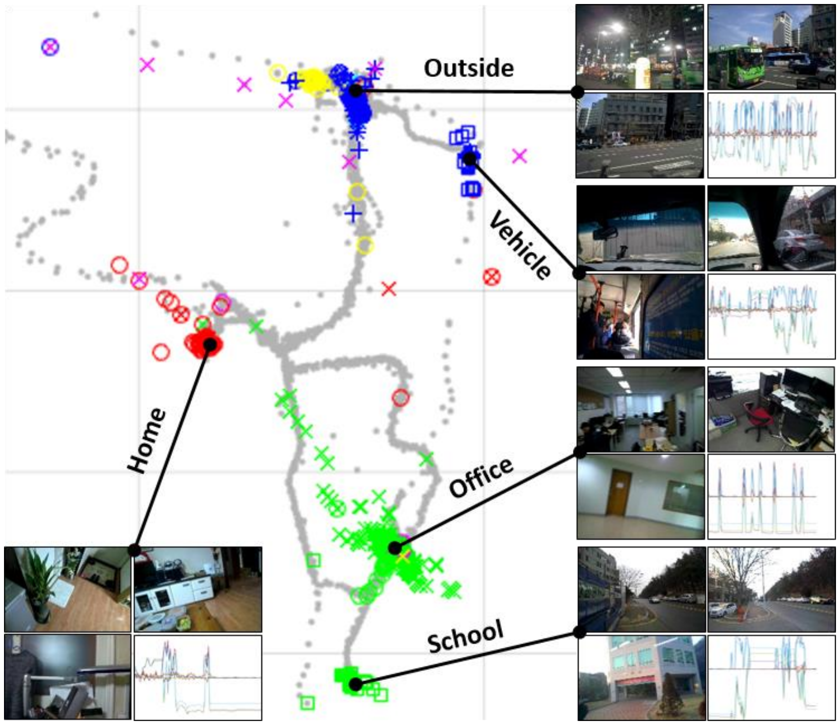
Research Goal

- ## Research Goal
  - **Multimodal sensor data from real daily life by using wearable devices**
  - **Preprocessing and feature extraction**
  - **Event entity classification: spatiotemporal location, scene, action**
  - **Event-activity mapping table learning for daily activity prediction**

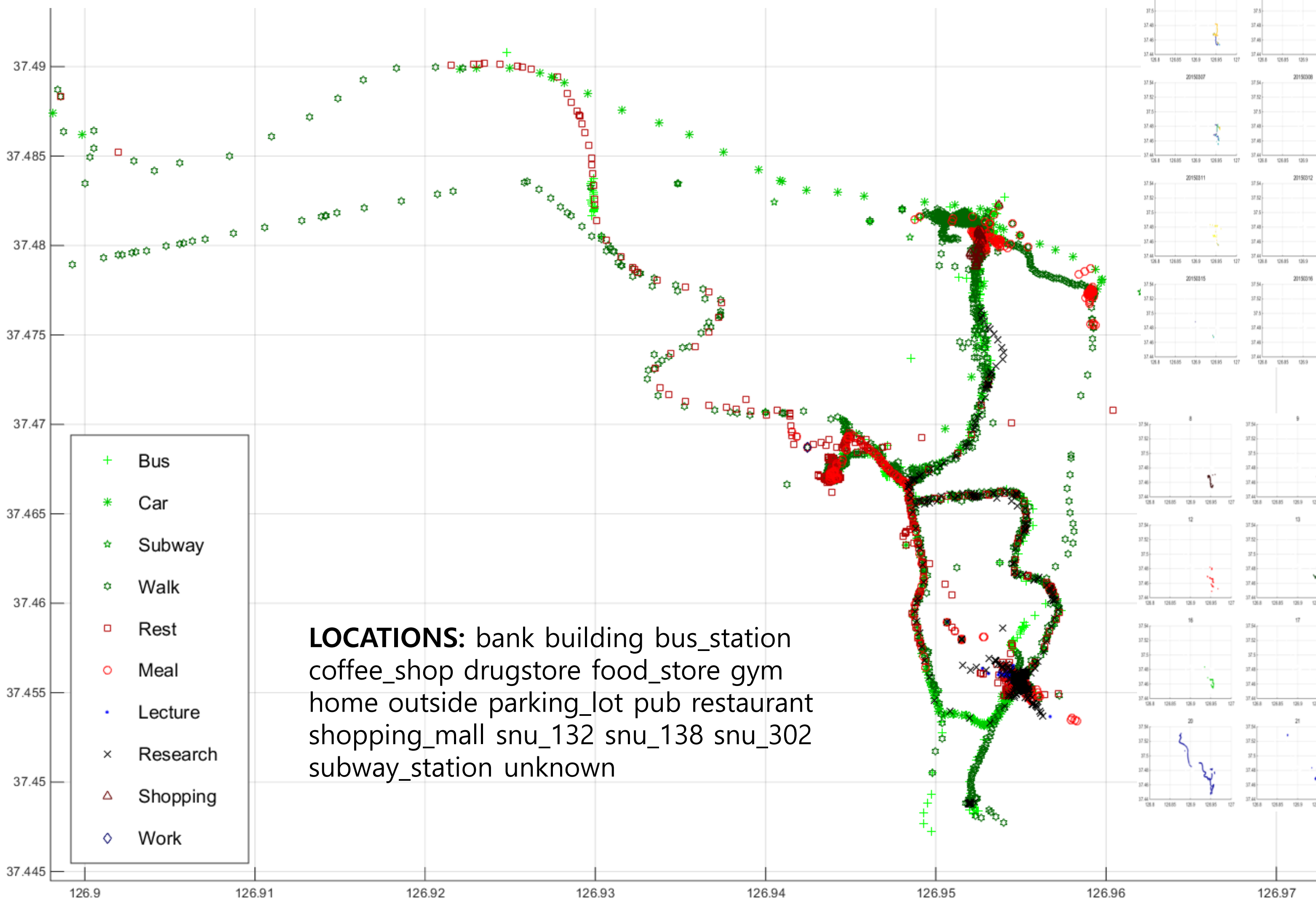


Wearable Sensor Data

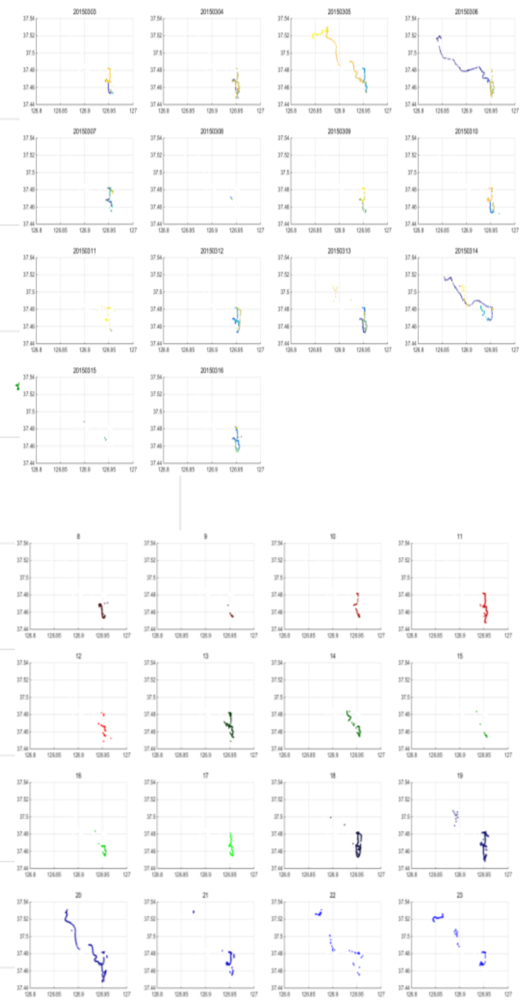
- Tools: Google glass, smartphone and a logging application
- Sensors: Camera, MIC, IMU, GPS (A-GPS)
- Logical Information: Location (4-Square API), Activity (logger app)
- Automatically/Manually labeled meta data



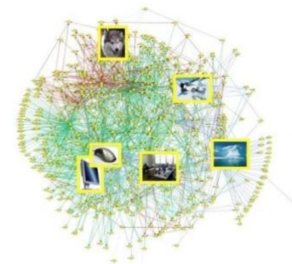
Location Context Classification



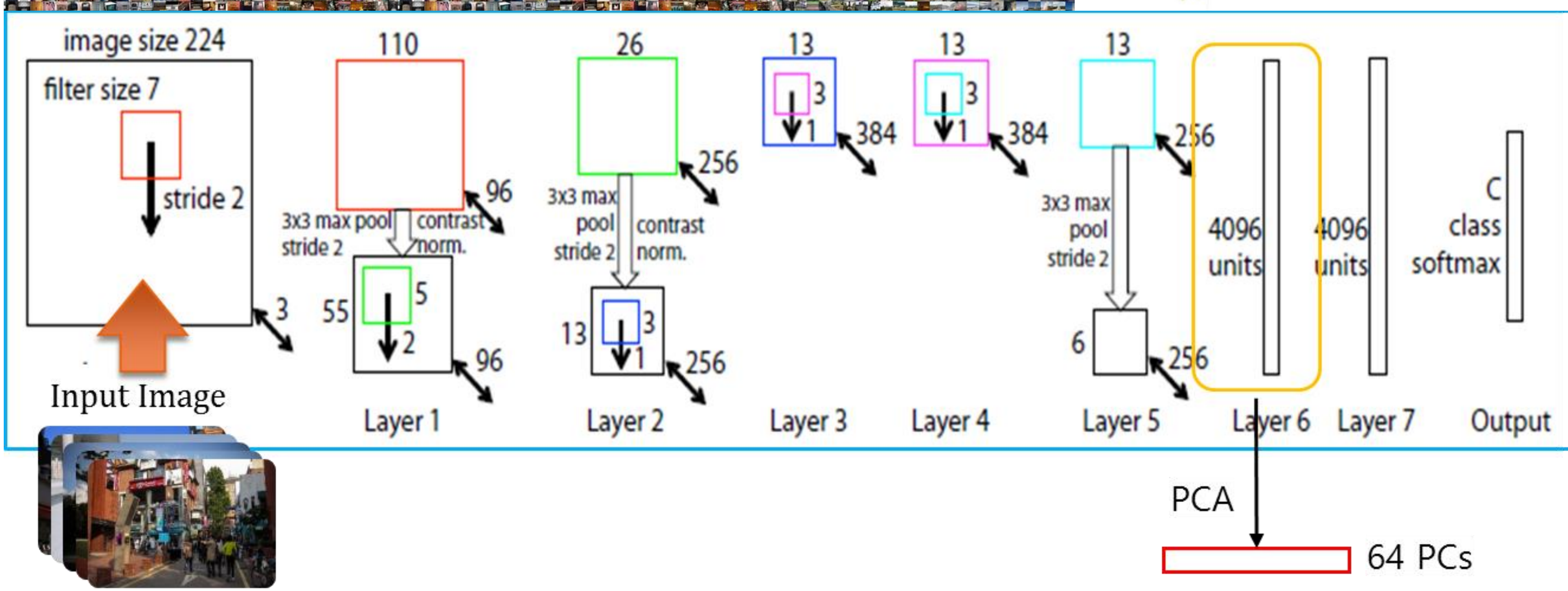
LOCATIONS: bank building bus_station coffee_shop drugstore food_store gym home outside parking_lot pub restaurant shopping_mall snu_132 snu_138 snu_302 subway_station unknown



Scene Context Classification



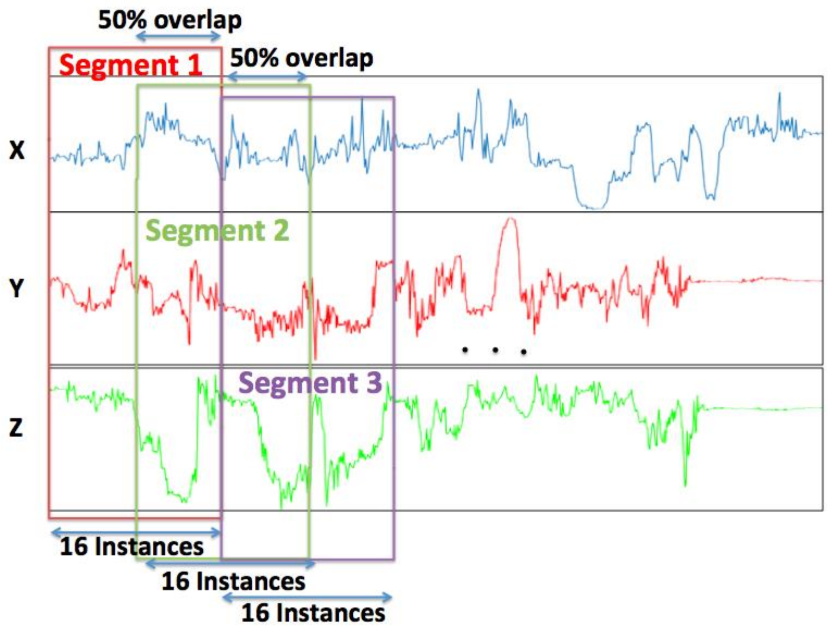
IMAGENET

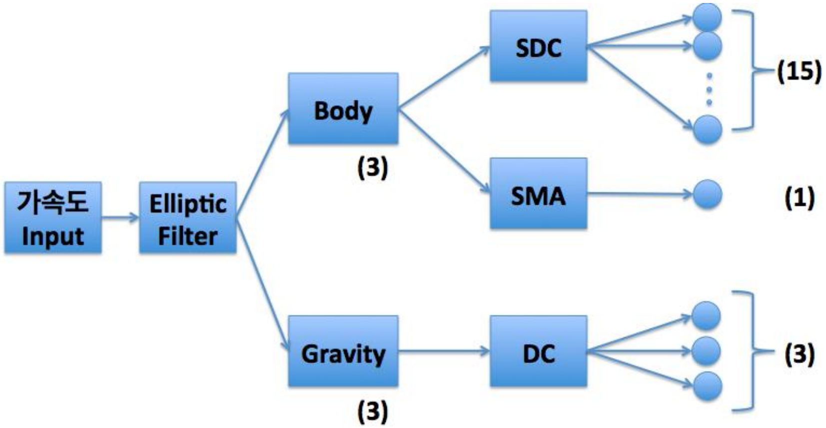


SCENES: bank beauty_salon bus bus_station car coffee_shop drugstore elevator food_court food_store garden gym hallway icecream_store living_room lobby office parking_lot platform pub restaurant restroom room seminar_room shopping_mall stairs street subway subway_station theater walk wine_bar

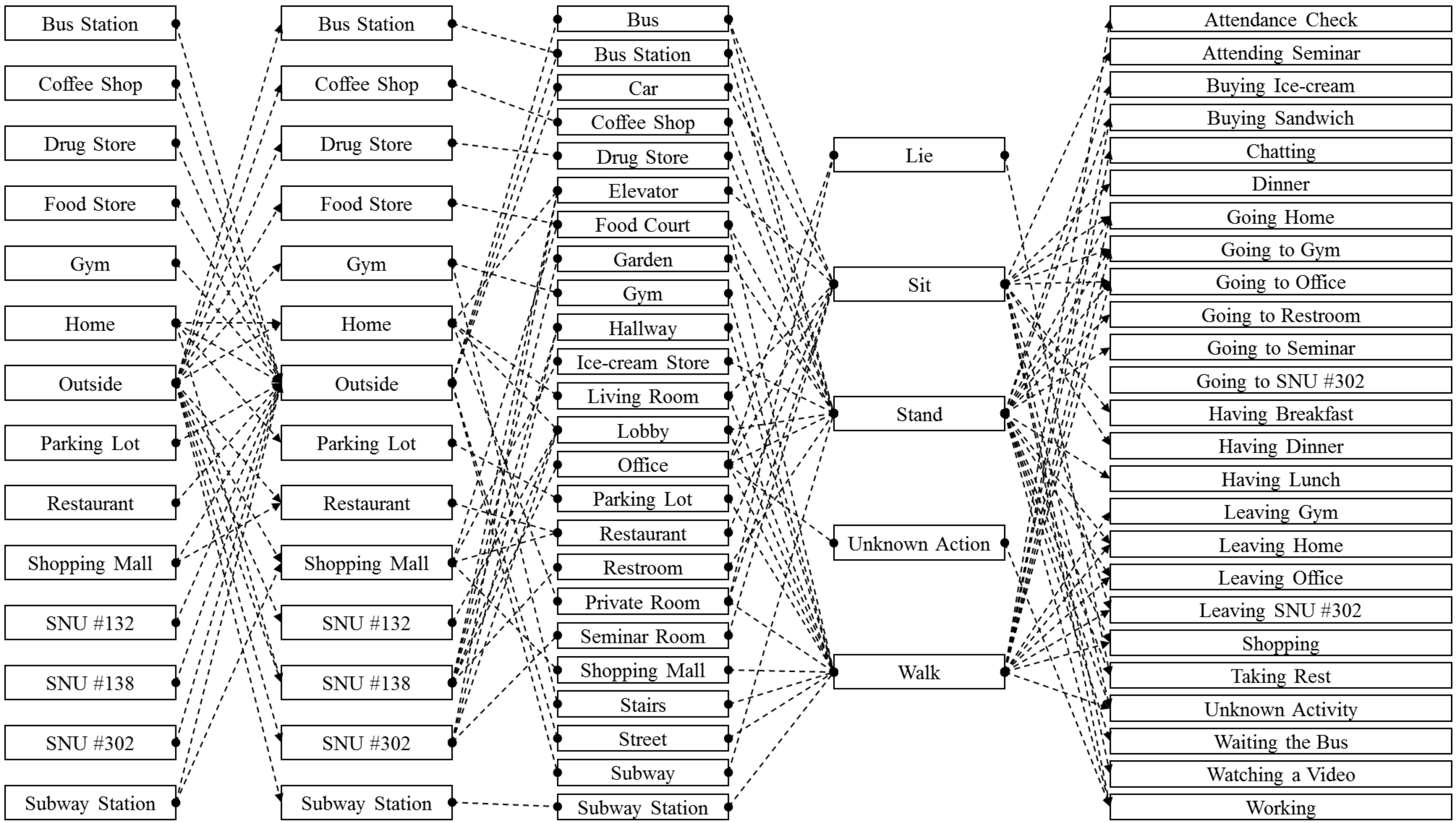
Action Context Classification

- **Sensors**
  - IMU sensor built in Google Glass
    - 3-axis accelerometer sensor
    - 3-axis gyro sensor
    - 3-axis magnetometer
- **Sensory features**
  - Delta coefficient (DC)
  - Shifted DC (SDC)
  - Signal magnitude area (SMA)
- **Action context classification**
  - Random forest
  - Lie, Sit, Stand, Walk, Unknown



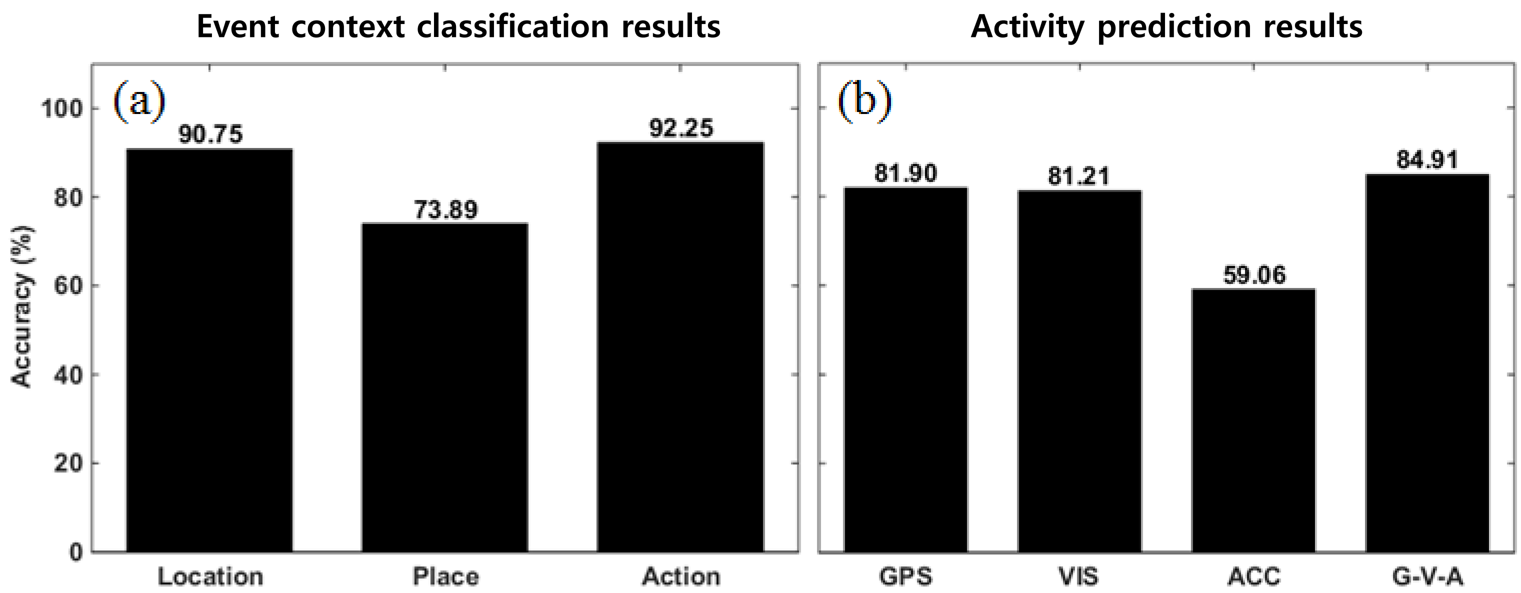


Event-Activity Mapping Table



Experimental Results

- 10 days' data excluding holidays are used
- Train and test data are carefully segmented to share all labels
  - Train: 7 days (2,3,7,9,10,11,14 March) / Test: 3 days (1,4,8 March)
- (a) Event context classification results
  - Location (DT), Scene (SVM), Action (RF)
- (b) Activity prediction from event-activity mapping table



Conclusion

- **Contributions**
  - Novel activity prediction framework based on high-level representation of event contexts
  - Wearable sensor data from real daily life is used to evaluate the framework
  - The event-activity mapping table predicted activities better than previous methods

- **Discussions**
  - More evaluation should be done using different people's data
  - Transferable learning of the event-activity mapping table
  - Neural network approach for the event-activity learning

THANK YOU