Locomotion & Location Determination & its Application to Activities of Daily Life (ADL) Recognition

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(NB Current members of the Lab, past members & their contribution are given later)

Outline

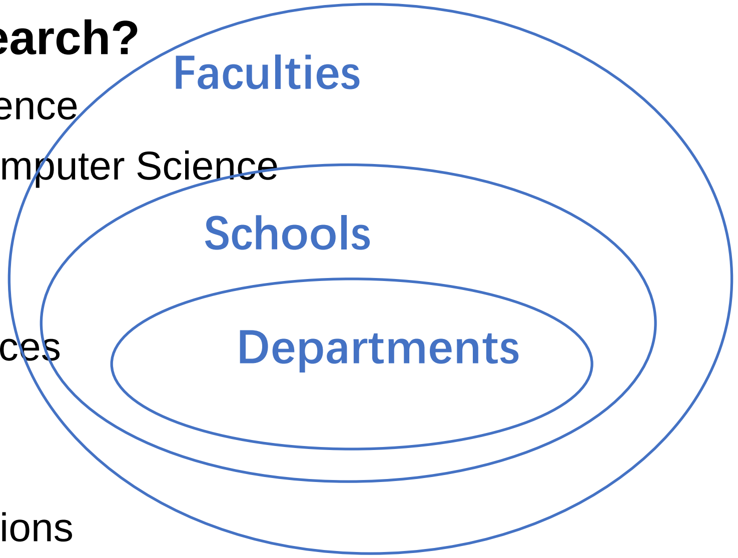
The aim of this guide is to explain what ADL is, what it involves and what is the range of technology choices to determine these

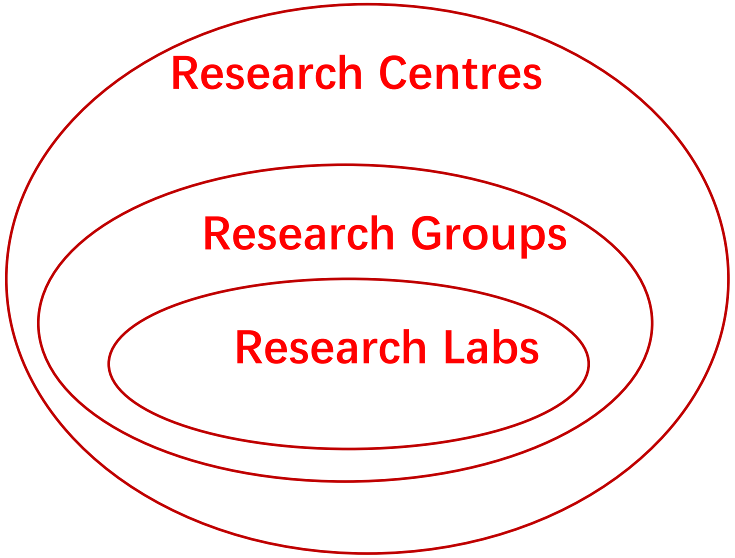
✓ **An overview of what ADL detection involves**

- Some current results from IoT2US Lab concerning ADL detection

But 1st a little about QMUL/EECS/IoT R&D

- **How to organise & manage research?**
- School of Engineering and Materials Science
- School of Electronic Engineering and Computer Science
- School of Mathematical Sciences
- School of Physics
- School of Biological and Chemical Sciences
- School of Business and Management
- School of Economics and Finance
- School of Politics and International Relations
- School of English and Drama
- School of Geography
- School of Languages, Linguistics and Film
- School of Law
- School of History
- Barts and The London School of Medicine and Dentistry





QMUL EECS Research groups

Research Groups

IoT

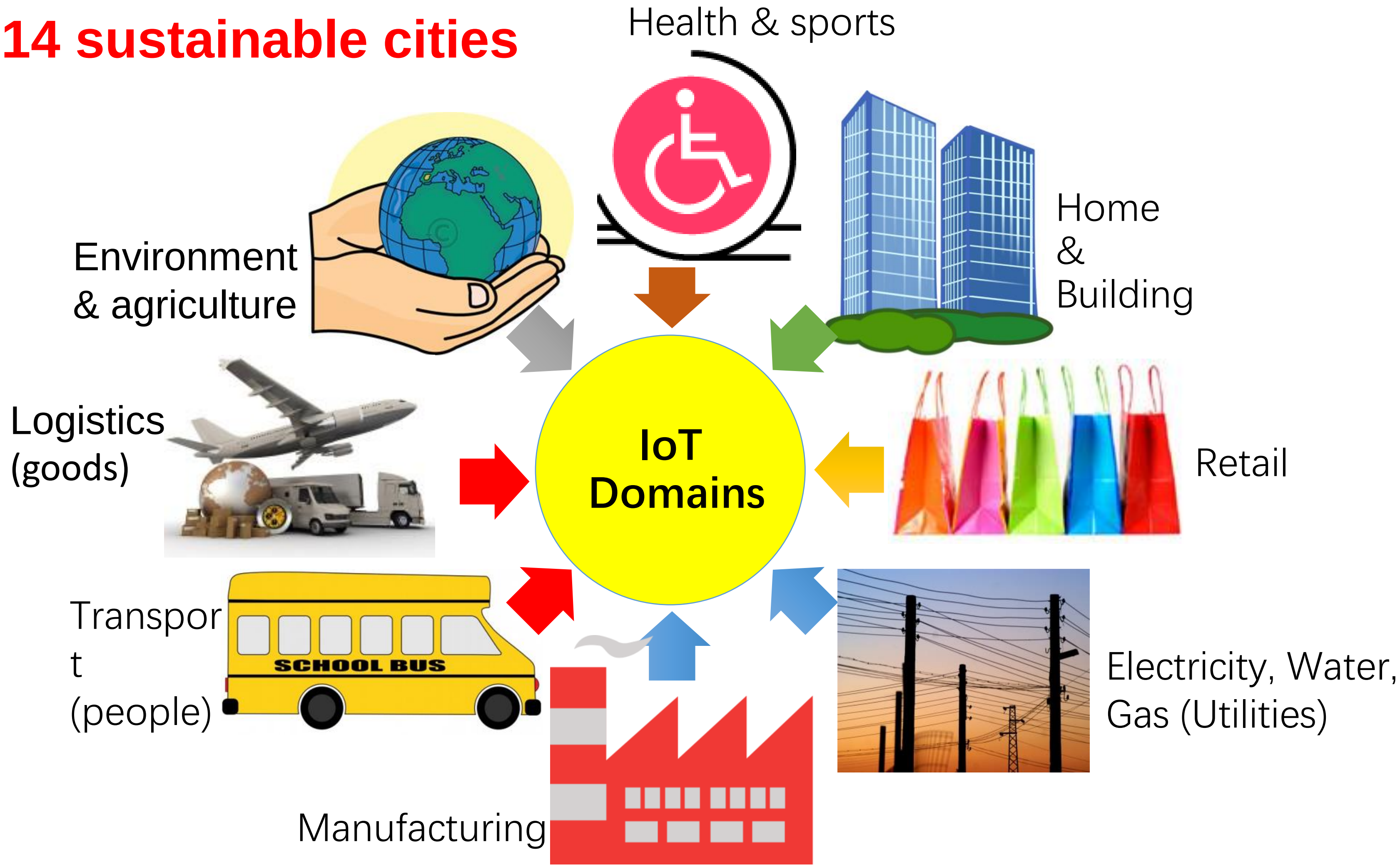
- Antennas and Electromagnetics - Centre for Advanced Robotics - Centre for Digital Music - Cognitive Science - Communication Systems - Computer Vision - Game AI - Multimedia and Vision - Networks - Risk and Information Management - Theory

Research Centres

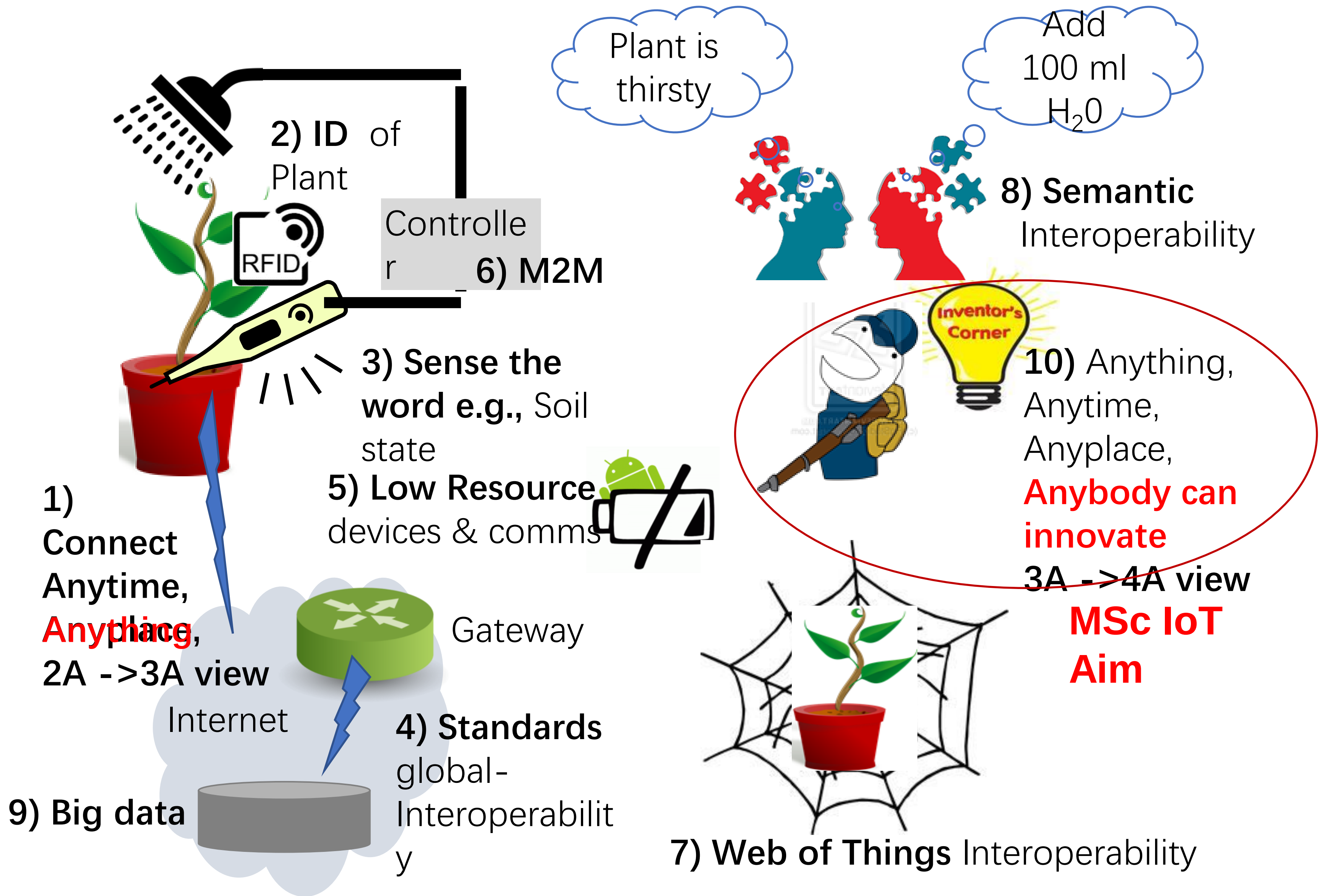
- Centre for Intelligent Sensing - QMedia

Classifying IoT by Problem/App Domain

- **Any domains missing?**
- **Are these domains independent?**
- **E.g., SDG 14 sustainable cities**



Classifying IoT by science/engineering



QMUL “IoT to Ubiquitous computing and Science (IoT 2 US) Lab

The IoT Laboratory has four main research and science aims:

- To leverage IoT to **promote more inclusive, deep citizen science** research & development, not just in to the UK, and in particular **to tackle the United Nations Sustainable Development Goals** in low and medium income developing countries
- To deploy IoT to **foster innovation creativity by anyone, connecting Anything, Anytime, Anywhere (4A view of IoT)**
- To **facilitate a cross-disciplinary approach to IoT** that spans computer science, electronic engineering, material science, physical science, natural science and social science.
- **To use IoT to tackle targeted challenges**, e.g., deeper profiling of human and animal behaviour through motion tracking and data analytics using both smart mobiles and with smart (physical) environments; user-centred privacy and security for smart (IoT) interaction, sustainable and energy-efficient IoT interaction.

What are ADLs(Activities of Daily Life)?

- ADLs are used as a measurement of a person’s functional status
- **Basics ADLs** are more essential for survival than ADLs
  - E.g., Personal hygiene, Continence management, Dressing, Feeding (& drinking), Ambulating/locomotion
- **Instrumental ADLs (IADLs)** are not necessary for fundamental functioning, but they let an individual live independently in a community
  - Companionship & mental support, transportation & shopping, preparing meals, managing medication, communicating with others, managing household tasks, managing finances

ADLs as Health Indicators

- Which of these is the most common locomotion/posture ADL - Lying/sleeping vs. sitting/working vs. standing vs. walking/running/ cycling vs. other ?
- We spend on average > 9 hours sitting > 7-8 hour sleeping
- Prolonged sitting ↑ risk of heart disease, diabetes, obesity,
- N.B for very young or old, getting up & down to sit is difficult
- We need others to assist us to sit
- Also can we differentiate sitting from other stationary ADLs such as standing, sleeping?

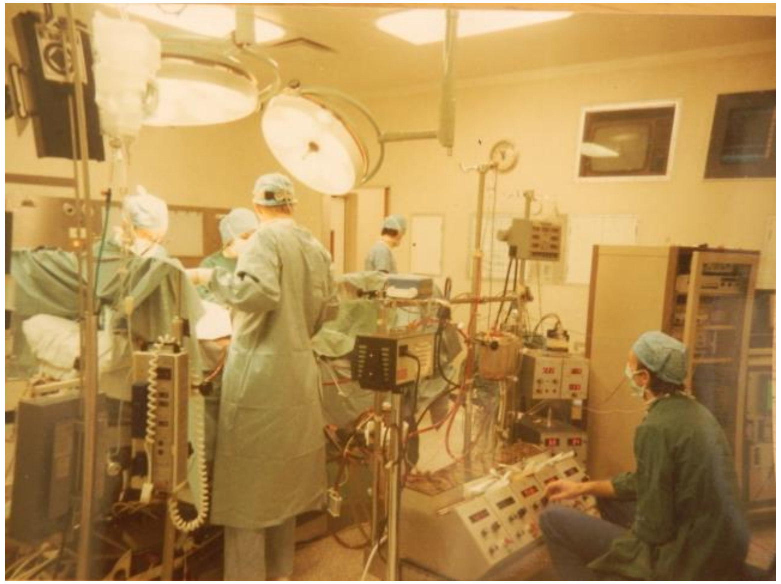
ADLs can help to determine:

- What our mental and physical well-being state is?
- If we can live by ourselves, independently, safely & healthily?
- How long can we do this / live for?

Sensing Locomotion and Location as a means to recognise, then analyse ADLs

- We have GNSS, inertial sensor devices (accelerometer)
- This type of comp. sci. seems standard, it's 'easy', it's a solved problem, no more research needed …

It's not even complex - it's not Brain Surgery or Rocket science



Sensing Locomotion and Location as a means to recognise, then analyse ADLs

Method 1: **Determine location from GNSS**

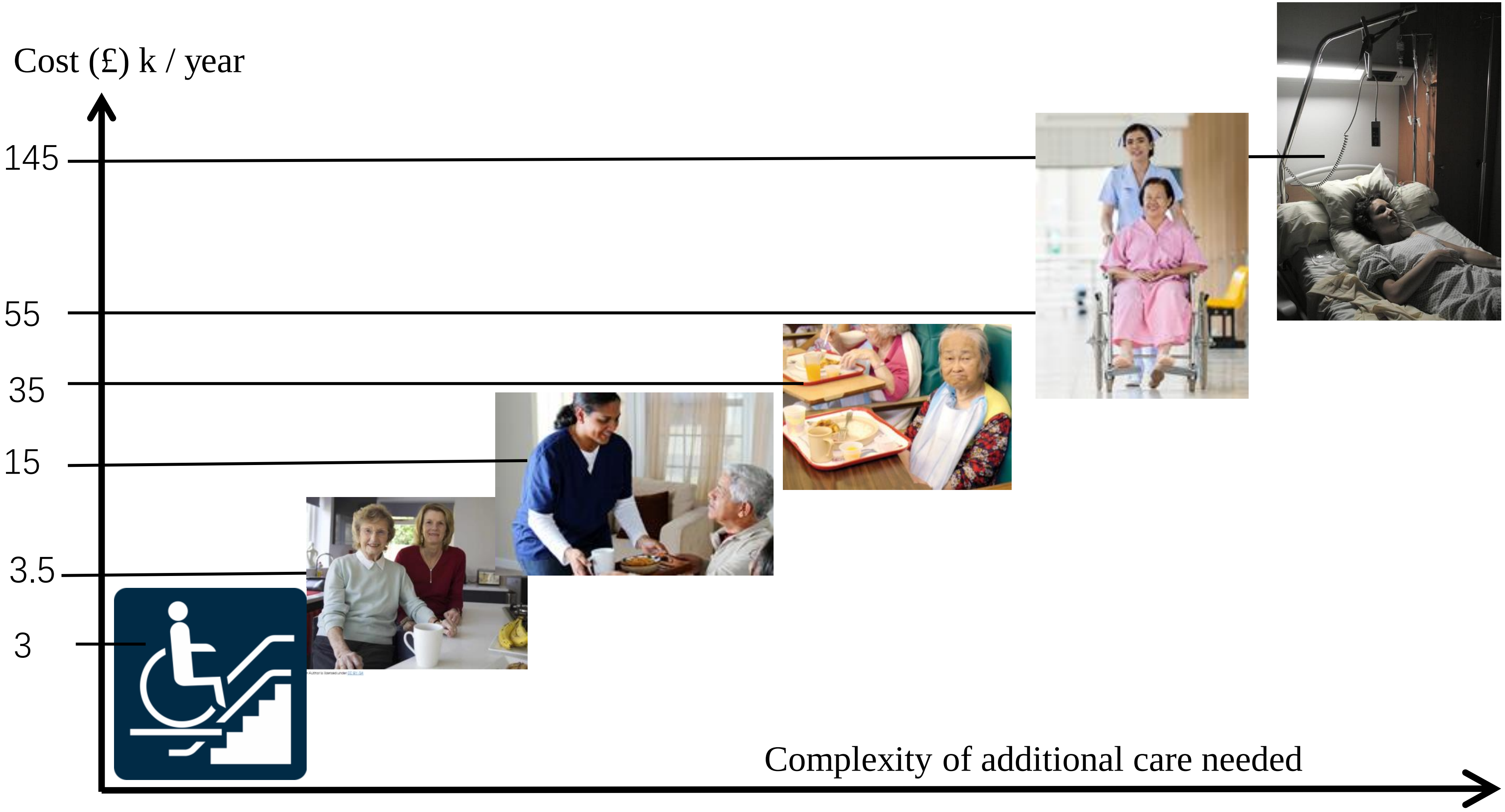
- Differentiate location w.r.t time to get speed
- Use speed to classify type of motion, e.g., walk, cycle, bus
- Identify locations that are Points of interest (POI) using stay time at POI
- E.g., EU Crumpet project (2000-2002)

Sensing Locomotion and Location as a means to recognise, then analyse ADLs

Method 2: **Determine motion using inertial sensor**

- E.g., using accelerometer in phone or wearable
- Integrate acceleration w.r.t time to get speed
- Identify activities using acceleration patterns
- Can combine with GNSS
- E.g., EU Sunset project (2011-2014) – play video

Not being able to perform ADLs metric: cost



ADL Location & Locomotion sensing challenges

- ↑ time spent indoors (>80%)

Indoor location sensing is harder than outdoor location determination

- No global indoor location sensor
- No global indoor maps
- Many locations for ADLs are personal - data authorisation, privacy issues
- Not just 2D but 3D spaces
- ↑ accuracy needed indoors as indoors space is more complex

Human behaviour variations occur with respect to …

- Individuals, small groups, crowds / public, cultural, situation

Some type of location vs. motion sensing

ADL Recognition

Location of activities

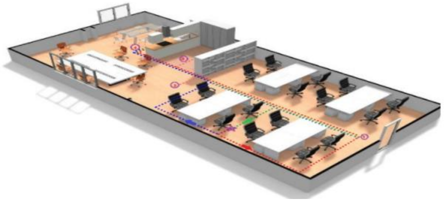
e.g., Café location implies an ADL

Eating/drinking? Chatting? Reading? All?

Location-free Locomotion activities

Walking, falling, running, cycling

Location-driven activities (location + locomotion



Going to fridge to take milk,
Going to the printer for printing

Posture

Human torso position, stand, balance on 1 foot, etf.

Micro-movements

Hand. Leg, chest, movement

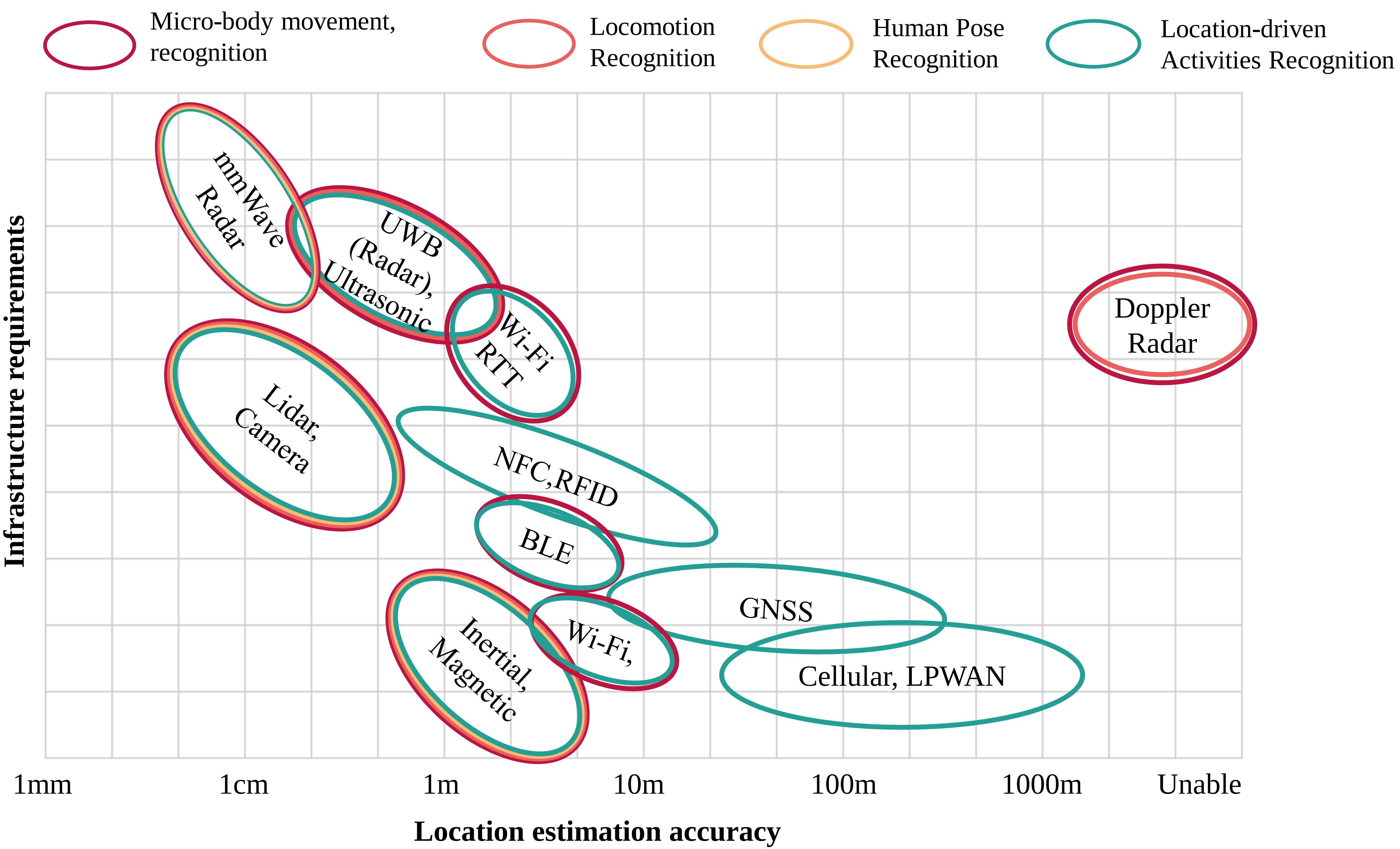
No single type of sensor can accurately detect all types of ADL

- Device-free (off-body) vs. on-body (e.g.,) wearable sensing
  - Where in physical environment to put motion sensor
  - Where on body to sense
- Movement versus location versus both sensing
- Accuracy of movement or location sensing
- Indoor versus outdoor versus both

About the Infrastructure Requirements for location & ADL determination

There are 2 kinds of infrastructure requirements for location determination development & end-use

- Device free / off-body devices may require additional wireless access-point (AP) devices to be installed in the physical environment
  - Requirements are low to do anything if existing communication infrastructure/APs can also be used for location determination
  - e.g., Cell phone, Wi-Fi APs, NB, end-user must carry an on-body receiver
  - Requirements can be higher, e.g., Bluetooth, if APs/Beacons need to be bought & installed
- 2nd infrastructure req., is for developer to build a signal map of any space in a prior calibration or training phase in order to derive locations from received signals in the operation or test phase
  - E.g., Wi-Fi, BLE
  - NB Recalibration/retraining is needed if the physical env. Changes
  - On-body receiver or transmitter is needed



Micro-body movement, recognition
Locomotion Recognition
Human Pose Recognition
Location-driven Activities Recognition
mmWave Radar
UWB (Radar), Ultrasonic
Wi-Fi RTT
Lidar, Camera
NFC,RFID
BLE
Inertial, Magnetic
Wi-Fi,
GNSS
Cellular, LPWAN
Doppler Radar
Infrastructure requirements
1mm
1cm
1m
10m
100m
1000m
Unable
Location estimation accuracy

Individual vs. Group VS. Large Group vs. Crowd Analysis

Most studies focus on detecting 1 (& not >1) individual (s)

- Individual & small Group:
  - Lidar, Camera
  - UWB Radar, Ultrasonic
  - mmWave Radar
  - Wi-Fi CSI
  - Doppler Radar
- Individual:
  - UWB tag
  - BLE
  - Wi-Fi fingerprint and Wi-Fi RTT (including RTT)
  - NFC,RFID
  - Inertial, Magnetic
  - GNSS
  - Cellular, LPWAN

- Large Group / crowd
  - Lidar, Camera
  - GNSS
  - Cellular, LPWAN

Challenges in ADL Analysis

- **Position & orientation implementation of transceiver & hence signal can vary**
- **Lots of variations in / noise for signals**: micro-movements (scratching head), signal attenuation (through other humans & other physical objects), orientation, environment vibration, …
- **Large variations in same type of movement by 1 human individual**, e.g., depends on energy levels, tiredness, physical environment, …
- **Large variations in same type of movement by different individuals**, e.g., depends on age, state of health, …

ADL non-functional requirements

- Human privacy preservation
  - Anonymity is often not enough
  - E.g., outdoor locations where time is spent indicates someone’s home, where someone works or often skips work
- Device and data Security
  - Unattended environment devices can get stolen or damaged
  - Data from any low resource devices has no security
- Device energy capacity – mains vs. battery
  - battery changing / recharging can a significant overhead

Activity Recognition Chain (ARC)

Define what ADLs, data, sensors, environments to use

Install sensors & test

Sense ADLs

Exchange & Store Data

R&D analysis algorithms

(optional) Supervised / activity data labelling - to know what really happened/verify accuracy of analysis

Maintain sensors, reconfigure, deinstall

Analyse/classify ADLs

Present / Report results to key stakeholders

ADL Trial Planning

Preplanning

- Specifying which ADLs to recognise, sensors to use, data to collect,
- Pre-trial/testing

Is the pre-planning this simple?

- Survey the location, its architecture, its layout where the ADLs occur, where to sense, etc.
- Ethics plan, e.g., to protect users privacy,
- Risk analysis plan, to mitigate against disruptions, failed or stolen equipment
- Recruit users and user intermediaries
- Specify & cost resources needed to undertake the study
  - E.g., to handle data volume, communication, etc.

Operational

- See previous slide

Operation cost for on-body & wearable location/ activity detection devices

- Energy: For wearable devices like smart band, smart watch, smartphones, they all need to be re-charged regularly to use.
- Hardware support: Wearable based system is usually based on built-in sensors like accelerometer, gyroscope and Magnetometer. Software is also required to get sensor data.
- Data transmission: Generally there are two ways to transmit data between devices, Bluetooth low energy and WIFI. For offline systems, data is stored locally. And for online systems, data is transmitted to cloud platforms via Wi-Fi or cellular communication.
- Data Storage: high frequency signals, e.g., 100 hz accelerometer can generate high data amounts
- Data analysis: data process usually divides into two stages: training stage and test stage.
- At the training stage, samples will be collected and processed to train our models. For example, for human activities recognition, we need to collect samples of target activities. Then after preprocessing including denoising, segmentation and labelling, all samples are feed into model to train.
- At test stage, new stream of data is firstly preprocessed and then feed into the model to recognize. Theoretically, date analysis at test stage can be processed automatically after training.

Some Core Issues in Data Science / AI R&D

- Is the data analysis about discovering unknown data clusters / groups / patterns (unsupervised learning, data mining) or about confirming if new data belongs to known groups (supervised learning, data queries)?
- How many data inputs are independent or dependent/inter-related?
  - Latterincrease the computation time
- How much data, how real-time, how long to process a sequence of data before a decision about an outcome is needed?
  - It's not just the processing time, it's also the data collection & data transmission time too.
- How to label/identify/specify known groups (for supervised learning)?
- Is the data analysis about classification versus regression (to estimate or predict the relationship between variables?
- Is the analysis non-learning vs. conventional learning vs. deep learning?
- Is it single method learning vs. ensemble (combined) learning methods?
- How much & what types of data are needed?
  - Overfitting – analysing/studying too small a data set & then generalising the implications to a far more variable dataset has serious flaws

Outline

The aim of this guide is to explain what ADL is, what it involves and what is the range of technology choices to determine these

- An overview of what ADL detection involves

✓**Some results from IoT2US Lab concerning ADL**

4 epochs of ADL research

4 epochs of research

- ✓ **2015-2020 indoor ADL analysis & GIS city-wide data analysis using multiple sensors**
  - ✓ **We came 3rd (2019) in the prestigious IPIN (International Conference on Indoor Positioning and Indoor Navigation) conf. competition track 3 – smartphone-based (off-site), up from 9th last year, competing against some of the world's leading companies, e.g., Intel, Tencent for location accuracy.**

Earlier research is summarised in an appendix (**TODO**)

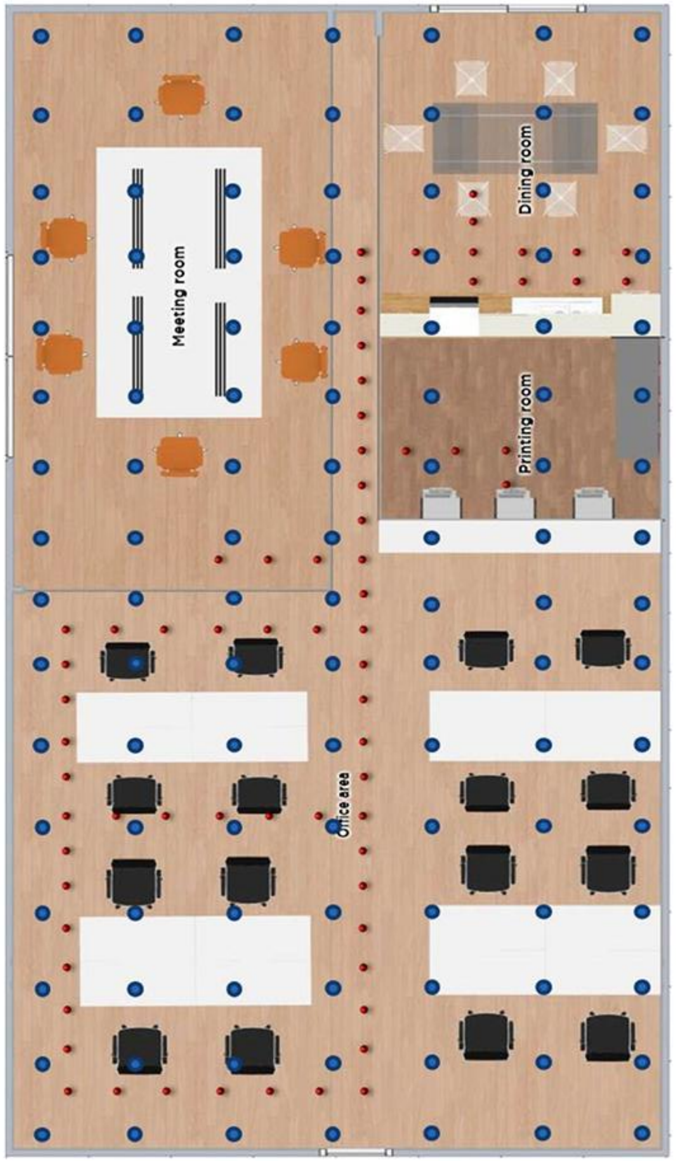
- 2011-2014 outdoor transport/locomotion recognition
- 2004-10: Indoor location determination, mobility profiling, multi-goal adaptive spatial routing; SunSpot A+GPS sensors; adaptive maps
- 2000-2003 Early GPS experiences tourism

2015-2020 indoor ADL analysis & GIS city-wide data analysis using multiple sensors

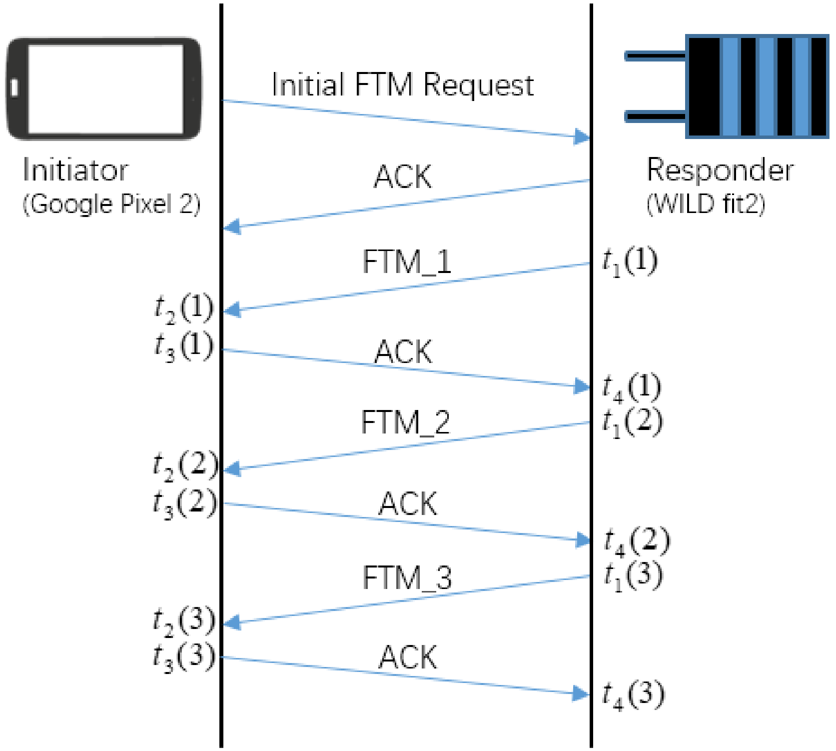
- Location-driven Wi-Fi ADL
- Wi-Fi RTT IPS (Indoor Positioning System)
- BLE IPS
- Lidar-driven indoor ADL
- Magnetic-field sensing IPS
- UWB IPS
- mmW Radar Indoor ADL
- Crowd (city-wide) ADL sensing and data analysis
- Car-driving

Improved Location-driven Wi-Fi ADL

- **Objective:** accurately identify 9 location-driven office activities, e.g., Leave office, Have a meeting, Print documents, Go to kitchen, Eat food, Make tea, Drink tea, Heat food, Have a drink
- **Method**: select most useful Wi-Fi access points / transmitters (don't just use too noisy ones); use artificial neural networks to estimate features for ranking their usefulness; extended dynamic time warping is used to match/cluster activity tracks in time & space.
- **Results & Conclusions**: achieved an average positioning accuracy of 1.4 m & 80% recognition accuracy for 9 location-driven activities



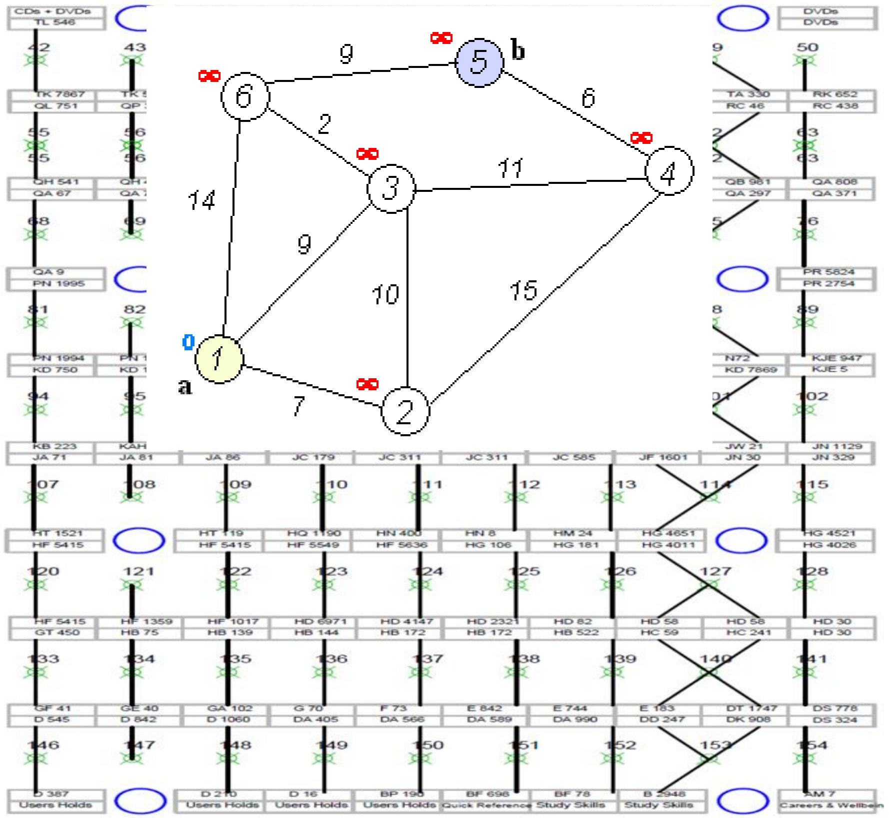
Wi-Fi RTT IPS



- **Objectives**: to develop & test a new more accurate IPS
- **Method**: use Wi-Fi return trip time (RTT) time measurements as a more accurate IPS
- **Results & Conclusions**: Average error of all these tests is 0.54 m -> far more precise then all existing Wi-Fi fingerprinting and propagation model based methods (generally considered to be 1.5 ~ 2 m).
- It requires a new type of Wi-Fi access point to be installed that supports RTT

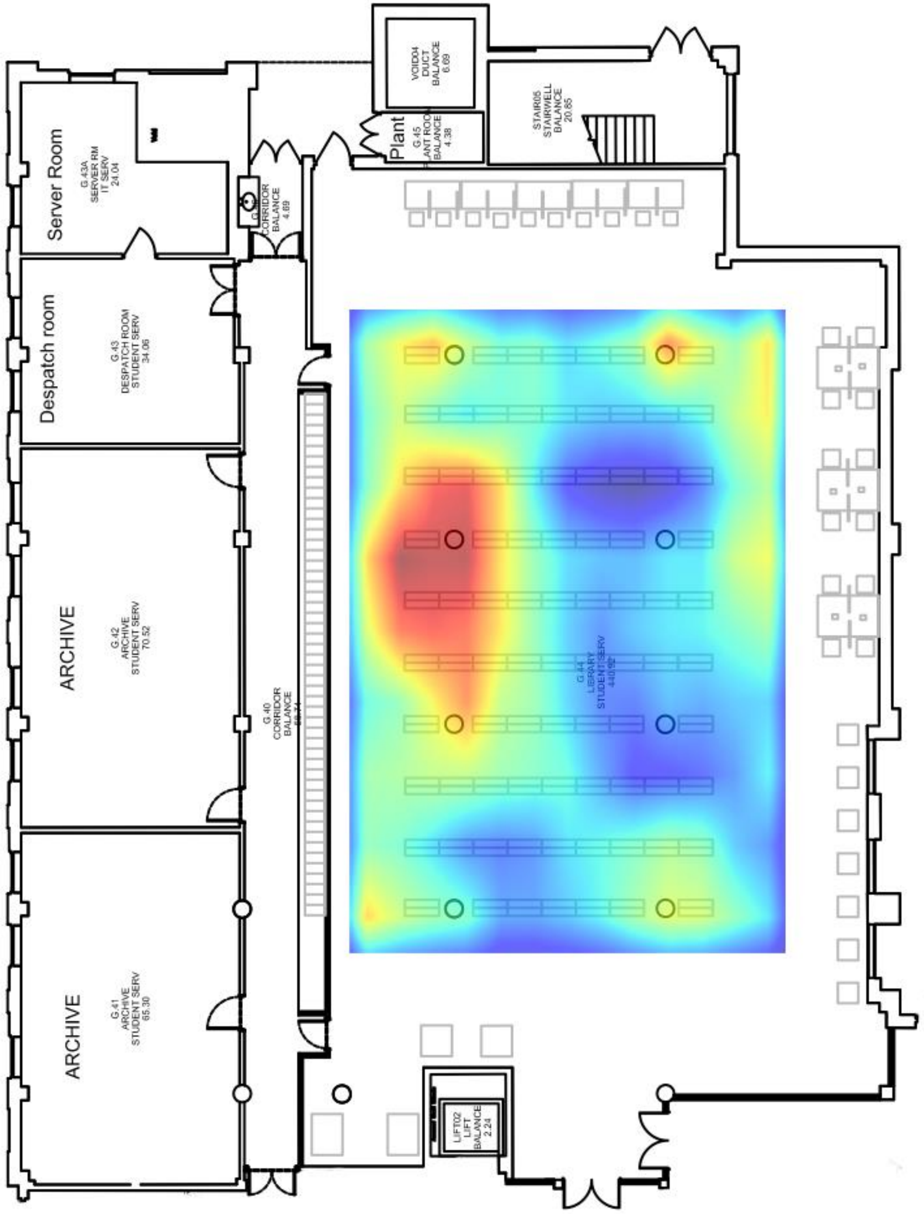
Bluetooth low energy (BLE) IPS (Indoor positioning system)

- **Objective**: R&D a BLE IPS to find & retrieve items at arms length in a physical retail space, e.g., books in a library
- **Method**: Array of 25 IBeacons (BlueBar) in a 18×30 m in a library room were placed 1m apart on the ceiling & walls; users use & hold a mobile phone as a BLE receiver, 2 users seek to retrieve books. Radio map of RSSI Beacons is created & then cross-correlated with an unknown signals from an unknown location to determine its location.
- **Results**: average positioning error of 0.9 m, i.e., can differentiate between physical space aisles between book-shelves to retrieve items at arms length.
- **Conclusions**: location accuracy is affected by the number of people between the beacons & receiver, direction of receiver to transmitter beacon, ...



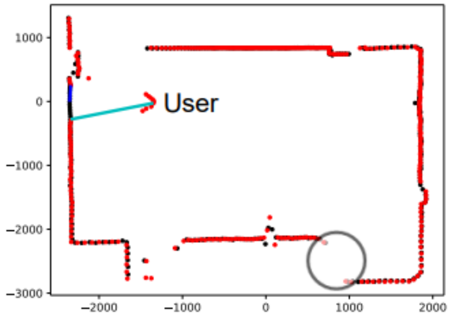
Magnetic-field (MF) IPS

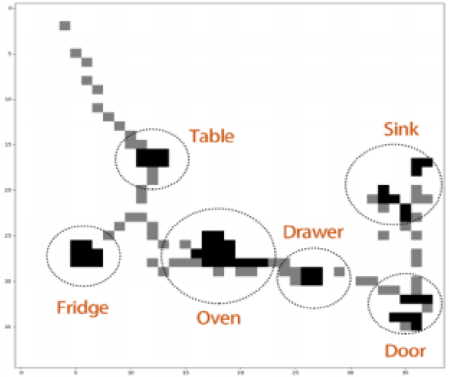
- **Objectives**: Create an IPS that is unaffected by moving humans, providing more time-invariant location information, unlike Wi-Fi, Bluetooth
- **Method**: Use smart phone to create radiomap of known MF patterns, then detect & match a new unknown RF pattern to derive unknown location
- **Results**: Validate in a library, retail-like space, with multiple metal shelves & pillars, positioning error is 1.8 m. Scalability issues: MF IPS pattern location accuracy drops as size of space increases
- **Conclusions**: use of magnetic field (MF), unlike typical Wi-Fi or Bluetooth positioning measurements, are unaffected by moving humans, providing more time-invariant location information. We proposed a method to detect the location quicker.



Lidar-driven Indoor ADL System

- **Objectives**: Use 2D lidar to track people and recognize location-driven daily activities.
- **Method**: A low cost, 2D, rotating Lidar system is used to collect the lidar radial distance and angle data. After converting the raw data to Cartesian coordinates, Hausdorff distance is used to detect the presence of a moving user. Then DBSCAN clustering algorithm is used to determine the number of users. Lastly RNN based human activity recognition classification system is built.
- **Results & Conclusions**: The results indicate that it can provide a centimeter-level localization accuracy of 88% when recognizing 17 targeted location-related daily activities.





UWB-driven Indoor ADL System

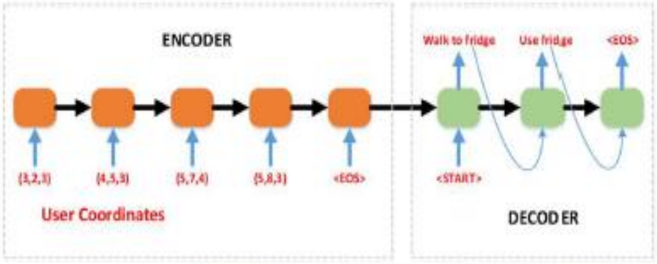
Objectives: Use UWB to accurately tracking people,
& use the seq2seq (RNN) model to classify daily
location-driven activities.

Method: Four UWB tags are used to built a system & a Kalman filter is used to improve the positioning accuracy

- Then a LSTM model is used to classify 38 activities based on trajectories.

Results & **Conclusions**: Validation shows that:

- UWB location determination method can provide decimeter level positioning accuracy &
- Good accuracy (79%) in recognising 38 location-related daily activities.



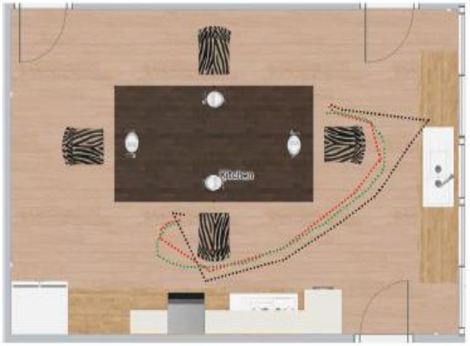
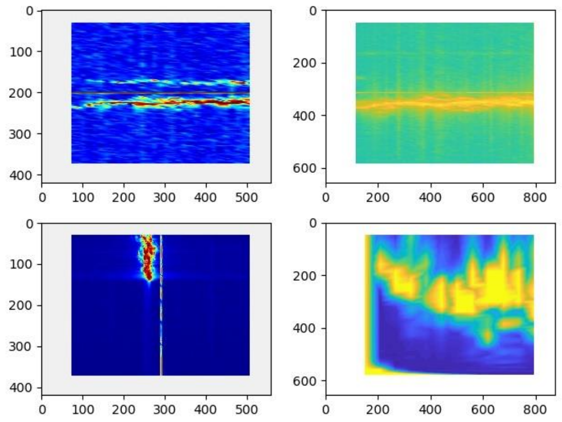


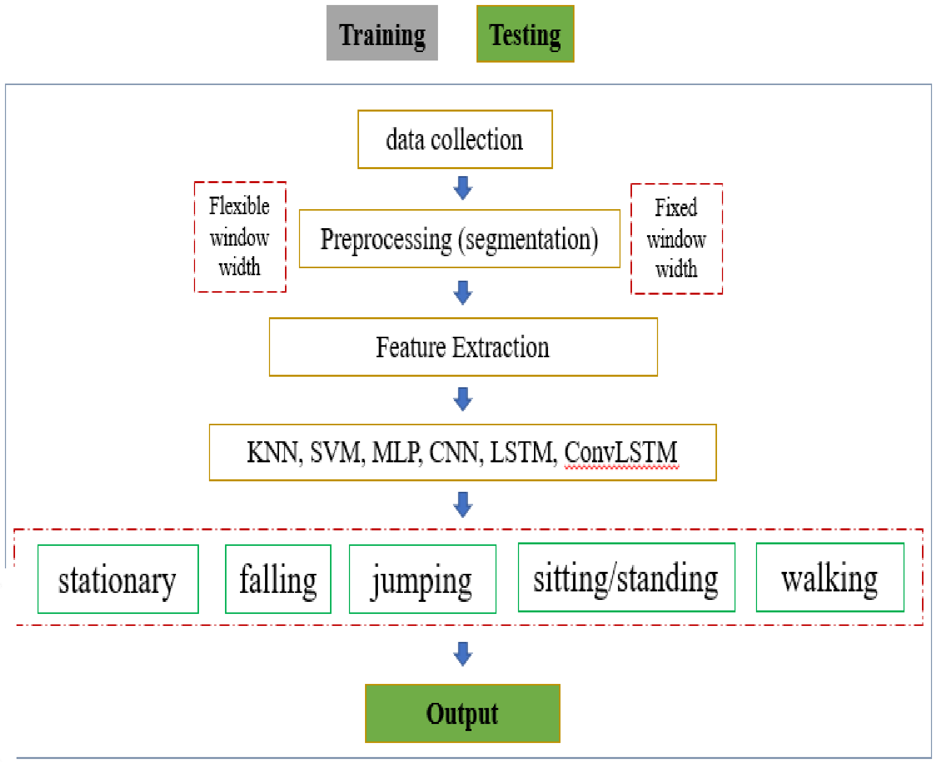
Figure 3. The 2D View and positioning performance.

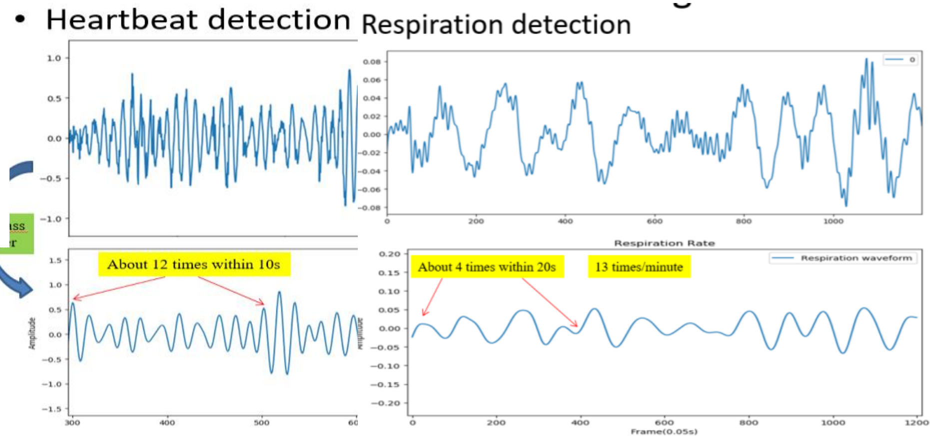
Millimetre Wave (mmW) Radar based ADL System

- **Objectives**: use mmW radar to build a HAR system that can recognize micros human activities, e.g., walking and vital signs, e.g., breathing
- **Method**: Signal processing algorithms (e.g. FFT, Wavelet transform) are used to get feature map and machine learning and deep learning algorithms are employed to recognize activities.
- **Results & conclusions**:
- Recognition accuracy is 98%.
- Requires 1 radar device per room



walking



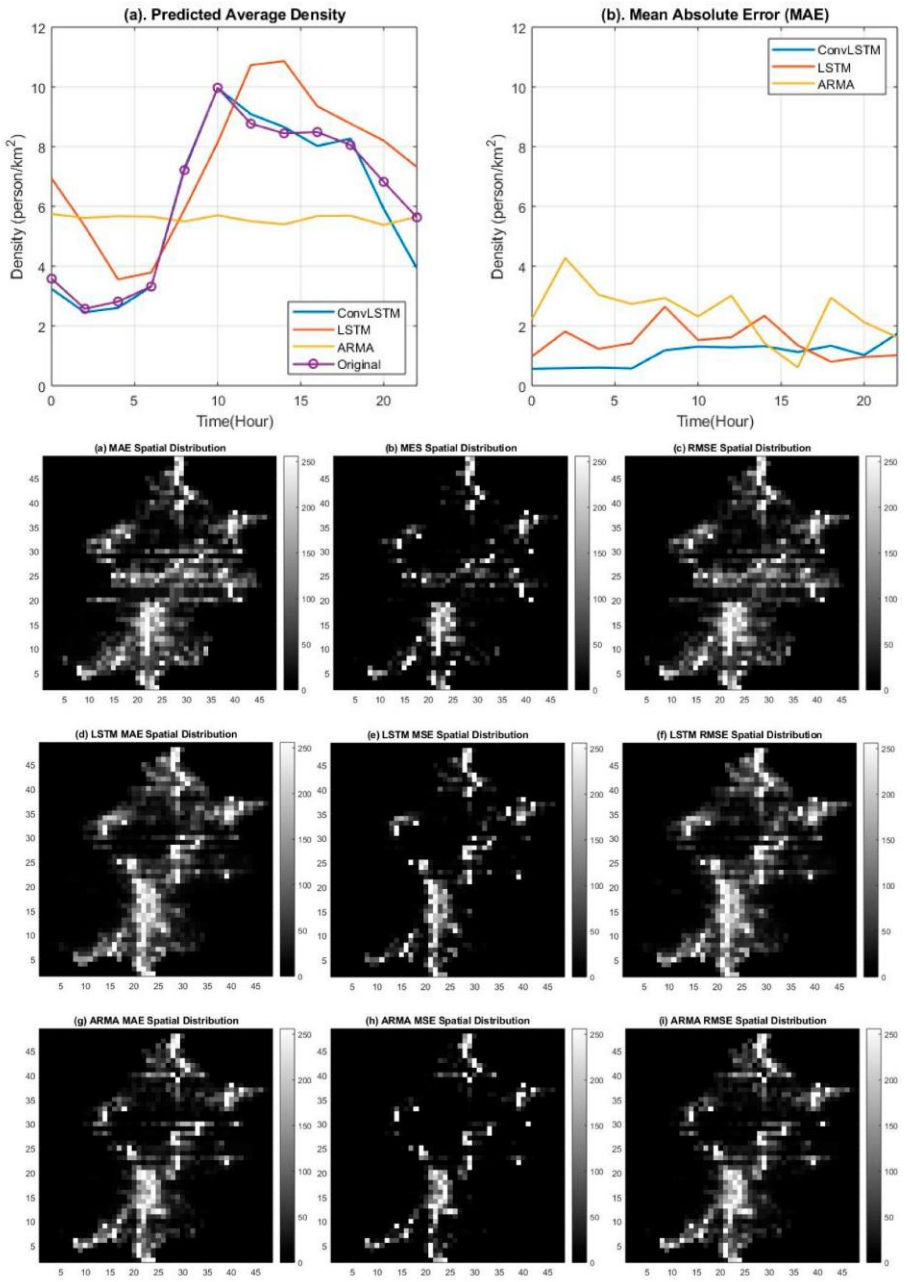


Radar detection of ADL

- Play video

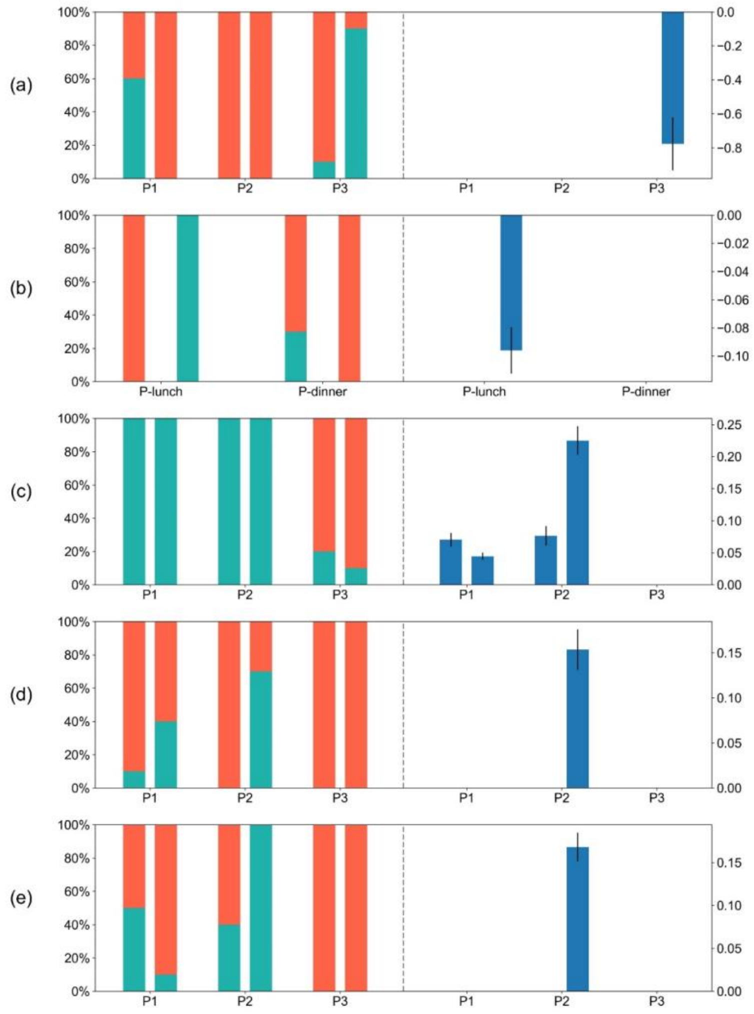
Prediction of People Density Distribution

- **Objectives:** using deep learning method to predict spatial-temporal distribution of people based on the Call Detail Record (CDR) dataset
- **Method:** Use CDR to map the dynamic people density distribution by kernel density estimation (KDE) method, and then input to a convolution long short-term memory (ConvLSTM) model
- **Results:** The mean absolute error of the predicted results of ConvLSTM ranged from 0.6 to 1.8 over 17 February 2015, which means that the model was much more stable and accurate than the other two baseline methods. Moran's I index for the error distribution was still lower than that of the other baseline methods in space
- **Conclusions:** the predicted density correlated much better with the original data at the temporal and spatial scales used when using ConvLSTM as compared to the other two methods, which do not consider the spatial autocorrelation.



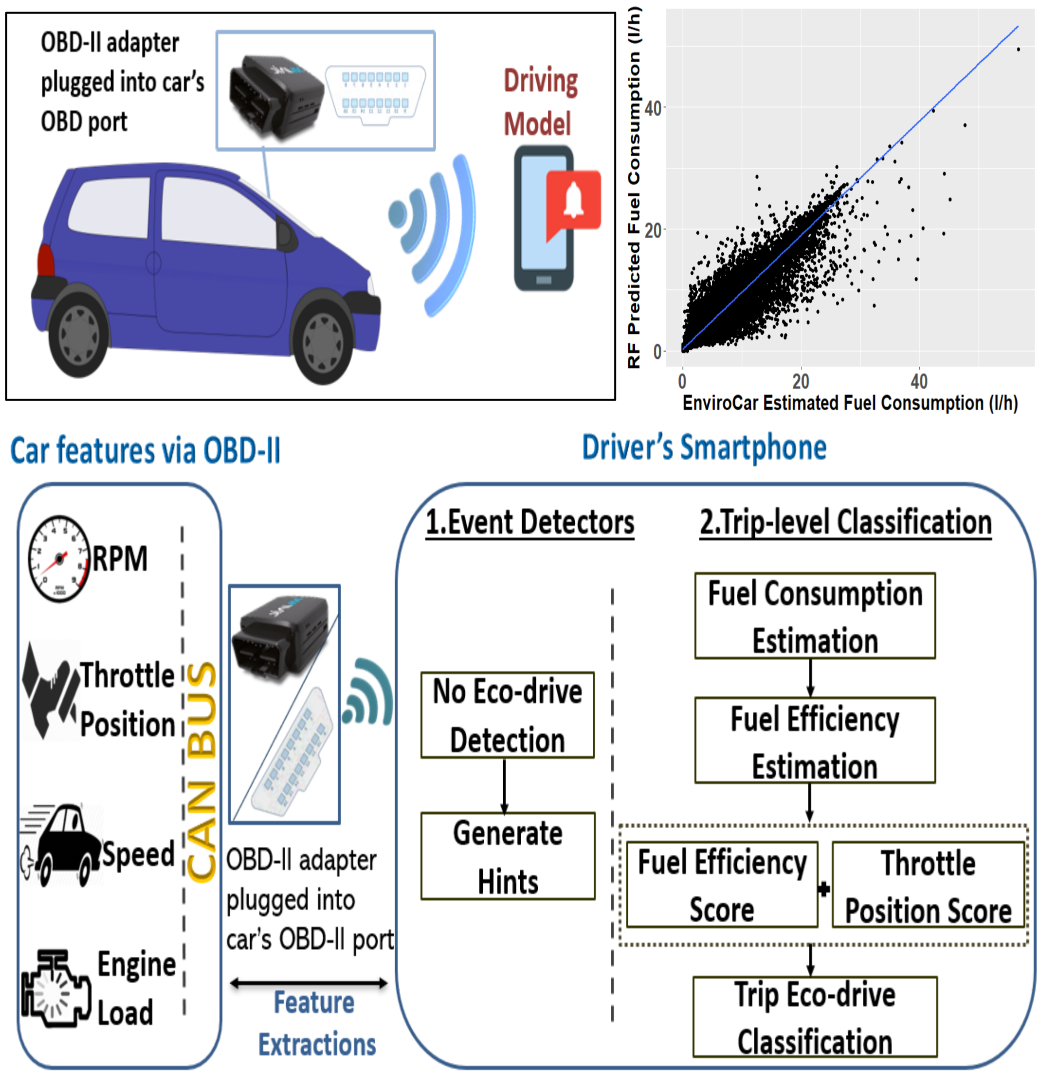
How Air Pollution affects People's ADLs (e.g., in Beijing, China)

- **Objectives**: detect how air pollution affects people's daily routine activity in Beijing.
- **Method**: Using people's density, air quality and other control data to input fixed effect model to estimate the correlation coefficient which can reflect the relationship between the people's activity and air pollution.
- **Results and Conclusions**: air pollution puts negative impact on people's entertainment options in afternoon (2 -6 PM), while it put positive impact on people's house-stay options in morning (6 -10 AM) and hours in the middle of a day (10 PM- 2 PM).
- Air pollutions lower people's desire to go to restaurant for lunch but put little significate influence on the choice to have dinner in restaurant.
- When $PM_{2.5}$ increase 50 μg/m^3, revenue of the restaurant would decrease 0.1 million RMB of whole Beijing.
- Transportation options are also affected: people tend to decrease walking & bike-riding itinerary but select bus or subway to avoid absorbing excessive polluted air.



Car-driving Gamification

- **Objectives:** Process vehicular data in real-time (specifically on driving efficiency), used to assist automotive drivers in promoting more fuel-efficient driving.
- **Method:** Use Fuzzy Logic for real-time feedback while driving and use Random Forest for instant fuel consumption estimation (& quantitative value as a gaming mechanism, i.e., an updated score) relying on 3 On-Board Diagnostic-II signals throttle position, RPM and car speed. Categorise driving style after each trip based upon fuel efficiency and throttle position.
- **Results:** Those inputs are controllable by drivers & fuzzy rules can provide real-time advice for driver. Those inputs + engine load are able to predict fuel consumption.
- **Conclusions:** Combining fuel efficiency with throttle position values for a eco-driving classification allows considering how dynamic driving behaviour is sometimes affected by other factors. Gamification motivation can lead to positive eco-driving improvement.



Outline

The aim of this guide is to explain what ADL is and the range of technology choices to determine these

- ✓Part A: On overview of what ADL detection involves
- ✓Part B: some previous & current results from IoT2US Lab concerning HAR, ADL

If you have a ADL problem that you need to solve, we invite you to consult with us at the IoT2US Lab.

Acknowledgements & References

The IoTUSLab especially acknowledge the following member who have heavily contributed to the lab yet have now moved on to do further great things:

- (Dr.) Zixiang Ma – @QMUL, 2015-2018, Now in the IoT division @Huawei (Nanjing)

N.B. Many research papers from the Lab can be found at under the publications tab at http://iot.eecs.qmul.ac.uk/, & on google scholar, ResearchGate, etc.

Appendix

- Slides to be added

Activities of Daily Life (ADL) as Health Indicators

How do I/others/the authorities know:

- What our mental and physical well-being state is?
- If we can live by ourselves, independently, safely & healthily?
- How long can we do this / live for?
- Some abnormal health states and the recovery back to normal are difficult to ascertain, e.g., state of mental health, how frail an elderly person is, how fast someone recovers from a physical injury.
- Whilst a doctor's health check-up can be used, these need a delayed appointment time, are performed infrequently and in non-daily life conditions.

- Lidar, Camera: 1.2.3.4
- UWB (Radar), Ultrasonic: 1. 2. 4
- mmWave Radar: 1.2.3.4
- Wi-Fi RTT: 1,4
- NFC,RFID: 4
- Wi-Fi, BLE: 1,4
- Inertial, Magnetic: 1,2,4
- GNSS:4
- Cellular, LPWAN: 4
- Doppler Radar: 1,2

1. Micro Movement Recognition

2. Locomotion Recognition

3. Human Pose Recognition

4. Location-driven ADL

Device free vs. Wearable

- Device free:
  - Lidar, Camera
  - UWB Radar, Ultrasonic
  - mmWave Radar
  - Wi-Fi CSI
  - Doppler Radar
- Wearable:
  - UWB tag
  - BLE
  - Wi-Fi (including RTT)
  - NFC,RFID
  - Inertial, Magnetic
  - GNSS
  - Cellular, LPWAN