INTRODUCTION TO SPATIAL SENSING AND REASONING FROM SENSOR DATA

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Module objective

Knowledge and understanding

- Understand the fundamentals of spatial reasoning from various types of sensor data

Key skills

- Design and evaluate various types of sensor data required for spatial reasoning

Spatial reasoning

- Global (absolute) position
  - Position within general global reference frame
  - Global Positioning System or GPS (longitudes, latitudes)
- Relative position
  - Based on arbitrary coordinate systems and reference frames
  - Distances between sensors (no relationship to global coordinates)
- Symbolic position information
  - “Interaction classroom”, “PGP canteen”

Introduction

Floor pressure

Ultrasonic time of flight

WiFi

Array microphone

Laser range-finding

Kinect 3D

Passive Infrared sensor

Reference:

- http://web.cse.ohio-state.edu/~xuan/courses/5432/5432_localization.ppt.
- https://www.sensorsmag.com/components/smartphone-sensor-evolution-rolls-rapidly-forward

Introduction

- Proprioceptive sensors *(internal)*
  - Measure values internally to the system (robot),
  - e.g. motor speed, wheel load, heading of the robot, battery status
- Exteroceptive sensors *(external)*
  - Information from the robots environment
  - Distances to objects, intensity of the ambient light, unique features.
- Passive sensors
  - Measure energy coming from the environment
- Active sensors
  - Emit their proper energy and measure the reaction, better performance, but some influence on environment
- What positioning accuracy do I really need and why?
  - How often do I need to determine an object's location?
  - How big is the area I need to cover?

Reference: https://www.eliko.ee/choose-right-indoor-positioning-system/

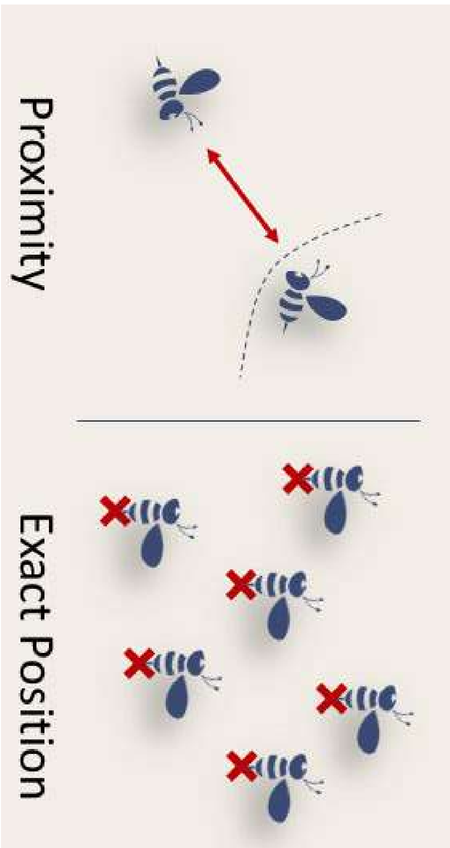
Spatial reasoning

- Positioning system consists of
  - Navigation sources: at known locations
  - Users: their location need to be determined

Information from location sensors	Positioning principle
Binary information if communication is possible or not	Proximity
Quality of communication link • Received signal strength (RSS) • Bit error rate (BER) • (RFID) read success rate	Fingerprinting
Time of arrival (TOA)	Trilateration
Time difference of arrival (TDOA)	Multilateration
Angle of arrival (AOA)	Angulation

Spatial reasoning: Proximity

- Proximity: User's position = position of closest navigation source



	BEACONS	GPS	WI-FI	NFC
Recommended for	In/near-store and micro-location use-cases	Macro-location and out of store use-cases	In-store use-cases	Close proximity, secure interaction
Some potential uses	In-aisle notifications and offers, in-store navigation, hands-free payment	Near-store notifications and offers, pre-arrival customer 'check-in'	In-aisle notifications and offers, in-store navigation, hands-free payment	Payments, product tagging
Ease of set up and maintenance	Medium	Medium-high	Medium	Medium
Range	Medium	Long	Medium-low	Close
Accuracy	Medium	Medium-low	Medium	High
Ease of use for consumer	Medium	Medium	Medium-high	Medium-high
Energy efficiency on consumer device	Medium-high	Medium-low	Medium-high	High

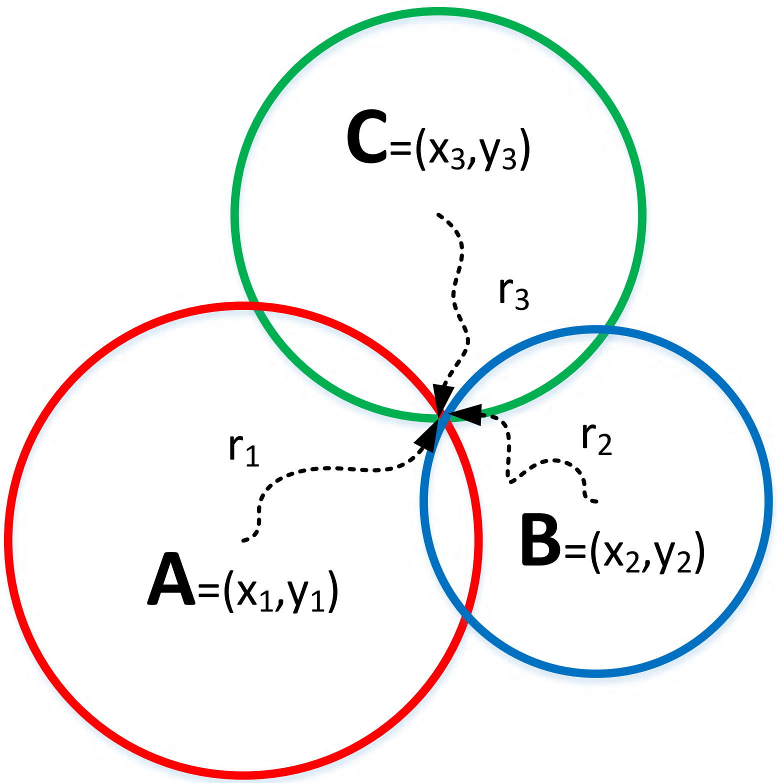
Reference:

- https://www.accenture.com/us-en/insight-beacons-location-based-technology-revolutionizing-how-retailers-business
- https://nanotron.com/EN/2017/04/19/professional-location-awareness-is-presence-proximity-and-tracking/

Spatial reasoning: Fingerprinting

- Use an n -dimensional space containing RSS vectors $(rss_1, rss_2, \cdots, rss_n)$ of reference points; n = number of navigation sources. Reference points described as tuples $(\text{coordinates}, \text{RSS vector}) = ((x, y), (rss_1, \ldots rss_n))$
- Nearest neighbour
  - Find reference point *ref* for which $d(RSS_{user}, RSS_{ref})$ is minimal
  - Decision: $POS_{user} := POS_{ref}$
- Multiple nearest neighbour
  - Find k (e.g. three) “closest” (see above) reference points
  - Decision: $POS_{user} := center\left(POS_{ref1}, \cdots, POS_{refk}\right)$
- Interpolation
  - Find three “closest” reference points
  - Use interpolation algorithm on triangle to obtain POS_{user}.

Spatial reasoning: Trilateration



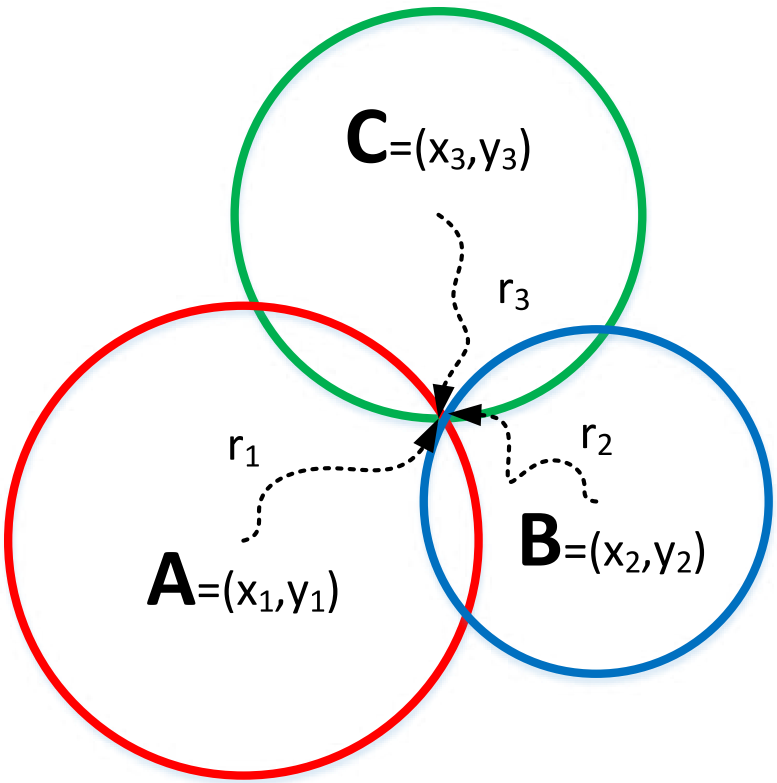
Time of Arrival (TOA)

- Foghorn is sounded precisely on the minute mark
- Mariner has an exact clock and notes elapsed time
- Distance = propagation time * speed of sound (~335 meter/second)

With three measurements, we have

$$(x - x_1)^2 + (y - y_1)^2 = r_1^2$$
$$(x - x_2)^2 + (y - y_2)^2 = r_2^2$$
$$(x - x_3)^2 + (y - y_3)^2 = r_3^2$$

Spatial reasoning: Trilateration



Time Difference of Arrival (TDOA)

- Uses propagation delay between mobile terminal and multiple base stations
- No global time
- Only time differences are known

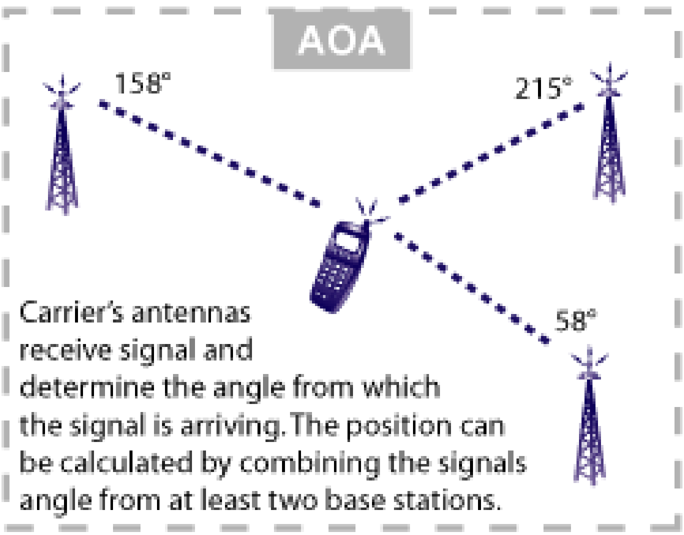
The travel time of a signal from a reference station to the current position is given by the distance divided by the signal propagation speed v:

$$t_1 = \frac{1}{v}\sqrt{(x-x_1)^2+(y-y_1)^2}$$
$$t_2 = \frac{1}{v}\sqrt{(x-x_2)^2+(y-y_2)^2}$$
$$t_3 = \frac{1}{v}\sqrt{(x-x_3)^2+(y-y_3)^2}$$

Spatial reasoning: Angulation

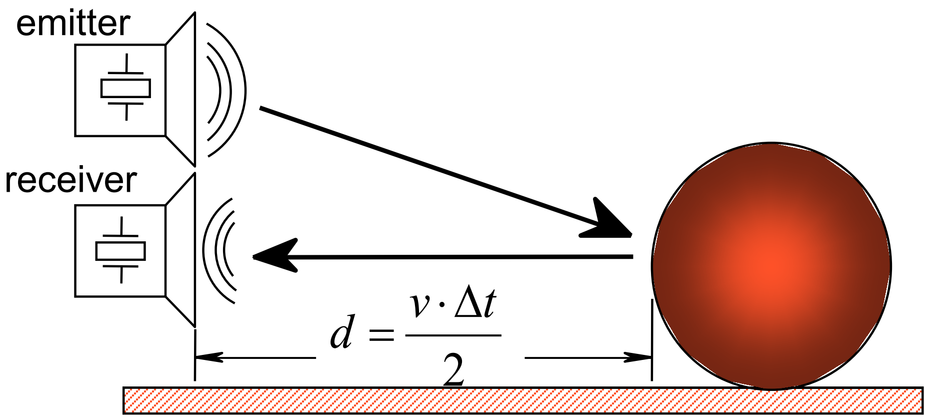
Angle of arrival (AOA)

- Base station measures angle to mobile terminal
  - Rotate antenna to the highest RSS value
  - Derive angle from RSS values of individual antennas in an antenna array.



Reference: http://www.e-cartouche.ch/content_reg/cartouche/LBStech/en/html/LBStechU2_poslabel1.html

Ultrasonic range sensor



http://www.robot-electronics.co.uk/shop/Ultrasonic_Rangers1999.htm

Operational principle

- An ultrasonic pulse is generated by a piezo-electric emitter, reflected by an object in its path, and sensed by a piezo-electric receiver. Based on the speed of sound in air and the elapsed time from emission to reception, the distance between the sensor and the object is easily calculated.

Main characteristics

- Precision influenced by angle to object
- Useful in ranges from several cm to several meters
- Typically relatively inexpensive

Applications

- Distance measurement

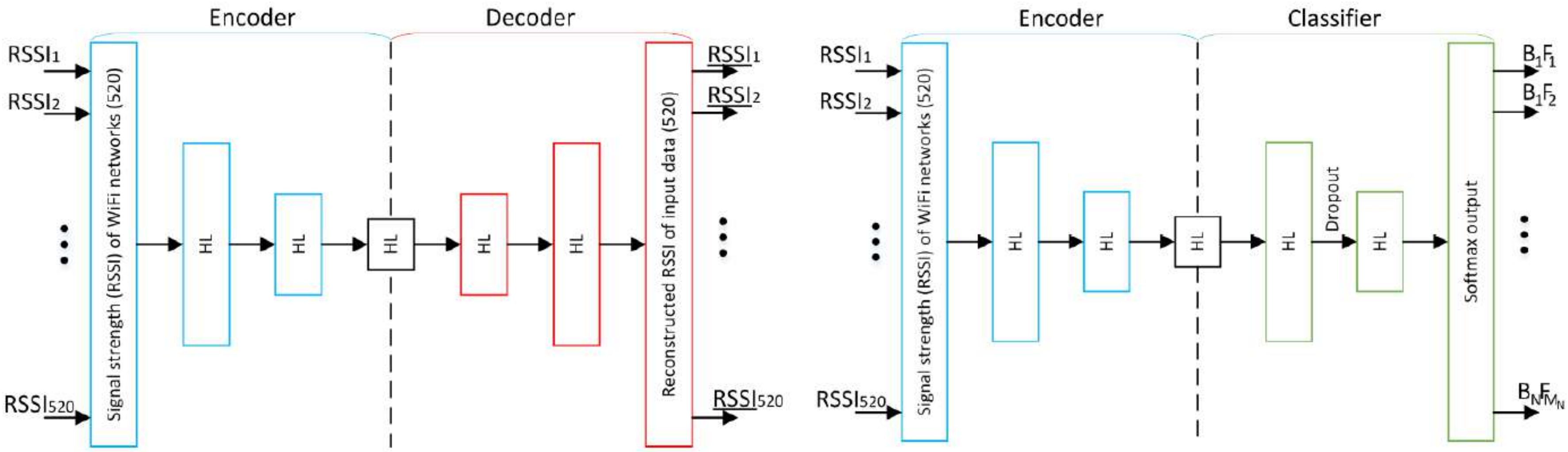
Example: UJIIndoorLoc

- The UJIIndoorLoc database covers three buildings of Universitat Jaume I (http://www.uji.es) with 4 or more floors and 110.000 m^2. It can be used for classification, e.g. building and floor identification, or regression, e.g. longitude and latitude estimation. It was created in 2013 by means of 20+ different users and 25 Android devices. The database consists of 19937 training/reference records and 1111 validation/test records. The 529 attributes contain the WiFi fingerprint, the coordinates where it was taken, and other useful information.

Table. Variables in the Dataset			
Column	Description	Units	Values
WAP001 - WAP520	RSSI received by device from given WAP	dBm	Integer values from -104 to 0 (weak to strong), 100 (no signal)
LONGITUDE	Longitude of position	meters	-7695.9387549299299000 to -7299.786516730871000
LATITUDE	Latitude of position	meters	4864745.7450159714 to 4865017.3646842018
FLOOR	Floor number	---	Integer values from 0 to 4
BUILDINGID	Building number	---	Integer values from 0 to 2
SPACEID	Integer identifying the space (lab, classroom, etc.)	---	Various integer values
RELATIVEPOSITION	Relative position with respect to the space	---	1 - inside, 2 - outside in front of the door
USERID	User identifier	---	Integer values from 0 to 18
PHONEID	Android device identifier	---	Integer values from 0 to 24
TIMESTAMP	UNIX time when example was recorded	---	Integer values

Reference: https://www.kaggle.com/giantuji/UjiIndoorLoc

Example: UJIIndoorLoc



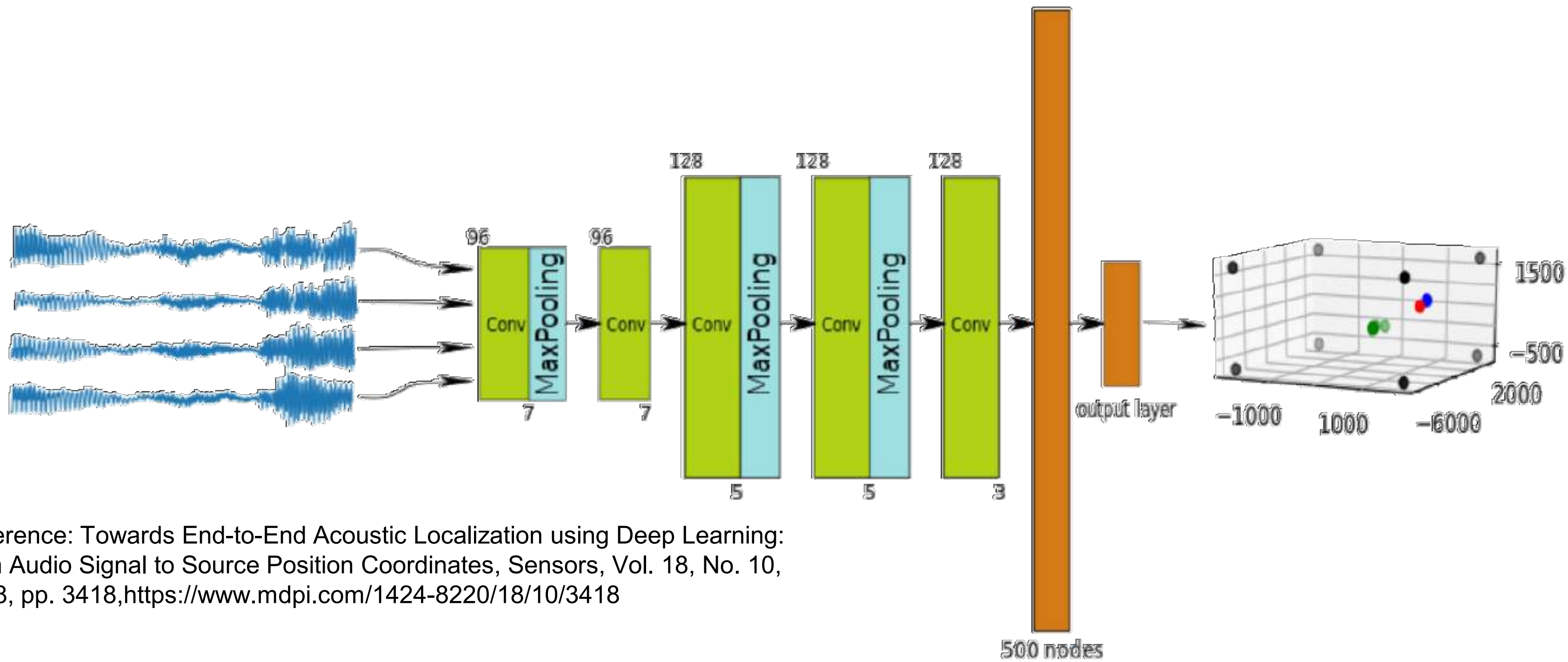
Layer (type)	Output Shape	Param #
dense_10 (Dense)	(None, 256)	133376
dense_11 (Dense)	(None, 128)	32896
dense_12 (Dense)	(None, 64)	8256
dense_16 (Dense)	(None, 128)	8320
dense_17 (Dense)	(None, 128)	16512
dense_18 (Dense)	(None, 13)	1677

Building and floor classification

Reference: M. Nowicki and J. Wietrzykowski, Low-effort place recognition with WiFi fingerprints using deep learning, https://arxiv.org/pdf/1611.02049v1.pdf

Spatial reasoning: Acoustic

Our system obtains the position of an acoustic source from the audio signals recorded by an array of M microphones. Given a reference coordinate origin, the source position is defined with the 3D coordinate vector $\mathbf{s} = (s_x \;\; s_y \;\; s_z)^\top$. The microphones positions are known and they are defined with coordinate vectors $\mathbf{m}_i = (m_{i,x} \;\; m_{i,y} \;\; m_{i,z})^\top$ with $i = 1, \ldots, M$. The audio signal captured from the i^{th} microphone is denoted by $x_i(t)$. This signal is discretized with a sampling frequency f_s and is defined with $x_i[n]$. We assume for simplicity that $x_i[n]$ is of finite-length with N samples. This corresponds to a small window of audio with duration $w_s = N/f_s$, which is a design parameter in our system.



Reference: Towards End-to-End Acoustic Localization using Deep Learning: from Audio Signal to Source Position Coordinates, Sensors, Vol. 18, No. 10, 2018, pp. 3418,https://www.mdpi.com/1424-8220/18/10/3418

Spatial reasoning: Vision

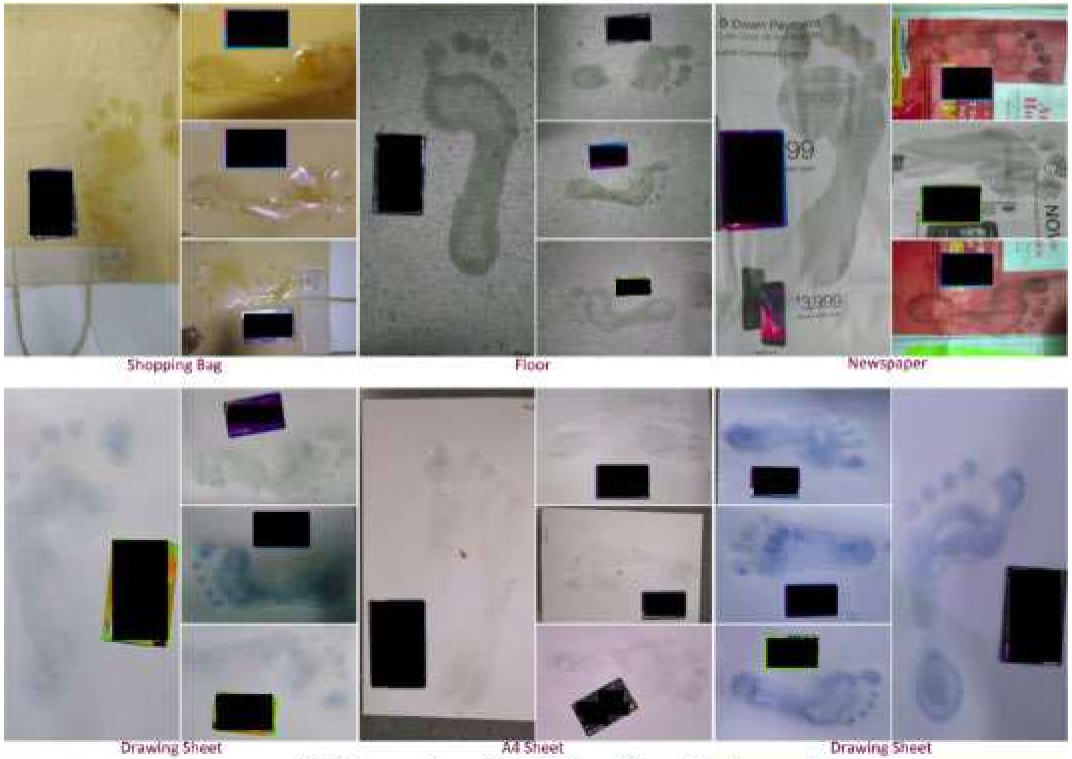
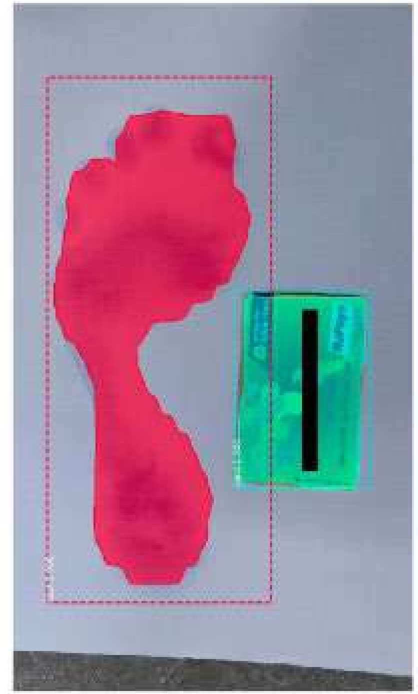


Fig-2: Impressions of wet feet on different background

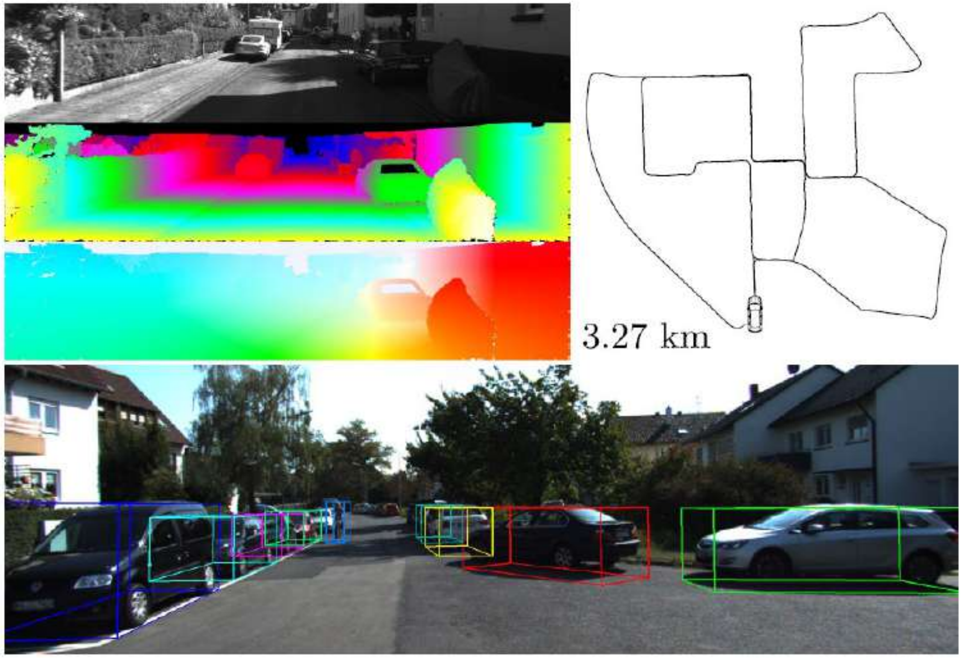


Height: 8.08 inches
Breadth: 3.41 inches
Arch type: High

Reference: https://labs.imaginea.com/post/measuring-feet-using-deep-learning/

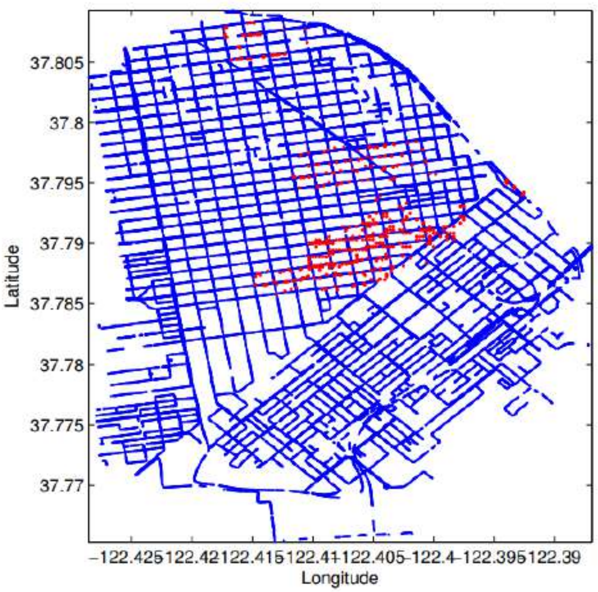
Example: KITTI dataset

- Two stereo cameras (1392×512 pixels)
- Laser scanner, GPS+IMU (inertial measurement unit)
- 6 hours at 10 frames per second.



Reference: http://www.cvlibs.net/datasets/kitti/

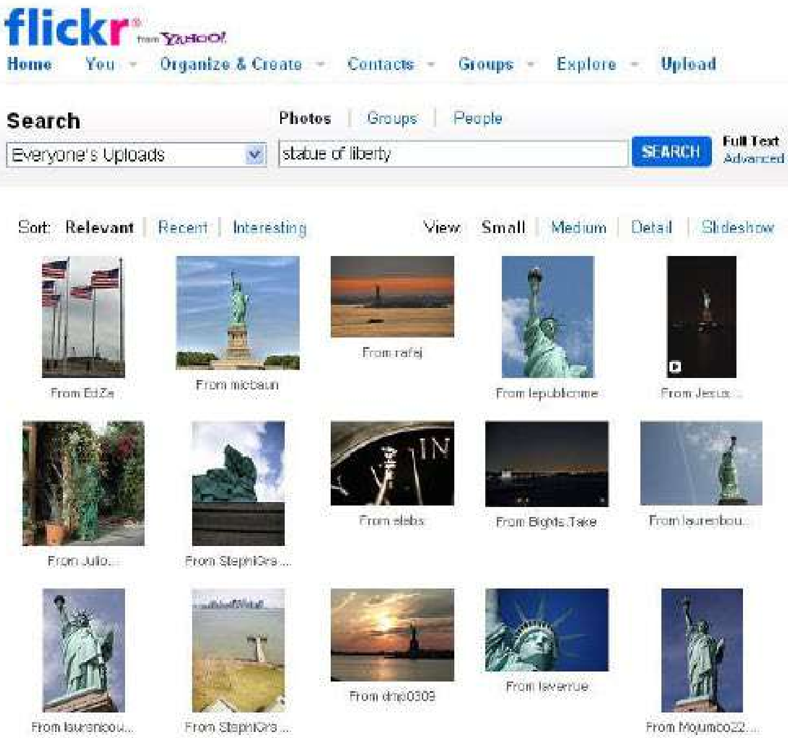
Spatial reasoning: Vision

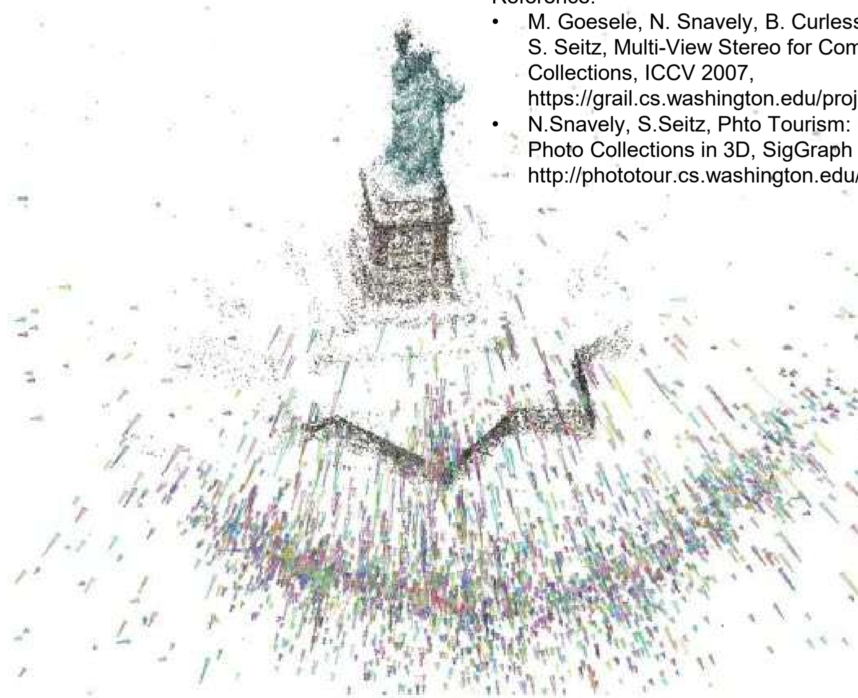


Reference dataset (blue dots) and query set (red dots)

Reference: D. Chen, G. Baatz, K. Koser, S. Tsai, R. Vedantham, T. Pylvanainen, K. Roimela, X. Chen, J. Bach, and M. Pollefeys. City-scale landmark identification on mobile devices, CVPR, 2011. http://semihyagcioglu.com/projects/image-geolocalization/

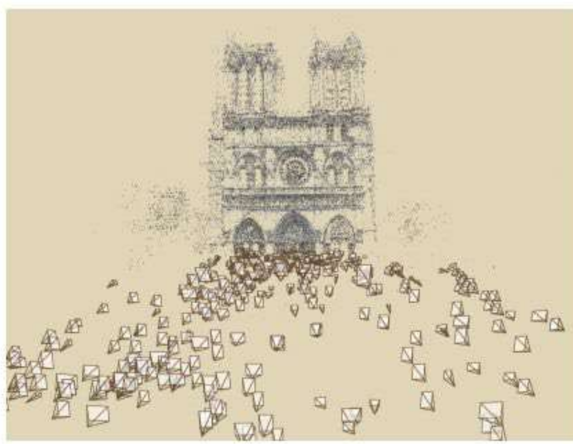
Spatial reasoning: Vision





Reference:

- M. Goesele, N. Snavely, B. Curless, H. Hoppe, S. Seitz, Multi-View Stereo for Community Photo Collections, ICCV 2007, https://grail.cs.washington.edu/projects/mvscpc/
- N.Snavely, S.Seitz, Phto Tourism: Exploring Photo Collections in 3D, SigGraph 2006. http://phototour.cs.washington.edu/



What we have learnt

- Motivation and application examples of spatial reasoning from various types of sensory data, such as
  - WiFi
  - Acoustic
  - Vision

Thank you!

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