A Cognitive Navigation Assistant for the Blind

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Inertial Localization

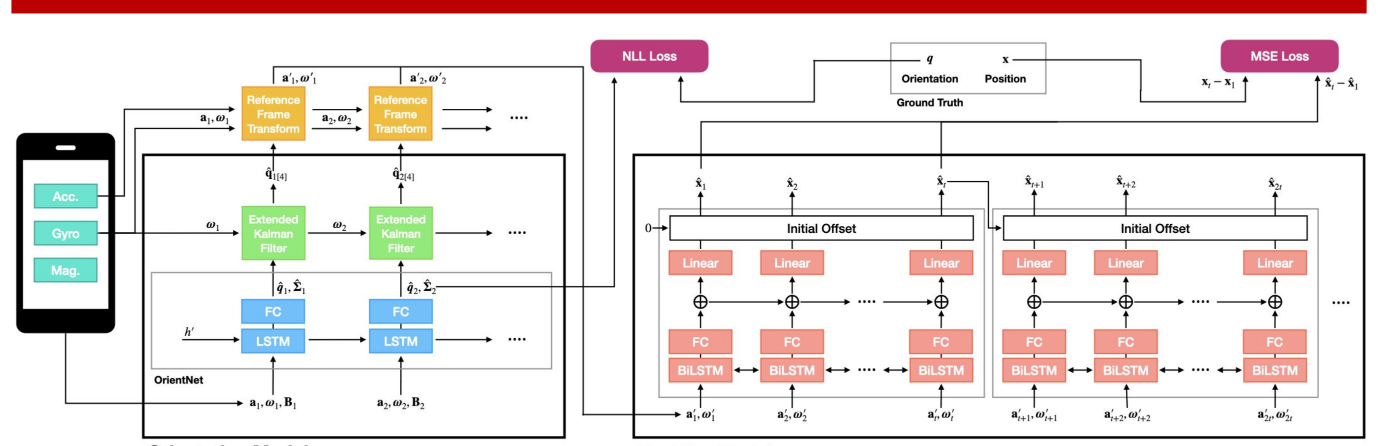
Overview & Motivation

- **Goal**: Enable accurate indoor pedestrian localization using smartphone IMUs to convey key environmental information to users: ego-location
- **Motivation:**
  - Ego-location forms basis of environmental understanding for navigation
  - IMUs consist of 3-axis accelerometers, gyroscopes, and magnetometers
  - IMUs require no pre-existing infrastructure, have low power draws, and are ubiquitous in modern smartphones

Related Work

- **IOnet** [5]: Early usage of deep networks (Bi-LSTM) to estimate user velocity from IMUs
- **RoNIN** [6]: Explores 3 deep architectures to improve velocity estimation of IOnet
- **TLIO** [7]: Filter-based approach to combine RoNIN-style velocity estimation with non-deep orientation estimation from gyroscope measurements
- **MUSE** [3]: Filter-based orientation estimation using gyroscope, accelerometer, and magnetometer
- **Brossard et al.** [4]: Deep method reduces gyroscope noise to improve gyroscope-only orientation estimation

Method



Overall Pipeline

1. Predict orientation from local-frame IMU signals
   - Learned Orientation Network (LSTM)
   - Trained to predict estimate + uncertainty of quaternion orientation
2. Filter orientation using manifold Extended Kalman Filter[1]
   - Operates in quaternion-preserving space
   - Combines low-drift Orientation Network & locally-accurate gyroscope measurements
3. Rotate local-frame IMU to global frame using orientations
4. Predict position from global-frame IMU signals
   - Learned Position Network (Windowed Bi-LSTM)
   - Trained directly with MSE Loss

Novel Dataset:

- 20+ hours of human walking, 15 Subjects & 3 Buildings

Results

- **Orientation Metrics**
  - *Angular RMS Error*: angle error of each point in trajectory

Comparison of Angular RMSE (Radians) in Different Buildings

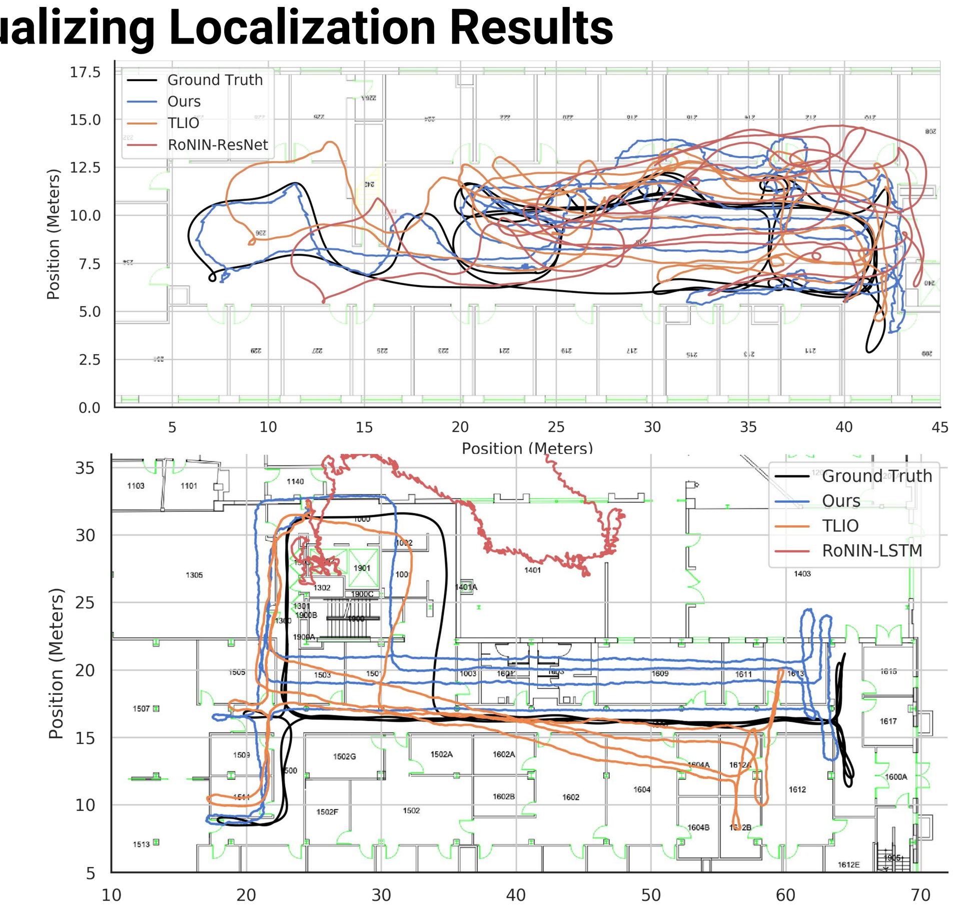
System	Bldg 1	Bldg 2	Bldg 3
iOS CoreMotion	0.39	0.37	0.40
MUSE	0.21	0.25	0.45
Brossard et. al. (2020)	0.23	0.30	0.47
OrientNet only (ours)	0.21	0.44	0.49
OrientNet+EKF (ours)	**0.08**	**0.10**	**0.14**

- **Position Metrics** [2]
  - *ATE*: error of each point in trajectory
  - *T-RTE*: error over windows of 1 minute in length
  - *D-RTE*: error over windows of 1 meter in length

Comparison of Position Error (m) in Different Buildings

Model	Building 1			Building 2			Building 3		
	ATE	T-RTE	D-RTE	ATE	T-RTE	D-RTE	ATE	T-RTE	D-RTE
PDR	25.70	14.66	2.50	21.86	19.48	1.66	12.66	12.74	1.09
R-LSTM	18.41	6.78	0.52	29.81	18.67	0.75	33.69	13.14	0.62
R-TCN	12.67	6.13	0.48	22.52	13.69	0.73	24.79	12.48	0.59
R-ResNet	10.48	6.20	0.53	35.44	15.71	0.49	14.11	11.78	0.60
TLIO	5.44	3.33	0.38	8.69	8.86	**0.33**	6.88	6.68	0.34
Ours	**4.99**	**2.37**	**0.34**	**8.33**	**5.97**	0.41	**6.62**	**2.86**	**0.26**

- **Visualizing Localization Results**



Conclusion

Main Contributions:

- Our orientation module outperforms existing traditional and data-driven methods in estimating orientation
- Our end-to-end system localizes better than state-of-the-art data-driven inertial approaches
- Our pipeline is a low-resource source of ego-motion understanding, allowing further systems to provide a better cognitive map of the surrounding environment

References

[1] Hertzberg, C. et. al. "Integrating Generic Sensor Fusion Algorithms with Sound State Representations through Encapsulation of Manifolds." Information Fusion Vol. 14. 2013.
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[5] Chen, Changhao, et al. "IONet: Learning to cure the curse of drift in inertial odometry." AAAI. 2018.
[6] Yan, Hang, et. al. "RoNIN: Robust Neural Inertial Navigation in the Wild: Benchmark, Evaluations, and New Methods." ICRA. 2019.
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BLE Beacon Localization

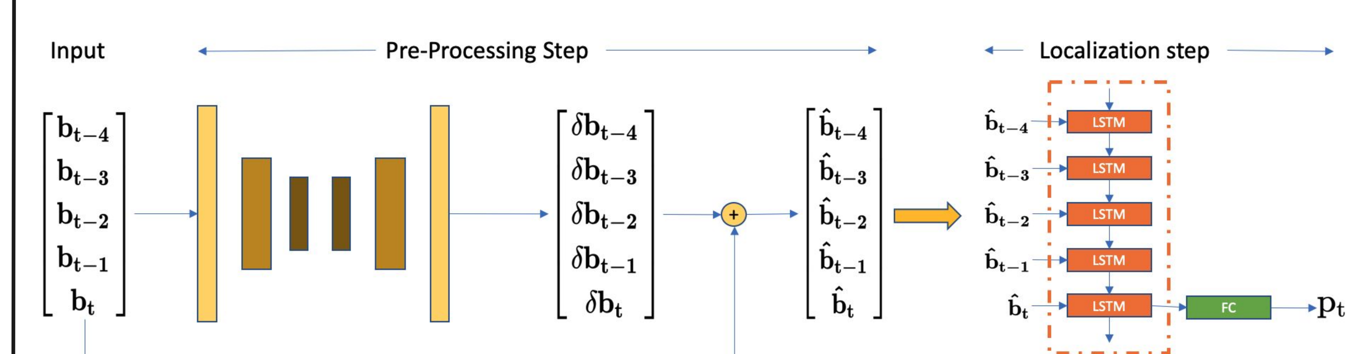
Overview & Motivation

- **Goal**: Accurate smartphone localization for indoor navigation using only RSSI received from a set of BLE beacons. Navigation app for both Android and iOS.
- **Motivation:**
  - BLE localization gives accurate (<1 m error) global positioning, accurate enough to provide navigation assistance for the blind and visually impaired.
  - Bluetooth chip present in all modern day smartphones, no extra sensors need to be attached to user devices.
  - Minimal infrastructure cost as BLE beacons are cheap.
  - Scanning for RSSI consumes very little power.

Related Work

- **Hilsenbeck et al.** [8]: Pedometer and WiFi RSSI based mobile indoor positioning.
- **Letchner et al.** [9]: Bayesian model based trilaterization on WiFi RSSI signal.
- **Hall et al.** [10]: Software Defined Radio (SDR) based localization using probabilistic model and Deep Learning.
- **DLRNN** [11]: End to end deep learning based localization using WiFi RSSI signals.

Method



BLE RSSI characteristics vary a lot between devices. In order to make our model generalize to multiple devices without specifically collecting data and training on each one, we propose a 2 step method -

- Pre-processing step: Maps RSSI measured by any modern smartphone to one which was part of the labeled training dataset.
  - Conv-Deconv Network
- Localization step: Predict the location of the smartphone from the matrix of RSSI signals received.
  - 2 LSTM layers followed by 2 fully connected layers.
- Localization loss + Position smoothness loss + Statistic similarity loss + Temporal smoothness loss

Dataset:

- 50 BLE beacons. Accurate ground truth using LIDAR scans. Data collection apps for Android and iOS.

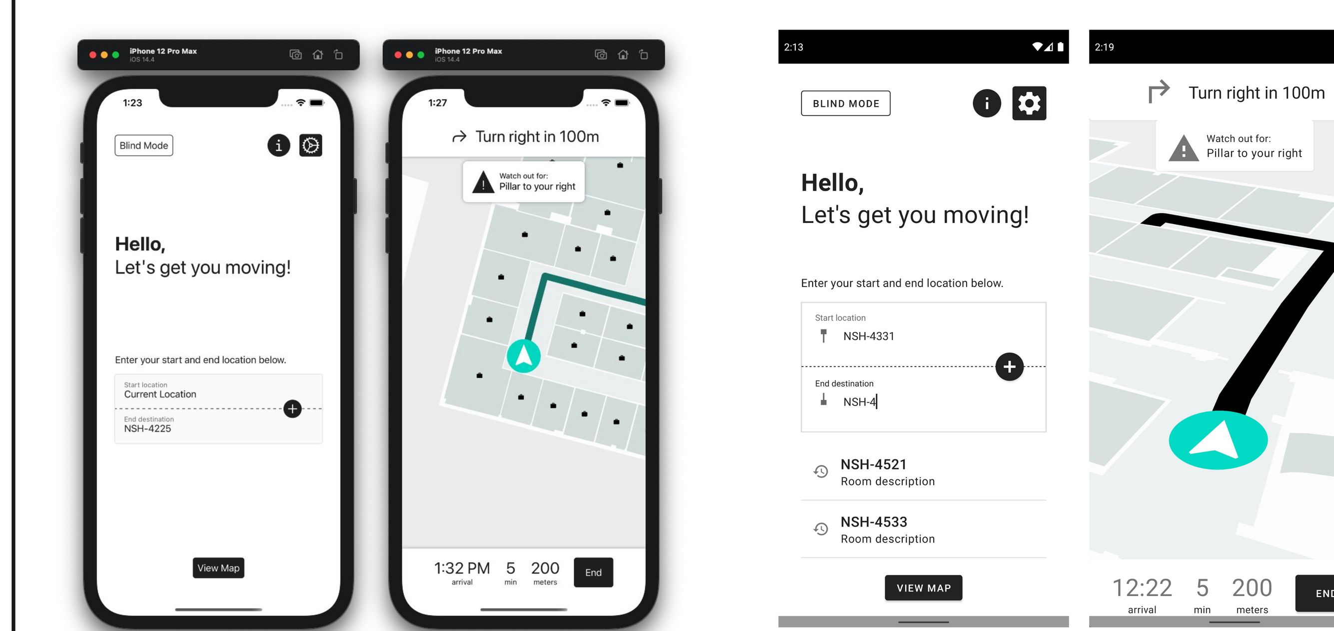
Results

Method →	KNN Reg		Bayesian		KRR+KF		DL-RNN		Proposed(Sup)		Proposed (Semi)	
Test on ↓	Mean	Std	Mean	Std	Mean	Std	Mean	Std	Mean	Std	Mean	Std
iPhone	1.1917	0.9298	1.5424	1.2267	1.7575	1.0770	1.0205	0.7712	**0.9409**	**0.7163**	0.9572	0.7741
Huawei	6.3579	9.595	4.8951	6.3216	3.0021	2.3075	2.2437	2.2014	1.7900	1.5515	**1.7370**	**1.3260**
Xiaomi	4.1781	7.2262	3.5959	4.2674	2.7569	1.9125	2.4360	3.0378	1.7014	1.3918	**1.6284**	**1.1280**
Pixel	1.9082	1.5561	2.1457	1.7167	1.8955	1.1816	1.4347	1.1638	1.2769	**1.0183**	**1.2687**	1.0341
Samsung	2.0139	2.5525	2.0843	2.3115	2.0767	1.2390	1.5282	1.1301	1.2898	1.0808	**1.2732**	**1.0310**
Average	3.0157	5.7190	2.7724	3.8090	2.2640	1.6644	1.6826	1.8650	1.3700	1.2080	**1.3462**	**1.0979**
Median	1.5230		1.7505		1.8884		1.2067		**1.0258**		1.0436	
90% ile	5.2514		5.5866		4.2660		3.2968		2.7689		**2.6601**	
Max	52.5572		48.3013		17.2977		31.9299		19.7231		**11.8294**	

Table : Evaluation results for different methods when trained using data from iPhone and Samsung phones

- Model trained on a specific phone is able to transfer to other phones that it has not seen at train time
- Localization error of 1.5-1.7 m on inexpensive phones without explicitly training on them.

Mobile App



iOS Android

- Helping people navigate requires a easy to use mobile app on both Android and iOS.
- Deployed our deep learning solution to the app
- Complete offline usage once the app is downloaded

Conclusion

- Our method performs similar to other parametric models trained specifically for the task of RSSI based localization.
- While other methods fail at transferring from one device manufacturer to other, out method performs comparably on previously unseen devices.
- An indoor navigation app with a sub-1m accuracy is crucial for people with vision disabilities.

References

[8]Sebastian Hilsenbeck, Dmytro Bobkov, Georg Schroth, Robert Huitl,and Eckehard Steinbach. 2014. Graph-Based Data Fusion of Pedometer and WiFi Measurements for Mobile Indoor Positioning. InProc-eedings of the 2014 ACM International Joint Conference on Pervasive and Ubiquitous Computing
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[10] Donald L Hall, Ram M Narayanan, and David M Jenkins. 2019. SDRBased Indoor Beacon Localization Using 3D Probabilistic MultipathExploitation and Deep Learning.Electronics8, 11 (2019), 1323.
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