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Learning Methods for Robust Localization

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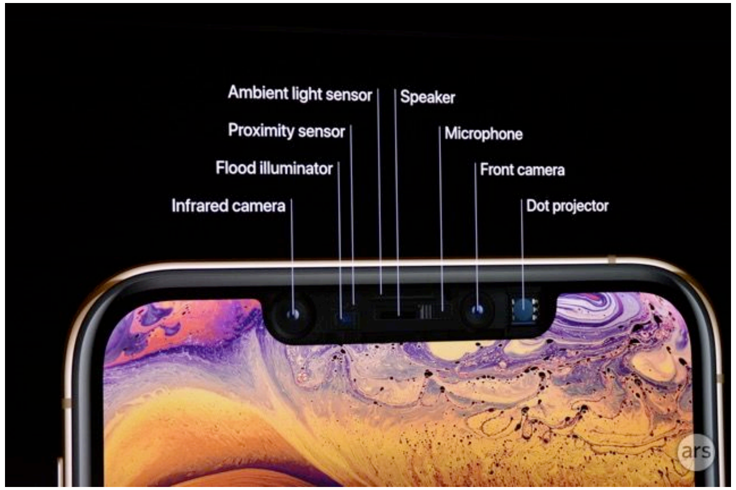
Motion Tracking with On-board Sensors

Self-driving Vehicles

GPS, IMU, RGB-Cameras, Lidar, etc.

Decision making, Motion Planning, sensing surroundings



Mobile Devices

Cameras, IMU, Magnetometer, GPS, etc.

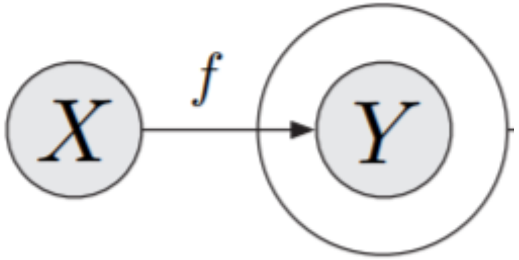
Pedestrian Navigation, Sports/Health Monitoring, First-responders Support

VR/AR Wearing Devices

Cameras, IMU, Magnetometer, Light sensors, etc.

Entertainment, Cooperative Work

From Model-based to Learning-based



X: Sensor Data, Images, IMUs, Lidar
Y: Self-motion, Location

f: Modelled by hand vs. machine (algorithms vs. deep neural networks)
Conditioned on current observations

Research Question

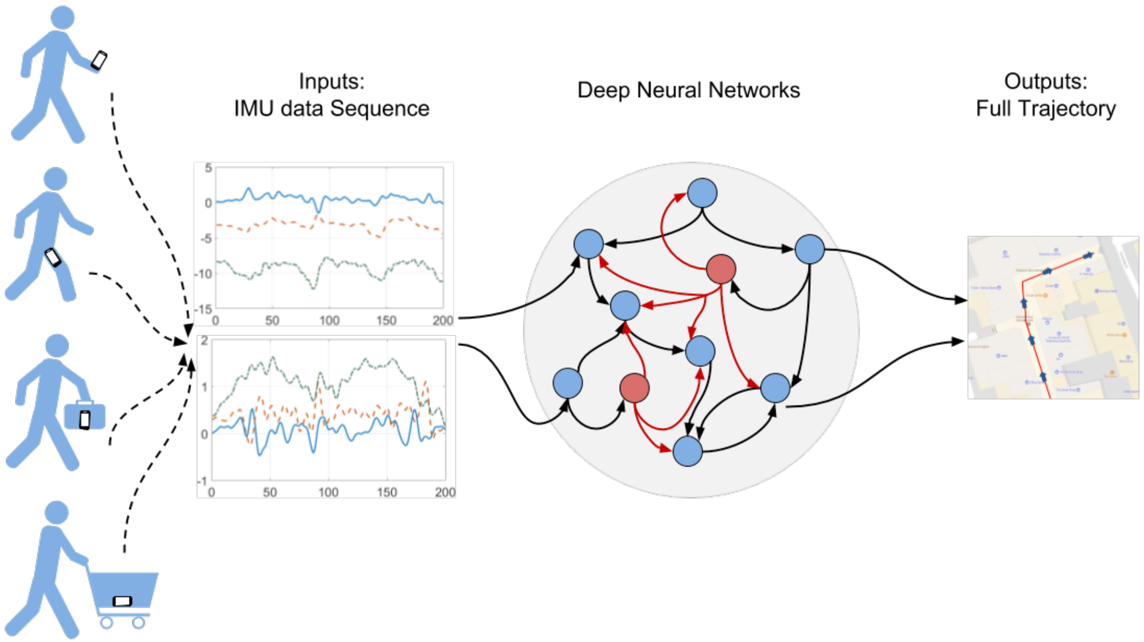
?

Can we develop learning methods to estimate self-motion using multimodal data to achieve accurate and robust localization without hand-crafted engineering?

1. Learning to Localize using Inertial Sensor

Inertial Sensor:

- ✓ Completely self-contained
- ✓ Is not influenced by environmental factors
- ✓ Widespread, deployed on smartphones, robots, drones
- ✓ Low cost, small-size, energy-efficient

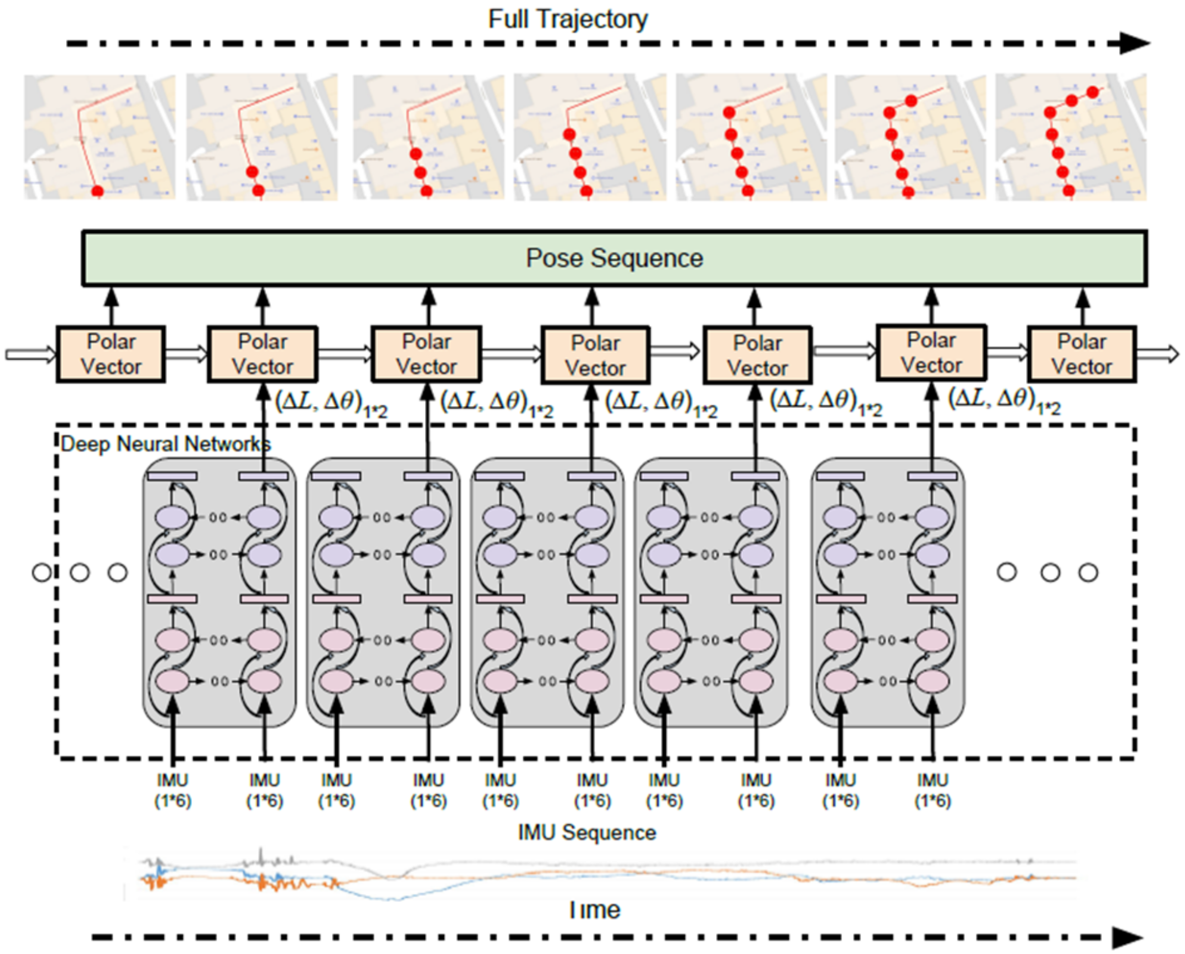


Problems:

- ✓ The measurements are corrupted with various error sources
- ✓ Double integration leads to unbounded system error
- ✓ Initialization and calibration is time-consuming

Inertial Odometry Neural Network (IONet)

- Inertial tracking problem as a sequential learning approach.
- The first deep neural network (DNN) framework that learns self-motion from raw IMU
- Generalise across different attachments, users/devices and new environment.
- Solve a more general motion, e.g. wheeled configurations



C. Chen, X. Lu, A. Markham, N. Trigoni. IONet: Learning to Cure the Curse of Drift in Inertial Odometry. AAAI-2018.

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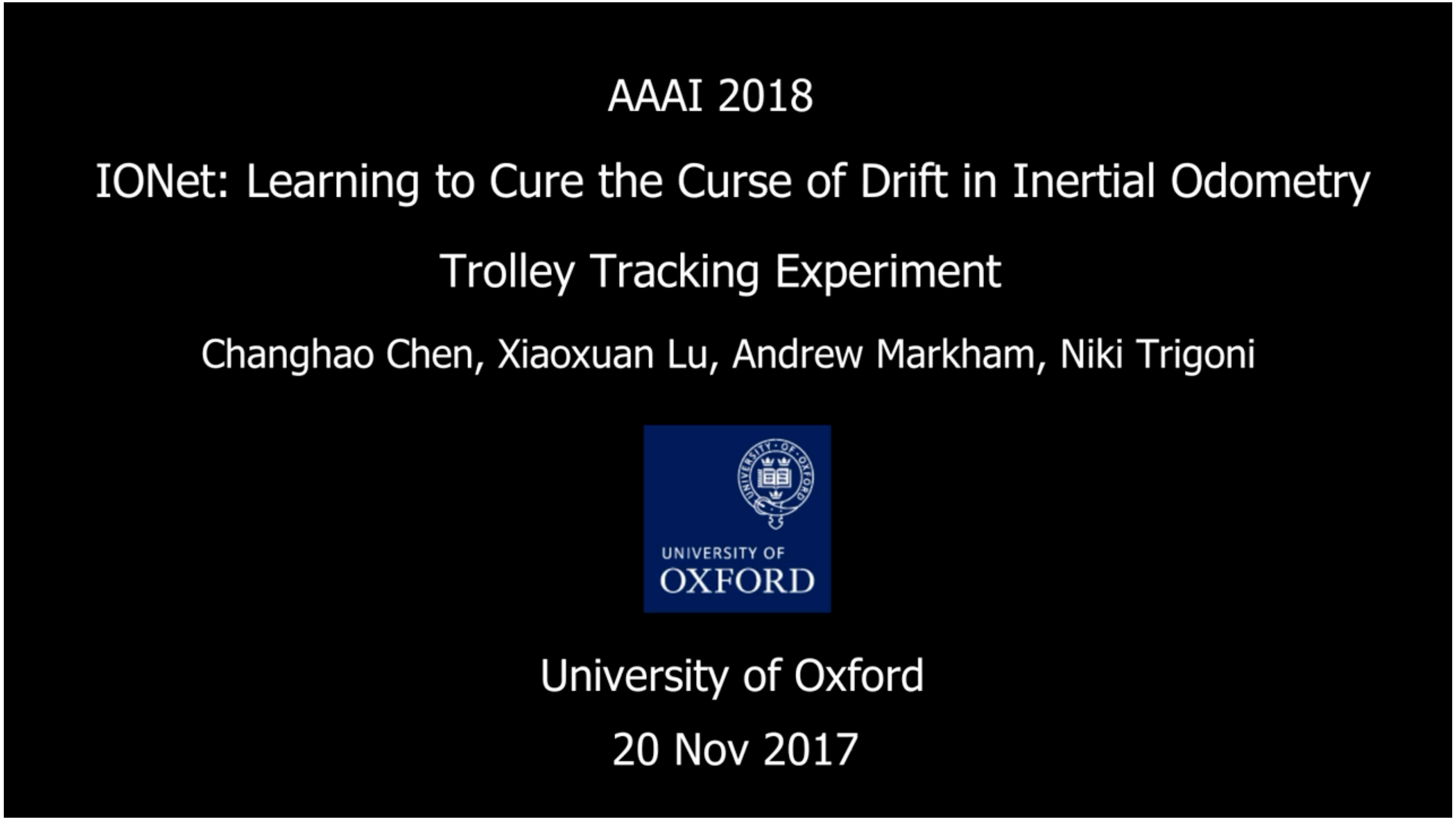
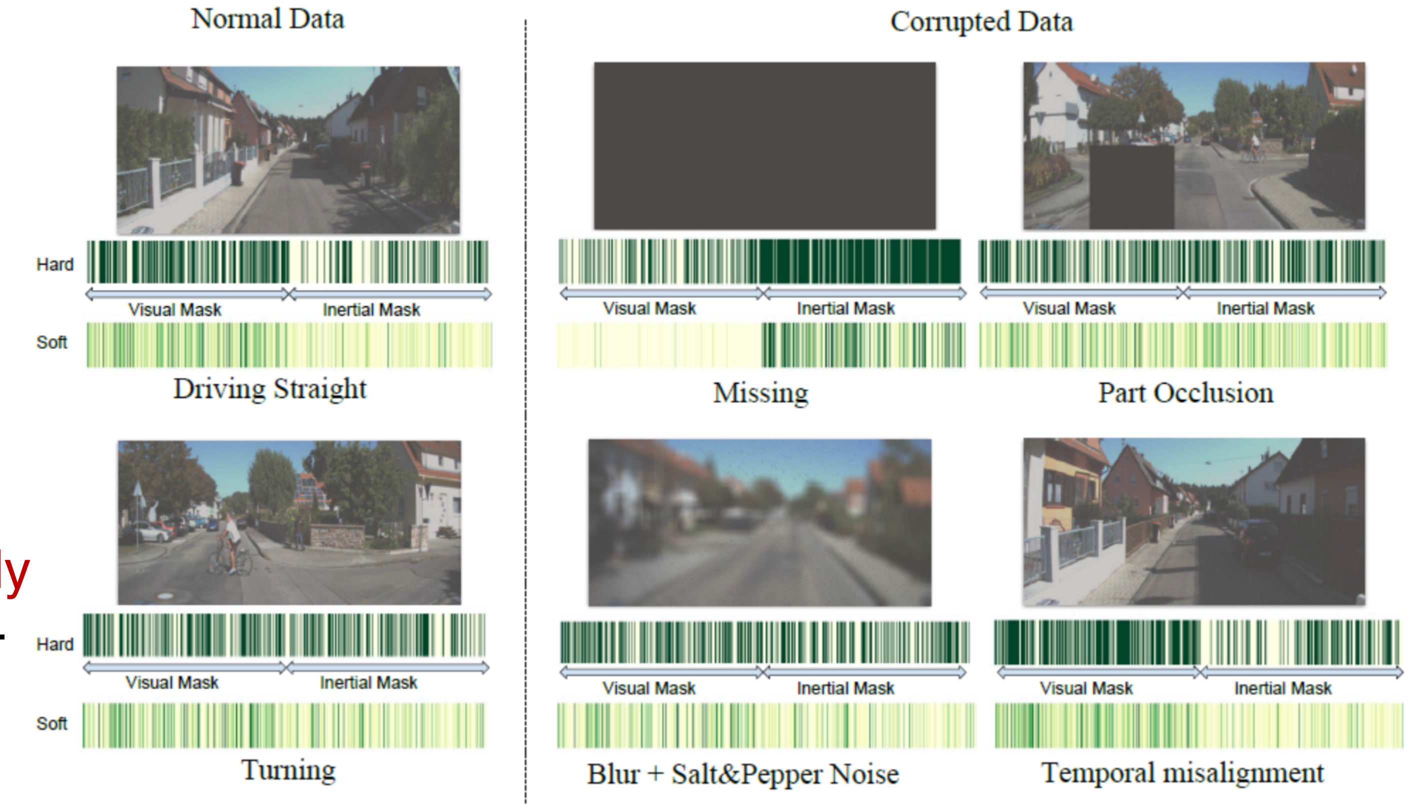
Trolley Tracking with Inertial Sensor Only



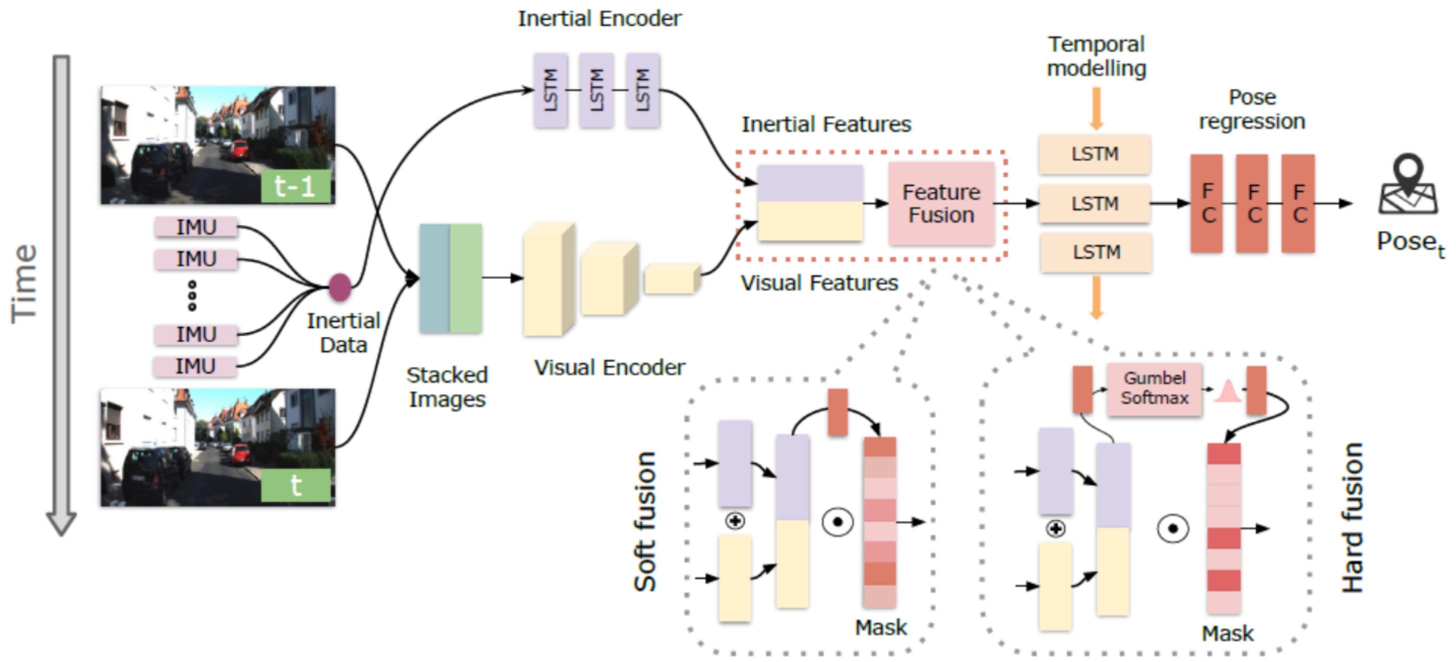
2. Selective Sensor Fusion

- ✓ Previous work rarely focus on incorporating robust fusion strategies for dealing with imperfect input sensory data.
- ✓ Real issues include camera occlusion or operation in low-light conditions, measurement noises, temporal or spatial misalignment between two sensors.
- ✓ The learning-based methods are not explicitly modelling the sources of degradation in real-world usages.
- ✓ Naively using all features before fusion will lead to unreliable state estimation.



C. Chen, S. Rosa, Y. Miao, C. Lu, W. Wu, A. Markham, N. Trigoni. Selective Sensor Fusion for Neural Visual-Inertial Odometry. CVPR-2019

Selective Sensor Fusion for Neural VIO



✓ A generic framework to learn feature selections from two modalities, enabling robust and accurate ego-motion estimation

✓ Our selective sensor fusion masks can be visualised and interpreted

✓ A new and complete systematic research on the accuracy and robustness of deep sensor fusion in presence of corrupted data

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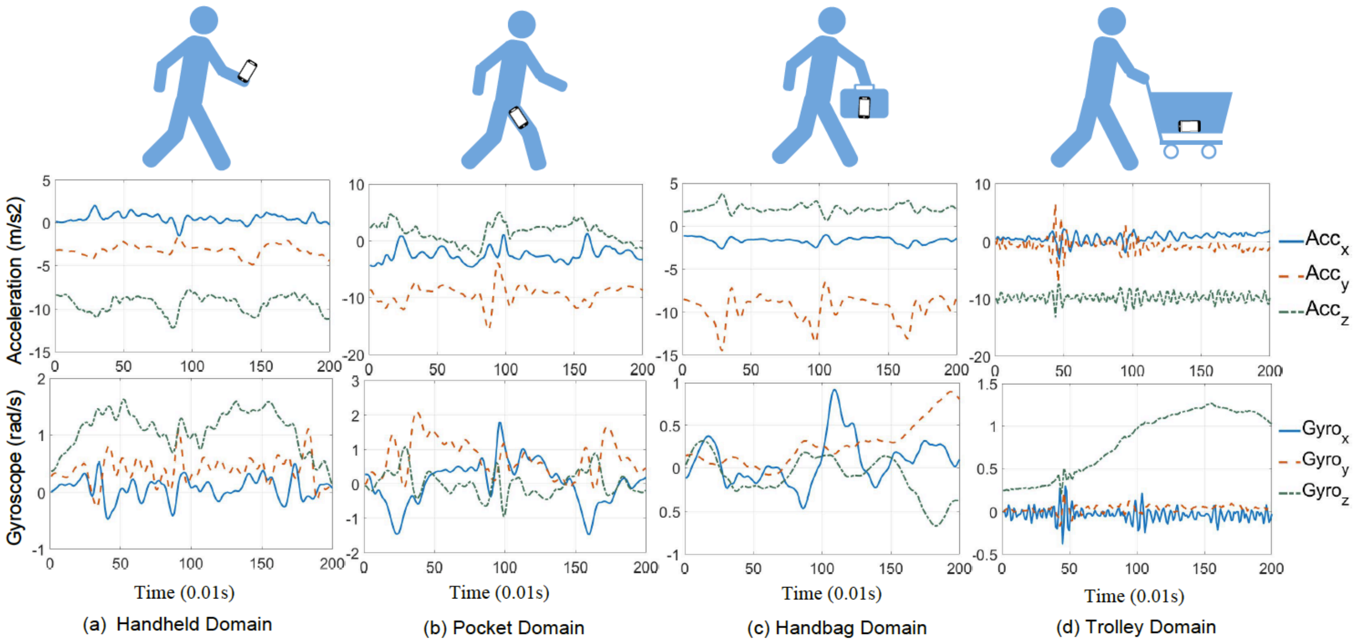
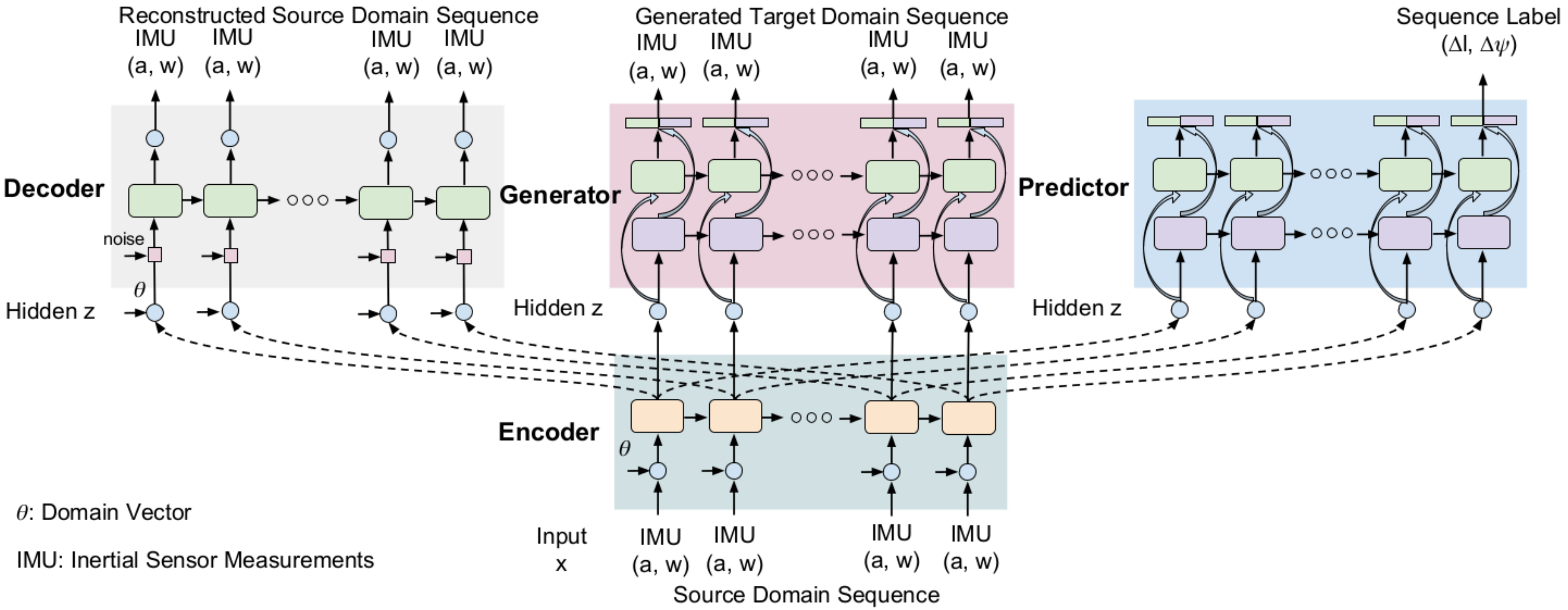
3. Sequential Invariant Domain Adaptation

- ✓ Huge domain shift/difference, e.g. handheld vs pocket
- ✓ Model trained in one domain is hard to generalise to new domain
- ✓ Labelled data are not easy to obtain, expensive, time-consuming, require extra infrastructure
- ✓ Current generative models work not well on long continuous data-series data



C. Chen, Y. Miao, C. Lu, L. Xie, P. Blunsom, A. Markham, N. Trigoni.
MotionTransformer: Transferring Neural Inertial Tracking Between Domains. AAAI-2019

SIDA



- ✓ A generic framework to transfer continuous long time-series sensory data
- ✓ using a shared encoder to transform raw inertial sequences into a domain-invariant hidden representation
- ✓ as no labelled or even paired data is required to achieve motion transformation in new domains.

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Transferring Across Motion Domains

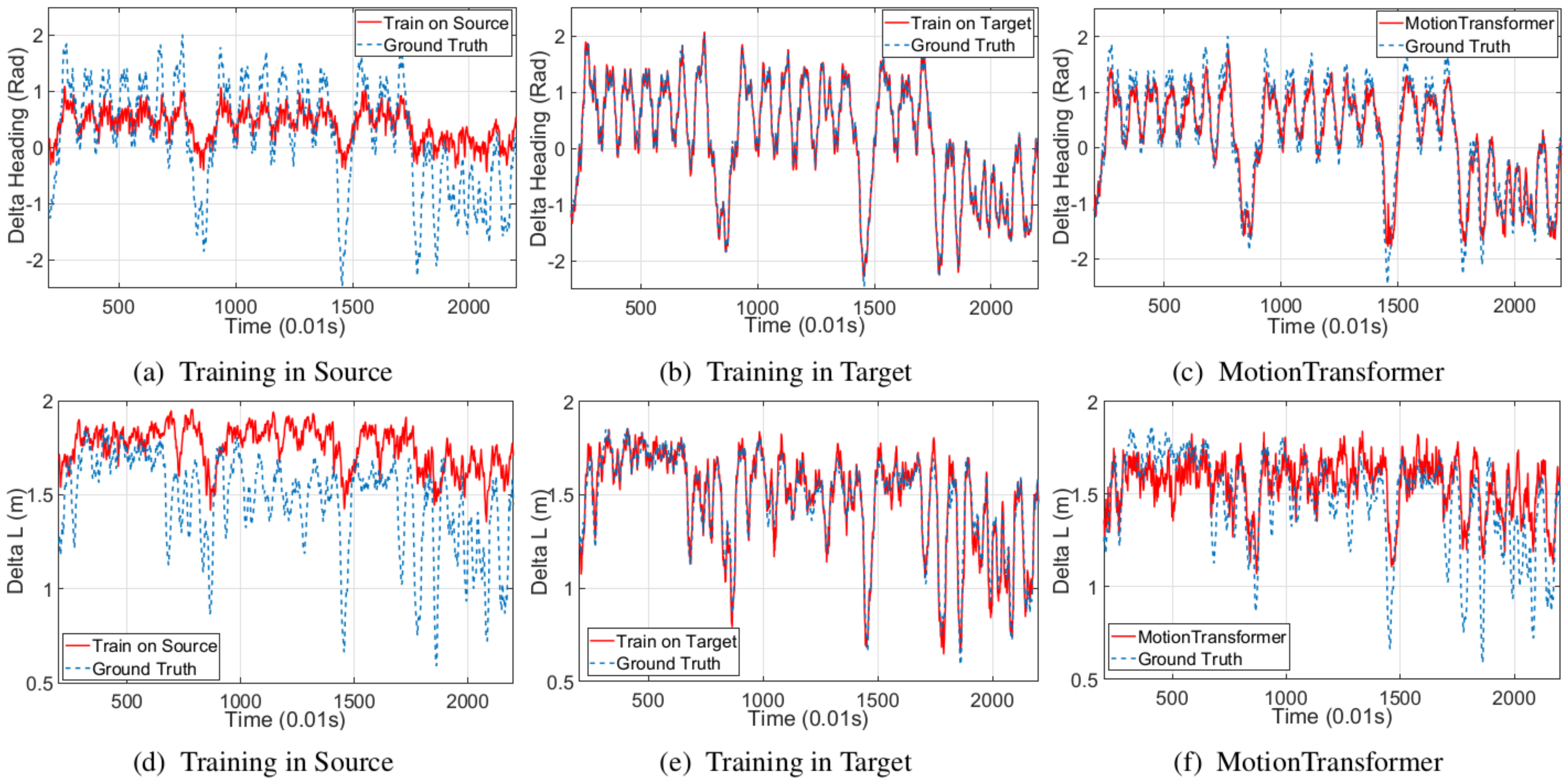

Figure 3: Heading displacement estimation from training in (a) source domain, (b) target domain and (c) MotionTransformer, and location displacement estimation from training in (d) source domain, (e) target domain and (f) MotionTransformer

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Inertial Tracking in Unlabelled Domains

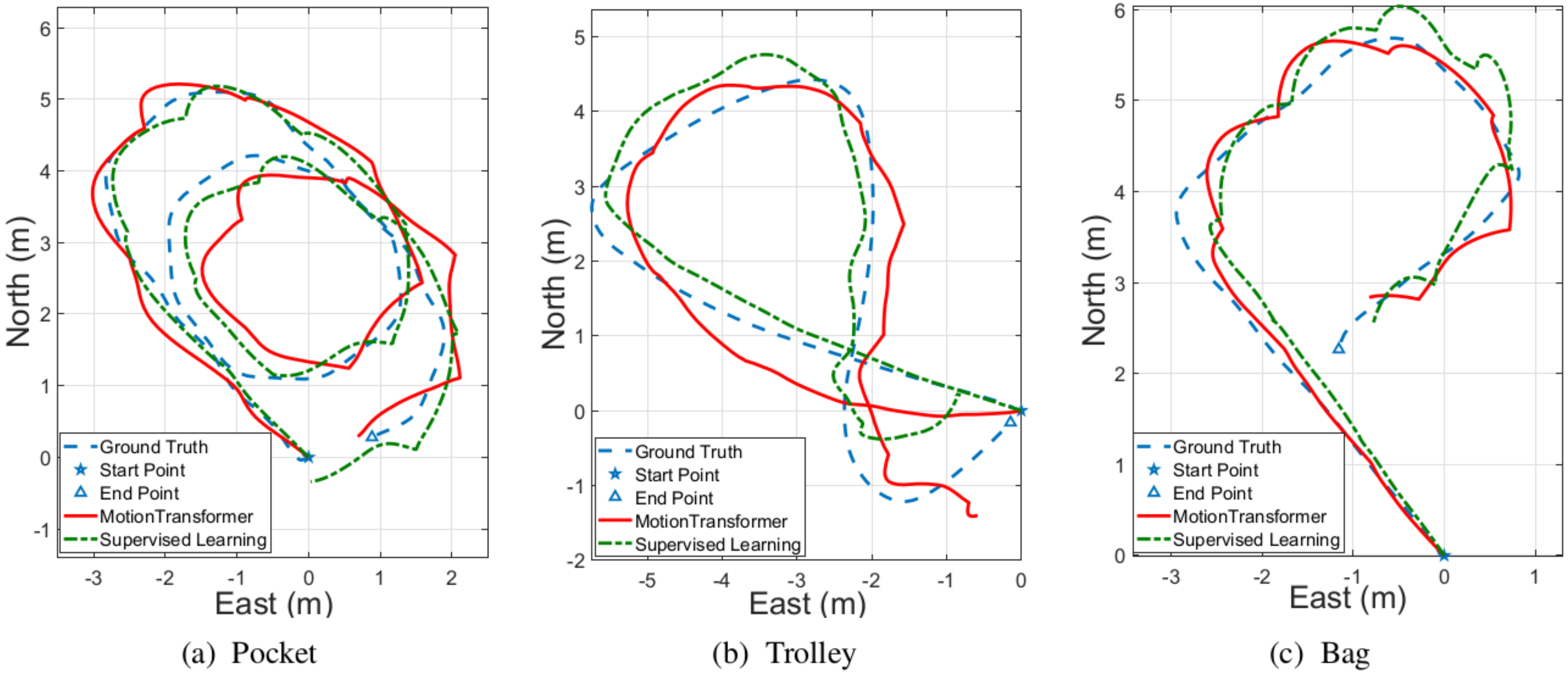

Figure 4: Inertial tracking trajectories of (a) Pocket (b) Trolley (c) Handbag, comparing our proposed unsupervised Motion-Transformer with Ground Truth and Supervised Learning.

Other contributions

Localization:

- DeepPCO: End-to-End Point Cloud Odometry through Deep Parallel Neural Network. IROS-2019
- AtLoc: Attention Guided Camera Localization. In submission
- DeepTIO: A Deep Thermal-Inertial Odometry with Visual Hallucination. In submission

Mapping:

- Simultaneous Localization and Mapping with Power Network Electromagnetic Field. MobiCom-2018
- milliMap: Robust Indoor Mapping with Low-cost mmWave Radar. In submission

Navigation:

- Learning with Stochastic Guidance for Navigation. NeurIPS-2018 workshop

Perception:

- Autonomous Learning for Face Recognition in the Wild via Ambient Wireless Cues. WWW-2019
- mID: Privacy-Preserving Tracking and Identification with Millimeter Wave Radar. DCOSS-2019
- Heart-Rate Sensing With a Robot Mounted mmWave Radar. In sumission

Thanks for your attention!

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