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IONet: Learning to Cure the Curse of Drift in Inertial Odometry

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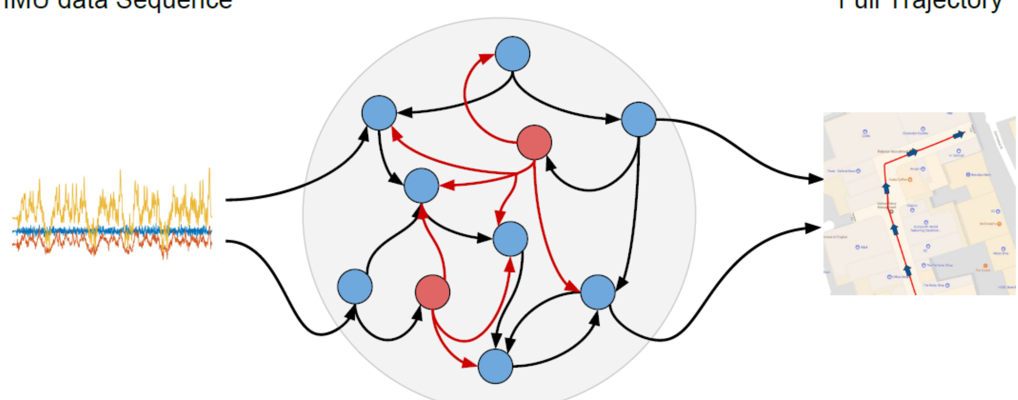
Why we study inertial localization

GNSS:

- serious attenuation and multi-path effect

Inertial sensors:

- Unique, completely self-contained
- Widespread, deployed on smartphones, robots, drones



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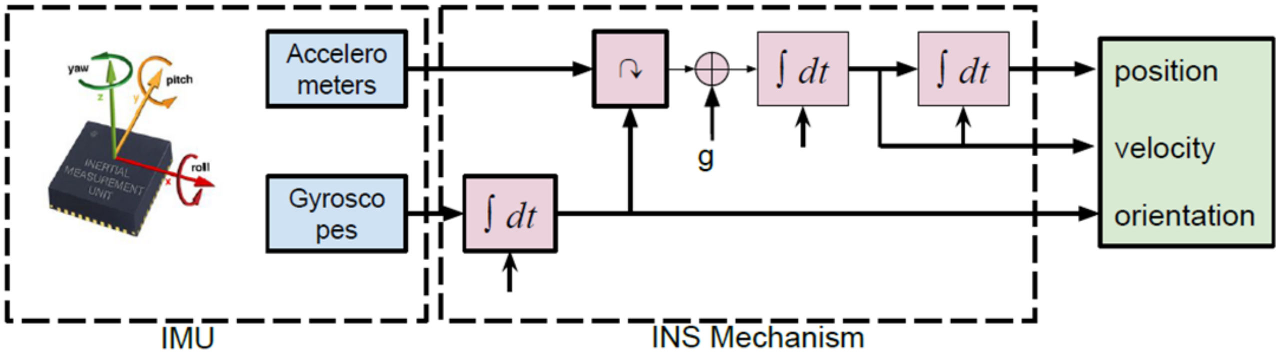
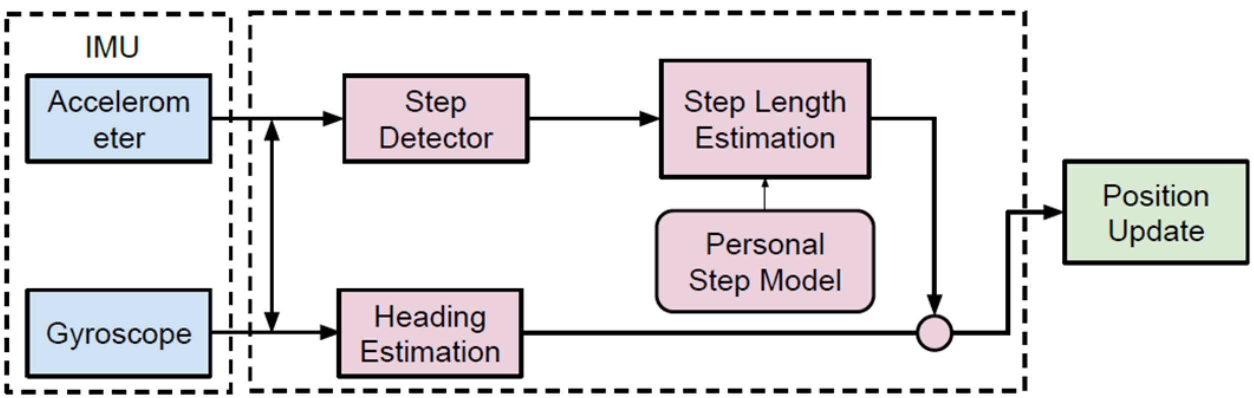
Indoor Pedestrian Navigation

Existing Methods:

Strapdown Inertial Navigation System (SINS)



Pedestrian Dead Reckoning (PDR)



The Curse of Drift

Attitude Update:

Relative Rotation Matrix

Direction Cosine

$$\mathbf{C}_b^n(t) = \mathbf{C}_b^n(t-1) * \mathbf{\Omega}(t) \tag{1}$$

$$\sigma = \mathbf{w}(t)dt \tag{2}$$

Angular Velocity

$$\mathbf{\Omega}(t) = \mathbf{C}_{b_t}^{b_{t-1}} = I + \frac{sin(\sigma)}{\sigma}[\sigma\times] + \frac{1-cos(\sigma)}{\sigma^2}[\sigma\times]^2 \tag{3}$$

Velocity Update:

Gravity

Velocity

$$\mathbf{v}(t) = \mathbf{v}(t-1) + ((\mathbf{C}_b^n(t-1)) * \mathbf{a}(t) - \mathbf{g}_n)dt \tag{4}$$

Location Update:

Accelerations

$$\mathbf{L}(t) = \mathbf{L}(t-1) + \mathbf{v}(t-1)dt \tag{5}$$

Location

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Tracking Down a Cure

$$[\underbrace{\mathbf{C}_b^n}_{\text{Orientation}} \quad \overbrace{\underline{\mathbf{v}}}^{\text{Velocity}} \quad \underbrace{\mathbf{L}}_{\text{Location}}]_t = f([\mathbf{C}_b^n \quad \mathbf{v} \quad \mathbf{L}]_{t-1}, [\underbrace{\mathbf{a}}_{\text{Accelerations}} \quad \overbrace{\underline{\mathbf{w}}}^{\text{Angular Velocity}}]_t) \qquad (6)$$

Location Update

$$\underline{\Delta \mathbf{L}} = \int_{t=0}^{n-1} \mathbf{v}(t)dt$$

- Break the cycle of continuous Integration
- Segment inertial data into independent windows

Sequence-based Model

Initial Velocity Gravity

$$(\Delta l, \Delta \psi) = f_\theta(\mathbf{v}^b(0), \mathbf{g}_0^b, \hat{\mathbf{a}}_{1:n}, \hat{\mathbf{w}}_{1:n})$$

Polar Vector

Inertial measurements

Location Update
$$\begin{cases} x_n = x_0 + \Delta l cos(\psi_0 + \Delta\psi) \\ y_n = y_0 + \Delta l sin(\psi_0 + \Delta\psi) \end{cases}$$

Inertial measurements

Polar Vector

$$(\mathbf{a}, \mathbf{w})_{200*6} \xrightarrow{f_\theta} (\Delta l, \Delta\psi)_{1*2},$$

Learning the parameters

$$\theta^* = \arg\min_\theta \ell(f_\theta(\mathbf{X}), \mathbf{Y})$$

Loss function

$$\ell = \sum \|\Delta\tilde{l} - \Delta l\|_2^2 + \kappa\|\Delta\tilde{\psi} - \Delta\psi\|_2^2$$

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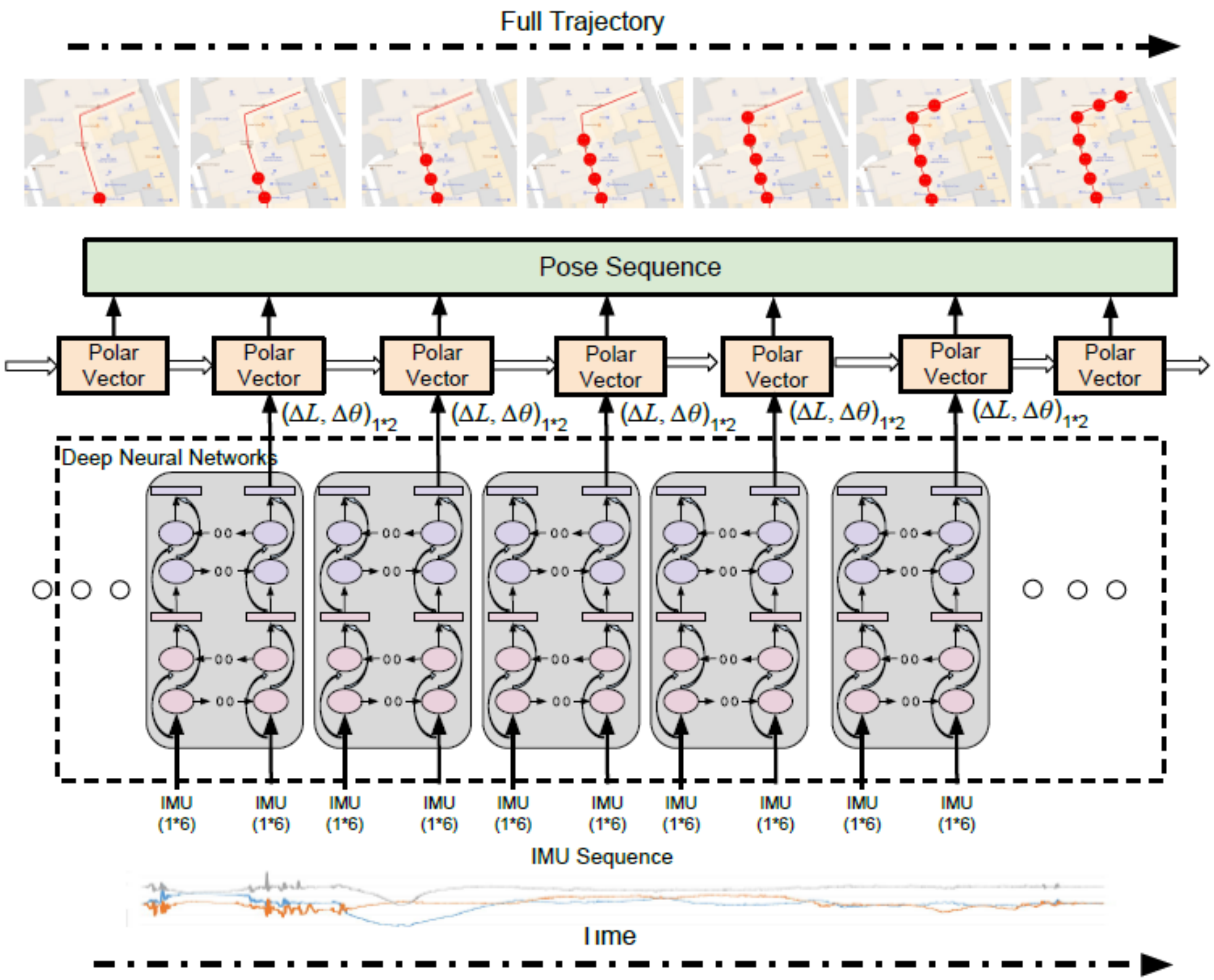
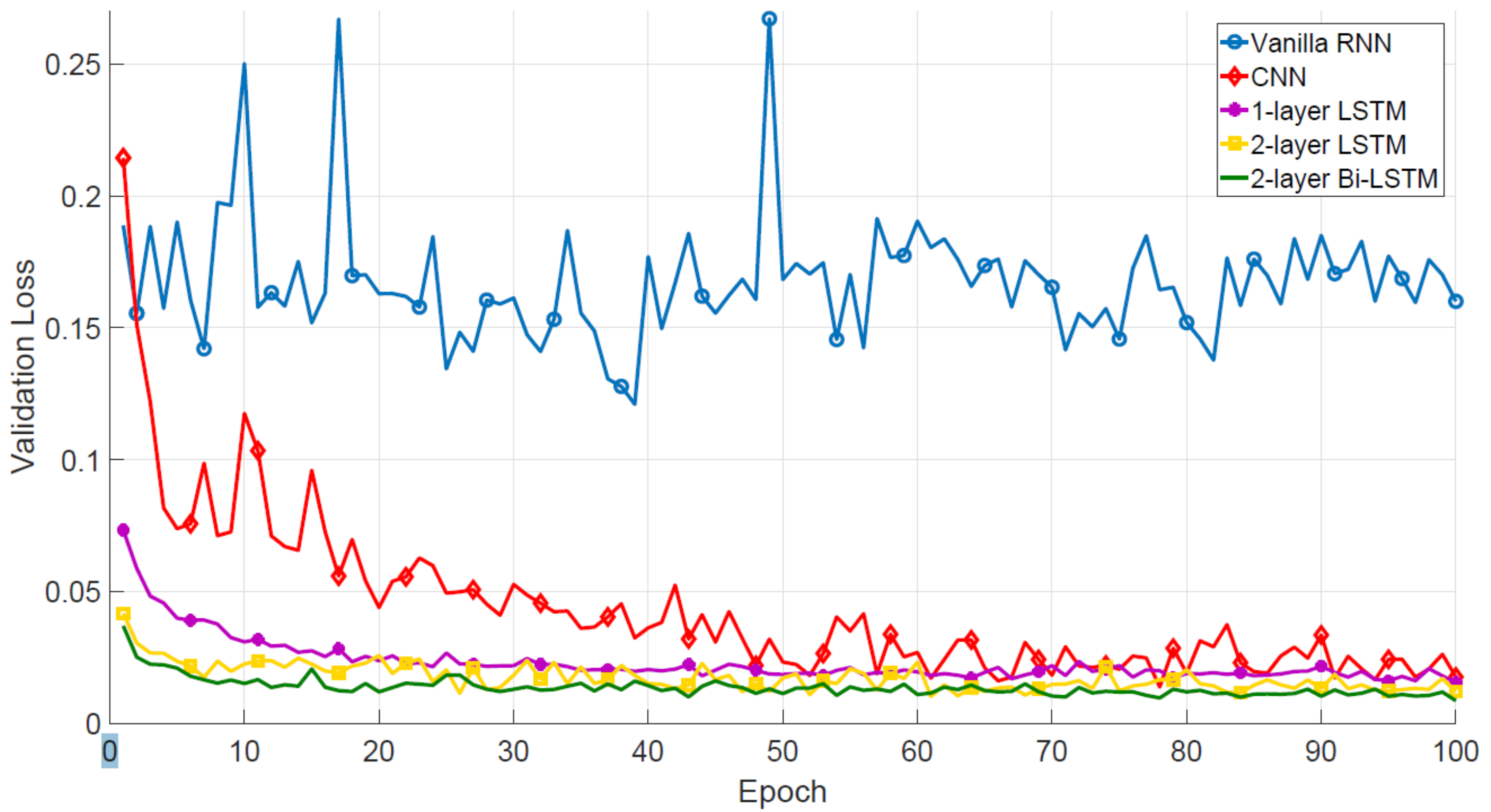


Figure 3: Overview of IONet framework

Comparison of Different Frameworks



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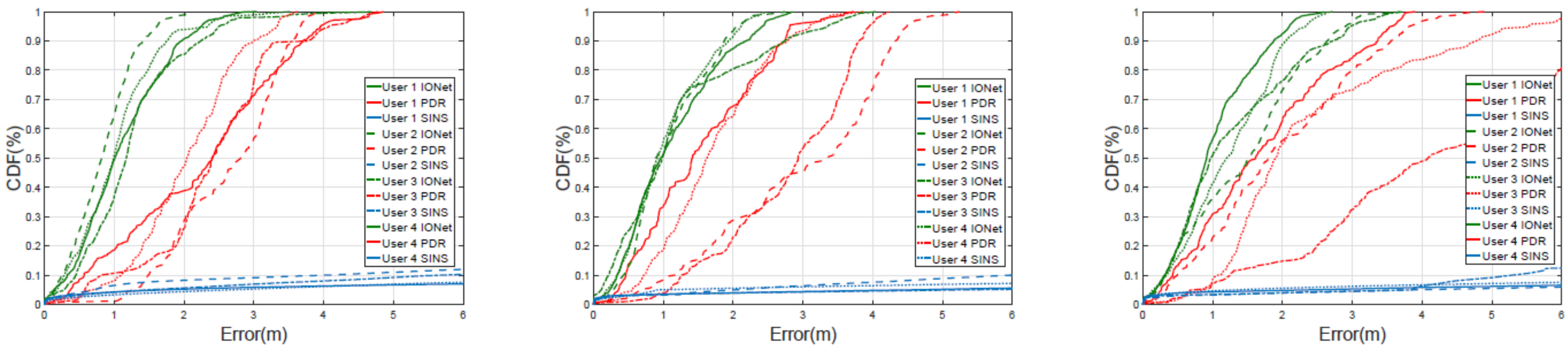
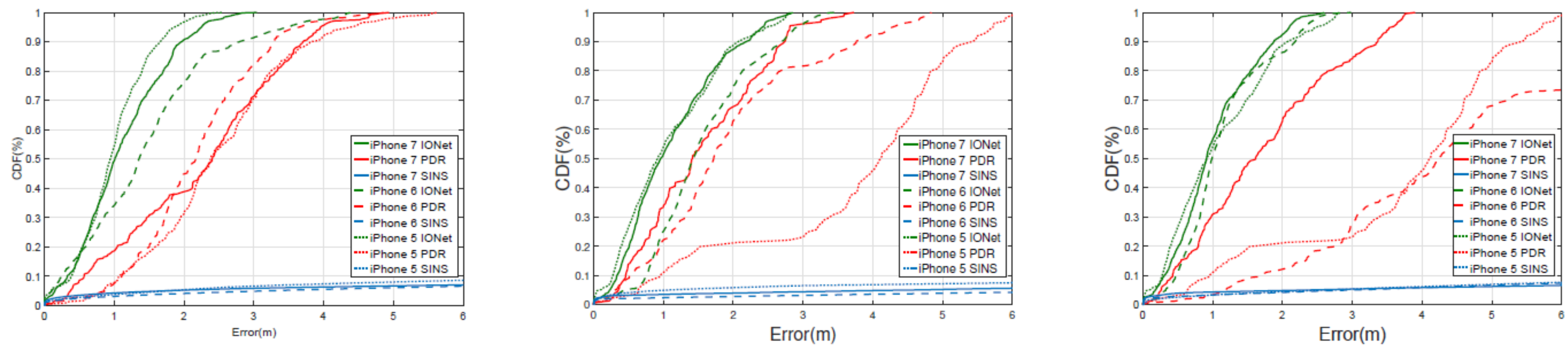
Tests Involving Multiple Users and Devices



(a) Handheld (b) In Pocket (c) In Handbag

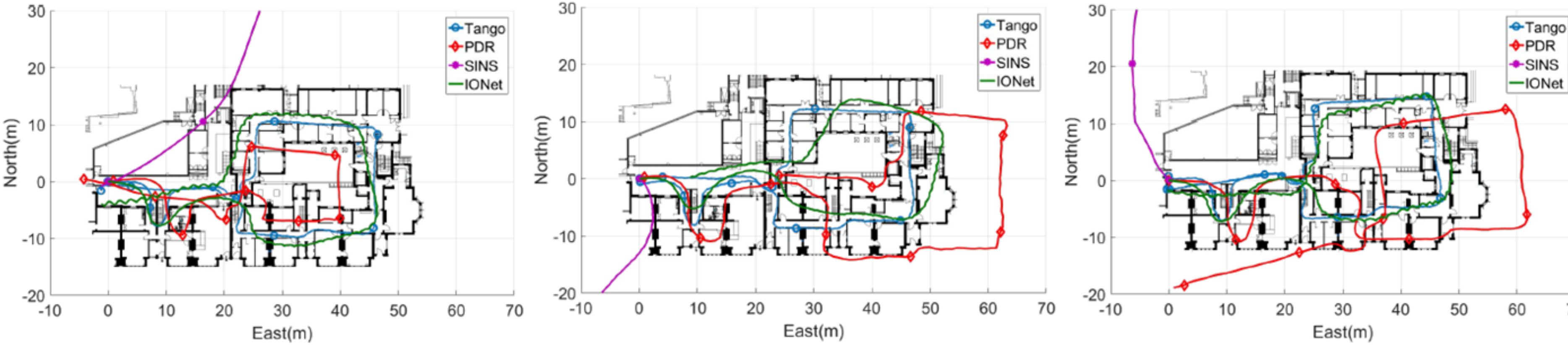
Figure 4: Performance in experiments involving different users.



(a) Handheld (b) In Pocket (c) Handbag

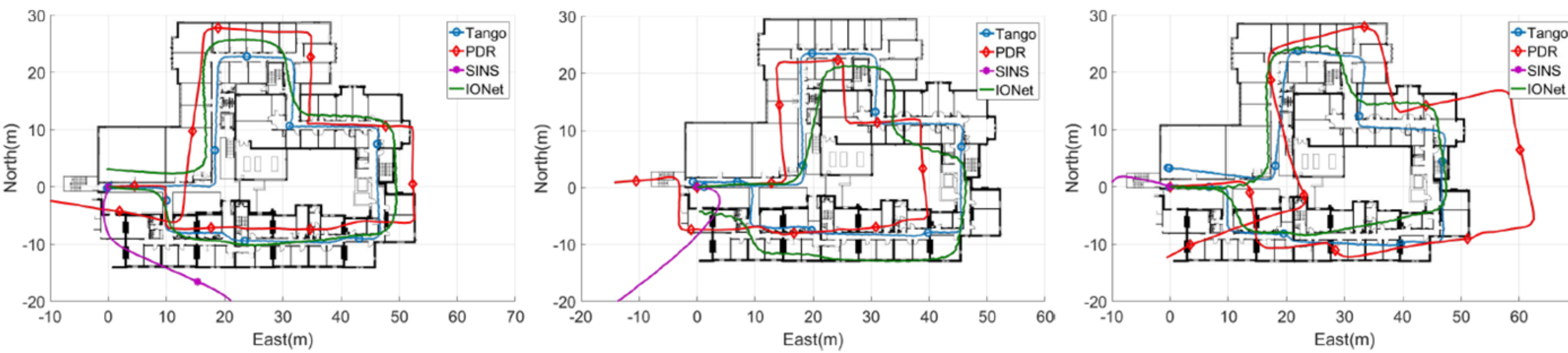
Figure 5: Performance in experiments involving different devices.

Large-scale Indoor Localization



(a) Handheld (b) In Pocket (c) In Handbag

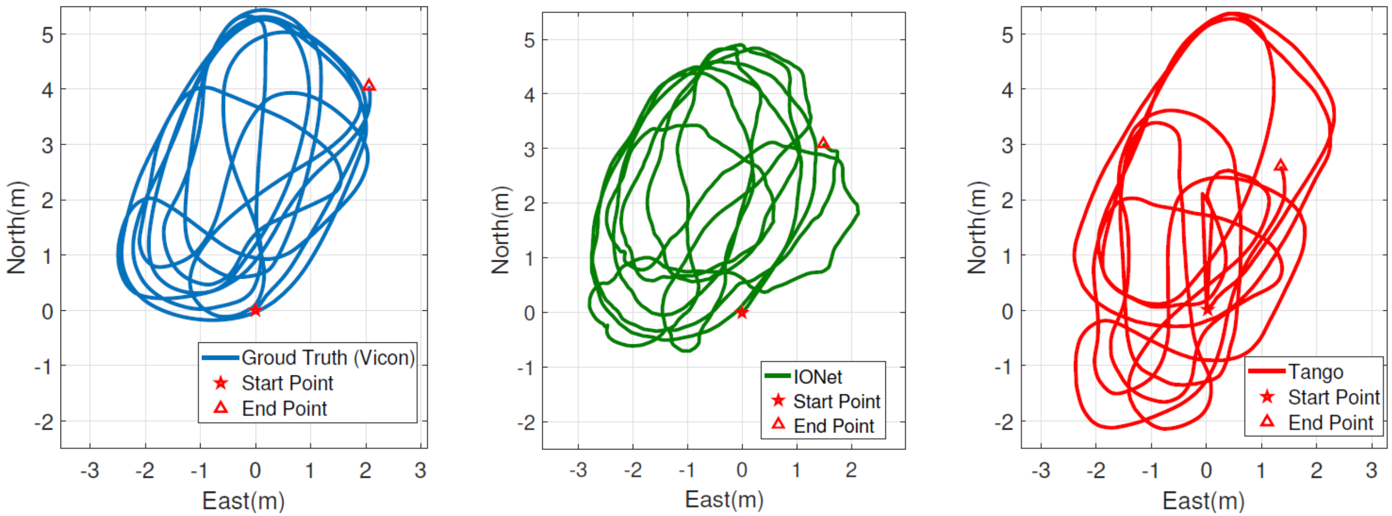
Figure 6: Trajectories on Floor A



(a) Handheld (b) In Pocket (c) In Handbag

Figure 7: Trajectories on Floor B

Trolley Tracking Experiment



(a) Ground Truth (b) IONet (c) Tango

Figure 9: Trolley tracking trajectories of (a) Ground Truth (b) IONet (c) Tango

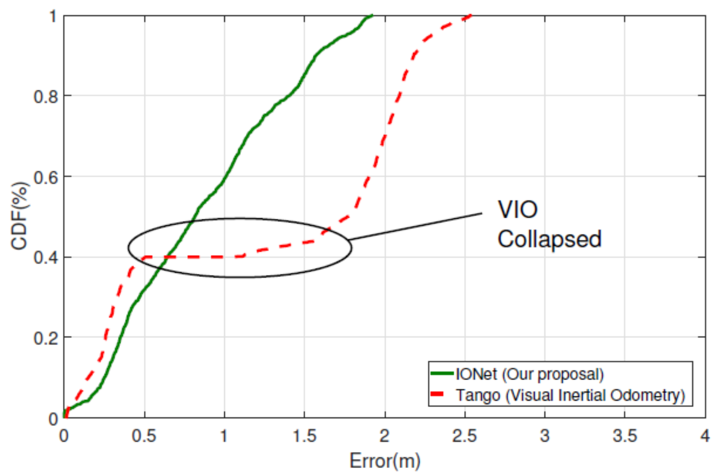


Figure 12: CDF of Trolley Tracking

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Contributions

- Cast the inertial tracking problem as a sequential learning approach.
- Propose the first deep neural network (DNN) framework that learns location transforms from raw IMU data.
- Conducted extensive experiments across different attachments, users/devices and new environment.
- In addition, our model can generalize to a more general motion.

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Thanks for your attention!

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