Infrastructure-free indoor localization

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Agenda

- Applications of Indoor localization
- Infrastructure-based vs Infrastructure-free
- Types of sensors and limitations
- Infrastructure-free approaches to indoor localization
- Machine learning/Deep learning approaches
- Problems to be solved

Applications of Indoor localization

- Retail stores (Target, Walmart, etc.)
- Medical monitoring (human activities)
- Intelligent home
- Industrial plants

Infrastructure-based Indoor localization

Definition: approaches that require additional hardware other than user’s device or require information about the environment

Examples:

- Wi-Fi:
  - Fingerprinting[1]
  - Known AP location[2]
- RFID[3]
- Building lights[4]
- Bluetooth[5]

Infrastructure-free Indoor localization

Definition: Using existing sensors on an off-the-shelf user device (phone, tablets, smartwatch, etc.)

Includes:

- IMU:
    - Accelerometer
    - Gyroscope
    - Compass/Magnetometer
- Light/Proximity sensor
- Front/Back-facing cameras
- GPS

The problem: Given onboard sensor measurements, can we calculate the a user's path close to the ground truth?

Sensors: Gyroscope

Measurement: 3 Axis angular velocity (rad/sec)

Properties:

- Low noise
- Has temperature-dependent bias
- Unavoidable drift from integration
- Works well in the short term, but inaccurate due to drift in longer period

gyro model: $\tilde{\omega} = \omega + b + \eta \qquad \eta \sim N\left(0, \sigma_{gyro}^2\right)$

true angular velocity

bias

additive, zero-mean Gaussian noise

- from gyro measurements to orientation – use Taylor expansion

have: angle at last time step

have: time step

$$\theta(t + \Delta t) \approx \theta(t) + \underbrace{\frac{\partial}{\partial t}\theta(t)}_{= \omega} \Delta t + \varepsilon, \quad \varepsilon \sim O\left(\Delta t^2\right)$$

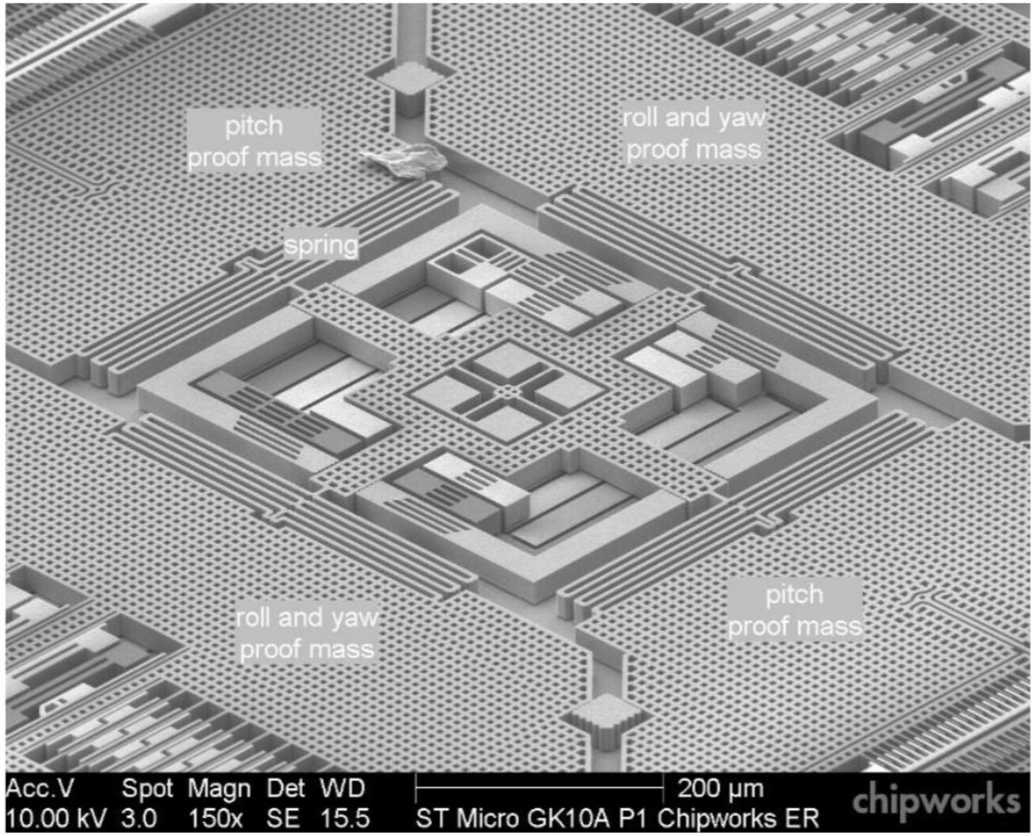
want: angle at current time step

have: gyro measurement (angular velocity)

approximation error!

Sensors: Gyroscope

MEMS (microelectromechanical systems) Gyroscope

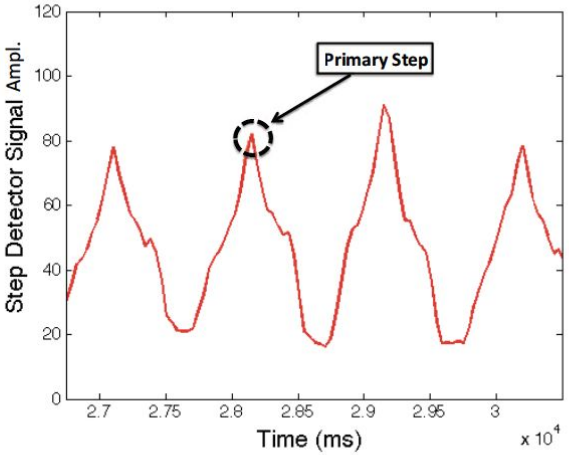


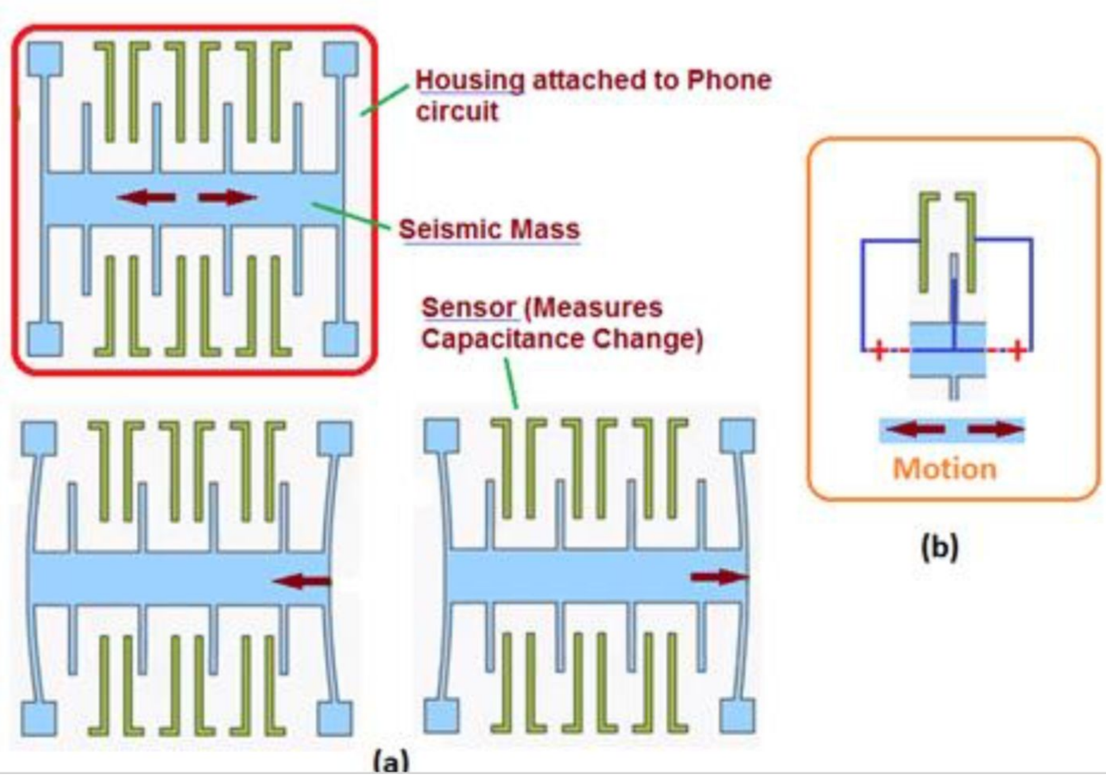
Sensors: Accelerometer

Measurement: 3 linear acceleration (m/sec^2)

Properties:

- Significant noise
- Unreliable in short-run
- Relatively accurate in long-term since no drift
- Points up with magnitude of 1g





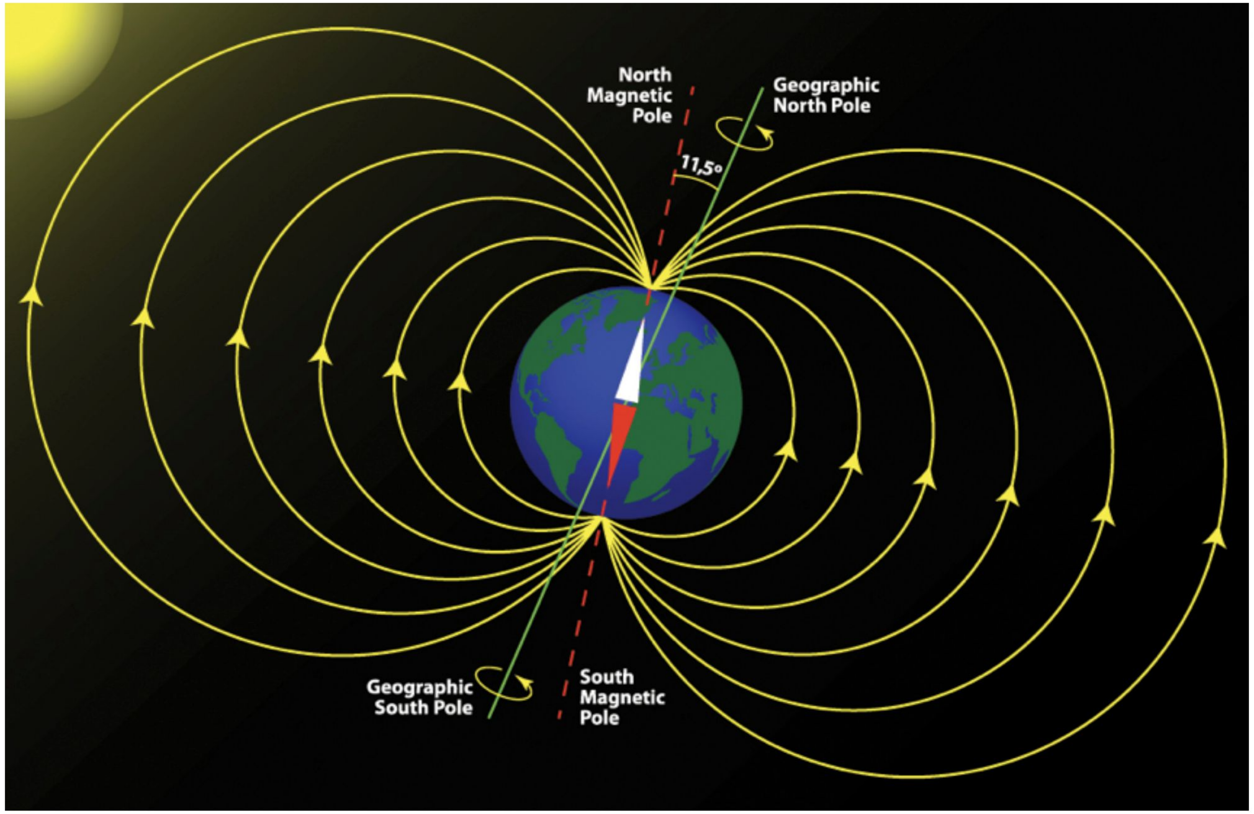
MEMS accelerometer

Sensor: Compass

Measurement: 3 orthogonal axis measuring magnetic field in uT

Properties:

- Affected by metal/electronics
- Complementary to accelerometer
- Varies with longitude and latitude, needs GPS calibration



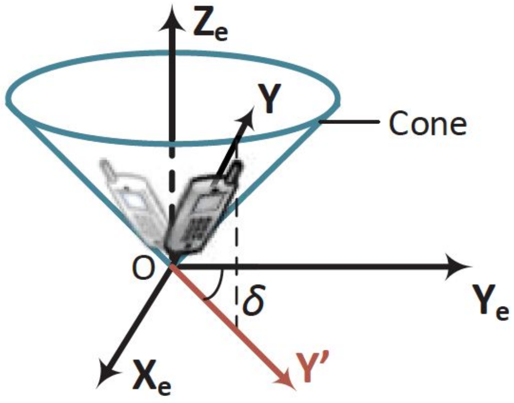
Sensor Fusion

1. Gyro + Acc (complementary filter) -> pitch&row

2. Acc + Magnetometer -> Yaw

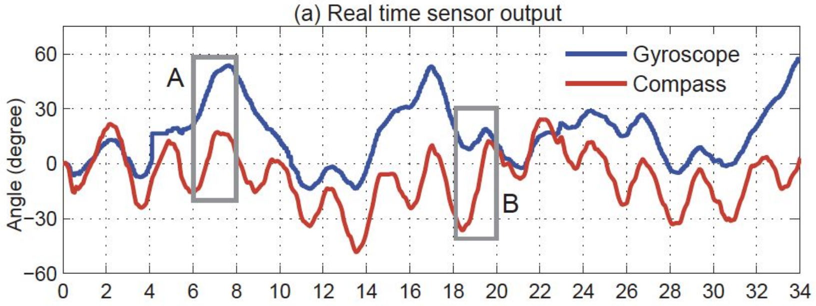
intuition:

- remove drift from gyro via high-pass filter
- remove noise from accelerometer via low-pass filter

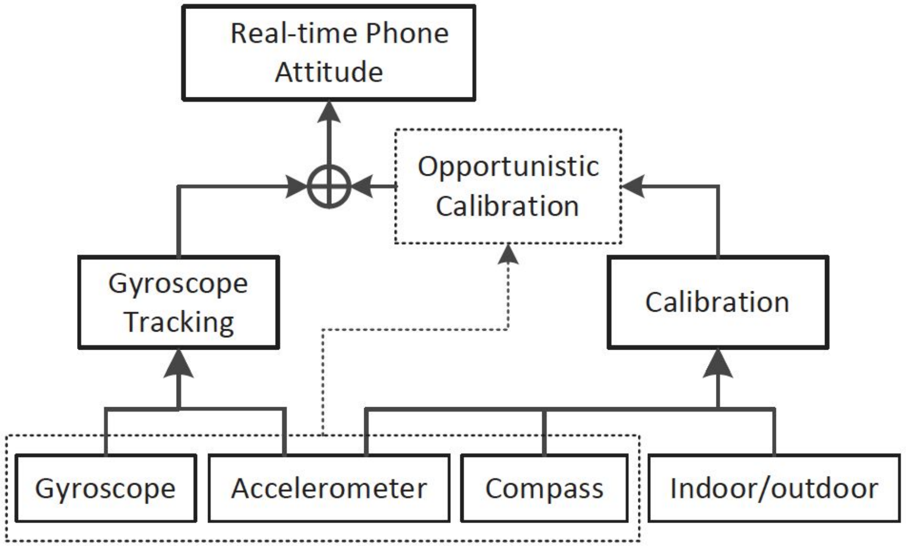


Infrastructure-free approaches to indoor localization

1. Pengfei Zhou, Mo Li, and Guobin Shen. 2014. **Use it free: instantly knowing your phone attitude**. In Proceedings of the 20th annual international conference on Mobile computing and networking (MobiCom '14)

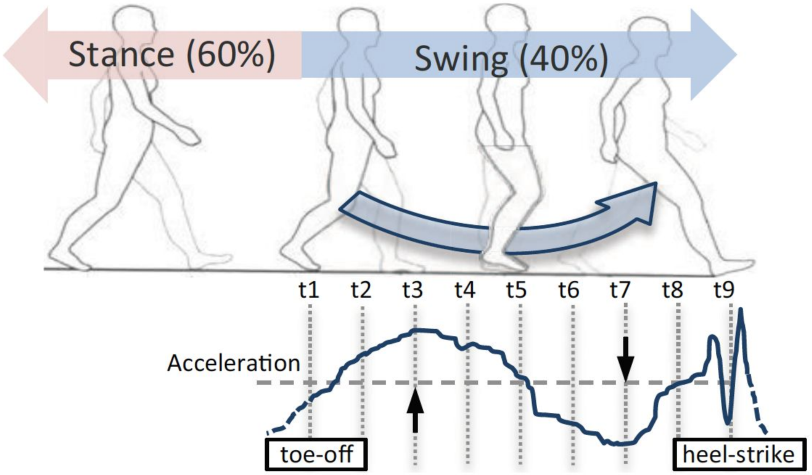


Takeaways:
- Compass can be very accurate when not corrupted
- Opportunistically calibration



Infrastructure-free approaches to indoor localization

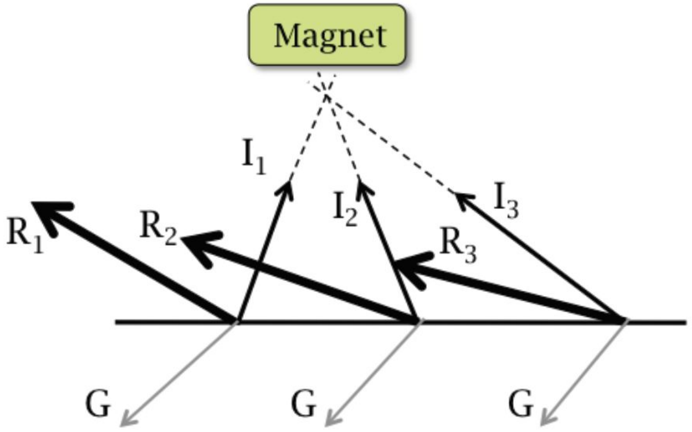
2. Nirupam Roy, He Wang, and Romit Roy Choudhury. 2014. **I am a smartphone and i can tell my user's walking direction**. In Proceedings of the 12th annual international conference on Mobile systems, applications, and services (MobiSys '14).



Takeaways:

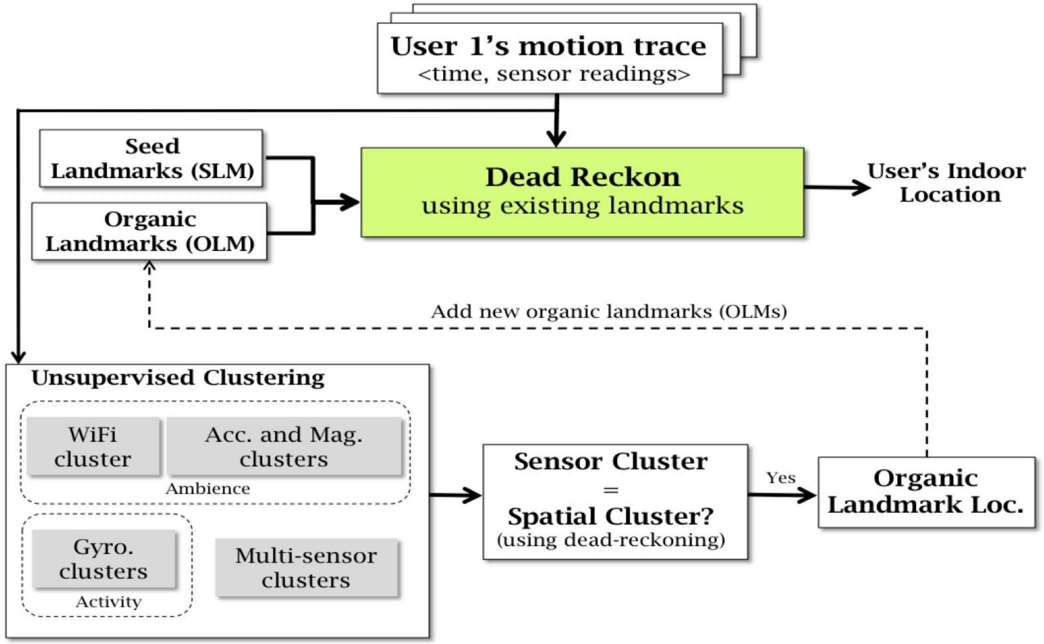
- Only a small portion of sensor data provides reliable information about local walking direction. Only a small portion of swing phase w/ minimum acceleration (around t7) provides useful information.

- Magnetometer readings can be corrected by identifying interference source and subtract the source.



Infrastructure-free approaches to indoor localization

3. He Wang, Souvik Sen, Ahmed Elgohary, Moustafa Farid, Moustafa Youssef, and Romit Roy Choudhury. 2012. **N**
war-drive: unsupervised indoor localization. In Proce
the 10th international conference on Mobile systems, applications, and services (MobiSys ‘12)。

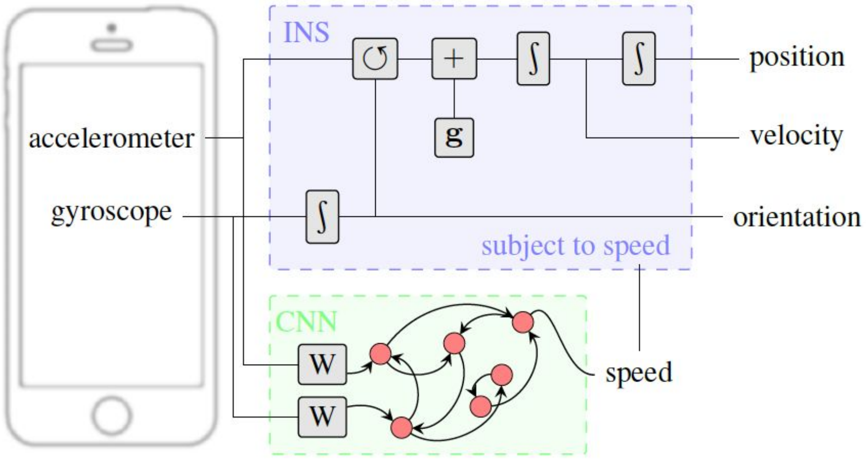


Takeaways:

- Landmarks in the environment (Wi-Fi signal strength, acceleration abnormalities, compass abnormalities) can be used to correct for the drift in dead-reckoning
- More users, more landmarks detected, more accurate the system will be.

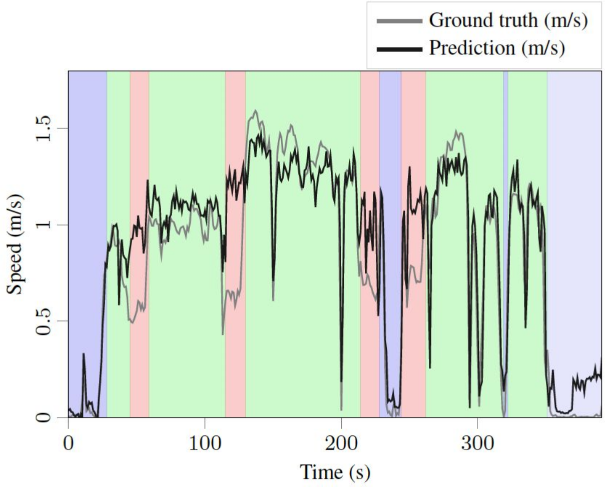
Machine learning/Deep learning approaches

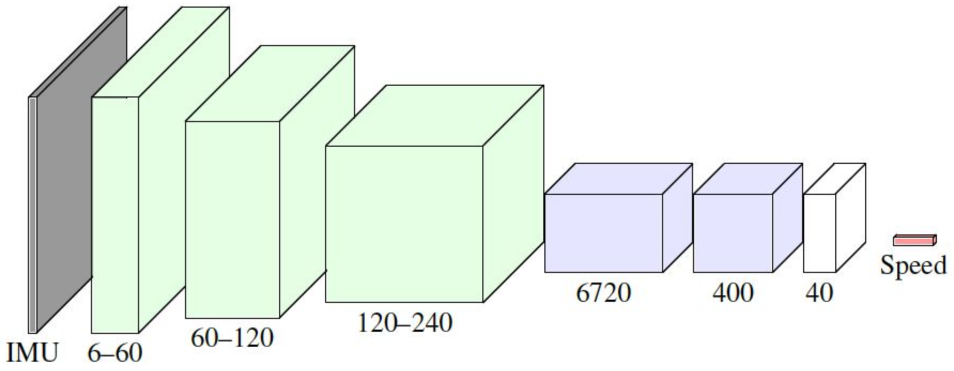
1. **Deep Learning Based Speed Estimation for Constraining Strapdown Inertial Navigation on Smartphones**.
A Cortés, Santiago; Solin, Arno; Kannala, Juho
eprint arXiv:1808.03485



Takeaways:

- Use CNN learned speed to constrain PDR

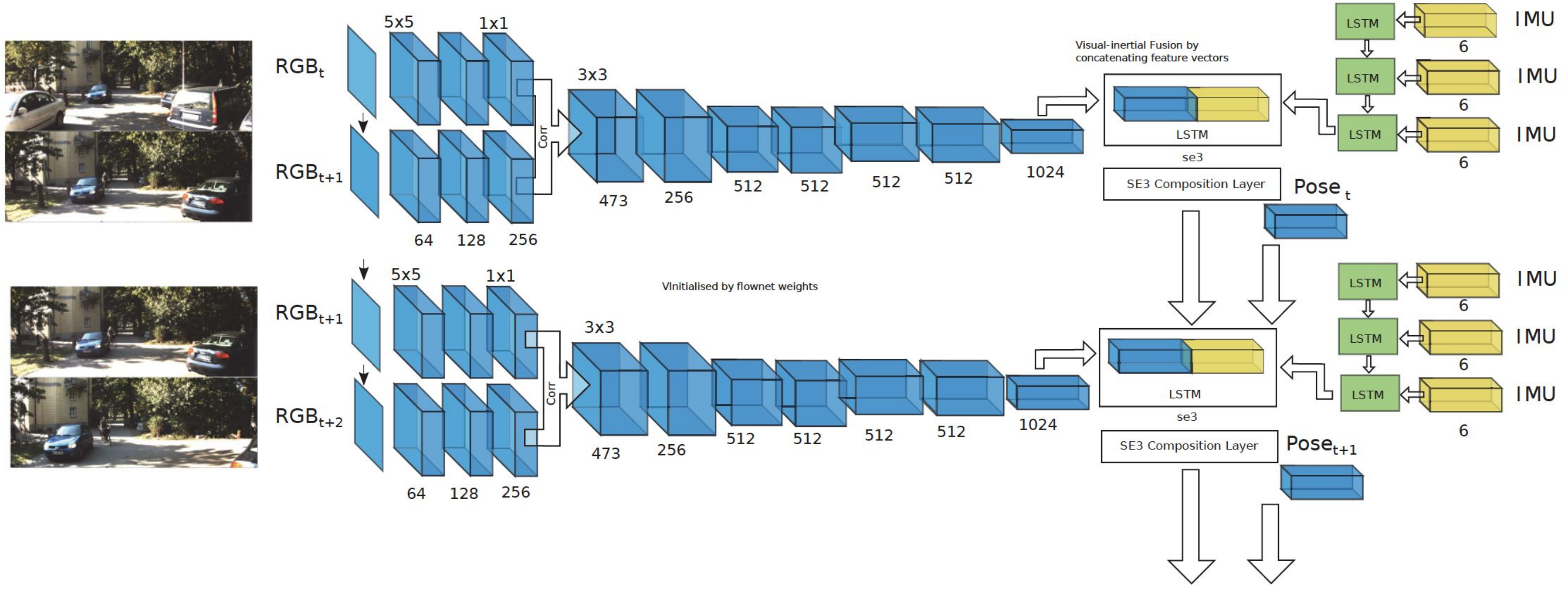




Machine learning/Deep learning approaches

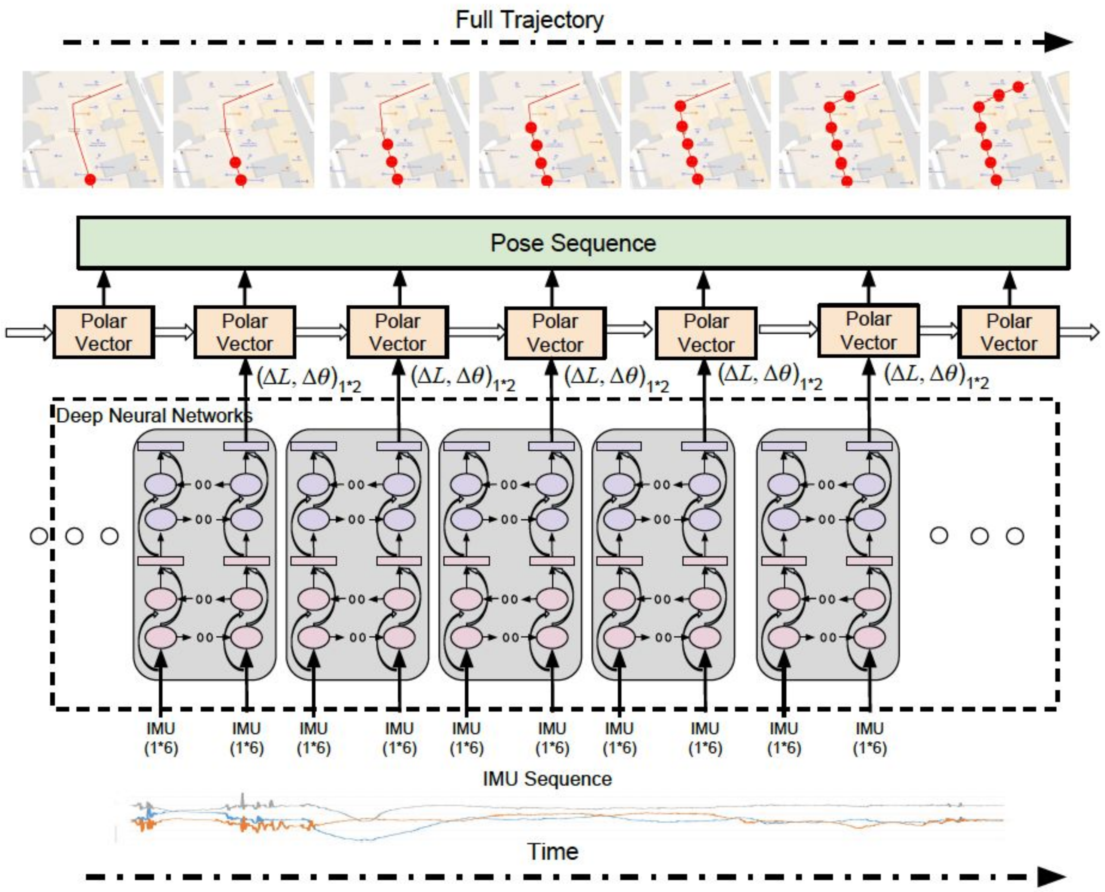
2. **VINet: Visual-Inertial Odometry as a Sequence-to-Sequence Learning Problem**
A Clark, Ronald; Wang, Sen; Wen, Hongkai; Markham, Andrew; Trigoni, Niki. J eprint arXiv:1701.08376)

Takeaways:
- Using visual cues to correct for IMU calculations.
- Core LSTM to remember past position (Pose)



Machine learning/Deep learning approaches

3. **IONet: Learning to Cure the Curse of Drift in Inertial Odometry**
A Chen, Changhao; Lu, Xiaoxuan; Markham, Andrew; Trigoni, Niki. eprint arXiv:1802.02209



Takeaways:
- Proved time windows are pseudo-independent.
- Bi-directional LSTM

Problems to be solved

- Required amount of data is large to train good model
- Few solutions for multi-floor localization
- Generalization abilities of model
  - Across different users
  - Across different use case scenarios

Thank you!