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Spectrum map construction optimisation schemes: Sampling and prediction

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Abstract. The proliferation of electromagnetic devices presents a significant challenge in developing effective techniques for spectrum monitoring, management, and security. The utilization of spectrum cartography has been acknowledged as a viable approach to address the aforementioned difficulties. This latter presents a variety of techniques aimed at enhancing the efficiency of the current spectrum mapping methodology. The subject matter can be categorized into two primary components, namely sampling and spectrum prediction. Sampling part includes methods to find the most valuable sampling points and methods of sampling hardware optimization. Spectrum prediction includes algorithms utilizing frequency-spatial reasoning techniques to estimate the target spectrum map by data from the nearby area, and algorithms utilizing ROSMP framework to estimate the spectrum map from past data. The introduction of techniques is divided into the 2 types, together with key algorithms and devices used in each method. Additionally, the letter lists some drawbacks of certain methods and discuss their development prospects.

Keywords: spectrum mapping, compressed sensing, QR block pivoting.

1. Introduction

With the rapid proliferation of intelligent terminals and the variety of ultra-wideband applications, the sixth generation (6G) wireless communication networks are facing significant challenges in spectrum mapping [1-3]. A spectrum map is a representation of the spatial distribution of the received signal intensity by projecting the received signal strength to the appropriate geographic coordinates in an area of interest. It can give details about how spectrum resources are used as well as how signal sources are distributed in an electromagnetic field [4-6]. Spectrum efficiency may be greatly increased by using spectrum maps to intelligent spectrum management [7,8]. According to the Federal Communications Commission (FCC), significant quantities of spectrum are not being used, incorporating analogue cellular phone and broadcast TVs, among other things [9], [10]. The objective of spectrum mapping is to generate a comprehensive spectrum map by leveraging spectrum situation awareness. This technology allows for the correlation of awareness outcomes with three-dimensional (3D) geographic locations in a corresponding manner. The utilization of spectrum maps enables radio frequency (RF) devices to effectively access unoccupied spectrum and circumvent areas with high levels of interference [11]. Consequently, it is unquestionable that, the development of spectrum mapping is vital and urgently needed in wireless communication research, which intends to create a spectrum map of interested regions to manage the spatial spectrum resources efficiently [12]. There are two main aspects can be taken into consideration to tackle with the spectrum mapping issues. One is about sampling, and the other one is about spectrum estimation algorithms. The following letter will introduce new methods in the 2 aspects respectively.

2. Optimization for sampling methods

The spectrum map, which can be thought of as a visible cartography based on the geolocation database, relies on sensors gathering power measurements to estimate the spectrum utilization in a certain area and determine the distribution of signal strength, so that it can be improved by optimizing the sampling session [11].

The first group of methods is about the algorithms to find the most valuable sampling points. Undoubtedly, the whole three-dimensional spectrum situation map will be precisely produced if the spectrum monitoring equipment performs a comprehensive sampling of the entire space, but at a significant energy and resource cost [11-13]. Conforming to Nyquist's sampling theory, it is imperative for the sample rate to be at least twice the bandwidth of the signal. Achieving Nyquist rate sampling becomes exceedingly challenging for a receiver with restricted power and hardware capabilities, particularly when confronted with a spectrum of considerable bandwidth that need monitoring. In contrast to Nyquist theory, compressed sensing (CS) [14-16], alternatively referred to as compressed sampling, obtains random discrete samples of the signal. These aforementioned samples are subsequently employed in a nonlinear reconstruction technique in order to replicate the original signal. The utilization of the signal's sparsity enables the CS method to attain significant signal reconstruction capabilities, especially when the number of measurements is limited. This aligns with our objective of approximating the complete three-dimensional wideband spectrum landscape by utilizing as few spectrum sample points as possible [11,17]. Furthermore, the utilisation of spatial diversity in transceivers can facilitate the allocation of the complete frequency spectrum to many users. This allocation strategy effectively reduces the spectrum sampling cost for each transceiver, hence enhancing overall sampling efficiency [11,17].

In [11], by leveraging the concept of joint sparsity in both spatial and frequency domains, the 3D compressed wideband spectrum mapping model is initially converted into a compressed sensing optimization problem that encompasses the space, frequency, and time domains simultaneously. Then, to optimize the spatial sampling sites, a QR block pivoting is used. Since there is typically little coherence across distinct frequency points, arbitrary frequency point selection is employed for every spatial position [11,17]. The choice of the spatial sample point, however, has a higher influence on the accuracy of scenario recovery since the 3D wideband spectrum situation has a strong correlation in the spatial domain, as stated by the law of signal propagation. Such that, achieving comparable performance to random sampling can be attained by utilizing a smaller number of sample locations, provided that the selected sampling locations effectively leverage the inherent qualities of the spectrum situation. After that, the reconstruction of the 3D wideband spectrum situation uses the alternating direction approach of multipliers. This method is tested to deliver superior spectrum situation recovery performance compared to conventional algorithms' shortcomings [11,17].

However, the method presented in [11] using right-triangular (QR) pivoting and quadrature, information loss will become the result of dimension reduction for guaranteeing the sparse matrix's column space size is no bigger than the sampling number. Additionally, the precision of the signal source localization is overemphasized in the spectrum situation recovery, which compromises the accuracy of signal strength assessment. Besides that, every spatial point inside the entire space is regarded as accessible which overlooks the condition that it seems to be impracticable for data-driven spectrum mapping in unauthorized locations where spectrum monitoring equipment are unable to cross the boundary for measurement [12].

In [12], the RCSM algorithm is introduced to optimize the sampling location and deal with the obstacle of inaccessible places. This correspondence discusses the implementation of distant spectrum mapping in a three-dimensional (3D) setting, with the objective of obtaining a comprehensive and

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precise 3D spatial power map of inaccessible regions, as depicted in Figure 1. First, the 3D space is converted into a spectrum power tensor, then denote the set of all distinct sample locations and assume the set of unreachable areas [12]. Secondly, given the lightweight nature and agile mobility of Unmanned Aerial Vehicles (UAVs), the utilization of UAVs is proposed to strategically choose sample places within accessible regions, so enabling the restoration of spatial power in areas that are otherwise inaccessible. Spatial power strength that is obtained is a result of combining signals from various points inside the designated three-dimensional space. This motivates us to exploit the inherent sparsity of spatial power distribution in order to undertake the subsequent investigation on remote spectrum mapping. In this section, an algorithm called the remote compressed spectrum mapping algorithm (RCSM) is proposed. This algorithm consists of two main components: optimization of spatial sample locations and estimation of spatial power in inaccessible areas [12]. Locating the sampling sites can be transformed to a greedy optimization problem. The greedy algorithm chooses a sampling location for each iteration that, when coupled with previously selected locations, maximizes the determinant. Finally, the simulation demonstrates the RCSM algorithms' superiority over conventional methods [12].

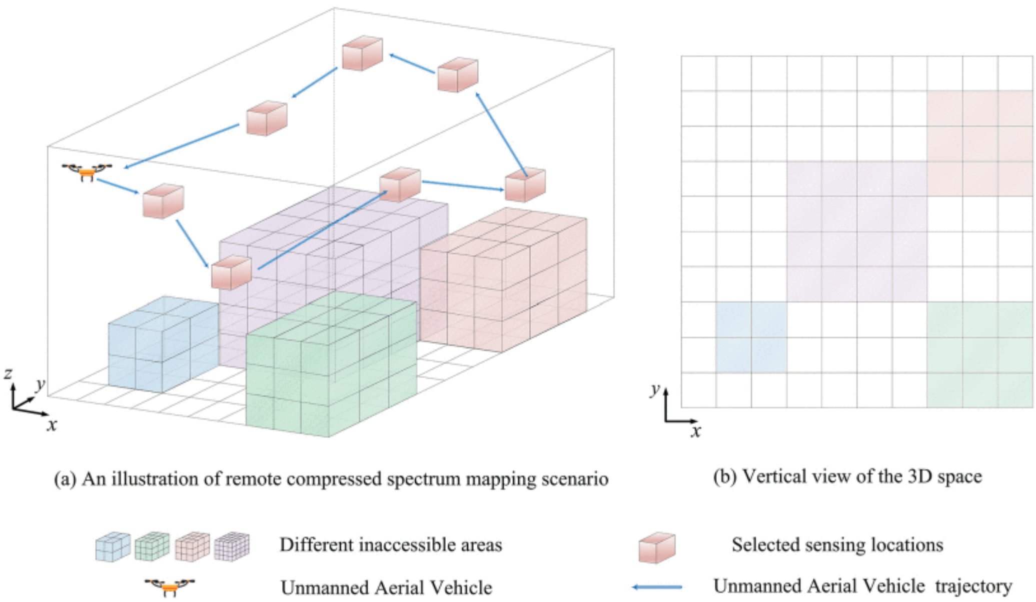

Figure 1. Graphical illustration of remote compressed spectrum mapping [21].

The second group of methods is about enhancing the sensors which are used to get raw data from sample points. The acquisition of raw data from the target location is an essential stage in spectrum cartography. In [18], a large amount of ground sensors was widely spread out, then saved the data for later analysis in a database. While the data in [19] was collected either by individual mobile users or by moving vehicles. Nevertheless, due to the short sample duration, spectrum cartography requires the pre-processing of raw data to forecast and complete the missing data. The techniques mentioned above solely concentrate on creating two-dimensional (2D) maps using information gathered from the ground or from sources of low-altitude radiation. The inclusion of aerial communication platforms should be given due consideration while examining the expansion of space-air-ground integrated communication networks, as they contribute to the development of a comprehensive 3D spectrum map [20].

In [20], a prototype for a spectrum mapping system based on unmanned aerial vehicles (UAVs) is introduced. The system is designed to autonomously navigate along a predetermined path and collect three-dimensional data on the electromagnetic spectrum. A UAV platform, a radio monitoring module, an air-to-ground (A2G) communication module, and a ground processing terminal comprise this system, as shown in Figure 2. The radio monitoring module created in [20] is attributed to its advantageous characteristics, including high mobility, low cost, and ease of deployment. It can gather and store

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spectrum data from 200 kHz to 8 GHz using a changeable antenna [20]. The A2G communication module is responsible for transmitting the gathered spectrum data and additional information to the data processing unit. Simultaneously, it receives the up-link control command. Finally, the spectrum map is created and shown by the ground processing module. This system predicts, completes, and merges the spectrum data before sending it to the cloud servers, where it is then used to rebuild a complete radio map spanning many domains, and shows significant advantages in managing radio frequency resources, determining the location of radiation sources, and detecting anomalous spectral activity [20].

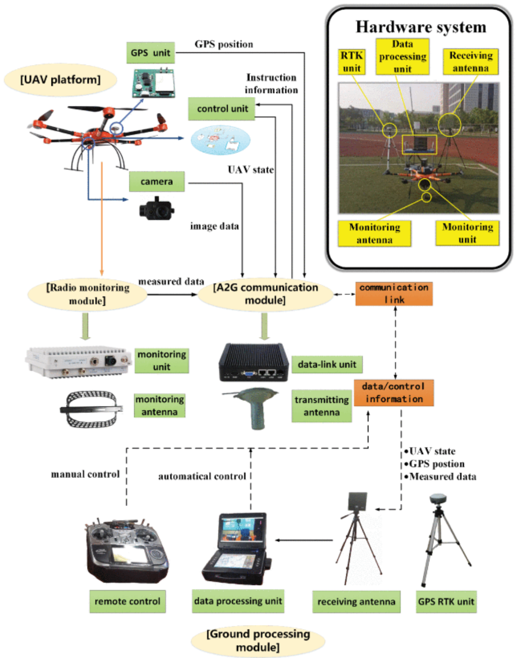

Figure 2. An overview of Hardware architecture [20].

3. Optimization for prediction algorithms

The vital work of spectrum mapping is to collect geo-localized measurements from disparate spectrum sensors and estimate the status of geographical places where measurement data is lacking, so that spectrum prediction algorithms need to be taken into consideration [21]. The existed approaches for creating spectrum maps can be categorized into two types: classic schemes that rely on spatial correlation, and schemes that combine frequency and spatial correlation. Nevertheless, the procedures that are based on spatial correlation necessitate the availability of measurement data inside the target sample region. In cases where there is a lack of signal information pertaining to the target frequency, the construction of spectrum maps becomes unfeasible. In contrast, the bulk of past endeavours have mostly utilized frequency correlation as a means of generating spectrum maps. However, it is important to note that this approach does not provide a guarantee of correctness in the absence of substantial data from the target [1,21,22].

The current joint frequency-spatial correlation-based systems that just employ frequency correlation without considering how differently frequencies fade throughout propagation. Two precise approaches for creating spectrum maps are put forward in [1] utilizing various frequency-spatial reasoning techniques. Also, to make the full use of frequency and spatial correlations completely and properly generate the target spectrum map, in [1], a model for representing joint frequency-spatial spectra is established. After that, two neural networks, namely a novel Conditional Generative Adversarial Network (CGAN) and a novel autoencoder, are constructed with the purpose of introducing two intelligent frequency-spatial reasoning approaches [1]. As for the method based on the novel autoencoder, the steps are shown in Figure 3. In this method, the spectrum maps are arranged in layers

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along the third dimension, taking into account the numerical relationship between frequencies within a certain fundamental radio propagation scenario. This makes single spectrum maps to be efficiently correlated throughout the frequency domain, and radio propagation environment frequency characteristics can be learnt in a three-dimensional (3D) structure. The proposed approach utilizes an autoencoder network to investigate the frequency and spatial features of the radio propagation environment. By training the model on these datasets, it acquires a comprehensive understanding of these properties, ultimately facilitating the generation of the desired spectral map. As for the method based on the novel CGAN, it shares the same progress of data collecting in 3D with the former method. The process of training the model involves the application of the generative adversarial training principle in the unique Conditional Generative Adversarial Network (CGAN), as depicted in Figure 4. Both sub-networks acquire knowledge about the radio propagation environment by earning the frequency fading characteristics in the frequency dimension and the spatial fading characteristics in the other geographical dimensions. The underlying notion guiding this approach to network parameter optimization is that, modifying the parameters of the discriminator and generator networks iteratively via backward propagation. This process aims to enhance the discriminating and construction performance of both sub-networks using a game-like mechanism. The primary objective of training the generator is to ensure that its generated output closely resembles the distribution of real spectrum data found in the datasets. This is done in order to make it difficult for the discriminator to differentiate between the artificially made false samples and the authentic ones. The objective of the discriminator training is to effectively ascertain the authenticity of the input 3D spectrum representation samples, distinguishing between actual and artificially generated data. Both two methods can capture intricate radio propagation features and rationalize the data distribution of target spectrum maps which accomplish a trade-off between computing speed and construction accuracy, making them suited for processing 3D data [1].

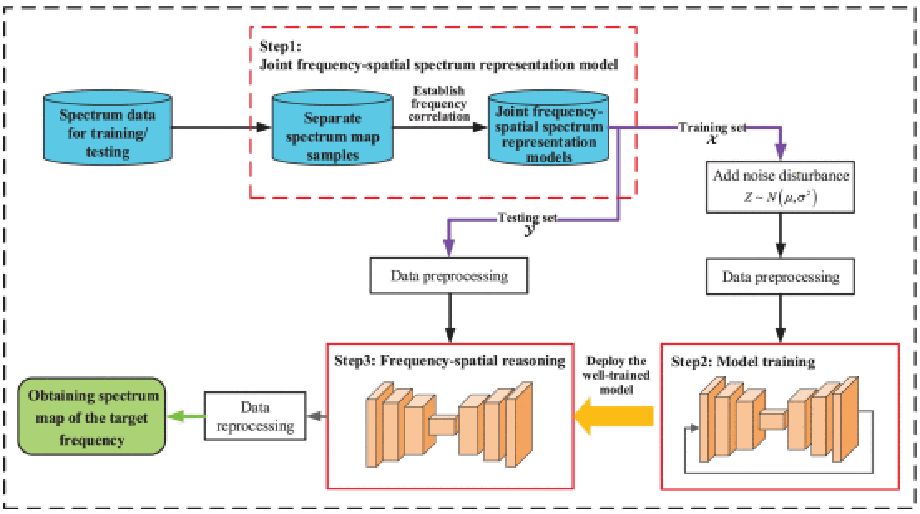

Figure 3. The proposed accurate spectrum map construction scheme using an intelligent frequency-spatial reasoning method [1].

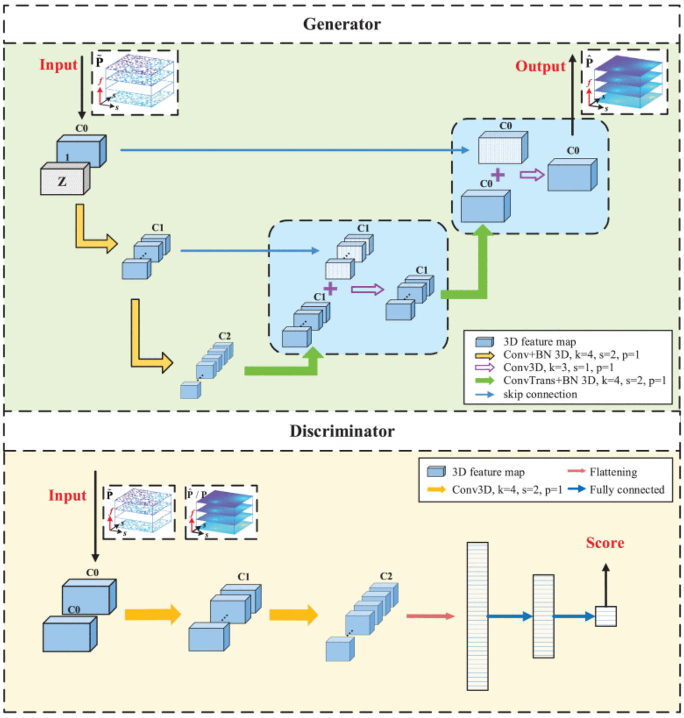

Figure 4. The proposed autoencoder structure [1].

Besides that, in [21], a non-parametric algorithm is introduced for creating spectrum maps. The received signal power is modelled as a linear combination of centred power functions at different places, and the weights, centroid locations, and exponent are simultaneously optimized using an alternating minimization approach. Similar to RBF-based approaches [23], the received signal power is modulated at each point as a weighted contribution from various functions. The K-means++ method [24] is used to meaningfully initialize the centroids positions while avoiding the performance instabilities caused by random selection. This non-parametric method is inspired by the functional form of most route loss models, and it is independent of transmitter and propagation environment factors.

Different from the above methods which need the frequency-special data at presence, in [25], a new method using the past data is introduced. Through the examination of the inherent structure of previous observations, the process of spectrum map prediction has the ability to estimate the spectrum map at every given point in time. The new method uses the reliable online spectrum map prediction (ROSMP) framework, which enables accurate spectrum map prediction even with faulty and incomplete historical observations [25], as shown in Figure 5. The problem of spectrum map prediction based on incomplete and incorrect historical observations is formulated as a joint optimization problem of tensor completion and subspace learning by effectively integrating the time series forecasting techniques. A robust online spectrum map prediction algorithm is designed by taking an alternating direction minimization procedure to efficiently solve the optimization problem.

[25]. In [25], a definition called tensor is used as cornerstone, which is firstly introduced by [26]. As the frequency and time, which are also crucial factors for the spectrum data, cannot be reflected, and the spectrum map just depicts the distribution of the signal intensity in space. Tensor pattern is introduced in [26] to demonstrate the expansion of work conducted on a two-dimensional spectrum map to encompass a three-dimensional or higher-dimensional spectrum map, thereby effectively representing the multi-dimensional characteristics inherent in spectrum data. In [26], a new approach to recover the spectrum map from the insufficient received signal strengths is introduced. The spectrum map prediction can be transformed into a tensor completion problem [26]. Then, there are many algorithms in other filed can be invoked such as the new multi-dimensional CS reconstruction formula from [27] and so on.

The algorithm presented in [28] seems to be the best choice as the simulation recommends, since it can predict larger missing areas of the spectrum data by functioning with fewer samples [26].

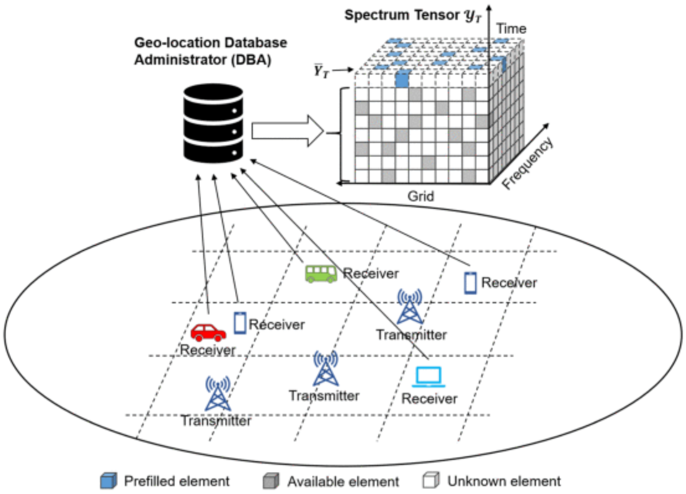

Figure 5. An exemplary database-driven spectrum map prediction system [25].

4. Conclusion

In this paper, several methods are introduced to optimize the existing spectrum mapping approach. They can be divided in two main aspects, one is about sampling, and the other is about spectrum prediction. In the first part, the sampling session can be improved both by finding the most valuable sample points and enhancing the sensor to get more accurate and comprehensive raw data. In the second part, the prediction session can be improved by using different algorithms. The need of raw data by these algorithms is also different. Because of this, all sorts of data, such as data about frequency and spatial correlations, data about signal attenuation model in the target district, and even data observed in the past can be used to conduct an accurate spectrum map. These methods make spectrum map much easier, more accurate and less costly than before, and largely contribute to the development profusion of intelligent devices and ultra-wideband services.

References

[1] F. Zhou, C. Wang, G. Wu, Y. Wu, Q. Wu and N. Al-Dhahir, "Accurate Spectrum Map Construction for Spectrum Management Through Intelligent Frequency-Spatial Reasoning," in IEEE Transactions on Communications, vol. 71, no. 7, pp. 3932-3945, July 2023, doi: 10.1109/TCOMM.2023.3267569.

[2] D. Lee, S. Kim, and G. B. Giannakis, "Channel gain cartography for cognitive radios leveraging low rank and sparsity," IEEE Trans. Wireless Commun., vol. 16, no. 9, pp. 5953–5966, Sep. 2017.

[3] D. Li, J. Cheng, and V. C. M. Leung, "Adaptive spectrum sharing for half-duplex and full-duplex cognitive radios: From the energy efficiency perspective," IEEE Trans. Commun., vol. 66, no. 11, pp. 5067–5080, Nov. 2018.

[4] L. Arvai and S. Homolya, "Efficient radio map update algorithm for indoor localization," in Proc. 21st Int. Carpathian Control Conf. (ICCC), High Tatras, Slovakia, Oct. 2020, pp. 1–5.

[5] J. Lu, S. Zha, J. Huang, P. Liu, G. Chen, and S. Xu, "The iterative completion method of the spectrum map based on the difference of measurement values," in Proc. IEEE 3rd Int. Conf. Signal Image Process. (ICSIP), Jul. 2018, pp. 1–5.

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

[7] X. L. Huang, Y. Gao, X. W. Tang, and S. B. Wang, “Spectrum mapping in large-scale cognitive radio networks with historical spectrum decision results learning,” IEEE Access, vol. 6, pp. 21350–21358, 2018.
[8] T. Fujii, “Smart spectrum management for V2X,” in Proc. IEEE Int. Symp. Dyn. Spectr. Access Netw. (DySPAN), Seoul, South Korea, Oct. 2018, pp. 1–8
[9] P. J. Kolodzy, “Spectrum policy task force report,” FCC, Washington, DC, USA, Tech. Rep. 02-135, Nov. 2002.
[10] M. K. Powell, “Facilitating opportunities for flexible, efficient, and reliable spectrum use employing cognitive radio technologies,” FCC, Washington, DC, USA, Tech. Rep. 03-108, Dec. 2003.
[11] F. Shen, G. Ding, Q. Wu and Z. Wang, "Compressed Wideband Spectrum Mapping in 3D Spectrum-Heterogeneous Environment," in IEEE Transactions on Vehicular Technology, vol. 72, no. 4, pp. 4875-4886, April 2023, doi: 10.1109/TVT.2022.3227168.
[12] F. Shen, G. Ding and Q. Wu, "Efficient Remote Compressed Spectrum Mapping in 3-D Spectrum-Heterogeneous Environment With Inaccessible Areas," in IEEE Wireless Communications Letters, vol. 11, no. 7, pp. 1488-1492, July 2022, doi: 10.1109/LWC.2022.3175820.
[13] H. Landau, “Necessary density conditions for sampling and interpolation of certain entire functions,” Acta Mathematica, vol. 117, no. 1, pp. 37–52, 1967.
[14] D. L. Donoho, “Compressed sensing,” IEEE Trans. Inf. Theory, vol. 52, no. 4, pp. 1289–1306, Apr. 2006.
[15] E. Candes and T. Tao, “Near-optimal signal recovery from random projections: Universal encoding strategies,” IEEE Trans. Inf. Theory, vol. 52, no. 12, pp. 5406–5425, Dec. 2006.
[16] Z. Tian and G. B. Giannakis, “Compressed sensing for wideband cognitive radios,” inProc. IEEE Int. Conf. Acoust. Speech Signal Process., Honolulu, HI, USA, 2007, pp. 1357–1360.
[17] F. Shen, Z. Wang, G. Ding, K. Li and Q. Wu, "3D Compressed Spectrum Mapping With Sampling Locations Optimization in Spectrum-Heterogeneous Environment," in IEEE Transactions on Wireless Communications, vol. 21, no. 1, pp. 326-338, Jan. 2022, doi: 10.1109/TWC.2021.3095342.
[18] X. Guo, Y. Zhang, Z. Chen, C. He and W. Hai, “Distributed Electromagnetic Spectrum Detection System Based on Self-organizing Network,” 2018 12th International Symposium on Antennas, Propagation and EM Theory (ISAPE), Dec. 2018, pp. 1–5.
[19] A. Chakraborty, M. S. Rahman, H. Gupta and S. R. Das, “SpecSense: Crowdsensing for efficient querying of spectrum occupancy,” IEEE INFOCOM 2017 - IEEE Conference on Computer Communications, May 2017, pp. 1–9.
[20] Q. Zhu et al., "DEMO Abstract: An UAV-based 3D Spectrum Real-time Mapping System," IEEE INFOCOM 2022 - IEEE Conference on Computer Communications Workshops (INFOCOM WKSHPS), New York, NY, USA, 2022, pp. 1-2, doi: 10.1109/INFOCOMWKSHPS54753.2022.9798206.
[21] S. Zha, J. Huang, Y. Qin and Z. Zhang, "An Novel Non-Parametric Algorithm for Spectrum Map Construction," 2018 International Symposium on Electromagnetic Compatibility (EMC EUROPE), Amsterdam, Netherlands, 2018, pp. 941-944, doi: 10.1109/EMCEurope.2018.8485015.
[22] A. Haniz et al., “Construction and interpolation of a multi-frequency radio map,” in Proc. Int. Conf. Robot., Electr. Signal Process. Techn., Dhaka, Bangladesh, Jan. 2019, pp. 632–637.
[23] M. Hamid and B. Beferull-Lozano, "Non-parametric spectrum cartography using adaptive radial basis functions", 2017 IEEE International Conference on Acoustics Speech and Signal Processing (ICASSP), pp. 3599-3603, 2017.
[24] D. Arthur and S. Vassilvitskii, "k-means++:the advantages of careful seeding", Eighteenth Acm-Siam Symposium on Discrete Algorithms, pp. 1027-1035, 2007.

[25] X. Li, X. Wang, T. Song and J. Hu, "Robust Online Prediction of Spectrum Map With Incomplete and Corrupted Observations," in IEEE Transactions on Mobile Computing, vol. 21, no. 12, pp. 4583-4594, 1 Dec. 2022, doi: 10.1109/TMC.2021.3081715.
[26] M. Tang, G. Ding, Z. Xue, J. Zhang and H. Zhou, "Multi-dimensional spectrum map construction: A tensor perspective," 2016 8th International Conference on Wireless Communications & Signal Processing (WCSP), Yangzhou, China, 2016, pp. 1-5, doi: 10.1109/WCSP.2016.7752600.
[27] C. F. Caiafa, and A. Cichocki, “Stable, robust, and super-fast reconstruction of tensors using multi-way projections,” IEEE Transactions on Signal Processing, vol. 63, no. 3, pp. 780-793, 2015.
[28] J. Liu, P. Musialski, P. Wonka, and J. Ye, “Tensor completion for estimating missing values in visual data.” IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 35, no. 1, pp. 208-220, 2013.