

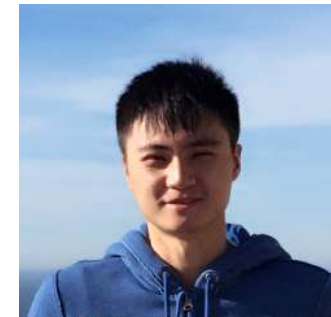
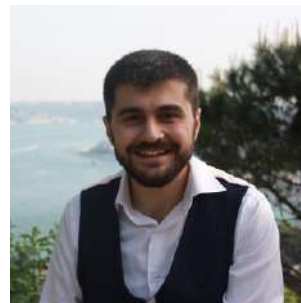
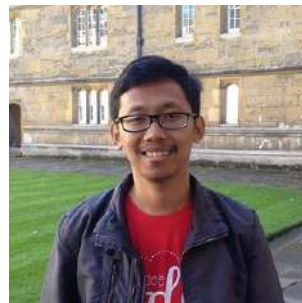
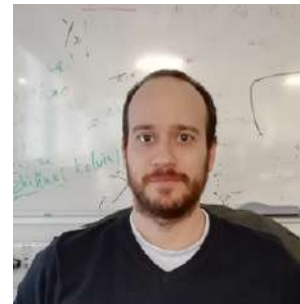
*Pervasive, Accurate and Reliable
Location Based Services for
Emergency Responders*



DISCLAIMER

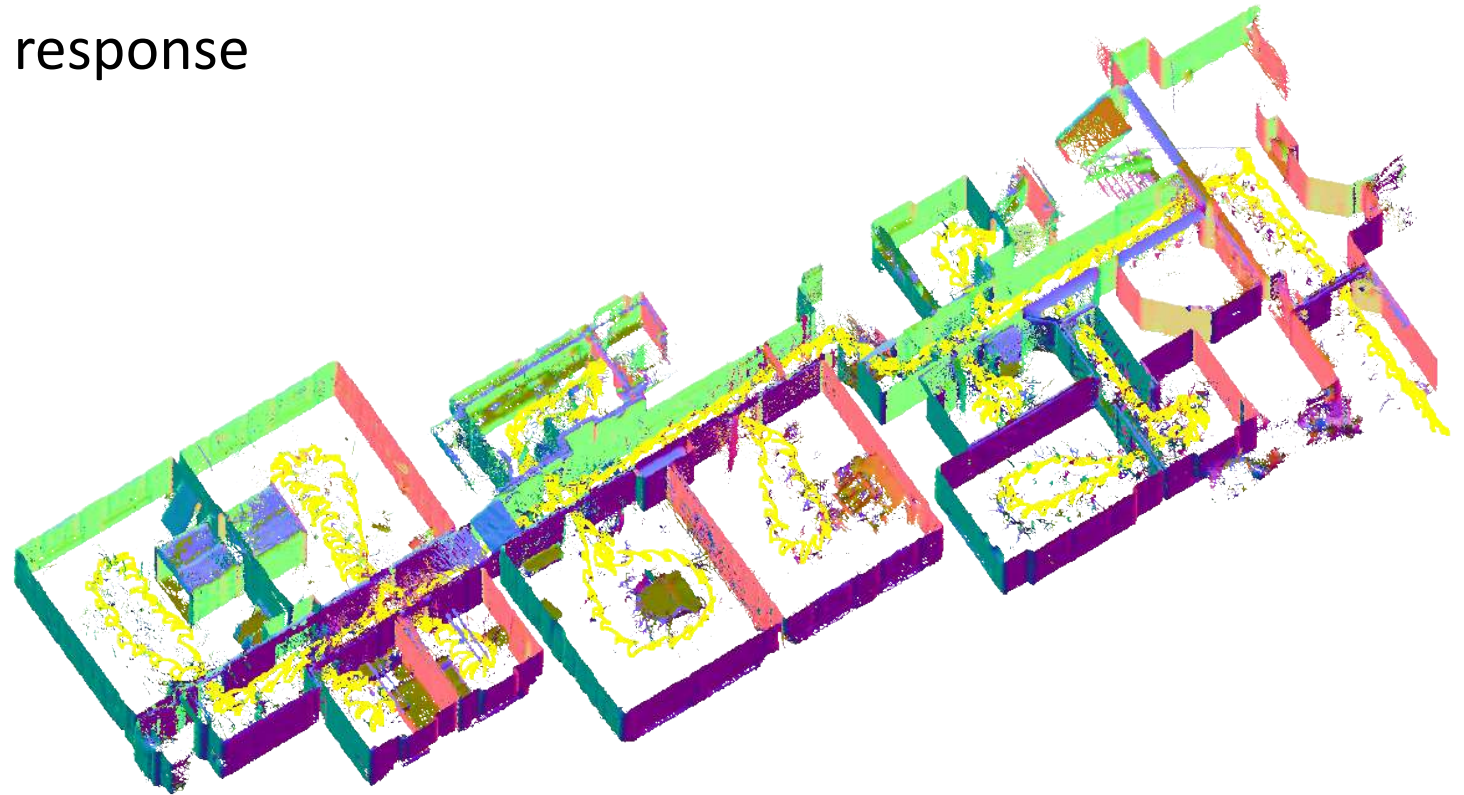
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Goal

To track first responders under *various* adverse conditions during emergency response scenarios



Visibility Constraints

Search and rescue procedures highly depend on visibility levels.
Smoke will limit the speed with which firefighters move.



Challenges under **good** visibility

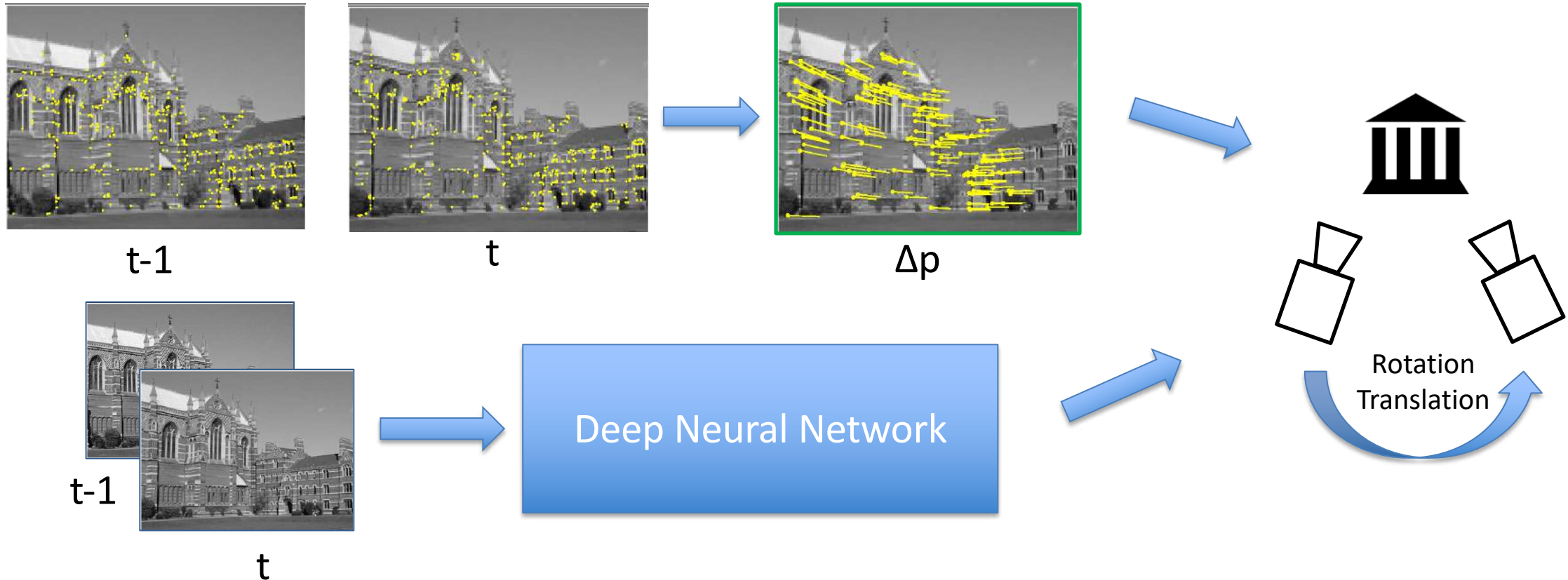
No GPS, Wi-Fi, or electricity is available.



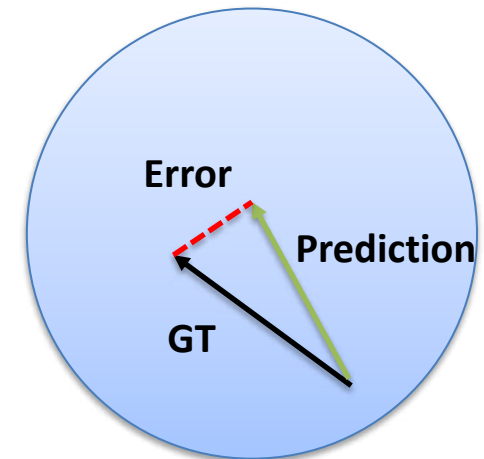
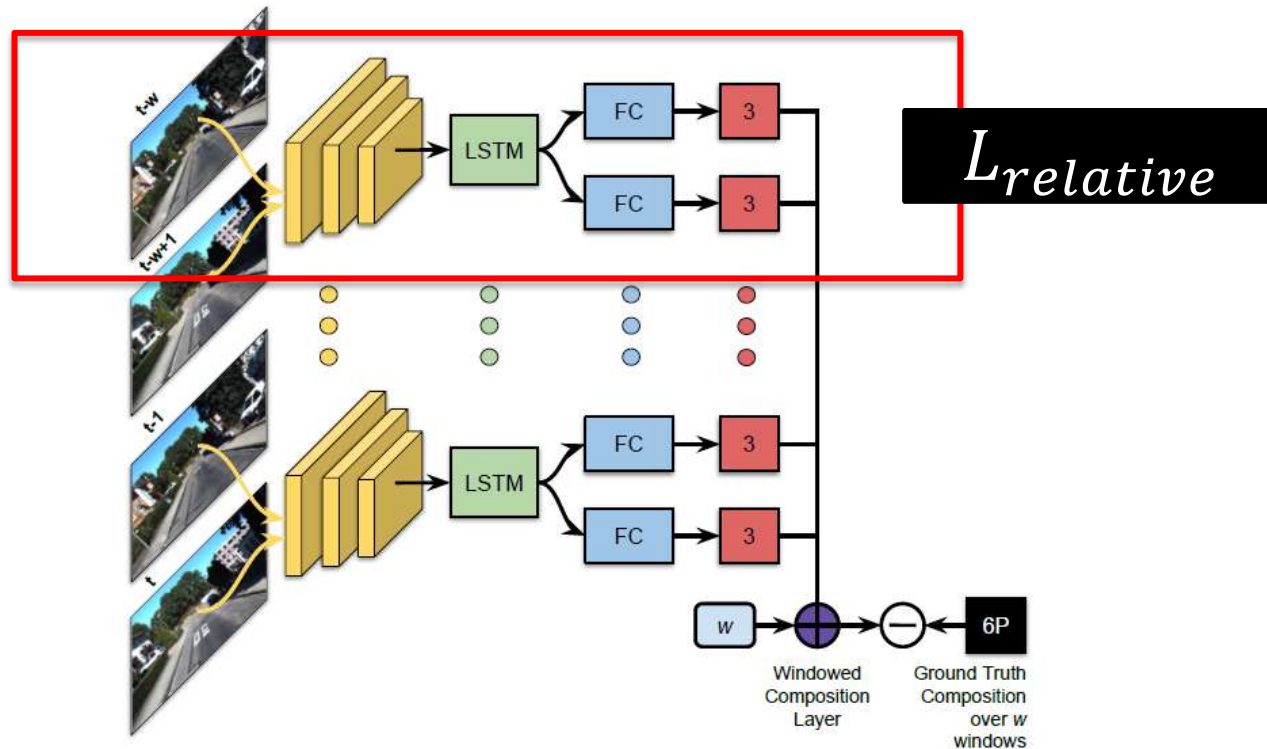
Current Challenges:

- Limited bandwidth
- Error due to frame-by-frame motion estimation
- Training data not always available

Visual Odometry



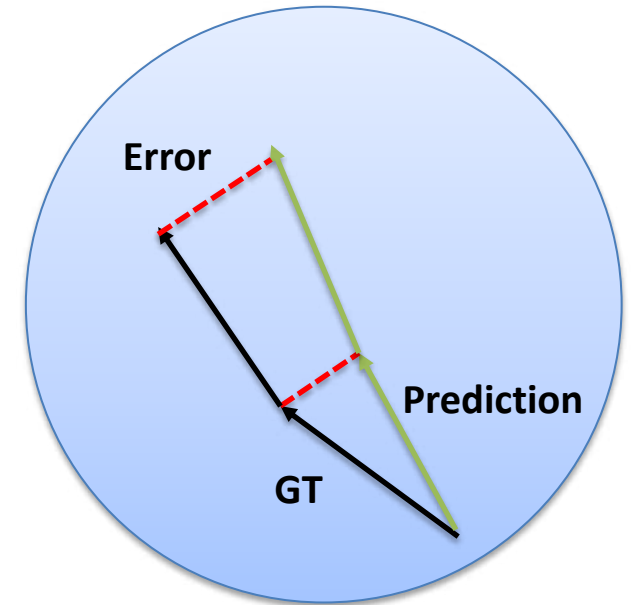
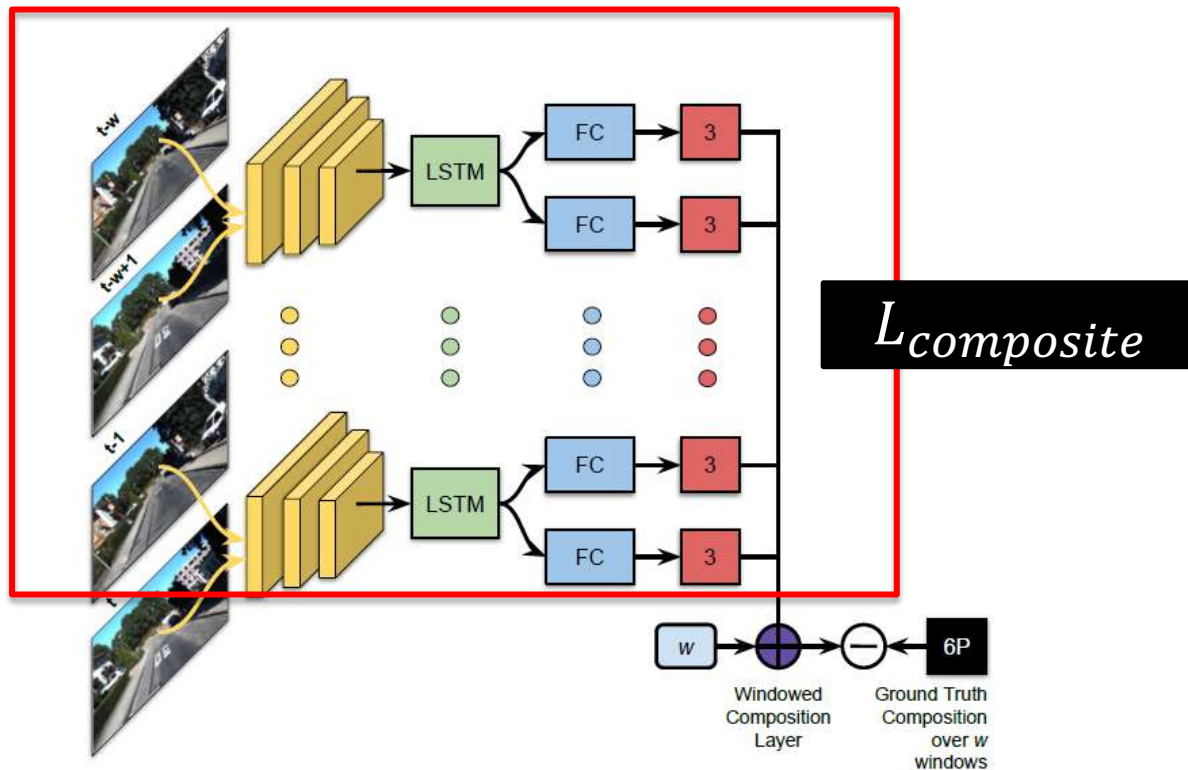
Visual Odometry with Geometry Aware-Curriculum Learning (GA-CL)



GA-CL: Gradually learning from $L_{relative}$ to $L_{composite}$



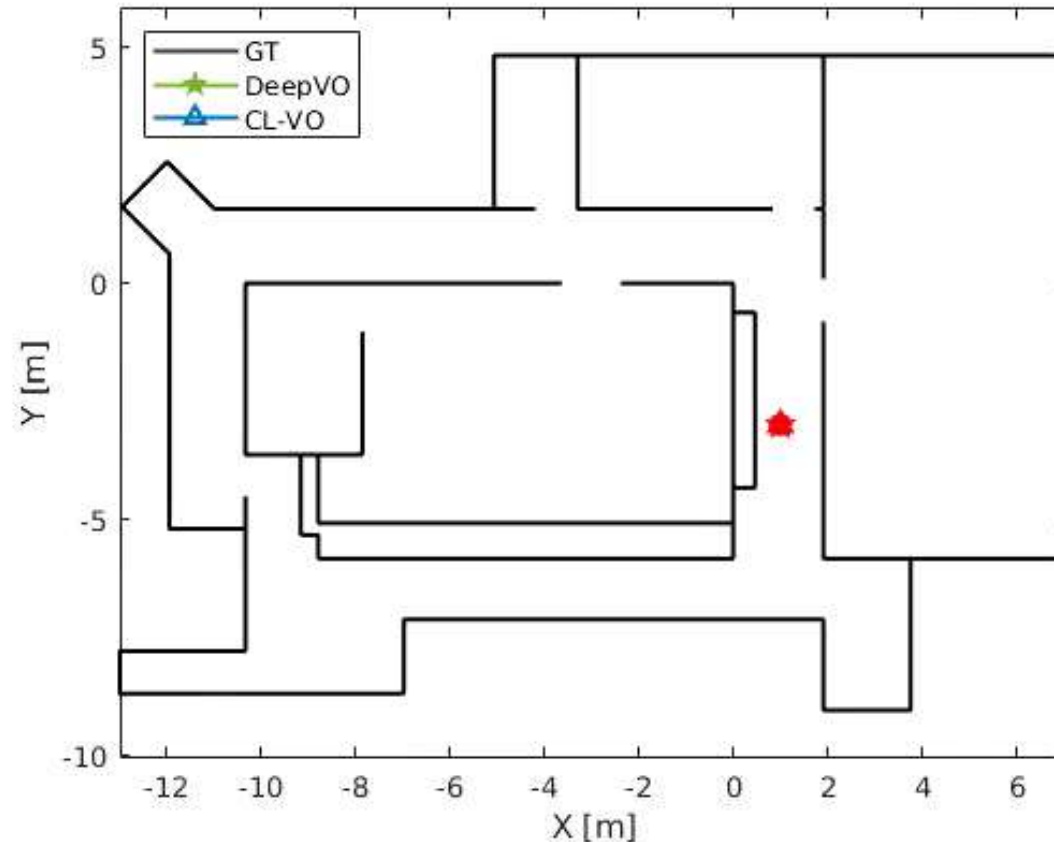
Visual Odometry with Geometry Aware-Curriculum Learning (GA-CL)



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Visual Odometry with Geometry Aware-Curriculum Learning (GA-CL)



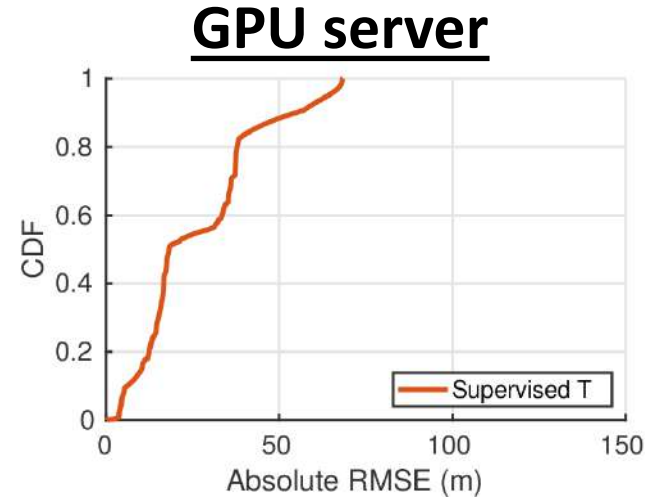
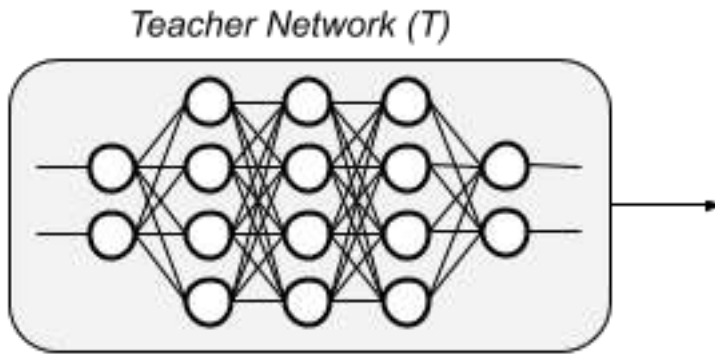
Visual Odometry with Geometry Aware-Curriculum Learning (GA-CL)

- GA-CL improves translation and rotation by 21% and 16% respectively compared to training with standard relative loss
- State-of-the art visual odometry results
- Where adequate illumination is available, accurate odometry is possible

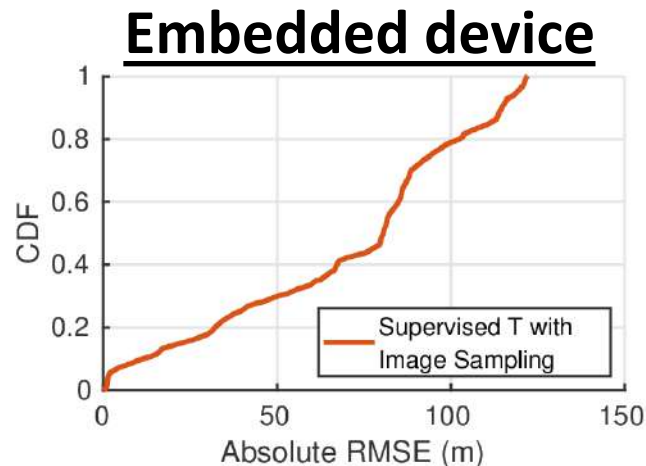
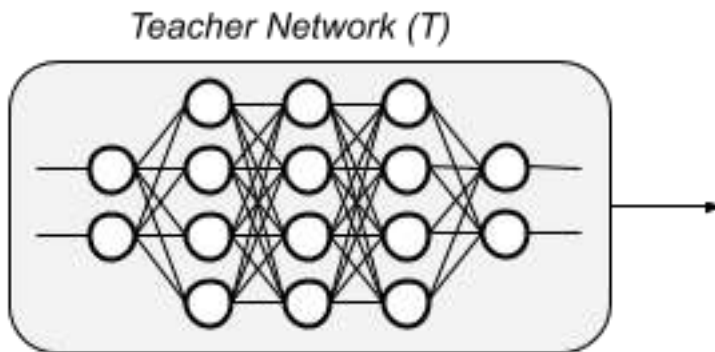


Efficient Deep Neural Odometry

Full input
Images
(32 fps)



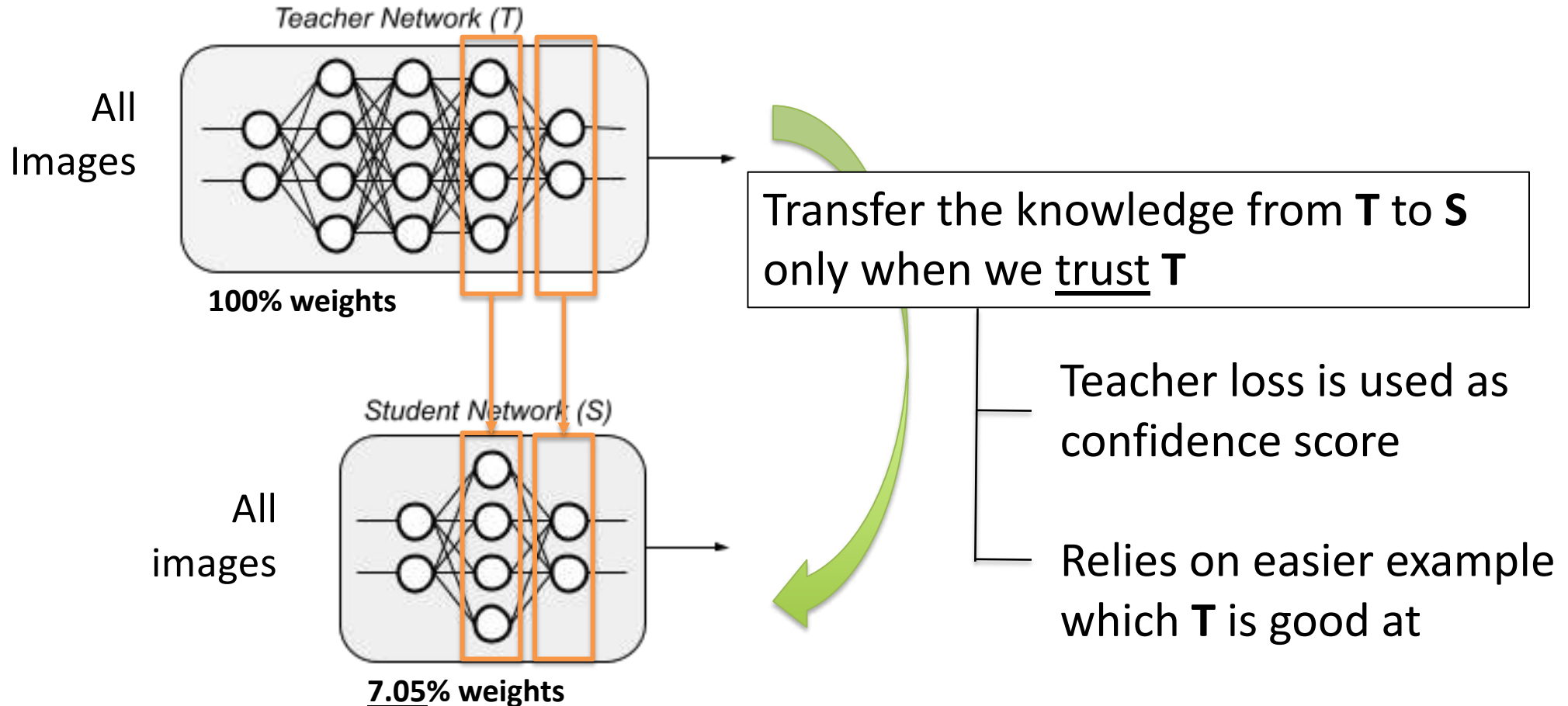
Sub-sampled
input
images
(12 fps)



Accuracy
drop 160%

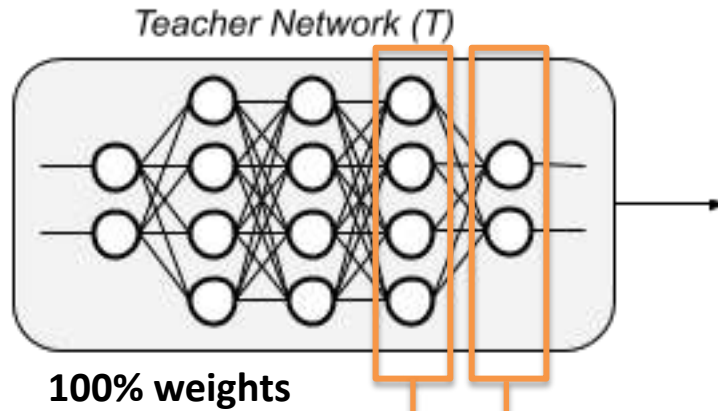


Efficient Deep Neural Odometry

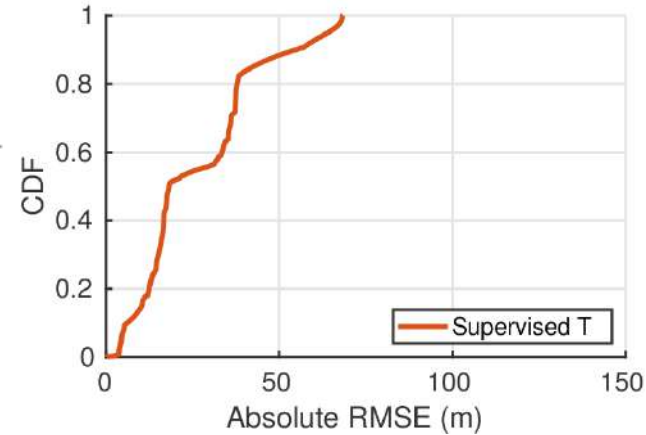


Efficient Deep Neural Odometry

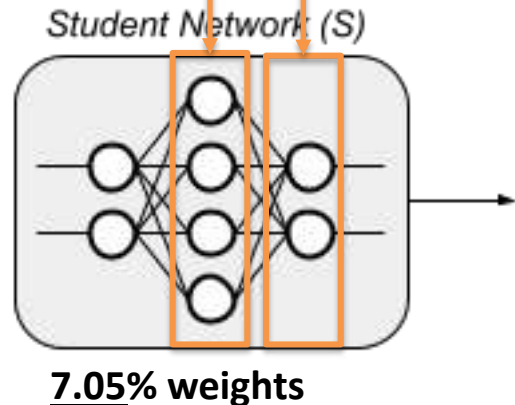
Full input Images (32 fps)



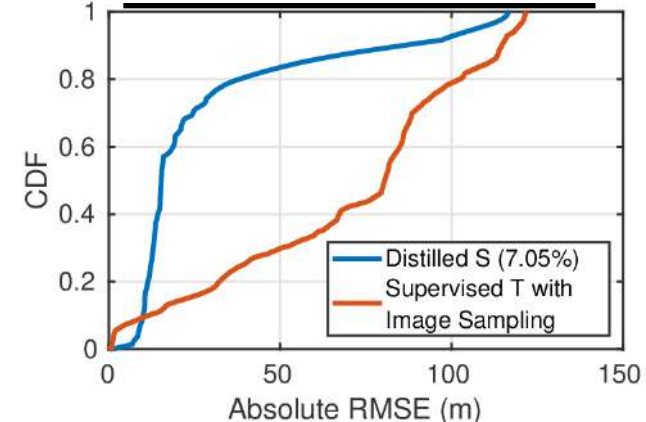
GPU server



Full input images (26 fps)



Embedded device



Accuracy drop 8.6%



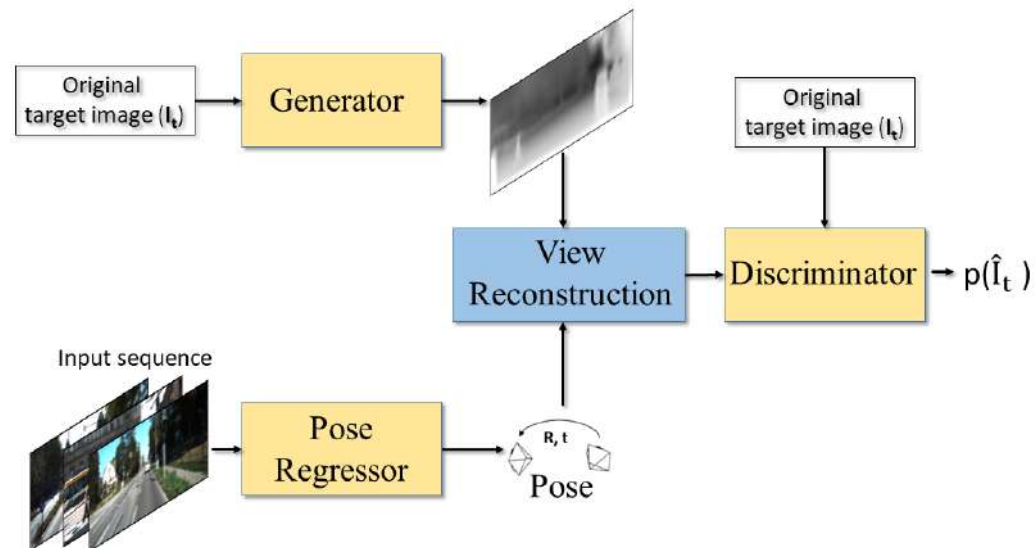
Efficient Deep Neural Odometry

- This component achieves the same (or even better) tracking performance with smaller computation and memory costs
- This will allow complex deep networks to be deployed to operate in real-time on mobile devices



GANVO: Unsupervised Deep Monocular Visual Odometry and Depth Estimation

- Supervised deep learning methods need plenty of labelled data
- GANVO provides a visual odometry solution for unknown environments
 - The idea is to create a supervisory signal by exploiting the geometry



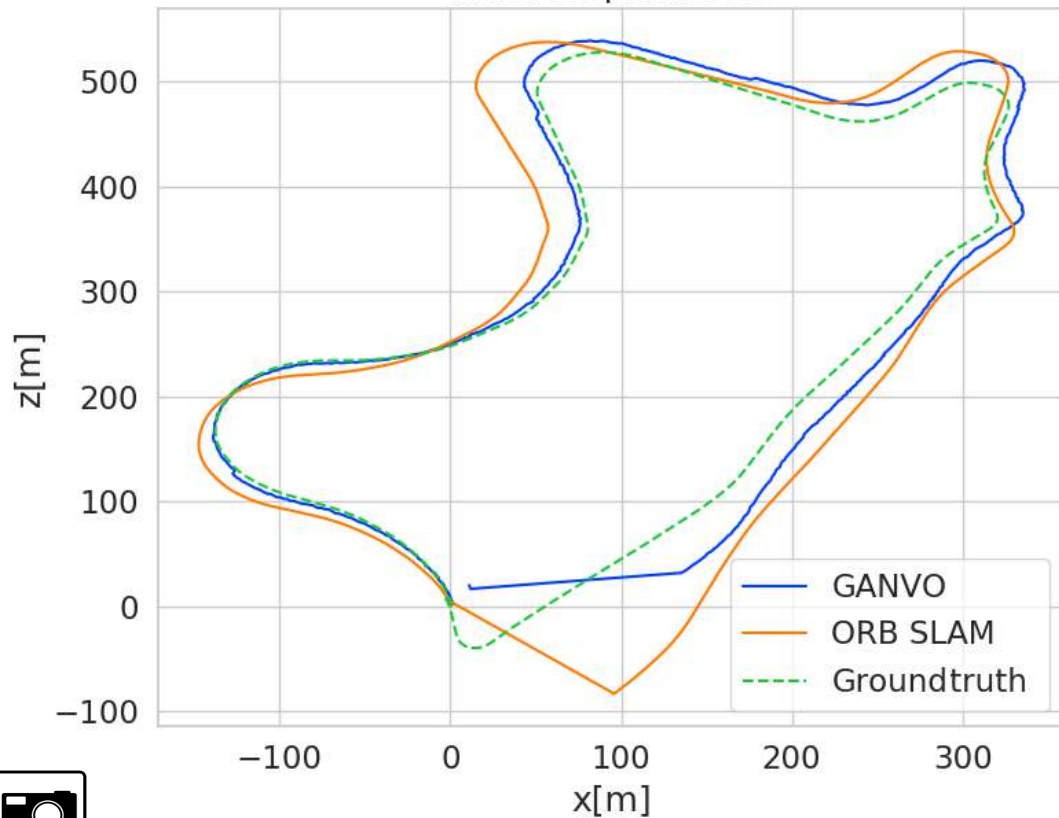
“GANVO: Unsupervised Deep Monocular Visual Odometry and Depth Estimation with Generative Adversarial Networks” – ICRA 2019

Yasin Almalioğlu, Muhamad Risqi U. Saputra, Pedro P. B. de Gusmao, Andrew Markham, and Niki Trigoni.

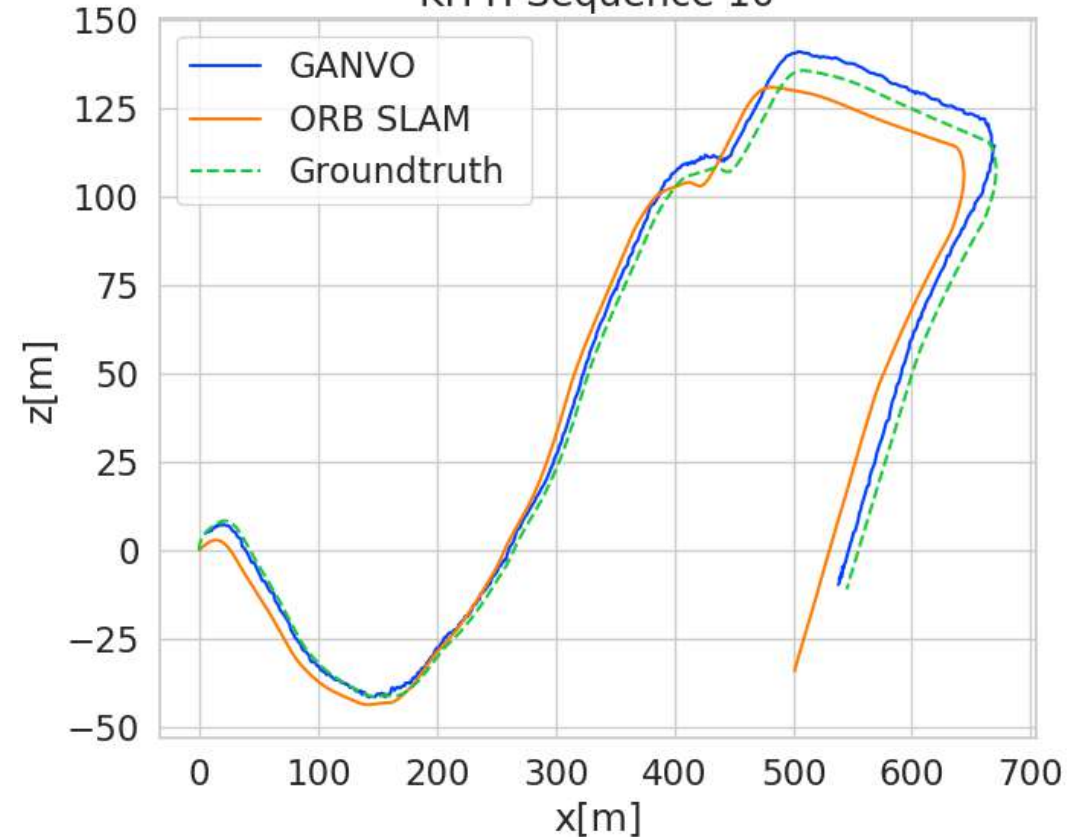


GANVO: Visual Odometry and Depth Estimation Results

KITTI Sequence 09



KITTI Sequence 10



GANVO: Visual Odometry and Depth Estimation

- State of the art tracking results without requiring any training (ground-truth) data
- Allows the tracking technique to adapt to new and unseen environments rapidly



Challenges under **constrained** visibility

Still no GPS, Wi-Fi, or even electricity is available.



Extra Challenges:

- Vision is compromised. Alternative equipment is required.
- Heat signature might not be enough to use thermal images.

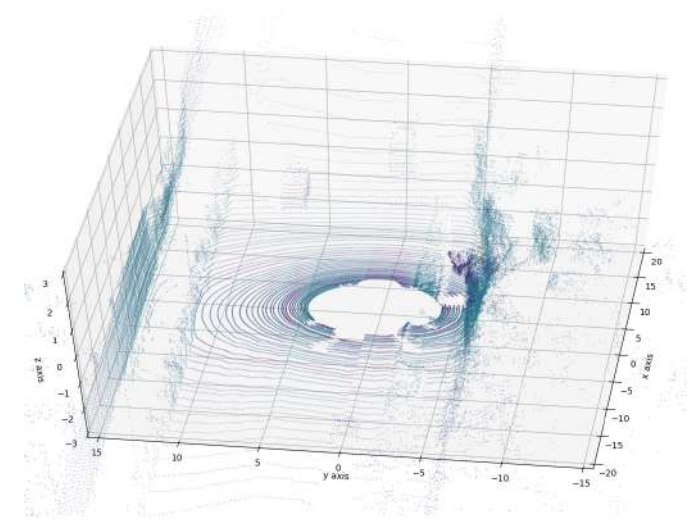


Lidar

DeepPCO: End-to-End Point Cloud Odometry through Deep Parallel Neural Network

Lidar is a reliable sensor in firefighters' scenario:

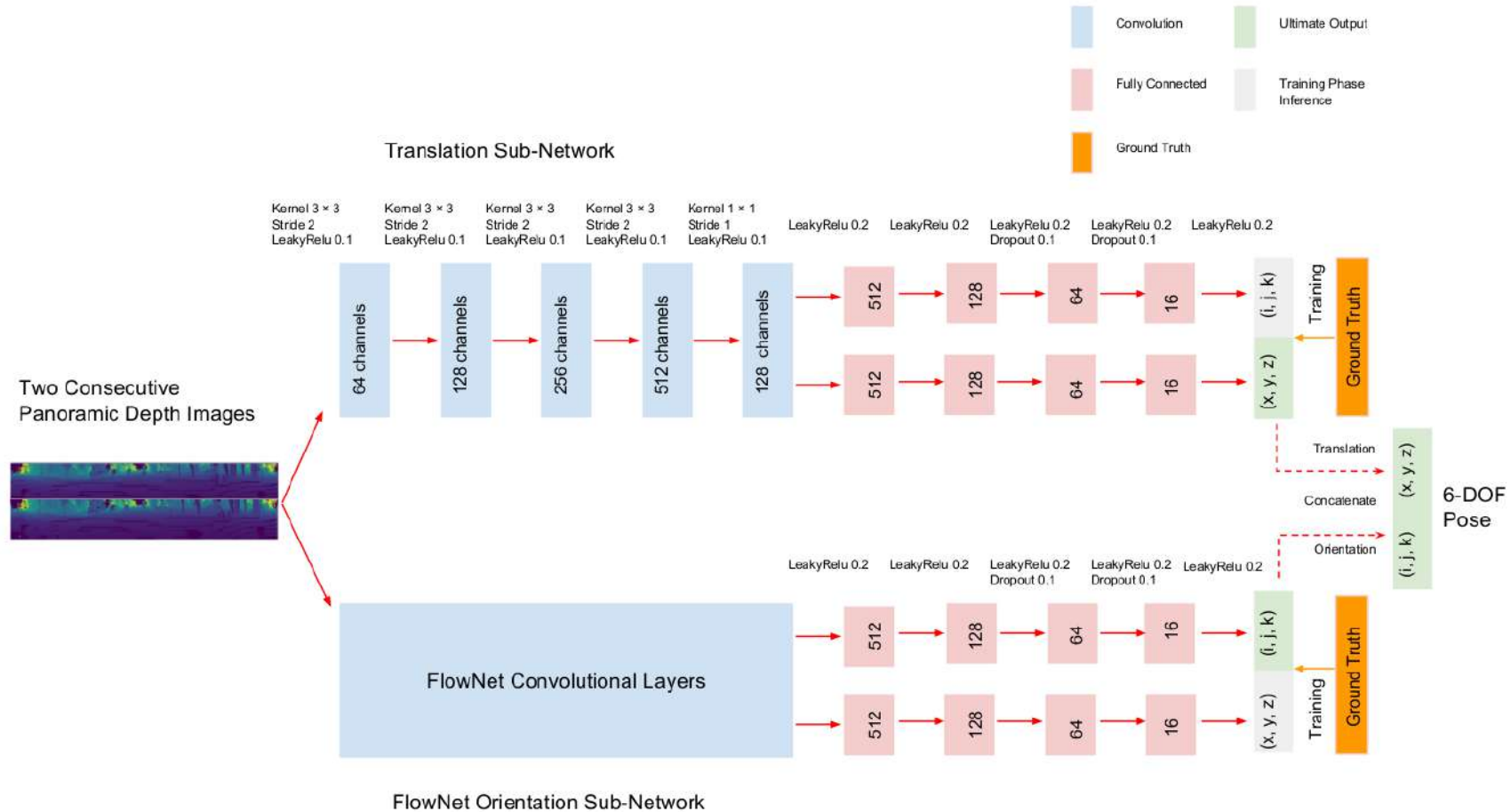
- It can perceive environment even in dark or dynamic indoor environment.
- It can create high-quality point cloud map which can assist firefighters.
- It can provide the accurate odometry, which can localize firefighters in real time.



"DeepPCO: End-to-End Point Cloud Odometry through Deep Parallel Neural Network" – IROS 2019

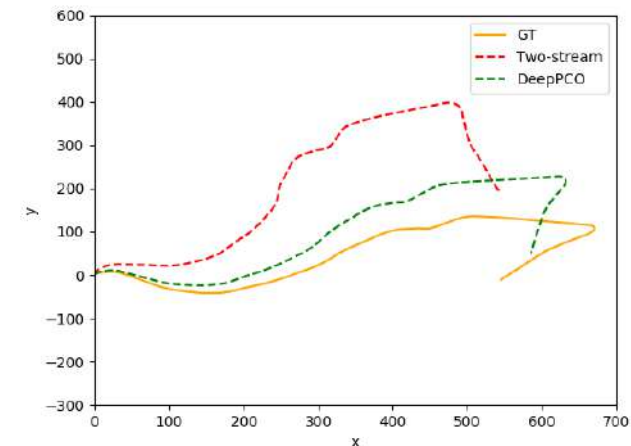
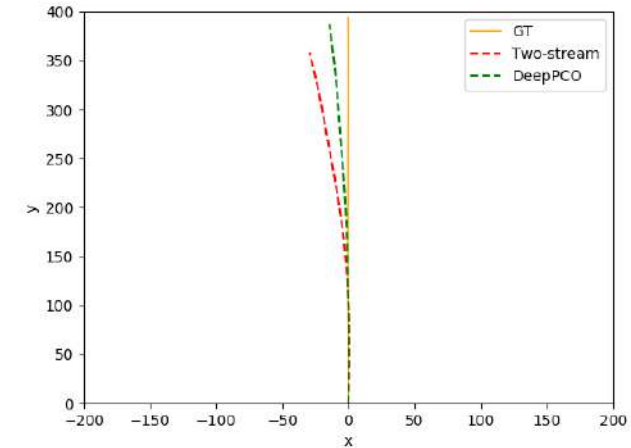
Wei Wang, Muhamad Risqi U. Saputra, Peijun Zhao, Pedro Gusmao, Bo Yang, Changhao Chen, Andrew Markham, and Niki Trigoni

DeepPCO: Architecture



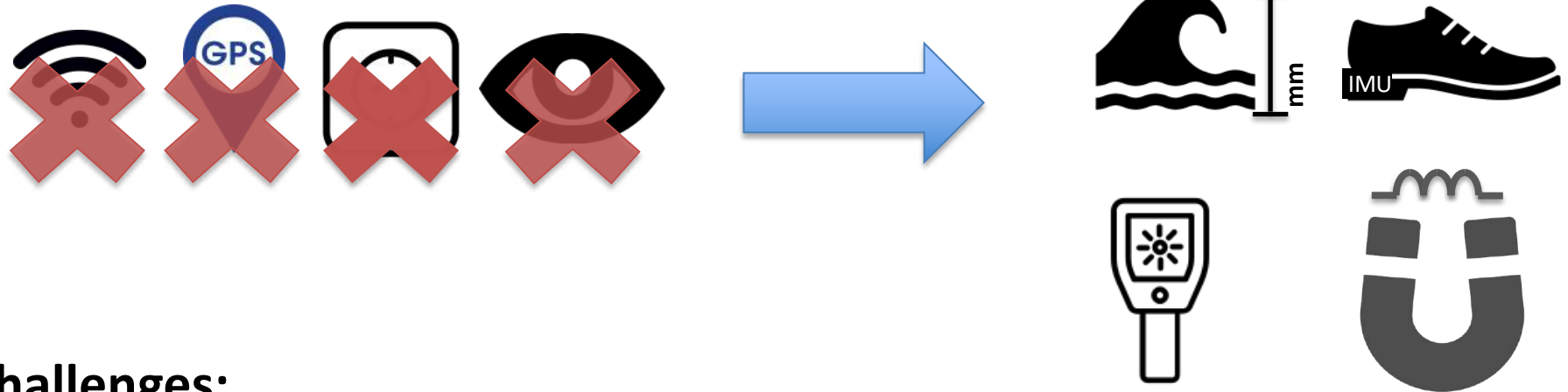
DeepPCO: End-to-End Point Cloud Odometry through Deep Parallel Neural Network

- Position and Orientation estimations are more accurate if estimated separately.
- Also gives you a point cloud map of the environment if needed.



Challenges under **NO** visibility

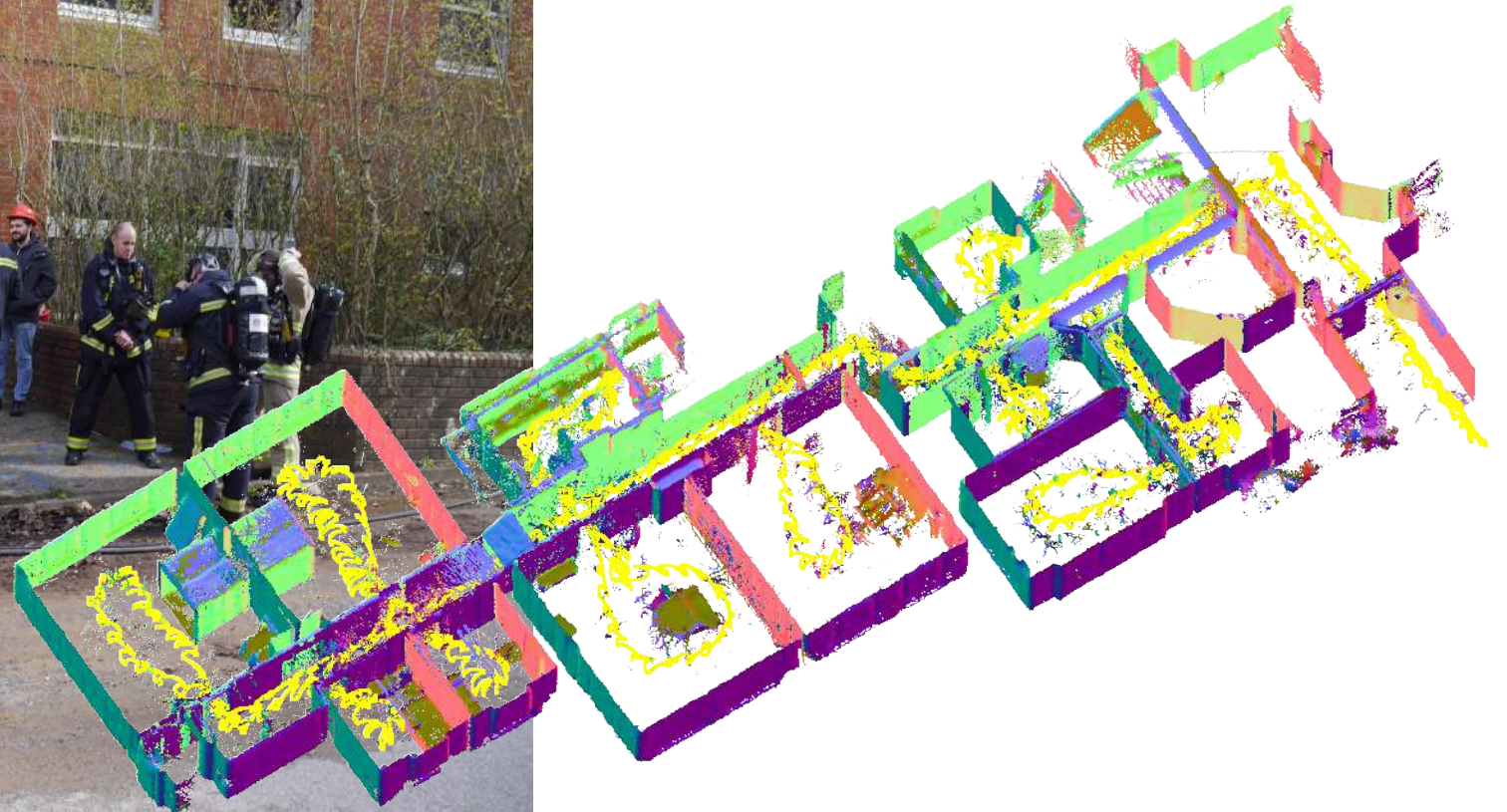
Still no GPS, Wi-Fi, or even electricity is available.



Extra Challenges:

- Vision is no longer reliable.
- Lidar no longer works.

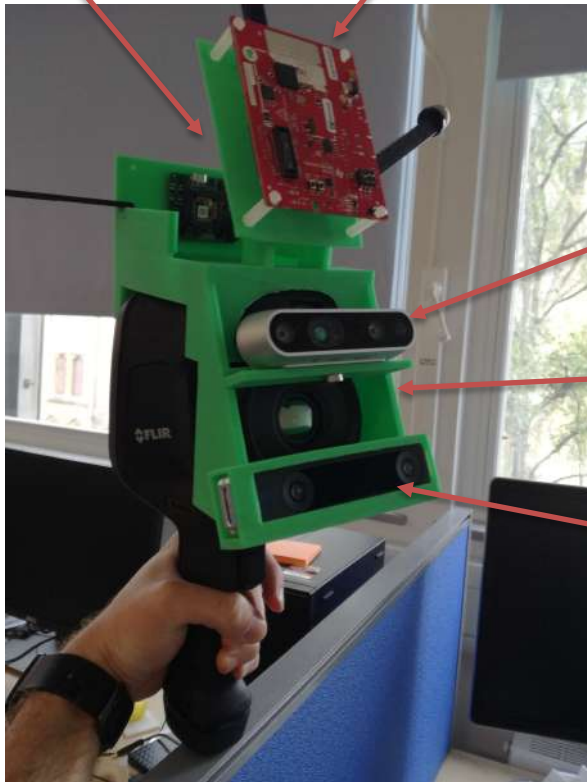
Data Collection - Training Facility



Data Collection - Training Facility

IMU

Millimeter wave



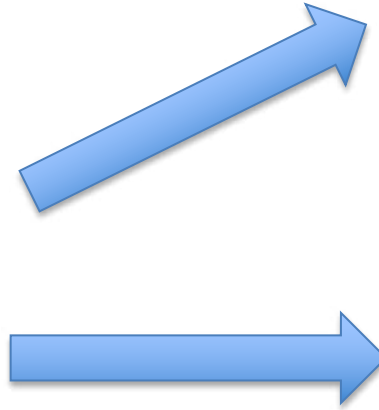
RGB+Depth

Thermal

Stereo



Data Collection - Training Facility



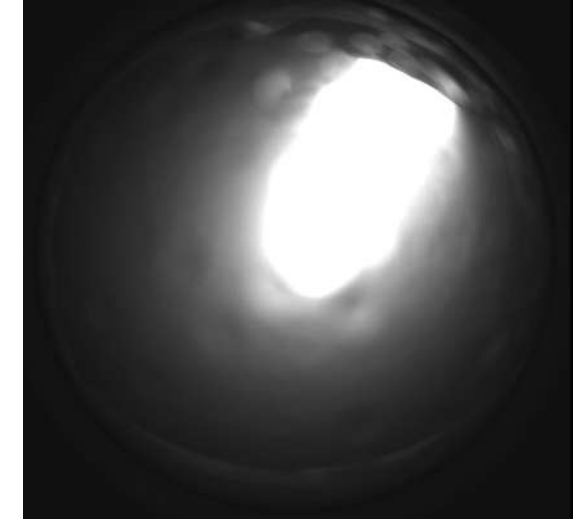
Data Collection - Training Facility

Issues:

- Extremely low visibility.
- Soot could lead to inability use laser/depth.

Issues:

- Temperature is controlled by watering the ceiling, which required sensor protection.
- Due to unpredicted motions, some sensors were disconnected.
- Flashlights caused white balancing to overcompensate





Foot-mounted inertial navigation

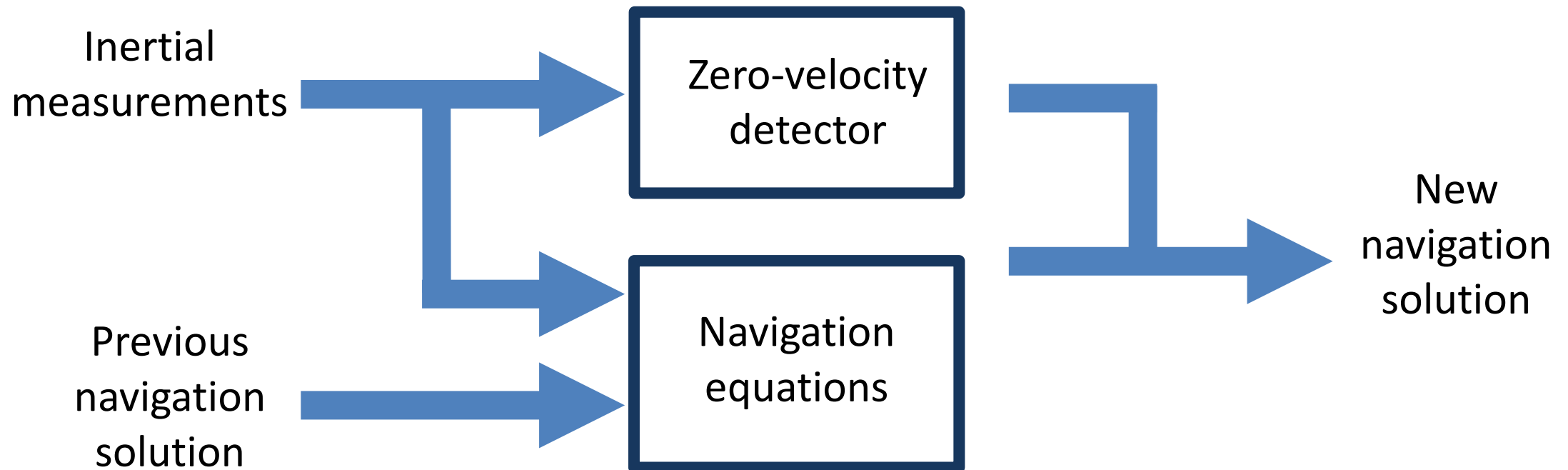
Odometry from foot-mounted inertial sensors



- Not dependent on environmental conditions
- Does not require external infrastructure
- Low-cost technology

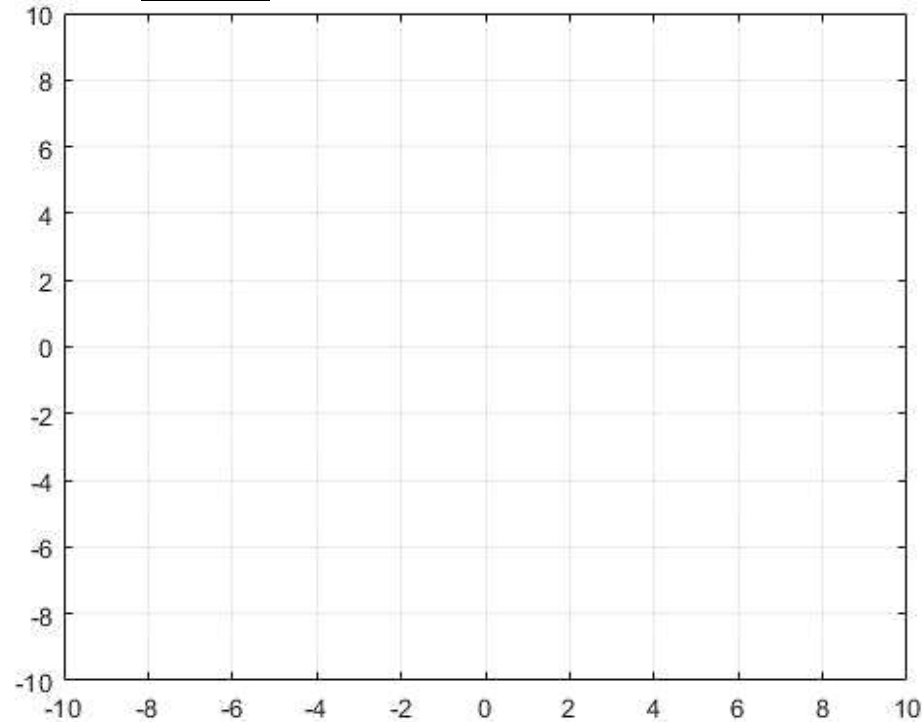


Zero-velocity-aided inertial navigation

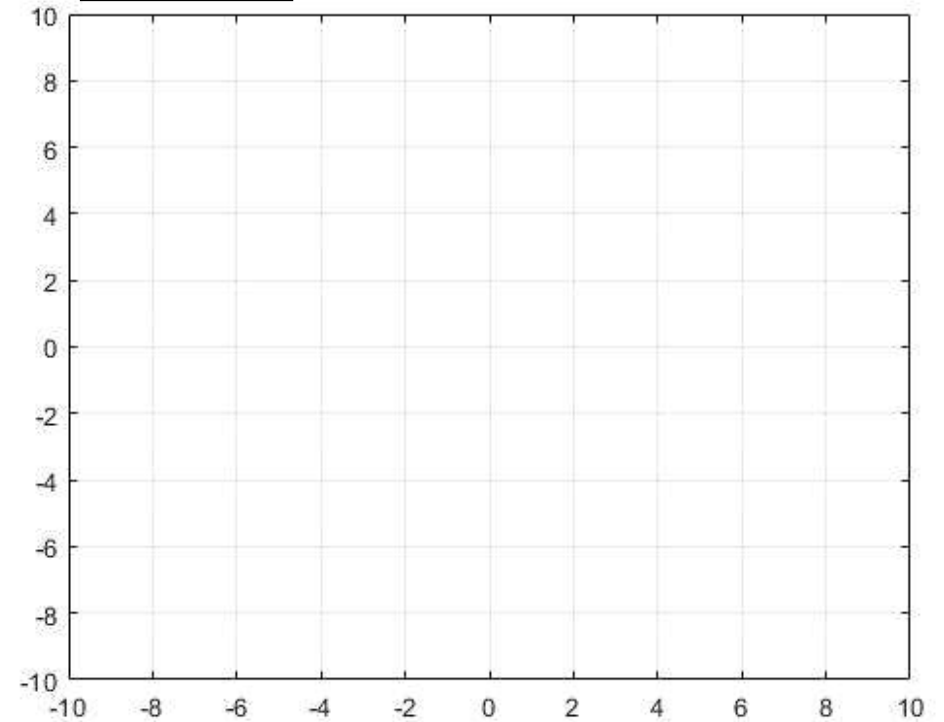


The effect of zero-velocity updates

With zero-velocity updates



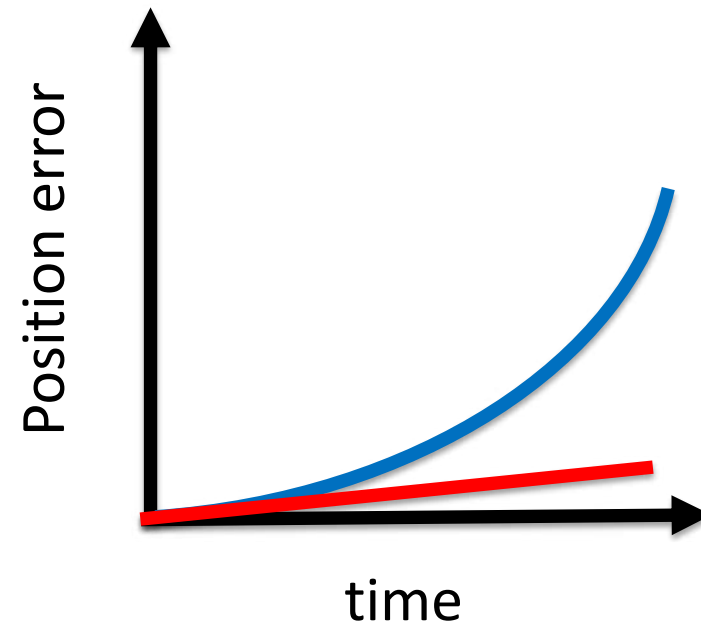
Without zero-velocity updates



Position error growth

Without zero-velocity updates: **Cubic** position error growth.

With zero-velocity updates: **Linear** position error growth.



Navigation	Navigation time
Stand-alone inertial navigation	A few seconds
Zero-velocity-aided inertial navigation	Several minutes



Zero-velocity Detection

Compute likelihood ratio: $L(\mathbf{z}_n) = \frac{p(\mathbf{z}_n|H_1)}{p(\mathbf{z}_n|H_0)}$

$L(\mathbf{z}_n) < \gamma$ γ $L(\mathbf{z}_n) \geq \gamma$
The foot is moving The foot is stationary

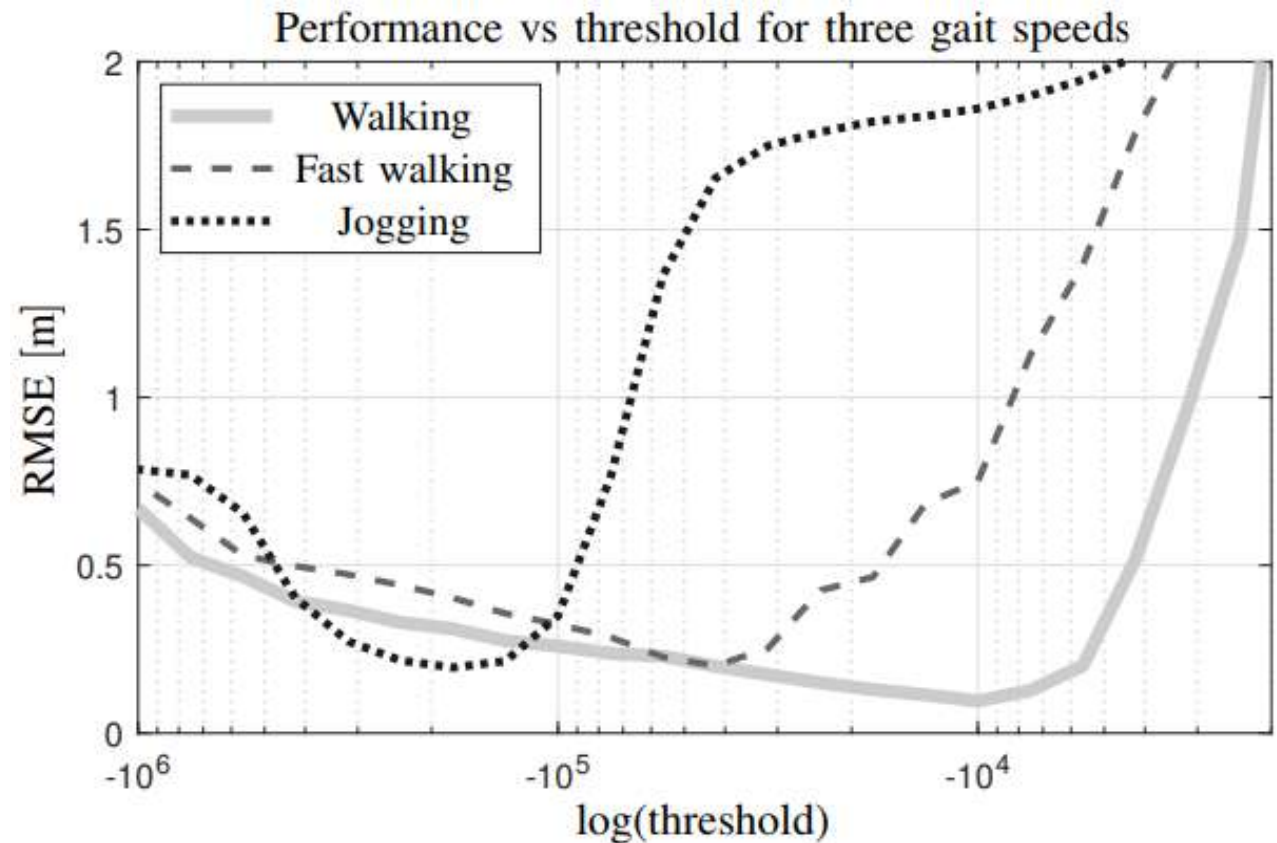


How set γ ? The optimal fixed γ depends on the velocity.



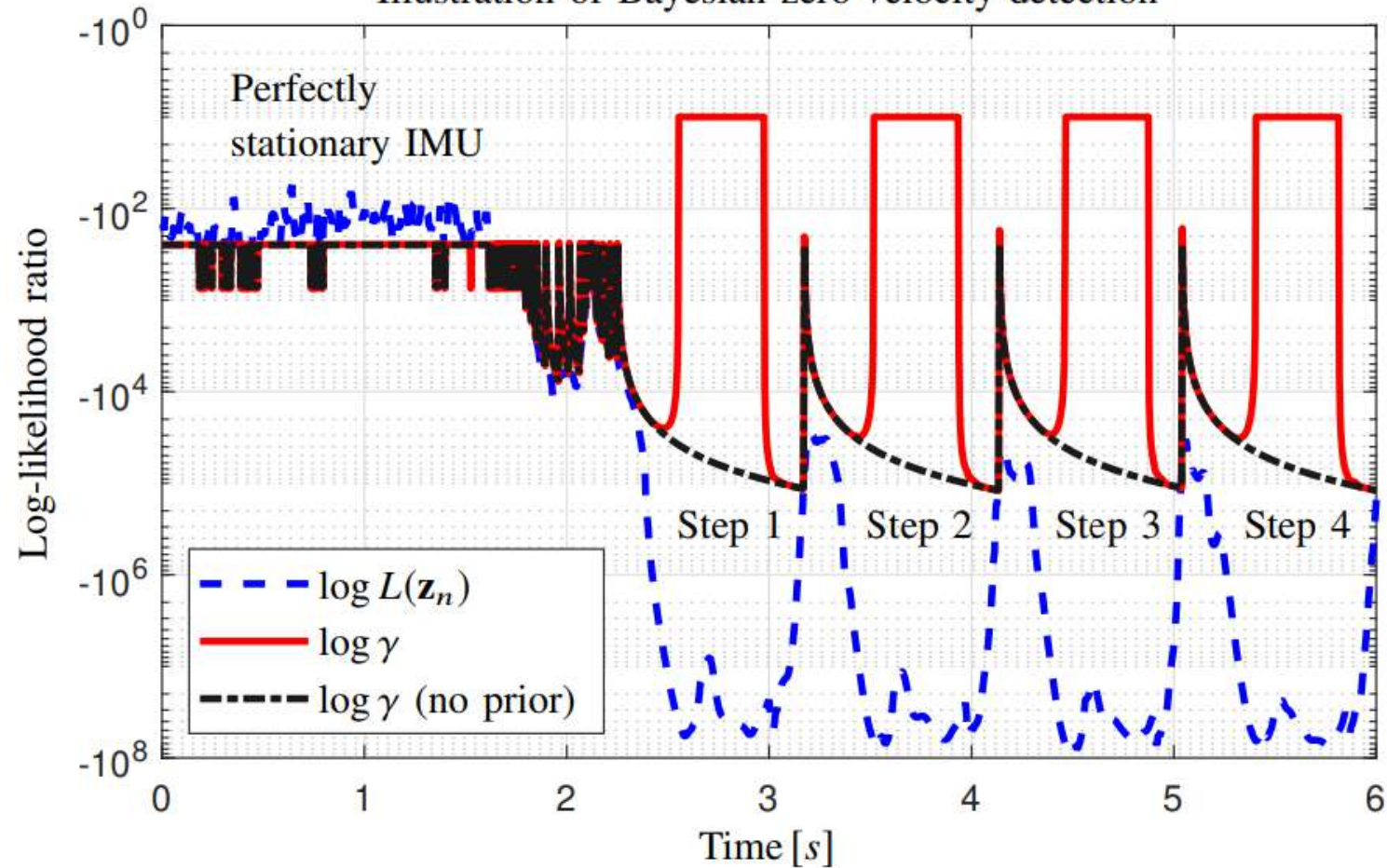
Challenges with zero-velocity-aided inertial navigation

- Position drift
- The optimal implementation is dependent on factors such as
 - gait speed
 - the walking surface



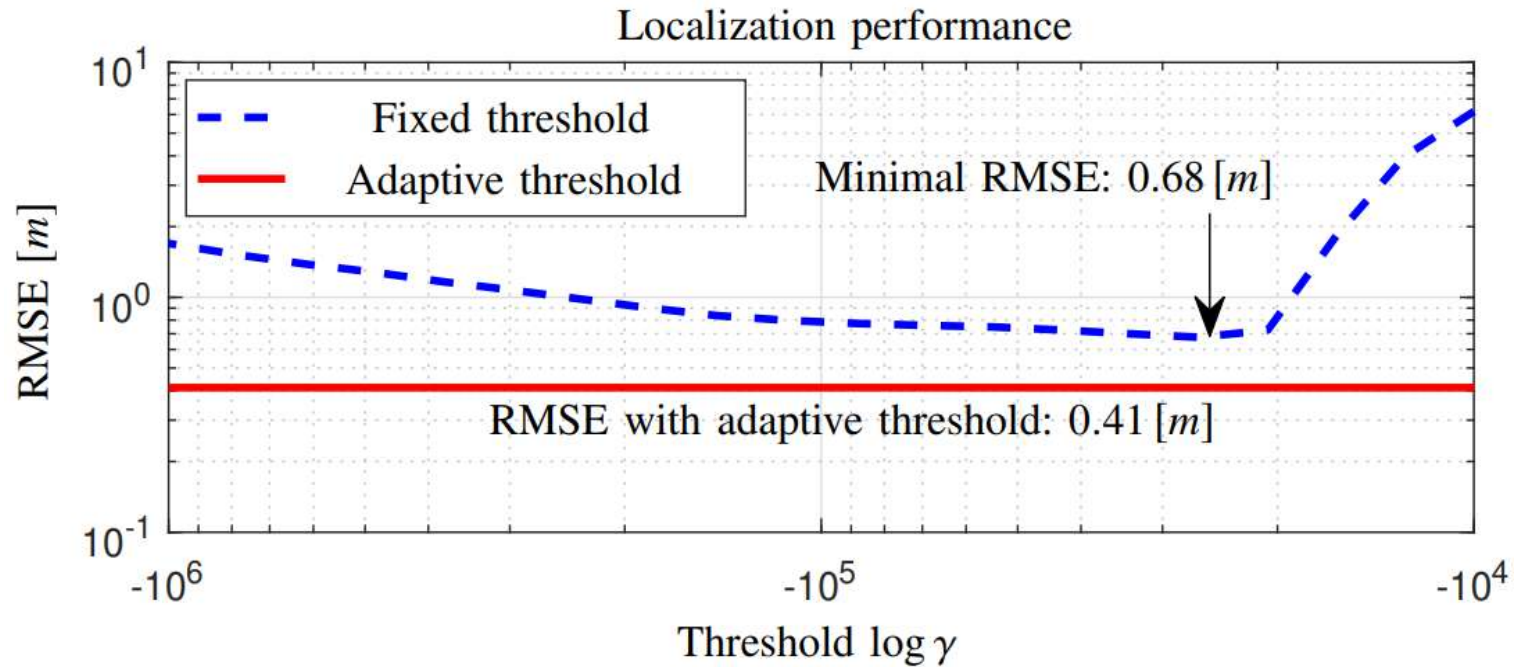
Adaptive Thresholding

Illustration of Bayesian zero-velocity detection



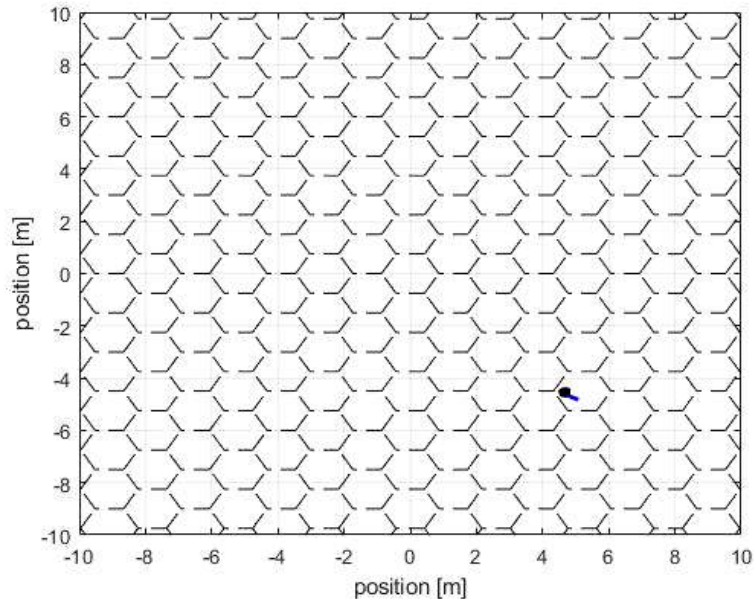
Performance Evaluation

After walking along a closed-loop trajectory with
an approximate length of 84 meter:

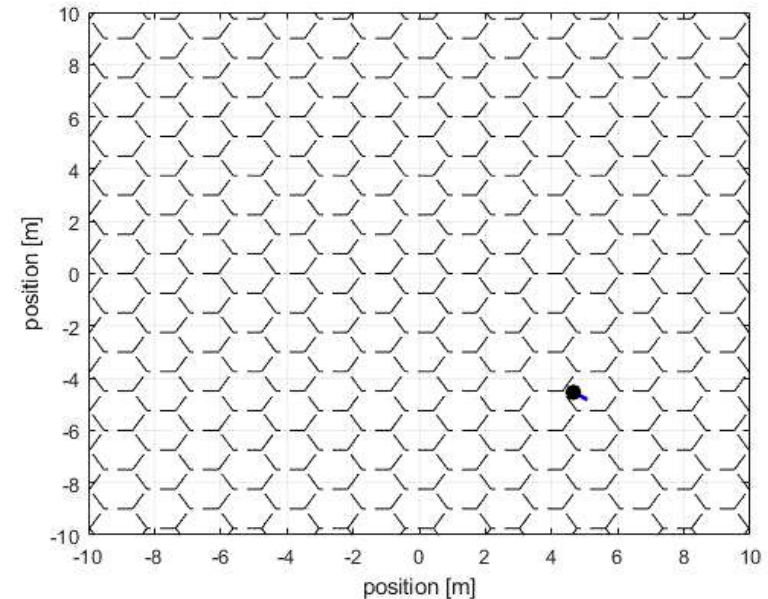


FootSLAM

FootSLAM



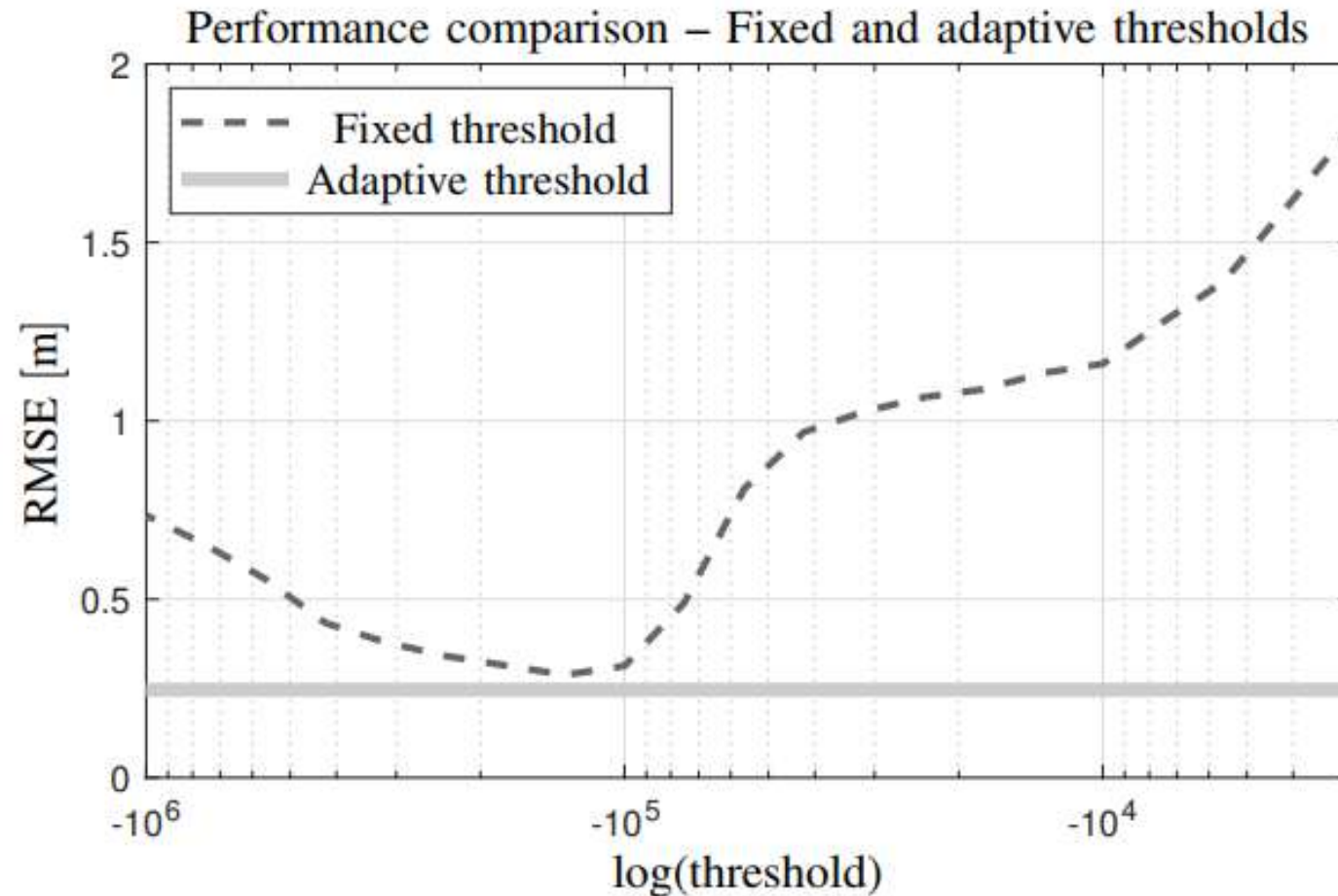
Inertial odometry



- Divide the navigation area into a grid of hexagons
- Learn the probability of moving from one hexagon to an adjacent one.



Calibration using FootSLAM



Foot-mounted inertial navigation

- Foot-mounted inertial navigation is a reliable navigation technology with no dependence on visibility, line-of-sight, or pre-deployed infrastructure.
- By adapting the zero-velocity-detection threshold it is possible to reach excellent performance despite variations in gait speed and environment conditions.





Magneto Inductive

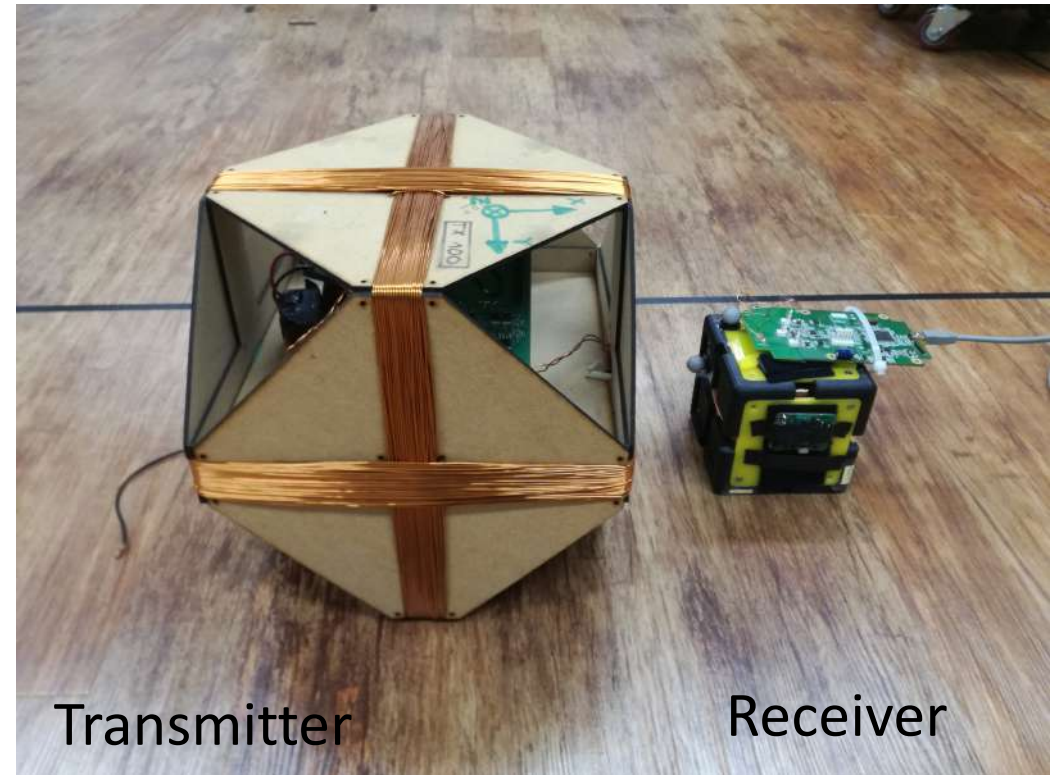
Magneto Inductive

Advantages:

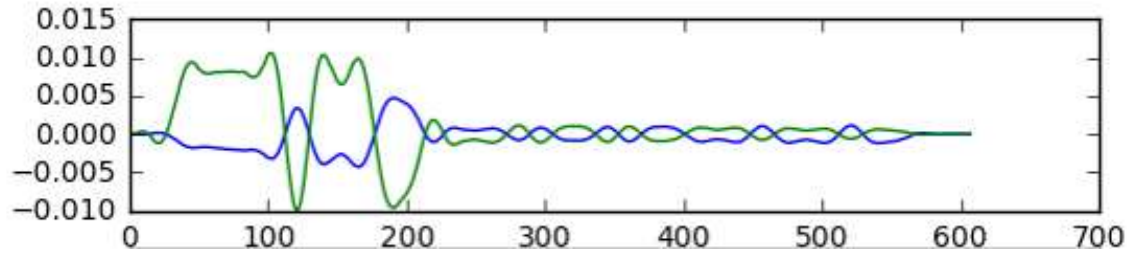
- Low frequency modulated magnetic fields provide accurate 3-D positioning
- MI does not suffer from multipath
- Penetrates the majority of materials (concrete, soil, people, water, vegetation) without loss
- Single transmitter provides 3-D positioning

Disadvantages:

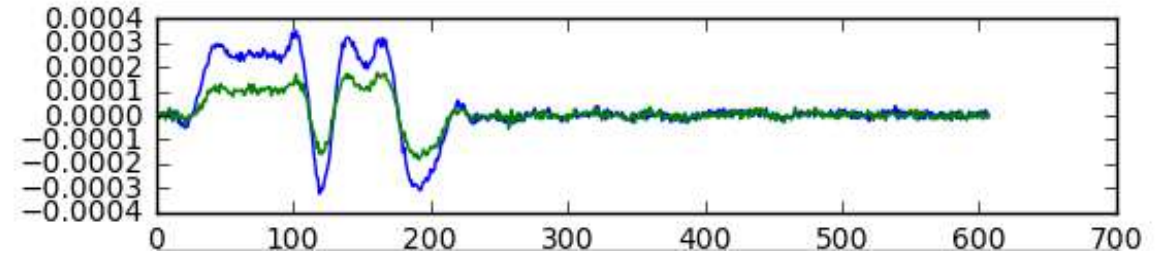
The signal amplitude decays quickly with distance, so that the signal received rapidly fades into noise with increasing distance



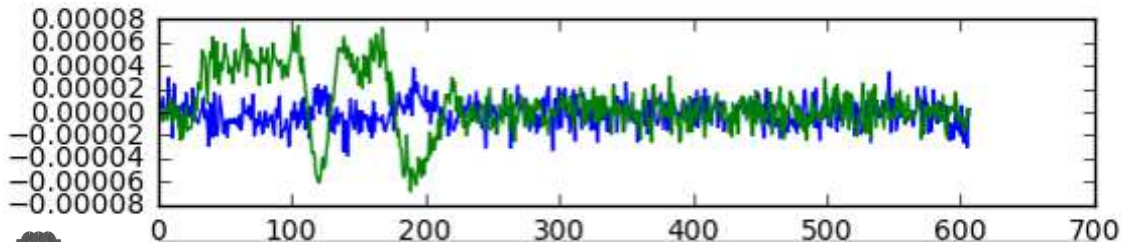
Rx at 3 m



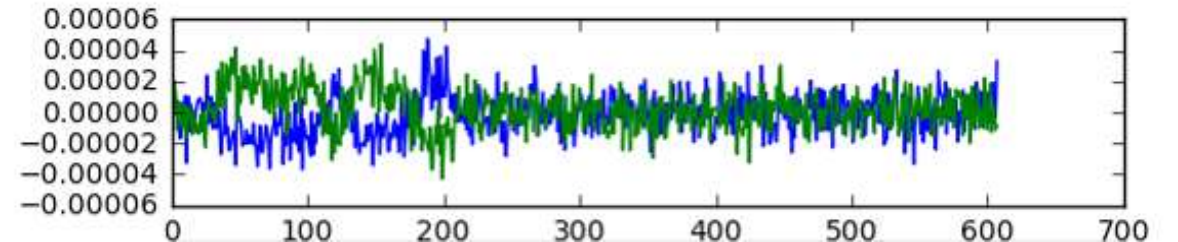
Rx at 10 m



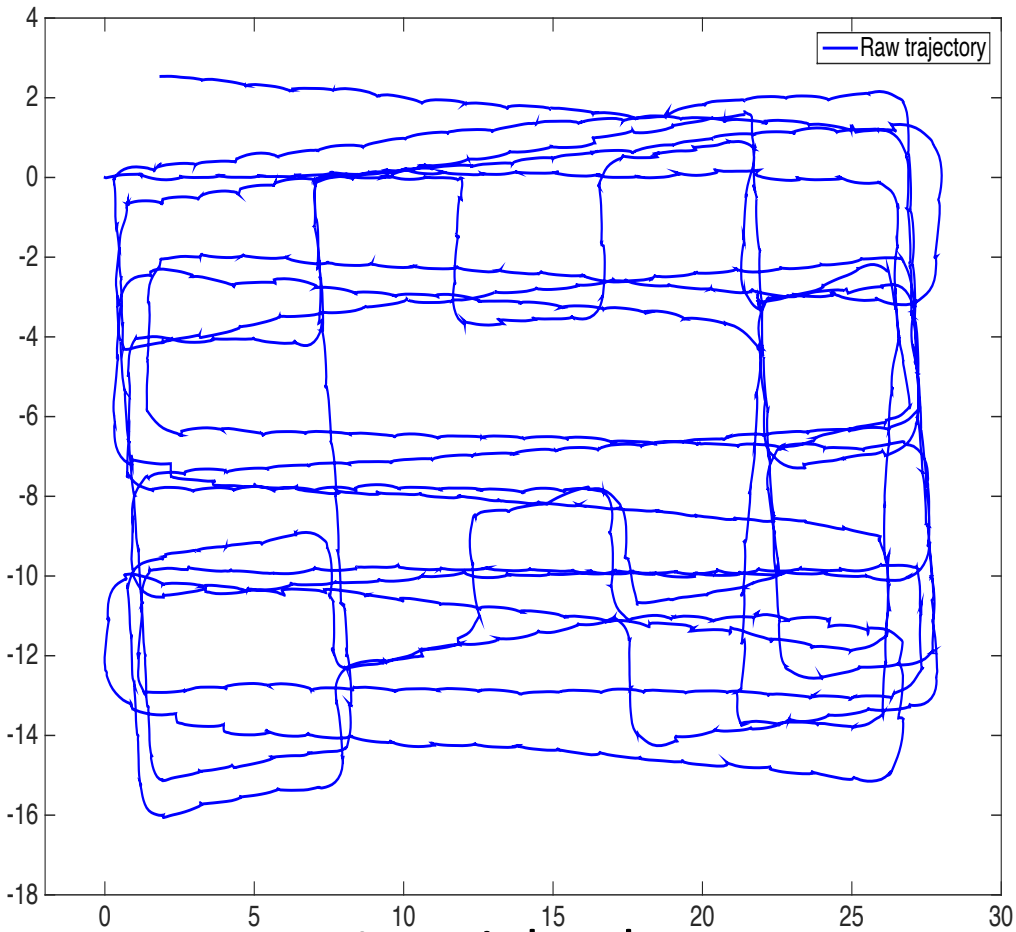
Rx at 20 m



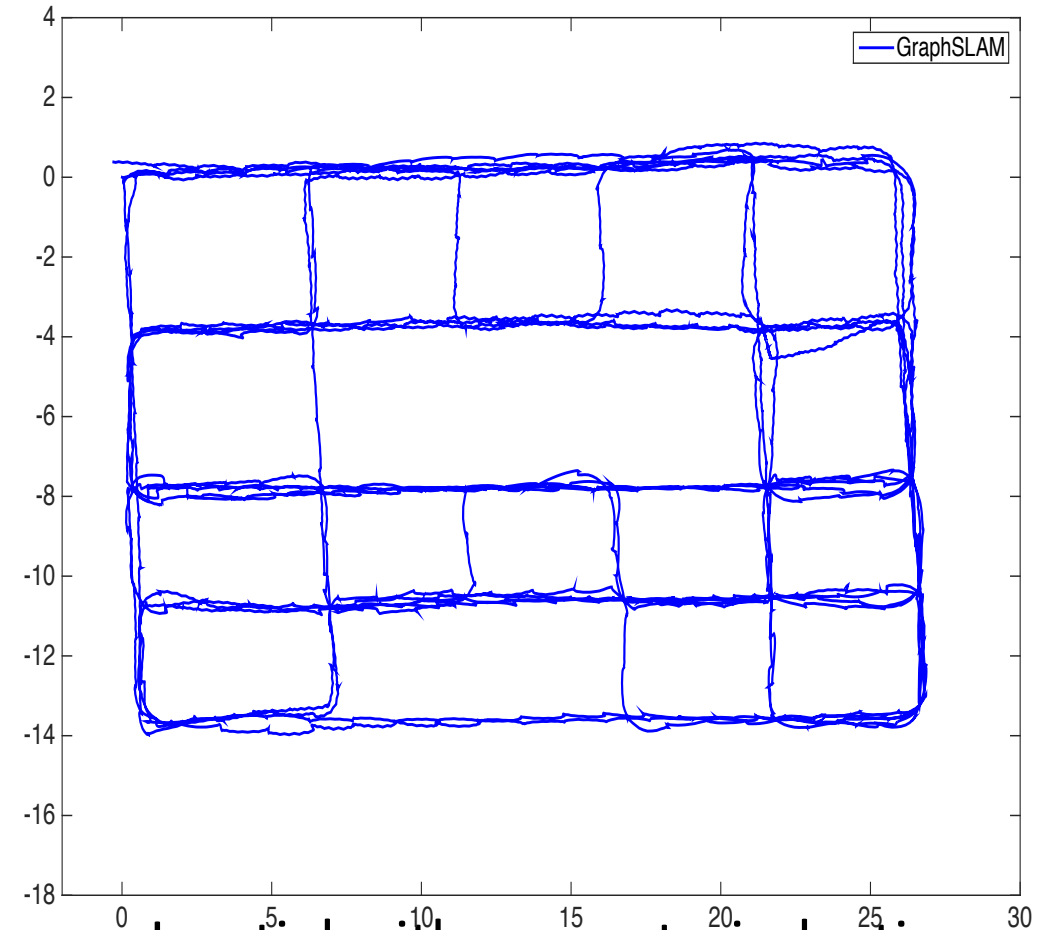
Rx at 30 m



Position Estimates



Inertial only



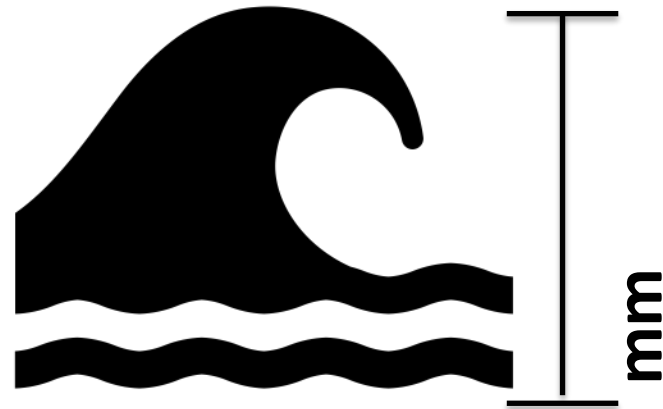
Inertial with magneto-inductive



Magneto Inductive

- Rapid amplitude decay also means higher accuracy within a specific range.
- Magneto Inductive can be coupled with Inertial Sensors to allow for graph optimization.





Millimeter wave

Millimeter Wave Radar

- Independent of illumination condition and infrastructure (e.g. GPS or Wi-Fi)
- Functional under poor visual conditions due to
 - thick smoke
 - heavy fog
 - high temperatures and
 - falling debris



Millimeter Wave Radar

Advantages:

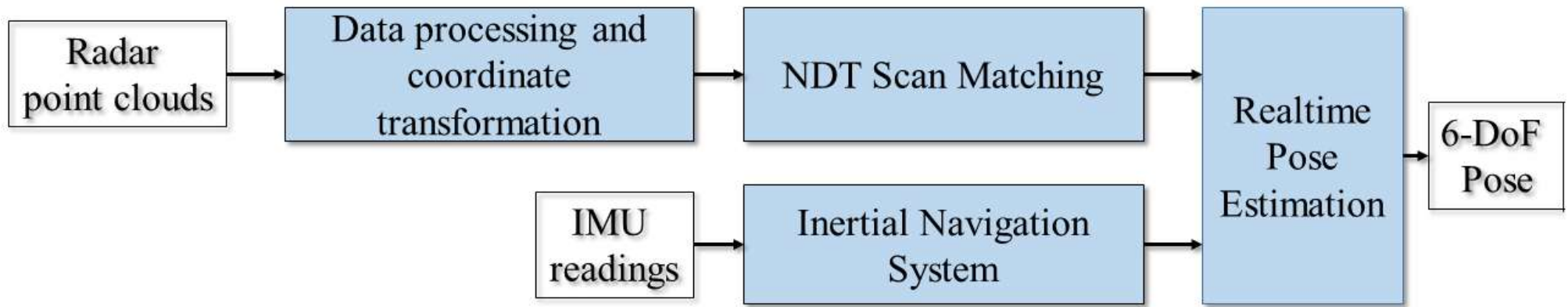
- Provides accurate range-measurement
- Gathers readings at close range, and
- Operates at low peak power

Challenges:

- Sidelobes—radiation sent in unintended directions and
- Multipath reflections that occur when a wave encounters additional reflection points before returning to the receiver antenna



Millimeter Wave Radar-Our Approach

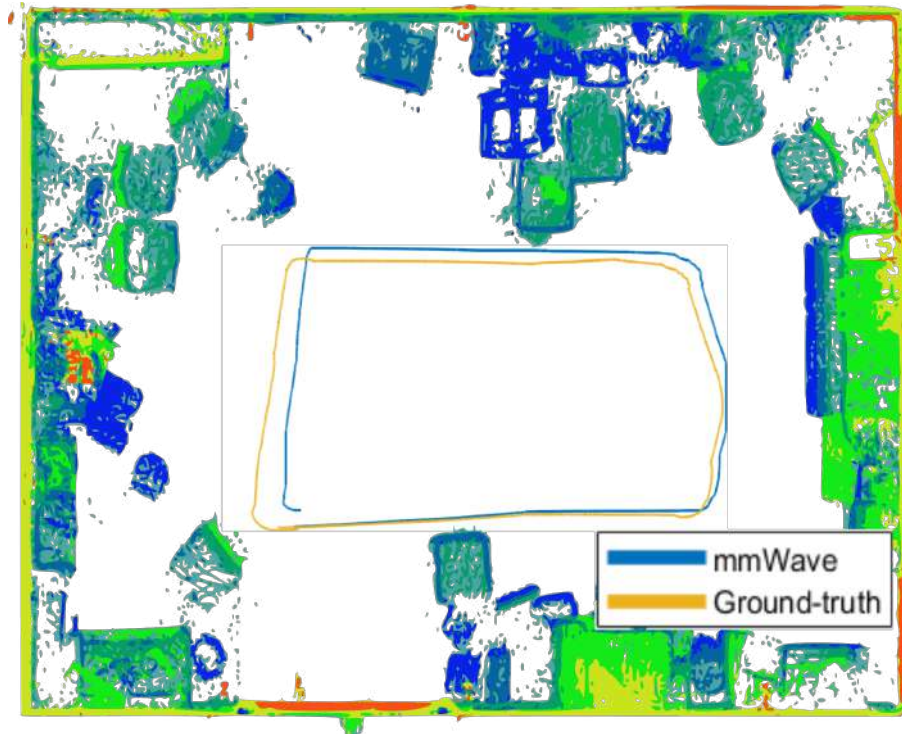


- **Idea:** To use MM-Wave short range radars as the main means for pose perception to improve the precision of pose estimates and map reconstruction
- Radar odometry based on the normal distributions transform (NDT) scan matching approach aided by IMU



Millimeter Wave Radar Odometry

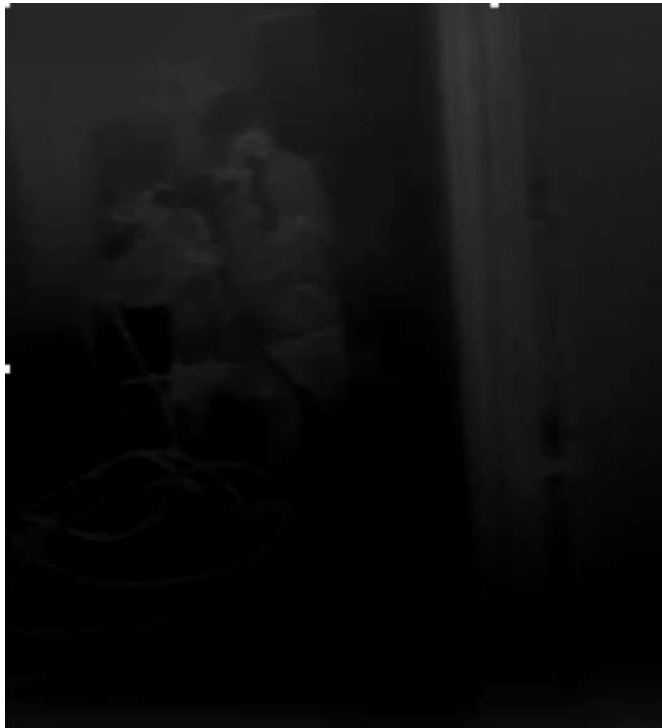
- Estimated trajectory compared with ground-truth trajectory



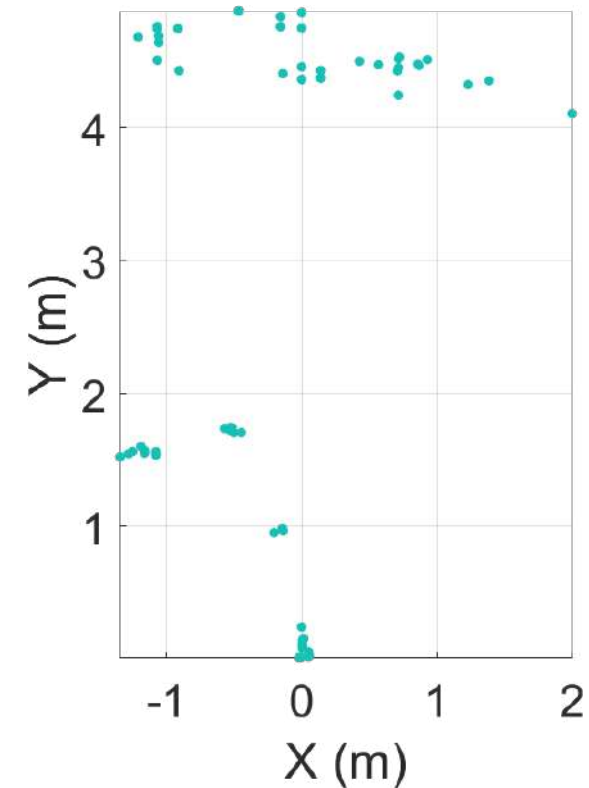
Millimeter Wave Radar

- Sparse measurements from radar scan in smoke-filled environment

Thermal data



Radar data



Millimeter Wave Radar

- Millimeter wave radar is a promising sensing technology capable of penetrating smoke.
- When compared to Lidar, Millimeter Wave radar produces fewer points, which in turn leads to faster processing.





Thermal

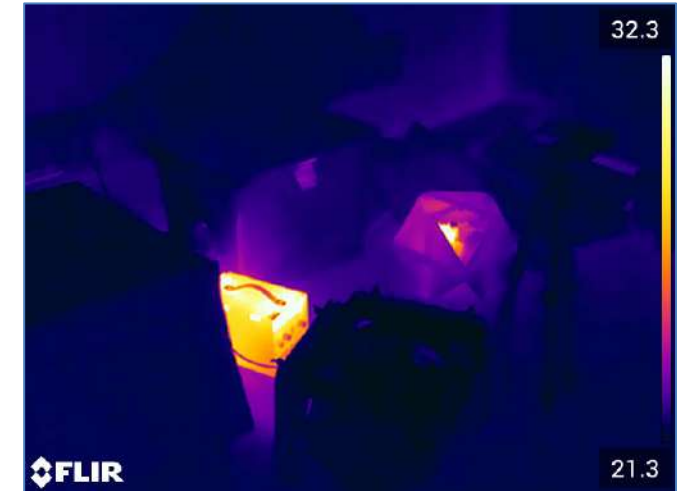
Thermal

Advantages:

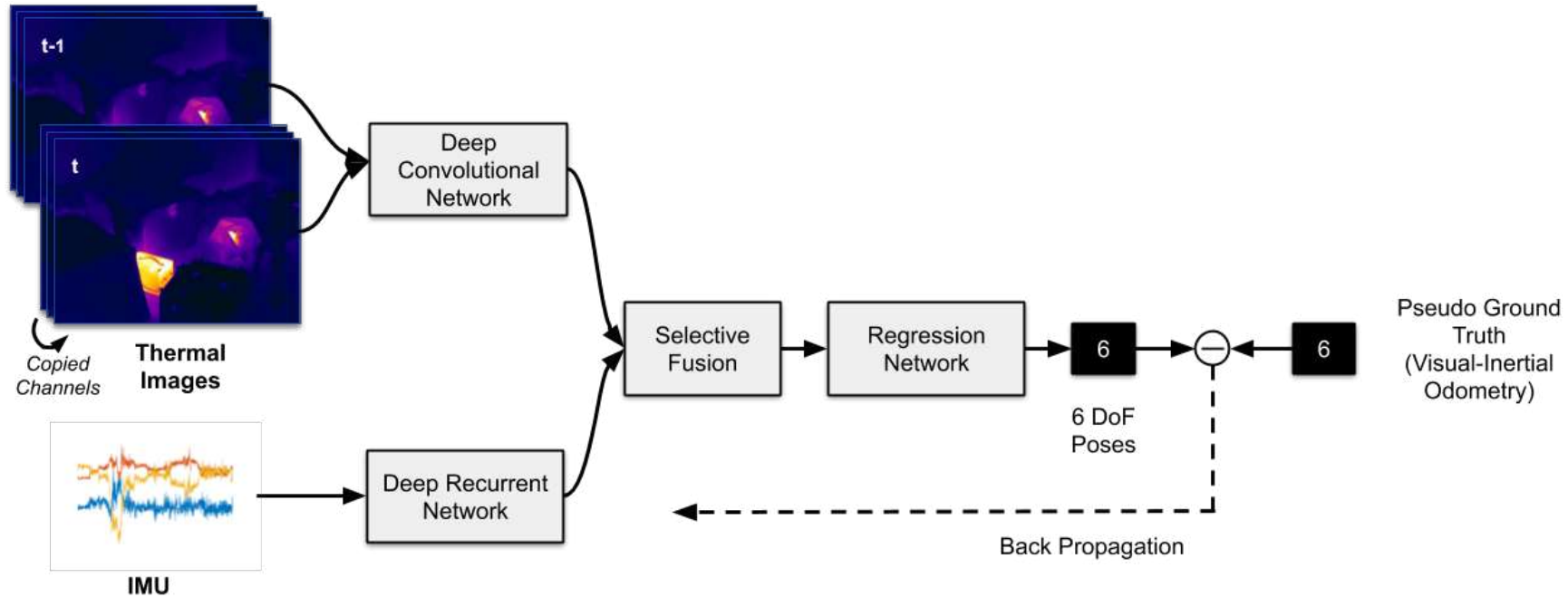
- Functional under heavy smoke, etc.
- Enough information to identify object's shape
- Ideally compatible with state-of-the-art algorithms for vision

Challenges:

- Lack of visual features
- Dynamic range depends on temperature
- Require Non-uniform Correction (NUC)



Deep Thermal-Inertial Odometry



- Train end-to-end with **raw thermal radiometric data + IMU**
- Augmentation
 - Random trajectory splitting
 - Mean shifting on radiometric data

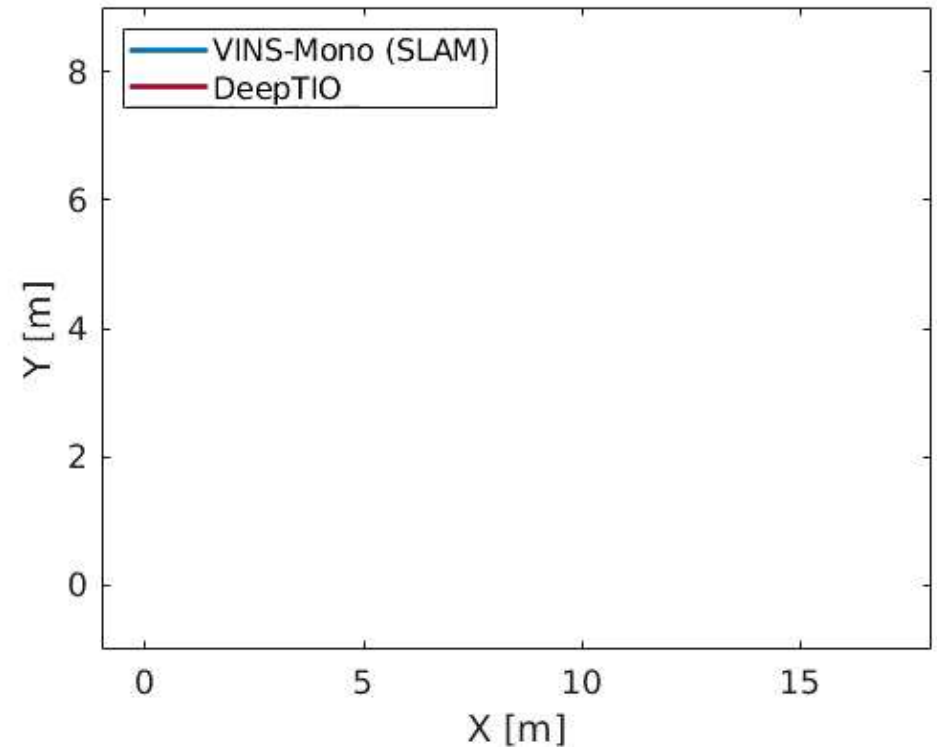


Deep Thermal-Inertial Odometry

Test in Oxford College Building

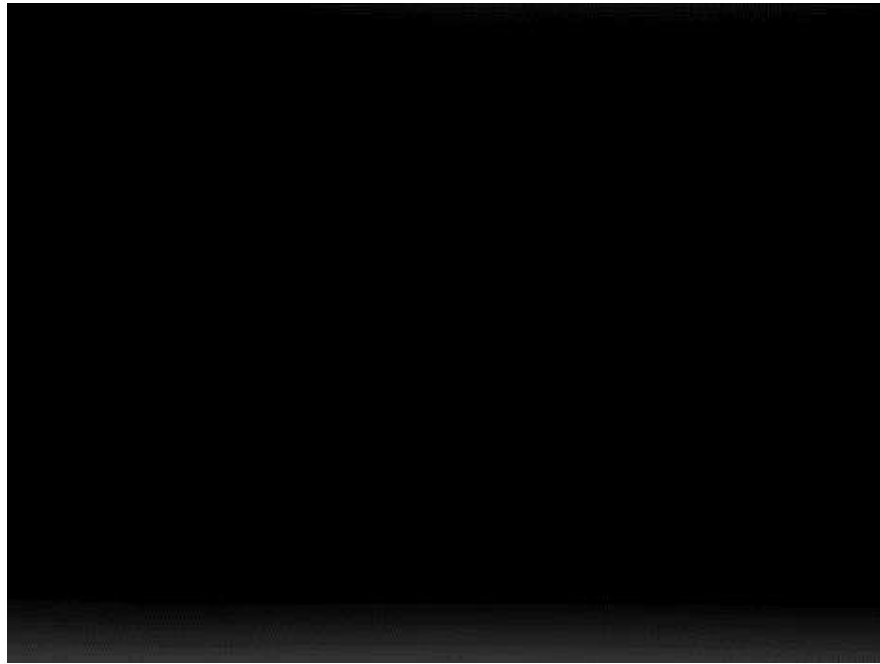


Radiometric data normalized to grayscale

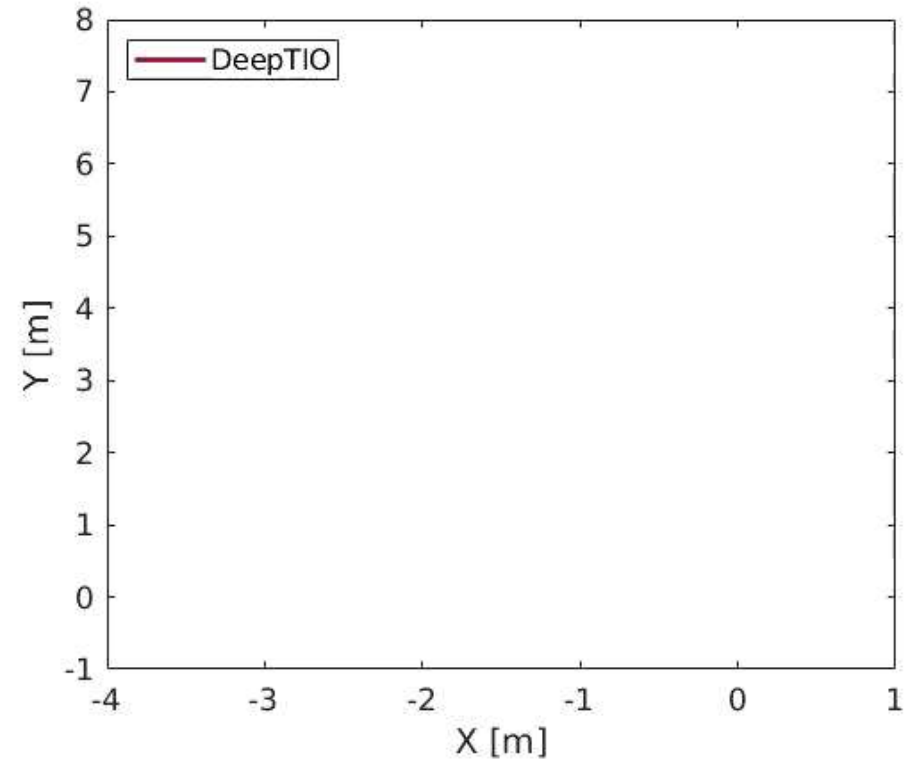


Deep Thermal-Inertial Odometry

Test in firefighter training facility with smoke-filled environment



Radiometric data normalized to grayscale

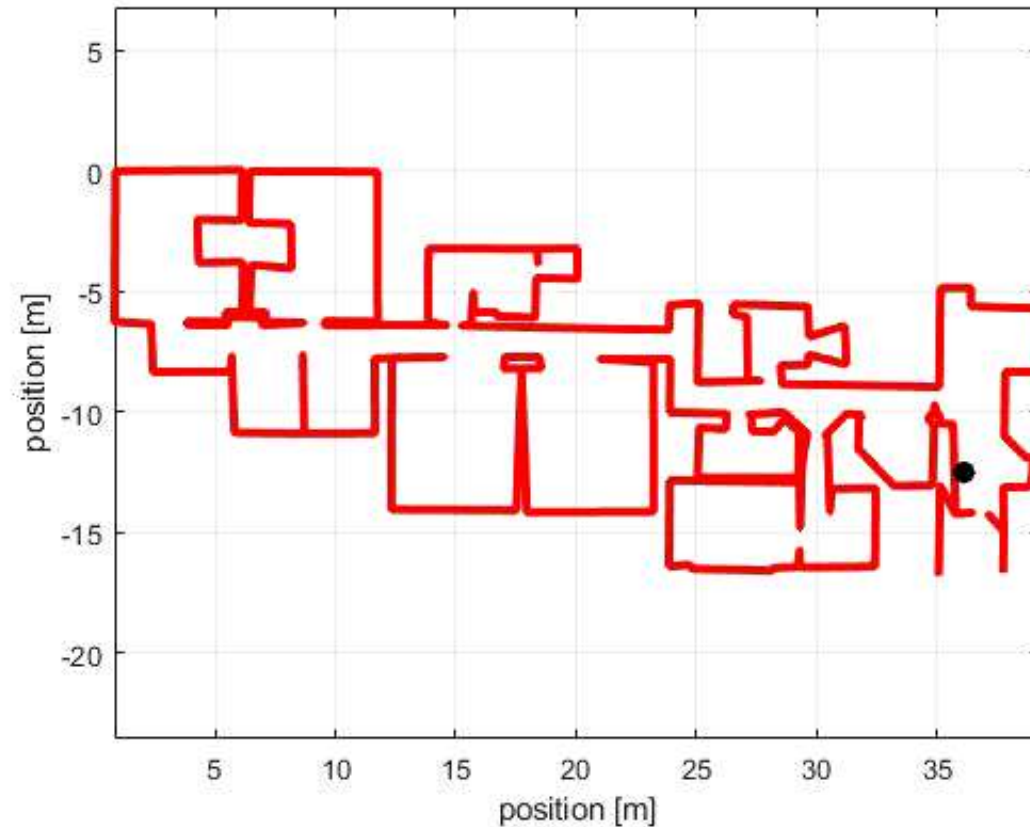


Deep Thermal-Inertial Odometry

- Thermal imaging is a common tool in firefighting
- This is the first work to consider using it to accurately track location



Foot-mounted inertial navigation



Summary

- Multi-sensor approach derisks the failure of a single sensor e.g. due to thick smoke or occlusions
- Individual components for odometry are progressing well
- Iterative approach of testing in the lab and in the wild is yielding benefits in balancing complexity and reality
- Next steps are selective sensor fusion and system integration
- One step closer to the goal of robust first responder tracking

Thank you

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RESCUE
SERVICE**



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**Next
Session**
2:40 PM