LocUNeT: Fast Urban Positioning Using Radio Maps and Deep Learning

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Introduction

- The **location** information of a **User Equipment (UE)** is essential for many **applications**, e.g. **emergency services, autonomous driving, intelligent transportation systems, 6G networks.**
- Global Navigation Satellite Systems **(GNSS)** **perform poorly** in **urban environments**, where the likelihood of line-of-sight (LOS) conditions is low. Hence, alternative approaches, which are **robust** to **non-LOS** conditions are **required.**
- **Received Signal Strength (RSS)** quantifies the received power **averaged over a limited time interval of the beacon frames and over the signal bandwidth**; hence it is not **subject to small scale fluctuations.**
- Reporting **RSS** information is a **standard feature** in most of the current wireless protocols and **does not require any further specific hardware at the UE**, whereas the time-based (ToA and TDoA) and angle-based (AoA) methods require high precision clocks and antenna arrays, respectively. .

Contributions

- **LocUNet:** A deep learning method for localization, based on the measured **(RSS)** of the beacon signals of Base Stations (BSs)(Or any wireless signal source with known location, e.g., WiFi-Hot-spots) at the UE to be localized, and the corresponding pathloss (for known BS power, pathloss is deducible from RSS, and vice versa) radio map estimates (via recently proposed **RadioUNet**) for each BS.
- LocUNet is **suitable for real-time applications**, thanks to the **RadioUNet**, a neural network-based radio map estimator, which can very accurately **approximate ray-tracing** simulations, but **much faster**.
- The proposed **LocUNet achieves state-of-the-art localization performance** and enjoys **high robustness to inaccuracies** of RSS input radio maps w.r.t. the actual RSS radio maps.
- We provide two simulated **novel datasets in the urban setting** to promote **realistic assessments of performances of RSS fingerprint and ToA ranging-based algorithms.**
- The **first work in the literature** to provide **numerical comparisons** among **numerous RSS fingerprinting and ToA ranging-based methods in a realistic urban setting.**

Two Novel Datasets For Urban Positioning

Prepared using **WinProp** [2] and **RadioUNet** [3], **publicly available** for the research community to **investigate the performances of RSS and ToA ranging-based localization algorithms** in **realistic urban setting.** See [1] for details.

- **RadioLocSeer: Simulated** and **estimated** (via **RadioUNet** [3]) **pathloss radio maps** under different simulation models (**Dominant Path Model (DPM)** and **Intelligent Ray-Tracing with 2 Interactions (IRT2)**), **along with the corresponding buildings, cars, BSs, and roads** in image format. UE (200 per map) and well-seperated BS locations (5 per map) are provided, as well.
- **RadioToASeer: Dataset of the ToA values** of the same maps of RadioLocSeer based on **DPM**, i.e., ToA values for potential UE locations are found based on the **dominant ray** (i.e., the multi-path-component with the highest energy, which is the **ray with shortest free space path**) that propagates from the BS to the UE location. Using this dataset yields **quasi-upper bounds for the performances of the ToA ranging-based methods.**

[2] R. Hoppe, G. Wölfle, and U. Jakobus,"Wave propagation and radio network planning software WinProp added to the electromagnetic solver package FEKO",Proc. Int. Appl. Computational Electromagnetics Society Symp. - Italy (ACES), Florence, Italy, March 2017, pp. 1–2.

[3] R. Levie, Ç. Yapar, G. Kutyniok, and G. Caire,"RadioUNet: Fast radio map estimation with convolutional neural networks",IEEE Trans. Wireless. Comm., 2021.

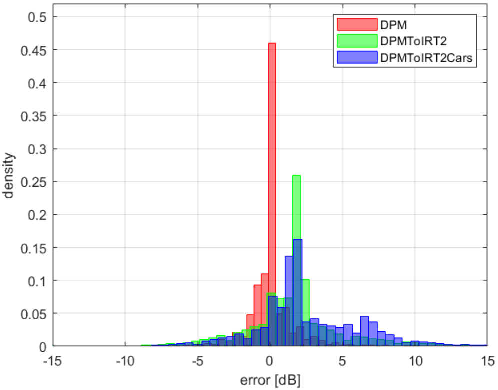
LocUNet Scenarios

- **DPM: Very optimistic scenario.** It is assumed that the real radio maps are exactly governed by **DPM simulations** and the radio map estimates are obtained by RadioUNet, which was trained in supervised fashion to estimate radio maps also under the DPM assumption. Hence, LocUNet enjoys having access to very high accuracy radio maps, where the inaccuracy of the available radio maps with respect to true radio maps is solely due to the prediction error of RadioUNet.

- **DPMToIRT2:** Different from the previous scenario, here, the pathloss measurements stem from **IRT2 simulations**, while the radio map estimations are obtained from RadioUNet (trained for DPM), as before.

- **DPMToIRT2Cars:** Similar setting as in DPMToIRT2, but the pathloss measurements stem from **IRT2 simulations** for an environment **with additional obstructions (cars)**, **unknown to LocUNet**. This scenario encompasses all the important sources of mismatch between the radio map estimates and the true real maps.

Histogram of Differences Between The Estimated and True/Simulated Radio Maps For The Considered Scenarios



LocUNet Structure

- A **UNet variant.**
- The final layer of LocUNet is **center of mass (CoM)** (μ_x, μ_y) of output $H(x, y)$ of the previous layer.
- We call $H(x, y)$ a **quasi-heatmap**, as its value at a point (x, y) in the map quantifies the **likelihood** of the UE to be located at this point, while admitting **negative** values due to the **LeakyReLu** being the **activation function.**
- The output of LocUNet is then given by **CoM**

$$\mu_x = \frac{\sum_{x=1}^{256} \sum_{y=1}^{256} xH(x, y)}{\sum_{x=1}^{256} \sum_{y=1}^{256} H(x, y)}, \quad \mu_y = \frac{\sum_{x=1}^{256} \sum_{y=1}^{256} yH(x, y)}{\sum_{x=1}^{256} \sum_{y=1}^{256} H(x, y)},$$

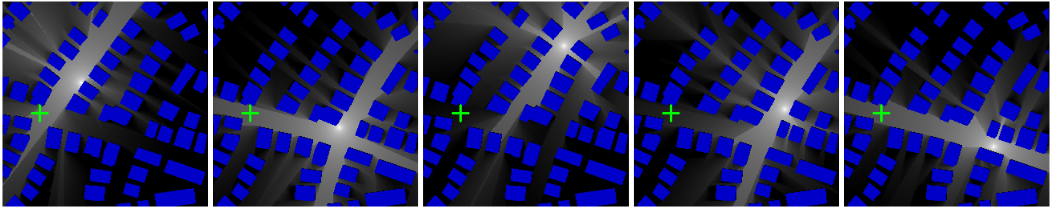
where 256 is the number of pixels along each axis.

Inputs of LocUNet

- **Necessary inputs:**
  - Pathloss measurements of UE from each BS
  - Radio map estimations for each BS
- **Optional inputs:**
  - Map of the buildings
  - BS positions as one-hot images
- See [1] for the details/technicalities of the input features.

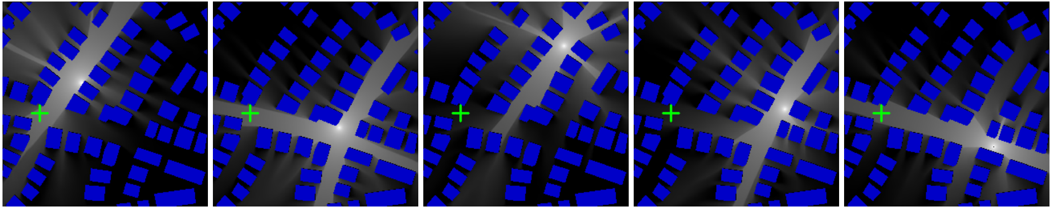
[1] Ç. Yapar, R. Levie, G. Kutyniok, and G. Caire, "Real-time outdoor localization using radio maps: A deep learning approach", arXiv preprint arXiv:2106.12556.

Dominant Path Model Simulations with WinProp [2]



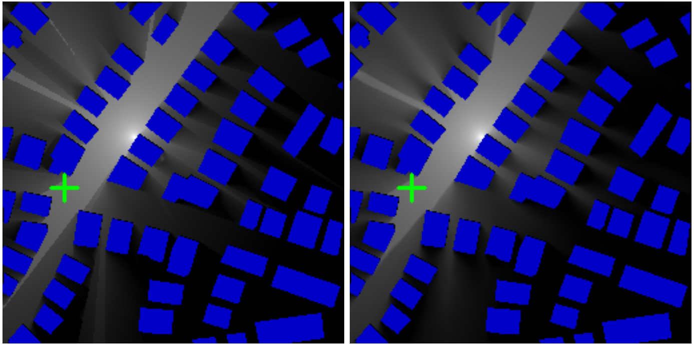
[2] R. Hoppe, G. Wölfle, and U. Jakobus,"Wave propagation and radio network planning software WinProp added to the electromagnetic solver package FEKO",Proc. Int. Appl. Computational Electromagnetics Society Symp. - Italy (ACES), Florence, Italy, March 2017, pp. 1–2.

Dominant Path Model Estimations with RadioUNet [3]



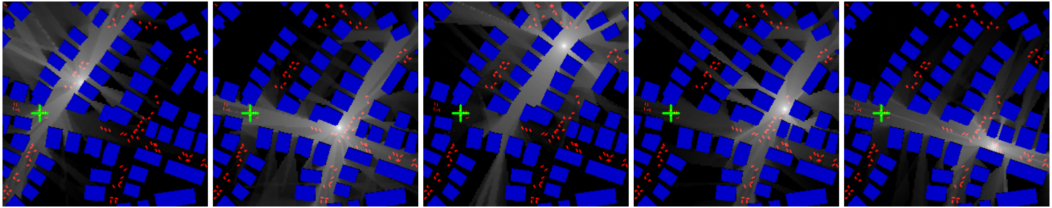
[3] R. Levie, Ç. Yapar, G. Kutyniok, and G. Caire,“RadioUNet: Fast radio map estimation with convolutional neural networks”,IEEE Trans. Wireless. Comm., vol. 20, no. 6, pp. 4001–4015, Feb. 2021.

DPM Simulation via WinProp vs DPM Prediction via RadioUNet



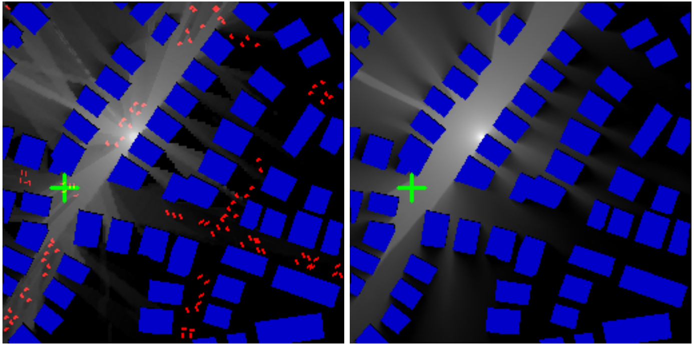
– Average difference between estimated and true/simulated radio maps (in dB): 1.66dB.

Intelligent Ray Tracing (IRT2) Simulations with Cars with WinProp [2]



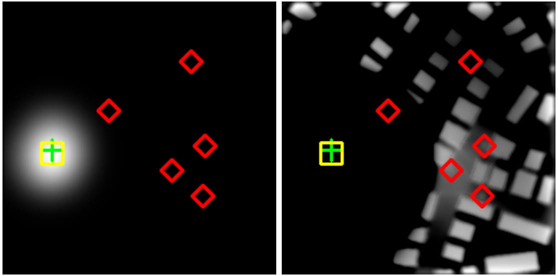
[2] R. Hoppe, G. Wölfle, and U. Jakobus,“Wave propagation and radio network planning software WinProp added to the electromagnetic solver package FEKO”,Proc. Int. Appl. Computational Electromagnetics Society Symp. - Italy (ACES), Florence, Italy, March 2017, pp. 1–2.

Intelligent Ray Tracing (IRT2) Simulations with Cars vs DPM via RadioUNet



– Average difference between estimated and true/simulated radio maps (in dB): 4.80dB.

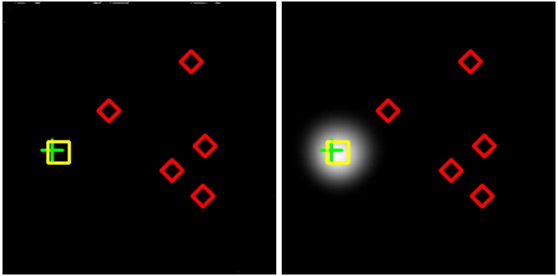
Example in DPM Scenario, positive and negative heatmaps



- Due to the choice of **LeakyRelu** as the **activation function**, the last layer before **CoM** can take negative values.
- We call the **positive** and the **negative part** of the **quasi-heatmap** **positive-heatmap** and **negative-heatmap**, respectively.

- **LocUNet Example in DPM Scenario** : We observe that the most of the energy (l_2-Norm) is concentrated in the **positive heatmap** and serves as a **belief map** about the position, while the **negative heatmap** serves a **disbelief map**, informing about where the UE is **not** likely to be located at.

Example in DPMToIRT2Cars Scenario, positive and negative heatmaps



- Due to the choice of **LeakyRelu** as the **activation function**, the last layer before **CoM** can take negative values.
- We call the **positive** and the **negative part** of the **quasi-heatmap** **positive-heatmap** and **negative-heatmap**, respectively.

- **LocUNet Example in DPMToIRT2Cars Scenario** : We observe that the most of the energy (l_2-Norm) is concentrated in the **negative heatmap(!)** (as **opposed to the previous scenario**) and now serves as a **belief map** about the position (Note that CoM is invariant to the multiplication of the quasi-heatmap by -1.)

Numerical Results (Comparison with Pathloss Fingerprint-Based Algorithms)

Table: Comparison with fingerprint-based methods.

Algorithm	MAE (m)	Run-Time (ms)
Scenario:DPM		
kNN [4]	7.01	$\sim$ 20
Adaptive kNN [5]	7.49	$\sim$ 20
LocUNet	**4.73**	$\sim$ **5**
Scenario:DPMToIRT2		
kNN [4]	23.38	$\sim$ 20
Adaptive kNN [5]	25.39	$\sim$ 20
LocUNet	**9.48**	$\sim$ **5**
Scenario:DPMToIRT2Cars		
kNN [4]	27.19	$\sim$ 20
Adaptive kNN [5]	29.51	$\sim$ 20
LocUNet	**13.15**	$\sim$ **5**

– We compare LocUNet with k-nearest neighbors (kNN) [4] method and an adaptive kNN variant [5] under the various scenarios previously described.

– LocUNet is especially good at dealing with the inaccuracies of the radio map estimations in the realistic setting (DPMToIRT2 Scenario).

[4] P. Bahl and V. N. Padmanabhan,“RADAR: An in-building RF-based user location and tracking system”, Proc. IEEE INFOCOM 2000, vol. 2, pp. 775–784

[5] J. Oh and J. Kim,“Adaptive k-nearest neighbour algorithm for WiFi fingerprint positioning”, ICT Express, vol. 4, no. 2, pp. 91 – 94, 2018, SI on Artificial Intelligence and Machine Learning”

A Remark on the performance improvement of LocUNet over kNN methods

– We attribute the **success of LocUNet** in accuracy and robustness to radio map estimations to its **fully-convolutional** nature, which takes into fully account the **neighborhood/spatial relations** in the radio map estimations, whereas the **kNN** method makes use of the spatial information **only** when the **CoM** of the **k-nearest-neighbors** are found in the final step. Note that both kNN and our method perform CoM as the last step and the found **k-nearest-neighbors** can be **interpreted** as a **heatmap.** However, the **k-nearest-neighbors** are solely **determined** by assigning each pixel a distance in the so-called signal space (RSS values) under a metric (we took the usual Euclidean, the square root of the sum of the squared residuals), which **totally disregards any spatial relation of the pixels.**
Our method, in contrast, benefits from the neighborship relations of the pixels thanks to its fully-convolutional nature and the prior information of the estimated radio maps are much more effectively utilized.

Numerical Results (Comparison with ToA Ranging-Based Algorithms)

Table: Comparison with ToA ranging-based methods which use the RadioToASeer Dataset.

Algorithm, #BS=5, $\sigma = 0.0001$, $b = 0.7$	**MAE (m)**	**(ms)**
POCS	37.89	$\sim$ **15**
SDP	**7.16**	$\sim$ 600
Robust SDP 1	7.55	$\sim$ 600
Robust SDP 2	7.63	$\sim$ 600
Bisection-based robust method	9.49	$\sim$ 16
Max. correntropy criterion method	12.45	$\sim$ 30
LocUNet Scenario:DPM	**4.73**	$\sim$ **5**

Algorithm , #BS=3, $b = 20$	$\sigma = 10$	$\sigma = 20$
POCS	47.37	48.82
SDP	24.76	39.43
Robust SDP 1	**23.95**	**36.56**
Robust SDP 2	26.96	37.81
Bisection-based robust method	25.37	38.18
Max. correntropy criterion method	31.25	45.72
LocUNet Scenario:DPMToIRT2Cars	**19.28**	

- We first evaluate ToA ranging-based methods subject to no additive ToA measurement noise.
- Then, under additive noise. $\sigma = 10, 20$m for ToA ranging-based algorithms. The number of anchor BS is here 3. Please see the longer arXiv version for the choices of the parameters and the details.

Summary

- Thanks to its **fully-convolutional** design, **LocUNet effectively utilizes radio map estimates** to achieve **state-of-the-art localization performance** and enjoys **high robustness to inaccuracies** of these input radio maps w.r.t. the actual radio maps.
- The proposed method **does not require pre-sampling of the environment**; and is **suitable for real-time applications**, thanks to the **RadioUNet**, a neural network-based radio map estimator, which can very accurately **approximate ray-tracing** simulations, but **much faster**.
- We provide two simulated **novel datasets in the urban setting** to promote **realistic assessments of performances of RSS fingerprint and ToA ranging-based algorithms.** We hope that researchers will benefit from our datasets to benchmark their proposed methods in realistic urban setting.
- To the best of our knowledge, this is the **first work in the literature to provide numerical comparisons among numerous RSS fingerprinting and ToA ranging-based methods in a realistic urban setting.**

Resources

- **The long version** *“Real-time Outdoor Localization Using Radio Maps: A Deep Learning Approach”* on **arXiv:** `https://arxiv.org/abs/2106.12556`

- **Datasets** available on **project homepage:** `https://RadioMapSeer.GitHub.io/LocUNet`

- **Code** on **GitHub:** `https://GitHub.com/CagkanYapar/LocUNet`

- **Compute capsule** on **CodeOcean:** `https://CodeOcean.com/capsule/7149386/tree`

Thank you!