



2022「中技社科技獎學金」

2022 CTCI Foundation Science and Technology Scholarship

境外生研究獎學金

Research Scholarship for International Graduate Students

Deep Learning-Based Location-Aware Services and Autonomous Drone Base Station Deployment Strategy for Beyond 5G Internet of Things Networks



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Abstract

The key aspect of our research is to develop an accurate and robust artificial intelligence-based location aware services (LASs), and an autonomous drone base station (DBS) deployment strategy to provide on demand and high-quality wireless services. This work includes two main contributions; (i) design a deep learning (DL)-based localization system to accurately figure out the devices locations in scalable environments, (ii) develop an autonomous deployment strategy for DBS based on deep reinforcement learning (DRL) to maximize network performance and communication coverage.

Research Focus

I. Localization System for Internet of Things (IoT)¹

Motivation

- ✓ A precise localization system is a key enabling technology for IoT applications and LASs.
- ✓ However, satellite-based positioning systems are not very reliable in rich-scattering environments and urban canyons.
- ✓ Thus, resulting in significant localization performance.
- ✓ Objective: design an accurate and robust DL-based fingerprinting outdoor positioning scheme in a scalable environment.

Proposed Localization System

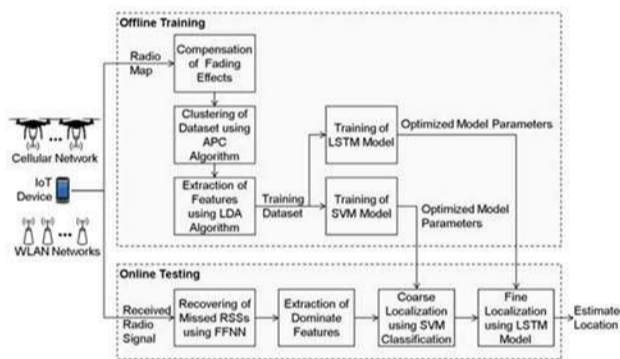


Fig 1. Overall system architecture of the proposed method.

Approach

- Short-range WLAN and long-range cellular signal fingerprints.
- Affinity propagation clustering (APC) is used for clustering the radio-map.
- Linear discriminant Analysis (LDA) for feature extraction method.
- SVM and LSTM algorithms for coarse and fine localization, respectively.

Partial Results

Table I. Positioning performance with Various Evaluation Metrics

Performance Metrics	Scheme-I	Scheme-II	Scheme-III	
Error Range	≤0.75 m	68.2%	74.12%	80.89%
Average Error (m)	≤1 m	73.5%	81.68%	91.37%
RMSE (m)	≤1.5 m	87.46%	92.74%	99.23%
Minimum Error (m)	0.74	0.46	0.42	
Maximum Error (m)	0.058	0.036	0.030	
	0.05	0.014	0.004	
	1.97	1.83	1.56	

Table II. Computation Time of the Proposed Positioning System

Scheme	Scheme-I	Scheme-II	Scheme-III
Computation time (s)	0.57	0.21	0.18

- The average error of the proposed scheme reached as low as 42 cm, and more than 91% of errors were below 1 m.

- The proposed positioning time was reduced by more than 63% by excluding insignificant features.

II. Synthetic Radio Map Construction Framework for Localization System²

- ✓ The accuracy of the localization algorithms largely depends on the quality and density of wireless radio maps. Researchers found that increasing fingerprints measurements at each reference location were increased positioning performance.
- ✓ However, dense fingerprint collection in large scale environments is time consuming and labor-intensive. Additionally, it is hard to determine how many signal fingerprints are needed to each reference location to improve positioning.
- ✓ Objective: an accurate and generalizable framework for an effective radio map construction method is proposed, which generates synthetic fingerprints from limited fingerprint measurements.

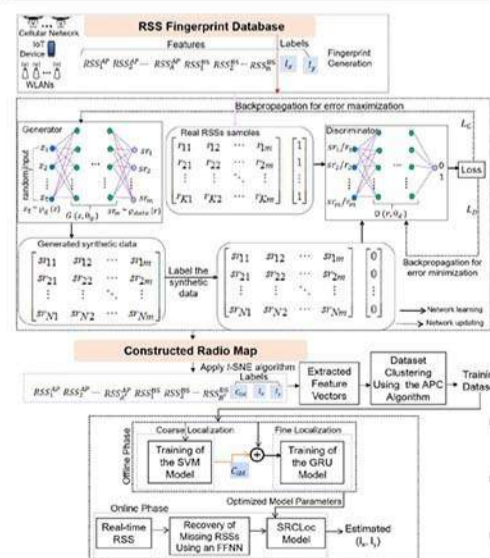


Fig 2. Structure of synthetic radio map construction method for localization system.

Approach

- Effective radio map construction framework
 - By using fewer measuring fingerprint samples and optimized deep convolutional generative adversarial nets.
- Reliable signal fingerprint feature extraction method
 - t-distributed stochastic neighbor embedding algorithm.
- SVM and GRU algorithms for coarse and fine localization, respectively.

Partial Results

- Model I- using constructed radio map features
- Model II- apply PCA on the constructed radio map
- Model III- apply t-SNE on the constructed radio map

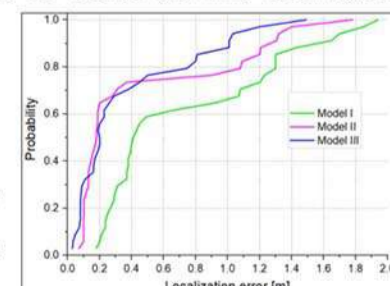


Fig 3. CDF of positioning errors under different learning methods.

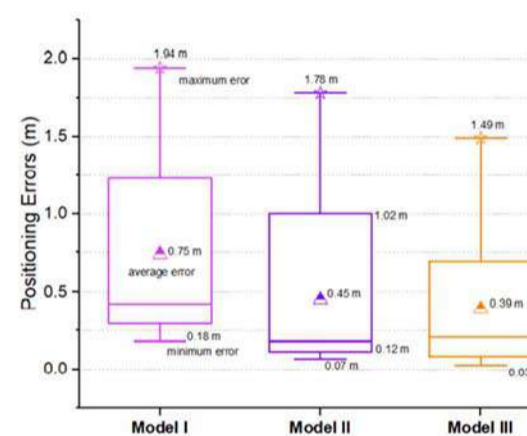


Fig 4. The distribution of positioning errors under real-time RSS readings in different positioning models (i.e., in RM7)

- Both PCA and t-SNE feature extraction techniques improve the positioning performance.
- The proposed fine positioning approach, model III, outperforms the others.
- The average positioning error is less than 39 cm, and more than 90% of the errors are less than 82 cm.
- Therefore, the combination of DCGAN, t-SNE, SVM-GRU algorithms improves positioning accuracy.

III. New Communication Paradigm with Drones³

Motivation

Drone Mounted Base Stations

- ✓ Are capable of providing wireless connectivity even without network infrastructure.
- ✓ Can adjust their locations quickly according to the distribution and movement of ground users.
- ✓ Enable flexible deployment in response to the spatial and temporal data traffic unevenness and in emergency communication scenarios

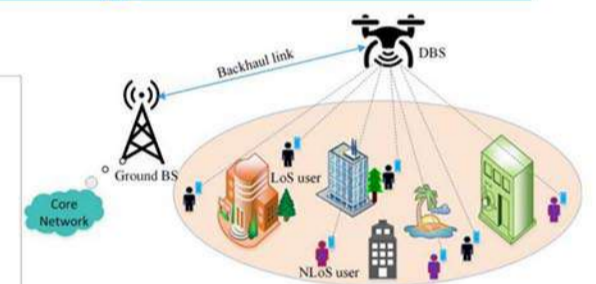


Fig 5. Drone-aided wireless communications system.

- Objective: maximizing the communication coverage and network throughput of ground IoT devices.

$$\arg \max_{L_d} \sum_{t=1}^K \Gamma_{u,d}(L_d) \times m_{u,d}(L_d)$$

- s.t. C1: $\Gamma_{u,d} \in \{0,1\}, \forall u \in K, \forall t$,
- C2: $P(C_d | u \in K) \cong 100\%$,
- C3: $m_{u,d} \geq m_{th}, \forall u \in K, \forall m \in M, \forall t$,
- C4: $M=0,1,2,\dots,m$,
- C5: $h_d^{min} \leq h_d \leq h_d^{max}, \forall t$,
- C6: $0 \leq u_{speed} \leq V_{max}$,

Partial Results

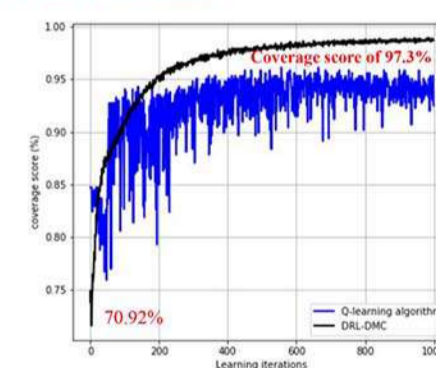


Fig 7. Communication coverage score.

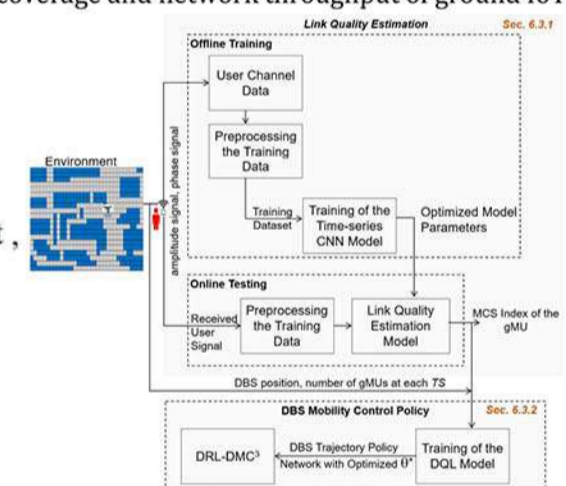


Fig 6. Proposed DRL-DMC³ method.

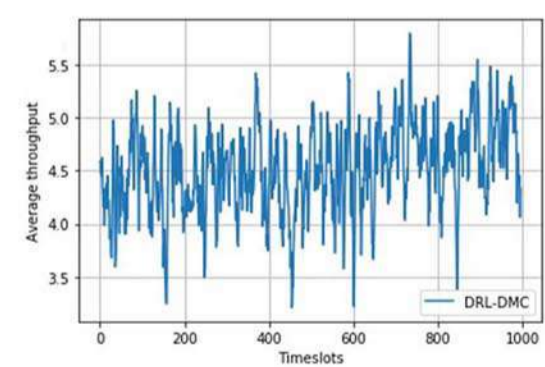


Fig 8. Average throughput performance in the movement scenario.

Publications

1. G.B. Tarekegn, R.-T. Juang, H.-P. Lin, A. B. Adege, and Y. Y. Munaye, "D_{FOPS}: Deep Learning-Based Fingerprinting Outdoor Positioning Scheme in Hybrid Networks," *IEEE Internet of Things J.*, vol. 8, no. 5, pp. 3717-3729, Mar. 2021.
2. G.B. Tarekegn, R.-T. Juang, H.-P. Lin, L.-C. Tai, Y. Y. Munaye, and M. A. Bitew, "SRCLoc: Synthetic Radio Map Construction Method for Fingerprinting Outdoor Localization in Hybrid Networks," *IEEE Sensors Journal*, vol. 22, no. 15, pp. 15574-15583, Aug. 01, 2022.
3. G.B. Tarekegn, R.-T. Juang, H.-P. Lin, Y. Y. Munaye, L.-C. Wang, and M. A. Bitew "Deep Reinforcement Learning-Based Drone Base Station Deployment for Wireless Communication Services," *IEEE Internet of Things J.*, vol. 9, no. 21, pp. 21899-21915, Nov. 01, 2022.

