ISSN:3007-9640 DOI: https://doi.org/10.70114/acmsr.2025.2.1.P209

A REM Based Localization Method of Emitter Outside the Sensing Boundary

Ying Gao [1, a] *, Longyu Niu [1, b], Xiao Wang [1, c], Tianqi Wang [1, d], and Biwu Chen [1, e]

[1] Department of Shanghai Radio Equipment Research Institute, Shanghai, China.

[a] gaoying0303@outlook.com, [b] 1246912178@qq.com, [c] xiaowanghit@163.com, [d] tianqiwang205@163.com, [e] cbw_think@whu.edu.cn

Abstract. As a visual representation of the electromagnetic spatial situation, a radio environment map (REM) integrates multi-dimensional radio scene information, clearly presents the distribution and utilization of spectrum resources through visualization. It can provide a large database for electromagnetic awareness analysis in electromagnetic environments. Although REMs have demonstrated their advantages in coverage optimization problem, most existing REM construction methods are primarily based on scenarios where the positions of transmission sources are known. Positioning methods based on REMs for emitters is greatly affected by the distribution of sensing terminals. For the case where emitter is outside the sensing boundary, the positioning accuracy is difficult to guarantee. Therefore, REM-based positioning techniques for transmission sources need further investigation. In this paper, we introduce an emitter localization method in the urban area based on the REM, combining with Kriging interpolation, and fitting the channel loss as a spatial random process with the spatial process drift and zero-mean spatial random fluctuations, locate the source of the emission that have no sensing data around. Simulation results show that this method can effectively localize the emitter.

Keywords: Electromagnetic space; radio environment map; emitter localization; barrier functions.

1. Introduction

Electromagnetic space, as an indispensable part of modern national space, has increasingly evolved as one of the primary arenas for human social activity during the information and intelligent ages. With the rapid expansion of the number of electromagnetic frequency equipment and systems, the structure of electromagnetic space has become increasingly complex and variable, forming a complex system of close interconnection and interaction interwoven by multiple subjects, various factors, and variables, in which the elements are input and output of each other, jointly shaping the dynamic and complex electromagnetic environment.

The concept of Radio Environment Maps (REMs) was first proposed by the U.S. Virginia technical team, aiming to build a database integrating multi-dimensional information such as device location and behavior, spectrum policy, geographic features and spectrum resources, and providing external assistance for cognitive radio networks [1]. Based on REMs data, French telecom company Orange Labs has developed a visual spectrum environment map using spatial correlation for data parsing and completion [2]. The Georgios B. Giannakis team at the University of Minnesota further expands the functions of REMs, obtaining spectrum density and channel gain maps through spatial, temporal, and frequency three-dimensional analysis to enhance the cognitive radio system's idle spectrum identification, user positioning, transmit power estimation, etc [3].

REM aids in optimizing the utilization of geolocation data, enhancing the effective management of spectral resources within wireless communication systems. It serves as a database containing

ISSN:3007-9640 DOI: https://doi.org/10.70114/acmsr.2025.2.1.P209

geo-located information, which is crucial for dynamic spectrum access in Cognitive Radio (CR) systems. REM facilitates decision-making across multiple applications, such as optimizing coverage[4], allocating resources [5], analyzing interference [6], estimating locations [7], and so on. The evolution of REM technology has been pivotal in advancing CR technology and enhancing the efficiency and reliability of wireless communication systems.

In [8], the authors using 49 sensors located into a 7×7 grids map. The emitter is located inside a grid, and when the activated sensor number reached 46, the error of the position is about 1m. In [9], the authors used received signal strength (RSS) and received signal strength difference (RSSD) to generate the REM, and in [10], the authors proposed a method to using the highest signal level sensors location and marked on the map, find the center of the polygon as the emitter location. While there's no sensing information near the emitter and the location of it is far from the center of the sensing boundary, the positioning capability will be decreased, so REM based emitter location algorithm still need to be explored.

The arrangements of this paper are as follows: Section 2 establishes the network architecture, Section 3 presents numerical simulation results. Finally, summary is drawn in Section 4.

2. Network Architecture

2.1 REM Model

To construct a REM, one approach known as "crowdsourcing" involves collecting wireless signal data from a large number of mobile devices or other wireless sensors distributed across a specific area. For instance, smartphones are often utilized due to their low cost and widespread availability. The collected data is then aggregated and analyzed to generate an REM that can be applied to various wireless applications. Crowdsourcing facilitates the efficient collection of data from multiple sources over a broad geographic region, like Fig.1 shows. [11]

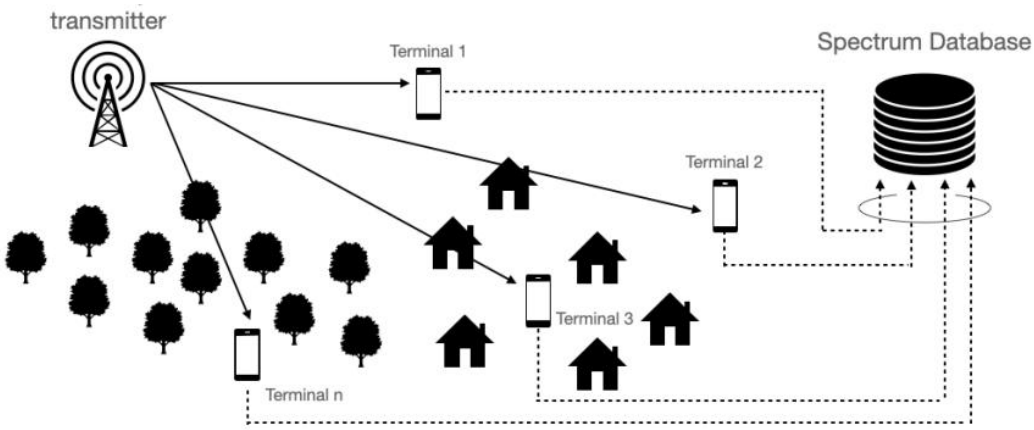


Fig.1 A concept of crowdsourcing

After collecting data from several devices, the spectrum database can base on the data information construct the REM.

2.2 Kriging Model

Ordinary Kriging is one of the most popular way to do the spatial interpolation for the REM. The method to interpolate the unknown value is like follows,

$$\widehat{P}(s_j) = \sum_{i=1}^{N} \omega\,(i) P(s_i), \tag{1}$$

where, $\omega(i)$ is the weight factor of the i-th terminal multiplied by the known value $P(i)$, and $\hat{P}(s_j)$ is the interpolated value of $P(s_j)$. Kriging minimizes the estimation error by optimizing the

ISSN:3007-9640 DOI: https://doi.org/10.70114/acmsr.2025.2.1.P209

$\omega(i)$. Additionally, ordinary Kriging assumes that $\mathbb{E}[P(s_i)] = \text{const.}$ over any i, besides, the spatial correlation property of $P(s_i)$ is static over the entire measurement area.

2.3 Emitter Localization Model

The received signal power can be regarded as the result of the transmitting source energy passing through the channel loss, which we model here as,

$$Q(\boldsymbol{s}) = \gamma(\boldsymbol{s}) + \xi(\boldsymbol{s}), \text{with } \boldsymbol{s} \in D, \tag{2}$$

where, $\gamma(s)$ denotes the spatial process drift, which is often known as the trend in geo-statistical terminology, $\xi(s)$ consists of the zero-mean spatial random fluctuations of the spatial model, which can be considered as shadowing effect. D indicates the 2-dimensional spatial domain, which can be considered as coverage region of interest. $\gamma(s)$ can be expressed as,

$$\gamma(\boldsymbol{s}) = P_{T_x} - \eta f(\boldsymbol{s}) = P_{T_x} - 10\eta log_{10}\left(d_{s_{T_x},s_i}\right), \tag{3}$$

where, P_{T_x} indicates the unknown emitter power, η presents the unknown pass-loss index, $d_{s_{T_x},s_i}$ presents the distance between the emitter and the receiver, the emitter location is unknown, and the receiver location is known.

Based on above knowledge, we presents a parameter estimation method based on nonlinear optimization, aimed at minimizing the sum of squared errors of a target function that is defined by receiver position coordinates $s_i(x_i, y_i)$, received power $Q(s)$, and the unknown parameters including transmission power P_{T_x}, path-loss exponent η, and emitter position s_{T_x} by using the data from the observation and interpolation (inside the sensing boundary).

Specifically, we first define an objective function that calculates the difference between the predicted values and the actual observations given the parameters, the objective function can be defined as,

$$f(\boldsymbol{m}) = \sum_{i=1}^{n}\left(P_{T_x} - 10\eta log_{10}\left(\sqrt{(x_i - x_0)^2 + (y_i - y_0)^2}\right) - Q(s_i)\right)^2, \tag{4}$$

where m is a vector containing four parameters $m = \left[x_0, y_0, P_{T_x}, \eta\right]^T$, we set the boundary constraints, in order to define the range of values of each variable has practical significance.

Next, we use Barrier Functions based Interior-Point Method to do the optimization. The Lagrange multipliers and Lagrangian function can be defined as,

$$L(\boldsymbol{m}, \lambda, \mu, \nu) = f(m) + \sum_{i=1}^{r}\lambda_i\, c_i(\boldsymbol{m}) + \sum_{j=1}^{p}\mu_j\left(\boldsymbol{m_j} - l_j\right) + \sum_{k=1}^{q}\nu_k\,(u_k - \boldsymbol{m_k}), \tag{5}$$

where $c_i(m)$ are inequality constraints, r is the number of inequality constraints, p is the number of lower bounds on the variables, and q is the number of upper bounds on the variables. A barrier function $\phi(m)$ can be defined as,

$$\phi(\boldsymbol{m}) = -\sum_{j=1}^{p}\log\left(\boldsymbol{m_j} - l_j\right) - \sum_{k=1}^{q}\log\left(u_k - \boldsymbol{m_k}\right), \tag{6}$$

where $m_j - l_j$ and $u_k - m_k$ are the distances to the lower and upper bounds, respectively. Finally, we solve the following unconstrained optimization problem,

$$\min_{\boldsymbol{m}}[f(\boldsymbol{m}) + \zeta\phi(\boldsymbol{m})], \tag{7}$$

where ζ is the barrier parameter, gradually reduce until convergence criteria are met.

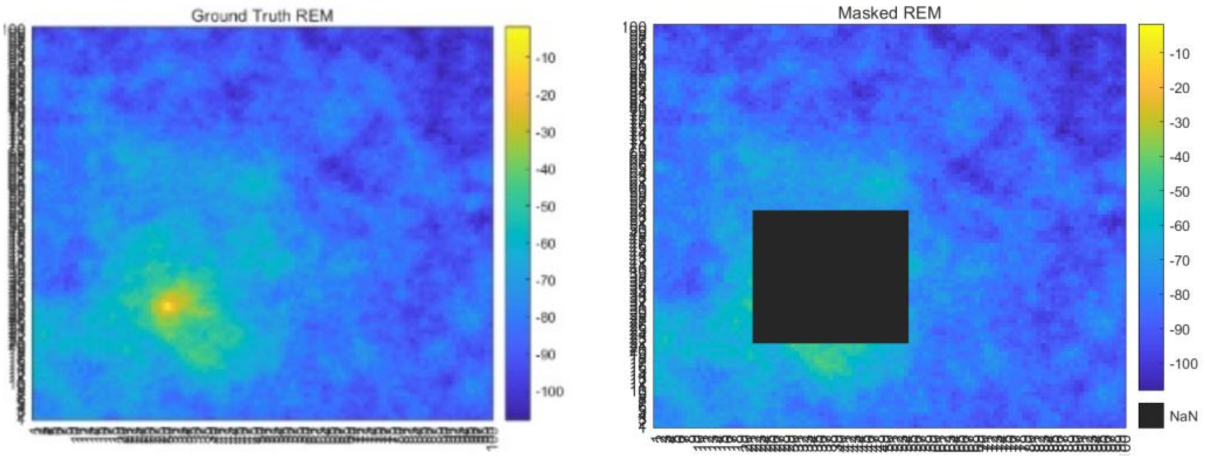
3. Experiment and Discussion

In this section, we give several simulations to check the performance under different conditions. We set the interested communication area is 500m × 500m. And we set the emitter location to (147,147). We masked a 165m × 165m area， where near the emitter and without any sensing information. The Ground truth radio map is generated by 10000 dataset, shown as Fig.2 (a), the masked area is shown as Fig.2 (b). The parameters are shown as Table 1 below.

Table 1. Simulation parameters

ISSN:3007-9640 DOI: https://doi.org/10.70114/acmsr.2025.2.1.P209

Obeserved area [m^2]	500 × 500	Center frequency [GHz]	3.5
Masked area [m^2]	165 × 165	Pass-loss index	4.5
Emitter loacation [m]	(147,147)	Standard deviation of W	6
Transmission power [dBm]	29	Reference diatance [m]	10

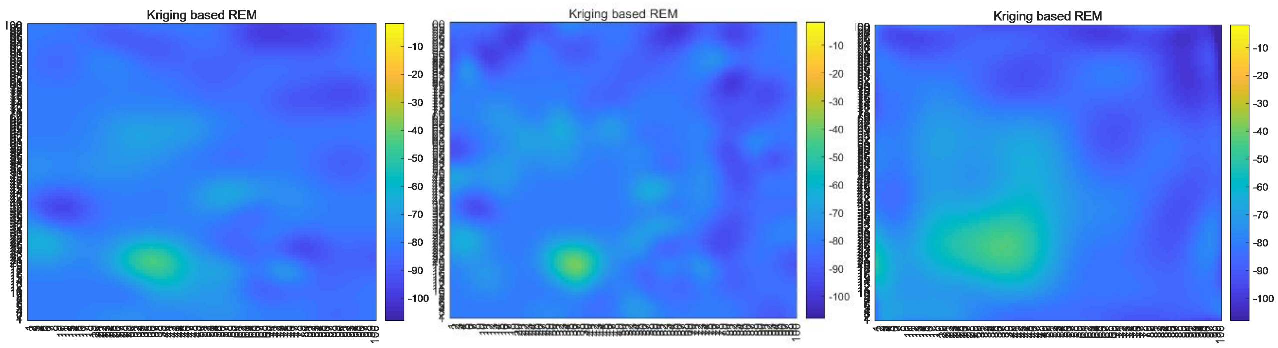


(a) (b)

Fig.2 (a) Ground truth REM (Generated by $N = 10000$ data); (b) Masked REM (remove data in the masked place)

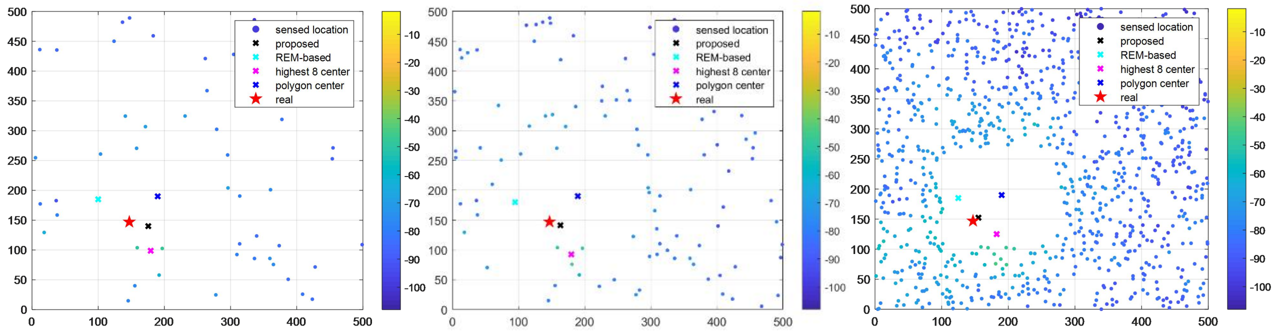
We compared our proposed method with some other localization methods: 1) REM based method: find the point with the highest value in the heatmap and output the coordinates of it as the emitter location; 2) highest 8 center method: find the highest value points in the north, south, east, west, northeast, northwest, southeast, and southwest 8 different directions, and then form a polygon with these eight points and take the coordinates of the center point as the location of the emitter; 3) polygon center method: take the center point of the polygon surrounded by edges of sensing.

Fig.3 represents the Kriging based REM and the location estimation results. Fig.3 (a) to (c) represent the Kriging based REM when the dataset size increased from 50 to 1000, respectively. The sensed data information is illustrated by the filled points with color bar in Fig.3 (d) to (f), the x marks are the estimated position of the emitter by different methods, and the red star mark is the real position of the emitter, the number of used dataset also increased from 50 to 1000, respectively. The emitter location errors (distances between estimated positions and the real position) are described in Table 2.



(a) (b) (c)

ISSN:3007-9640 DOI: https://doi.org/10.70114/acmsr.2025.2.1.P209



(d) (e) (f)

Fig. 3 (a) REM constructed by Kriging (N = 50); (b) REM constructed by Kriging (N = 100); (c) REM constructed by Kriging (N = 1000); (d) Localized result by N = 50; (e) Localized result by N = 100; (f) Localized result by N = 1000.

Table 2. Emitter location error

Unit(m)	N = 50	N = 100	N = 1000
proposed	29.5327	17.1459	9.7925
REM based	60.4401	61.5873	43.9090
highest 8 center	58.1051	63.7122	41.7642
polygon center	60.8112	60.8112	60.8112

Although Kriging interpolation is known as one of the best interpolate method for geo-location concerned problem, when there's no sensing information near the emitter, Kriging may select the point with the highest value as the emitter instead. This will lead a big error when the emitter is far from the center of the un-sensed area polygon. Our proposed method solved this problem by combining with the channel estimation, and illustrated a better performance.

4. Summary

In this paper, we introduced a localization method for emitter by using Kriging interpolation combined with barrier functions based interior-point channel estimation method. Kriging is used in REM construction and solve the transformation problem of discrete sensed point to the whole map, and channel estimation helps Kriging interpolation overcome the constraint of the highest sensing value. Simulation results illustrate when the emitter is far from the center of the un-sensed area, this method has a good performance.

Acknowledgements

This work was supported by the National Natural Science Foundation of China (42301467).

References

[1] Defense Advanced Research Projects Agency (DARPA). (n.d.). Advance RF Mapping [Web page]. Retrieved September 26, 2024, from https://www.darpa.mil/program/advance-rf-mapping.

[2] A. Galindo-Serrano, B. Sayrac, S. Ben Jemaa, J. Riihijärvi and P. Mähönen, "Harvesting MDT data: Radio environment maps for coverage analysis in cellular networks," 8th International Conference on Cognitive Radio Oriented Wireless Networks, Washington, DC, USA, 2013, pp. 37-42.

[3] P. Kaniewski and E. Golan, "Localization of Transmitters in VHF Band Based on the Radio Environment Maps Concept," 2019 Communication and Information Technologies (KIT), Vysoke Tatry, Slovakia, 2019, pp. 1-6.

ISSN:3007-9640 DOI: https://doi.org/10.70114/acmsr.2025.2.1.P209
[4] H. Braham, S. B. Jemaa, G. Fort, E. Moulines and B. Sayrac, "Fixed Rank Kriging for Cellular Coverage Analysis," in IEEE Transactions on Vehicular Technology, vol. 66, no. 5, pp. 4212-4222, May 2017.

[5] E. Dall'Anese, S. -J. Kim and G. B. Giannakis, "Channel Gain Map Tracking via Distributed Kriging," in IEEE Transactions on Vehicular Technology, vol. 60, no. 3, pp. 1205-1211, March 2011.

[6] K. Sato and T. Fujii, "Kriging-Based Interference Power Constraint: Integrated Design of the Radio Environment Map and Transmission Power," in IEEE Transactions on Cognitive Communications and Networking, vol. 3, no. 1, pp. 13-25, March 2017.

[7] F. Burmeister, Z. Li, N. Schwarzenberg, A. Traßl, R. Jacob and G. Fettweis, "Quantifying the Impact of Localization Error on Indoor Channel Prediction Using REMs," GLOBECOM 2022 - 2022 IEEE Global Communications Conference, Rio de Janeiro, Brazil, 2022, pp. 5372-5377.

[8] Ezzati, N., Taheri, H., Tugcu, T.: Optimised sensor network for transmitter localisation and radio environment mapping. The Institution of Engineering and Technology, IET Communications, pp. 2170–2178, 10(16) (2016).

[9] S. Alfattani and A. Yongacoglu, "Indirect Methods for Constructing Radio Environment Map," 2018 IEEE Canadian Conference on Electrical & Computer Engineering (CCECE), Quebec, QC, Canada, 2018, pp. 1-5.

[10] M. Suchanski, P. Kaniewski, J. Romanik, E. Golan and K. Zubel, "Radio Environment Maps for Military Cognitive Networks: Deployment of Sensors vs. Map Quality," 2019 International Conference on Military Communications and Information Systems (ICMCIS), Budva, Montenegro, 2019, pp. 1-6.

[11] Y. Gao and T. Fujii, "A Kriging-Based Radio Environment Map Construction and Channel Estimation System in Threatening Environments," in IEEE Access, vol. 11, pp. 38136-38148, 2023.