

Spectrum Hole Geolocation via Deep Learning-Assisted Non-Cooperative Sensing

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Abstract—Accurate spectrum hole geolocation (SHG) is essential for efficient dynamic spectrum access. NCSS enables direct mapping between sensing decisions and sensor locations, but sparse observations limit spatial reconstruction. This paper proposes a deep learning-assisted non-cooperative spectrum sensing (NCSS) framework for SHG in Internet of Things (IoT) environments. The approach combines Voronoi-based mapping with an Attention U-Net architecture to reconstruct spectrum hole distributions from dispersed binary decisions. The proposed method improves reconstruction accuracy and consistency, approaching cooperative sensing performance without requiring information exchange among sensors.

Keywords—Dynamic Spectrum Access, Spectrum Sensing, Spectrum Hole Geolocation, Internet of Things, Deep Learning, Attention U-Net.

I. INTRODUCTION

The limited capacity of the radio frequency spectrum represents a significant challenge for the deployment of new telecommunication services. This constraint is largely associated with rigid spectrum allocation policies, which grant exclusive access rights to primary users (PUs) and, as a consequence, often lead to the underutilization of several frequency bands. In view of the rapid evolution of fifth-generation (5G) networks, the Internet of Things (IoT), and emerging sixth-generation (6G) technologies, the development of more efficient, flexible, and adaptive spectrum management strategies has become increasingly essential [1].

In this context, Dynamic Spectrum Access (DSA) has emerged as a flexible alternative to conventional static allocation schemes. DSA enables secondary users to opportunistically access underutilized frequency bands, provided that harmful interference to PUs is avoided, thereby improving the overall efficiency of spectrum utilization [2]. Cognitive radio

plays a central role in enabling DSA by allowing wireless devices to autonomously sense the radio environment and adapt their transmission parameters according to spectrum availability [3]. Spectrum sensing is commonly formulated as a binary hypothesis testing problem, in which the objective is to determine the presence ($\mathcal{H}_1$) or absence ($\mathcal{H}_0$) of a PU signal. Its performance is typically assessed in terms of the probability of detection (P_d) and the probability of false alarm (P_{fa}) [4].

Based on the outcomes of the sensing process, spectrum hole geolocation (SHG) aims to identify inactive or shadowed regions within the coverage area of a PU. The accuracy of this process is commonly quantified by the spectrum hole geolocation detection rate (SHGDR). However, the effectiveness of SHGDR is strongly influenced by the adopted sensing strategy. Cooperative spectrum sensing (CSS) can enhance detection reliability by allowing multiple users to share sensing information, but this cooperation may reduce spatial precision due to the aggregation of measurements from different locations. In contrast, non-cooperative spectrum sensing (NCSS) relies on independent local decisions. Although NCSS is more vulnerable to propagation impairments, it enables a more direct association between each sensor's physical location and the existence of a spectrum hole, which is particularly relevant for spatial mapping applications [5].

To overcome the limitations imposed by sparse sensing data in NCSS scenarios, deep learning techniques have been increasingly investigated for the reconstruction of spatial spectrum maps from limited observations. In particular, convolutional autoencoder-based architectures and models with skip connections, such as U-Net, have demonstrated strong capability in capturing spatial dependencies in reconstruction tasks. By exploiting the inherent spatial structure of the data through convolutional layers, these networks can infer spectrum map characteristics with greater accuracy than conventional interpolation-based methods, which generally do not fully exploit the available structural information [6].

A. Related Works

Recent studies have addressed spectrum cartography and spectrum hole geolocation through cooperative, non-cooperative, and learning-based strategies. In [5], a CSS approach constructs availability maps using overlapping sensor clusters over a test grid. Although this improves global detection reliability, the clustering process reduces spatial resolution and increases uncertainty near spectrum hole boundaries. To mitigate these limitations, [7] proposes an NCSS architecture based on independent local decisions, where IoT sensor detec-

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tions are mapped through Voronoi partitioning and heuristic geometric interpolation. However, its performance degrades under severe fading, indicating the need for methods capable of better capturing spatial channel variations.

Deep learning has emerged as a promising alternative to conventional interpolation-based techniques. In [8], an inpainting autoencoder reconstructs spectrum maps from sparse measurements by learning propagation patterns from historical data. Similarly, [9] employs a residual convolutional autoencoder with skip connections for PSD map completion, improving feature extraction and reconstruction accuracy. More advanced architectures have also been proposed, including RobUNet [6], which combines U-Net, attention mechanisms, and residual connections to improve generalization in complex environments. Autoencoder-based radio map estimation is further investigated in [10], while [11] introduces a CVAE with spatial attention and binary sampling masks for PSD estimation from incomplete maps.

Despite these advances, most learning-based spectrum cartography methods focus on continuous power regression, which requires complex measurements and increases communication, energy, and processing costs. Such requirements limit their applicability in massive and resource-constrained IoT networks. Therefore, there remains a need for approaches that combine the low-overhead nature of NCSS with the spatial modeling capability of deep learning, particularly through boundary reconstruction strategies inspired by architectures such as U-Net [12].

B. Contributions

Motivated by these considerations, this work proposes a deep learning-assisted framework for SHG based on autonomous SSIIoT nodes operating in NCSS environments. The proposed approach integrates an Attention U-Net architecture into a database-driven DSA system to reconstruct spectrum hole maps directly from individual binary sensing decisions. Unlike most deep learning-based approaches for spectrum cartography, which primarily focus on continuous power estimation, the proposed method operates directly on binary sensing outcomes. This characteristic makes the framework particularly suitable for resource-constrained IoT environments, where reducing sensing, communication, and processing complexity is essential. Therefore, the main contributions of this paper are: i) the development of a deep learning-assisted NCSS framework for SHG in database-driven IoT environments; ii) the use of Voronoi-based mapping to convert sparse binary sensing decisions into structured spatial representations; iii) the integration of an Attention U-Net architecture to reconstruct spectrum hole maps by learning non-linear spatial boundaries; and iv) the performance evaluation of the proposed method under different SNR levels and node densities, showing improved SHGDR over conventional NCSS approaches and performance close to CSS without requiring cooperative information exchange.

II. SYSTEM MODEL

The considered system comprises N IoT-based spectrum sensing devices, hereafter referred to as SSIIoT nodes, randomly distributed over an $L \times L$ geographical area. The

network follows a decentralized non-cooperative sensing architecture, in which each SSIIoT node performs spectrum sensing independently, based exclusively on its local observations and without exchanging information with neighboring nodes. During a given sensing interval, the baseband signal vector received by the i -th SSIIoT node, denoted by $\mathbf{y}_i \in \mathbb{C}^{n \times 1}$, is expressed as

$$\mathbf{y}_i = h_i \mathbf{x} + \mathbf{v}_i, \quad (1)$$

where $\mathbf{x} \in \mathbb{C}^{n \times 1}$ is the PU transmitted signal, generated as an oversampled Quadrature Phase Shift Keying (QPSK) sequence that inherently exhibits temporal correlation. The complex scalar $h_i \in \mathbb{C}$ captures the channel gain between the PU transmitter and node i , while $\mathbf{v}_i \in \mathbb{C}^{n \times 1}$ denotes the additive white Gaussian noise (AWGN) vector.

The channel gain h_i accounts for large- and small-scale propagation effects and is defined as $h_i = G_i a_i$, where a_i denotes the multipath fading component. This coefficient is modeled as Rician fading, with the Rice factor K_i in dB following a Gaussian distribution, i.e., $K_i \sim \mathcal{N}(\mu_K, \sigma_K^2)$. Based on empirical urban measurements reported in [13], the parameters are set to $\mu_K = 1.88$ dB and $\sigma_K = 4.13$ dB. The term $G_i = \sqrt{P_{r,i}/P_t}$ represents the local mean channel gain, incorporating path-loss and shadowing effects, where $P_{r,i}$ is the average received power at the i -th SSIIoT node and P_t is the PU transmit power.

The average received power $P_{r,i}$, expressed in dBm, is

$$P_{r,i}^{\text{dBm}} = 10 \log_{10} \left[10^3 P_t \left(\frac{d_0}{d_i} \right)^\eta \right] + S_i, \quad (2)$$

where d_i is the distance between the PU and the i -th node, d_0 is the reference distance, and η is the path-loss exponent. The term S_i denotes spatially correlated log-normal shadowing [14]. To emulate realistic coverage irregularities, including spectrum holes, S_i is generated from a spatial correlation matrix based on an exponential decay model [15]. The resulting matrix is decomposed via Cholesky factorization and multiplied by a standard Gaussian vector, assigning a location-dependent shadowing attenuation to each SSIIoT node according to its physical coordinates.

To account for hardware and environmental heterogeneities, the noise variance at node i fluctuates around an average value $\bar{\sigma}^2$, given by $\sigma_i^2 = (1 + \zeta u_i) \bar{\sigma}^2$, where $u_i \sim \mathcal{U}[-1, 1]$ and $\zeta \in [0, 1]$ dictates the variability scale.

Moreover, given the spatial variability of both signal and noise, an average system-wide Signal-to-Noise Ratio (SNR) is defined to standardize link quality for performance evaluations

$$\text{SNR} = \mathbb{E}[P_{r,i}] \cdot \mathbb{E} \left[\frac{1}{\sigma_i^2} \right]. \quad (3)$$

To detect the PU signal, the n -sample vector is first mean-centered and divided into $K = n/M$ non-overlapping segments of length M . The local Sample Covariance Matrix (SCM) of order M at node i is then estimated as

$$\mathbf{R}_i = \frac{1}{K} \sum_{k=1}^K \mathbf{z}_{i,k} \mathbf{z}_{i,k}^\dagger, \quad (4)$$

where $\mathbf{z}_{i,k} \in \mathbb{C}^{M \times 1}$ is the k -th segment. This allows robust SCM estimation from a single observation window while preserving statistical structure.

Based on $\mathbf{R}_i$, local detection is performed using the Pietra-Ricci Index Detector (PRiDe), chosen for its favorable trade-off between performance, complexity, and latency [16], [17], [18]. Letting $r_{i,z,k}$ denote the (z, k) -th entry of $\mathbf{R}_i$, its average entry $\bar{r}_i$ is

$$\bar{r}_i = \frac{1}{M^2} \sum_{z=1}^M \sum_{k=1}^M r_{i,z,k}. \quad (5)$$

The corresponding PRiDe test statistic for node i is

$$T_{\text{PRiDe},i} = \frac{\sum_{z=1}^M \sum_{k=1}^M |r_{i,z,k}|}{\sum_{z=1}^M \sum_{k=1}^M |r_{i,z,k} - \bar{r}_i|}. \quad (6)$$

Node i infers PU presence ($\mathcal{H}_1$) if $T_{\text{PRiDe},i} > \gamma_i$, where γ_i is a decision threshold configured for a target probability of false alarm (P_{fa}). Otherwise, the band is deemed vacant ($\mathcal{H}_0$).

III. PROPOSED RECONSTRUCTION FRAMEWORK

The proposed approach adopts a NCSS strategy for spectrum hole identification. Within this framework, each SSIoT node independently computes the PRiDe statistic and produces a local binary decision indicating the presence or absence of the PU signal. After the local sensing stage, a preliminary spatial representation is generated through Voronoi tessellation. Specifically, the sensing area is partitioned into convex regions, each associated with a single SSIoT node. The binary decision produced by a given node is then assigned to its corresponding Voronoi cell. To provide a standardized input for the subsequent learning stage, a discrete 50×50 grid is superimposed over the sensing area. Each pixel in this grid is labeled according to the binary state of the Voronoi region in which it lies, thereby yielding a coarse spatial map. The overall processing pipeline is shown in Fig. 1.

The objective of the proposed methodology is to convert these Voronoi-based maps into accurate reconstructions of the SHG map. To this end, a deep learning-based reconstruction stage is employed, using an Attention U-Net architecture. This model is capable of learning complex non-linear boundaries and mitigating the geometric distortions caused by sparse sensing deployments.

A. Attention U-Net architecture

Building upon the Voronoi-based representation described above, the reconstruction stage is implemented using an Attention U-Net architecture. The network takes as input a two-channel tensor of size $50 \times 50 \times 2$, composed of the Voronoi map and a binary mask indicating the spatial locations of the sensing nodes. This formulation allows the model to jointly exploit spatial structure and measurement availability. The architecture of the proposed model is summarized in Table I.

The architecture follows the encoder-decoder paradigm of U-Net [12], where the encoder progressively extracts hierarchical feature representations through convolution and pooling

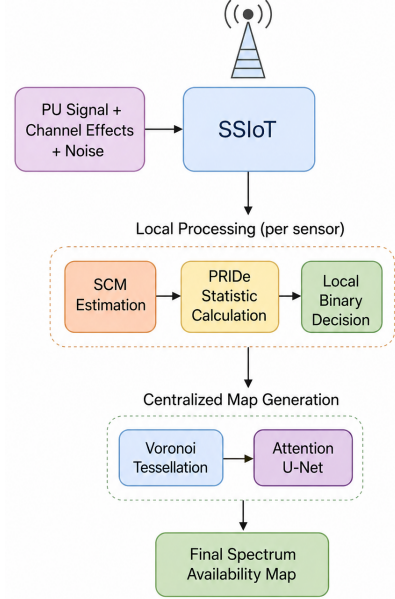


Fig. 1: Proposed SHG framework.

TABLE I: Architecture of the proposed Attention U-Net model.

Stage	Operation	Output size
Input	Voronoi map + sensing mask	$50 \times 50 \times 2$
Padding	Zero padding	$64 \times 64 \times 2$
Encoder 1	Conv. block + max pooling	$32 \times 32 \times 32$
Encoder 2	Conv. block + max pooling	$16 \times 16 \times 64$
Encoder 3	Conv. block + max pooling	$8 \times 8 \times 128$
Bottleneck	Conv. block + dropout 0.25	$8 \times 8 \times 256$
Decoder 1	Upsampling + concat. + conv. block	$16 \times 16 \times 128$
Decoder 2	Upsampling + concat. + conv. block	$32 \times 32 \times 64$
Decoder 3	Upsampling + concat. + conv. block	$64 \times 64 \times 32$
Output	1×1 conv. + sigmoid + cropping	$50 \times 50 \times 1$

operations, and the decoder restores spatial resolution via upsampling layers combined with skip connections. These connections enable the recovery of fine-grained spatial details by directly propagating high-resolution features from the encoder to the decoder.

Each convolutional block consists of two 3×3 convolutional layers with ReLU activation and batch normalization, followed by a spatial attention module. The attention map is obtained from channel-wise average and maximum pooling and applied to the feature map to modulate its spatial response [19]. Additionally, dropout is applied in deeper layers of the network to improve generalization and mitigate overfitting. Finally, a 1×1 convolution with sigmoid activation is used to generate a pixel-wise probability map, representing the likelihood of spectrum hole presence at each spatial location.

B. Training Strategy

The dataset consists of 225,000 samples generated under multiple sensing conditions, including different SNR levels and node densities. The data is split into 60% for training, 20% for validation, and 20% for testing, ensuring that all subsets contain representative configurations of the considered scenarios. The model is trained using a hybrid loss function that combines binary cross-entropy (BCE) and Dice loss. BCE

accounts for pixel-wise classification errors, while the Dice term improves the spatial overlap between the predicted and ground-truth maps, which is particularly important in binary segmentation tasks [20].

The proposed network is trained using the Adam optimizer with an initial learning rate of 3×10^{-4} and a batch size of 128. To improve generalization, early stopping is applied based on the validation loss, and the learning rate is reduced when the validation performance stagnates. On the test set, the model achieves an accuracy of 0.8517, an F1-score of 0.8143, a precision of 0.8128, and a recall of 0.8158. These results indicate that the proposed approach effectively reconstructs spectrum hole regions from sparse binary sensing decisions, maintaining a balanced trade-off between correct detection and false alarm control in NCSS-based SSIIoT scenarios.

IV. RESULTS

The simulations are conducted in a square sensing area with side length $L = 9000$ m, where $N = 500$ SSIIoT nodes are randomly distributed. The PU is located at $(x_{PU}, y_{PU}) = (2L, 2L)$ m and transmits with power $P_t = 5$ W. The propagation model considers a path-loss exponent $\eta = 2.5$, a reference distance $d_0 = 0.1$ m, an SNR of -5 dB, and a noise variability factor $\rho = 0.5$. Each SSIIoT node collects $n = 1500$ samples per sensing round, and a total of 10000 sensing rounds are simulated. The multipath fading follows a Rician distribution, with Rice factor mean $\bar{K} = 1.88$ dB and standard deviation $\sigma_K = 4.13$ dB. Spatially correlated shadowing is modeled with standard deviation $\sigma_s = 7$ dB, correlation length $\Lambda = 0.8$ times the number of grid rows, and covariance matrix order $M = 15$. Spectrum holes are defined using a received-power threshold of $P_{rx,th} = -100$ dBm, while the probability of false alarm is set to $P_{fa} = 0.2$. Under this configuration, the Voronoi-based map obtained from the NCSS decisions is used as input to the proposed deep learning-based reconstruction model.

Fig. 2 presents the SHGDR distribution over 10000 simulation runs under the considered simulation setup. The proposed model achieves an average SHGDR of approximately 84% with a variance of 0.0047. Under comparable conditions, the NCSS method reported in [7] achieves an SHGDR of 77.2% with a variance of 0.0054, whereas the CSS scheme in [5] reaches approximately 85% with a variance of 0.005. These results show that the proposed approach substantially improves the performance of the NCSS baseline and achieves results close to those of CSS. Moreover, the lower variance indicates greater stability across independent simulation runs, while the absence of cooperative information exchange preserves the decentralized and low-complexity nature required for SSIIoT-based deployments.

Fig. 3 illustrates a representative example of the proposed SHG reconstruction process. Specifically, Fig. 3(a) presents the ground-truth SHG map, whereas Fig. 3(b) shows the initial Voronoi-based representation obtained from the NCSS decisions and used as input to the proposed model. The reconstructed map produced by the model is depicted in Fig. 3(c). It can be observed that the proposed approach is able to recover the SHG map from individual and spatially

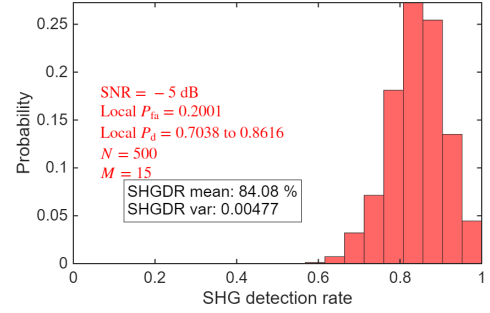


Fig. 2: Histogram of SHGDR for the proposed model.

dispersed sensing decisions, effectively capturing the main spatial structure of the spectrum hole distribution and reducing the geometric distortions introduced by the initial Voronoi-based representation.

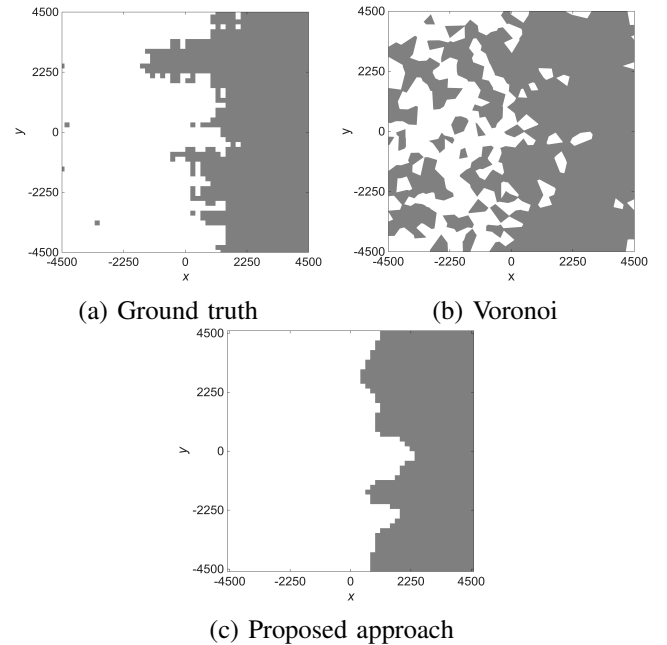


Fig. 3: Reconstruction example of the SHG map.

Fig. 4 presents the SHGDR as a function of the SNR, comparing the heuristic method proposed in [7] with the proposed learning-based approach. The results show that the proposed model consistently outperforms the heuristic baseline over the entire SNR range. This performance improvement is particularly evident at low SNR values, indicating that the proposed approach provides greater robustness under adverse channel conditions. As the SNR increases, the performance of both methods tends to converge; however, the proposed model continues to achieve superior SHGDR values. Furthermore, Fig. 5 shows the SHGDR as a function of the number of SSIIoT nodes, assessing the impact of network density on the performance of both methods. The proposed approach consistently achieves higher SHGDR values for all considered node configurations, demonstrating its ability to improve spectrum hole geolocation accuracy under different sensing densities. Moreover, the reduced variability observed in the proposed method indicates a more stable behavior across distinct sensing

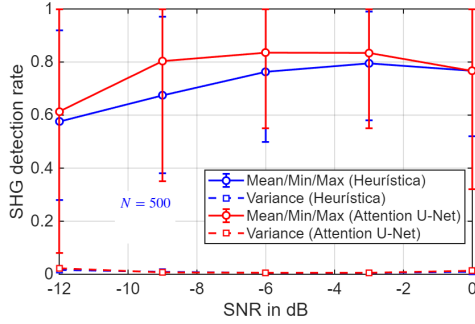


Fig. 4: SHGDR versus SNR comparing the heuristic method proposed in [7] and the proposed approach.

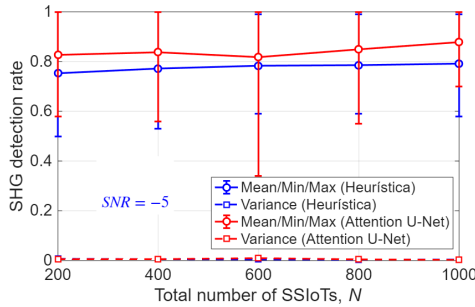


Fig. 5: SHGDR versus the number of SSIIoTs, comparing the heuristic method in [7] and the proposed approach.

scenarios.

Overall, the obtained results confirm that the proposed learning-based framework enhances SHG performance in NCSS scenarios by effectively exploiting spatial information from sparse binary sensing decisions. The consistent gains observed across different SNR levels and network densities demonstrate the robustness and generalization capability of the proposed approach under diverse channel and deployment conditions.

V. CONCLUSION

This paper proposed a deep learning-assisted NCSS framework for spectrum hole geolocation in database-driven IoT environments. The proposed method combines Voronoi-based spatial mapping with an Attention U-Net architecture to reconstruct SHG maps directly from individual binary sensing decisions, eliminating the need for cooperative sensing. The results show that the proposed approach improves the SHGDR compared with conventional NCSS methods and achieves performance close to CSS, while preserving the simplicity and low-latency advantages of non-cooperative architectures. Moreover, its stable performance under different channel conditions demonstrates its robustness for practical deployment. These findings highlight the potential of integrating deep learning with NCSS to enhance spectrum awareness in resource-constrained IoT networks. Future work will address more complex propagation scenarios and model complexity reduction for real-time implementation.

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