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Cooperative Spectrum Sensing in Cognitive Radio Networks: Leveraging AI and Machine Learning for Enhanced Spectral Awareness

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Abstract

The scenario for wireless communication capacity is expanding very quickly, so we are onset of shifting from the usual set bandwidth sharing to flexible bandwidth control with the help of smart radios. The main issue with smart radios is having strong spectrum awareness, which is often hurt by channel issues and the difficult signal strength problem. Working together to sense the spectrum helps fix this problem by combining sensing choices made locally. This paper gives a detailed look at how AI/ML, especially Deep Learning (DL) and Deep Reinforcement Learning (DRL), have been added to collaborative spectrum sensing systems from 2020 to 2025. It seems the research is moving in two main ways: first, focusing on finding the important features to categorize data, and second, using policy-based methods to improve performance. However, when facing real-world problems like heavy calculations, power usage, and strong, tricky attacks such as Lower Edge Band, AI/ML security plans using ML are increasingly what we aim for. Two main areas for future work are emerging: using Federated Learning for 6G network setups while focusing on federated learning paths ,and using Transfer Learning while concentrating on transfer learning routes.

Keywords: Cognitive Radio Networks, Dynamic Spectrum Access, Cooperative Spectrum Sensing, Deep Learning.

I. INTRODUCTION AND FOUNDATIONAL PRINCIPLES

A. The Spectrum Crisis and the Paradigm Shift to Cognitive Radio (CR)

The explosion in wireless devices has rocketed demand for radio spectrum to unprecedented heights--and exposed just how inflexible the old model of managing spectrum really is. The same rigidity explains why so many licensed bands sit underutilized. Cognitive Radio enables Dynamic Spectrum Access, whereby unlicensed secondary users can opportunistically tap into "spectral holes" in times when the licensed primary users aren't availing of a given frequency.

Spectrum Sensing is the heartbeat of this idea, the essential building block that makes CR work [1][2]. It has to rapidly and reliably detect if a Primary User is present, so we can fill in the spectrum efficiently without compromising the PU by harmful interference. [3].

B. Primarily, in order to quantify architectural constraints

Being solely dependent on one secondary user (SU) for sensing the spectrum is very unstable because of some basic physics limits. Problems in the channel path, such as heavy shadowing, fading, and a large path loss, demolish the possibility of a successful detection [4] and [5].

Conventional sensing approaches have their strengths but also face some disadvantages. One such widely used technique in Energy Detector (ED) sensing is highly susceptible to a problem called SNR-Wall effect [6]. The uncertainty in noise suppresses the possibility of sensing PU signals in the ED approach below a threshold SNR level [6]. Additionally, in a half-duplex cognitive radio network, heavy self-interference is introduced in sensing due to SU's transmission, making it difficult to detect the channel state [7].

CSS arose from a resilience need to cope with these challenges [8]. CSS takes advantage of cooperative gains by aggregating local decisions from a number of geographically dispersed SUs at a Fusion Center (FC) to improve the probability of correct detection (Pd) and the probability of false alarm (Pfa) [4] and [8].

C. Introduction

Conventional stochastic algorithms do not work well a in dynamic wireless channel, which accelerates AI/ML research in spectrum sensing for solving this problem [9]. AI/ML algorithms have faster, better, and more reliable performance under uncertain communications channels compared with conventional algorithms [9], [10]. Especially in overcoming the SNR Wall, a deep learning algorithm can tap into meaningful structural information in modulation signals to attain an excellent receiver performance without CSI/noise statistics [6].

Moreover, DL, in particular, can automatically learn complex patterns in the data without relying heavily on pre-defined models of signals, thus achieving significant performance gains [9], [2], [6]. Hence, the role of the FC will transform from being a mere combination device for decisions to a learning-enabled hub which can change strategies and conduct advanced analysis of data [11].

II. MACHINE LEARNING PARADIGMS IN COOPERATIVE SPECTRUM

Since 2020, CSS research with machine learning has split mainly into two paths: detecting signals via supervised or unsupervised learning, and using deep learning to optimize strategies.

A. Supervised vs. Unsupervised Learning Approaches

1) Supervised Learning for Feature Classification

Supervised methods are trained on labelled data drawn from actual observed signals - in particular, the Support Vector Machines, the Logistic Regression, and the K-Nearest Neighbours are compared in this paper. [12], [13]. Their performance relies critically on the quality and representativeness of the extracted features, like energy samples (ES), decomposition features (DE), or generalized features (GP) [13]. Comparisons have been drawn that show SL models, including SVM and LR, can achieve stable accuracy at about 89% to 90% in CSS frameworks [12].

2) Unsupervised Learning via Clustering

Unsupervised learning, especially K-means clustering, plays a significant role in the classification of the observed energy vectors or signals into predefined clusters representing idle or occupied states, respectively [12]. The dependence on a priori precise knowledge of noise power and explicit thresholds on decision-making is also minimized. It has been analyzed that the K-means clustering algorithm outperformed quantitatively in highly noisy and severe fading channels with a slight edge over classical fusion rules [8], [12], [14].

B. Deep Learning Architectures for Automatic Feature Extraction

In fact, DL architectures have thus far widely been adopted because they inherently overcome the necessity for manual feature engineering by automatically learning complex, high-level features directly from raw input data, such as I/Q samples [2], [9].

1) Convolutional Neural Networks

CNNs are at the heart of "Deep Sensing." By using representations at multiple layers, multi-layered architectures capture non-linear relationships optimally. For example, the CSS-CNN framework, proposed in 2020 achieved a detection probability of Pd= 90% at an SNR of -16dB with a false alarm rate of P_{fa} = 0.01 in distributed SU systems [15].

2) Deep Recurrent Architectures and Hybrids

Recurrent Neural Networks (RNNs) and their variants, such as LSTM and Bi-GRU, capture temporal dependencies and sequential patterns in PU activity. Hybrid models, like CNN-RNN, can combine spatial feature extraction by CNNs with temporal analysis by RNNs to significantly improve the accuracy in spectrum sensing, particularly in low SNR conditions.

3. Graph Neural Networks (GCNs)

The cooperative sensing network is inherently a graph structure. Graph Convolutional Networks GCNs, like GCN-CSS 2023, are designed to model the dynamic and time-varying relational dependencies among collaborating SUs [17]. GCN-based models demonstrate robustness against topological changes, achieving high reliability with reported results of Pd = 100% at -8dB [15], [17].

4. Residual Networks (ResNet)

Deep residual networks (ResNet) are utilized in more complex sensing scenarios, showing competitive performance with respect to high detection probability Pd = 95.78% in a Rician channel) and notably low time response, suggesting strong candidates for real-time dynamic systems [15], [18].

III. DEEP REINFORCEMENT LEARNING FOR OPTIMAL CSS AND RESOURCE MANAGEMENT

DRL optimizes the whole policy of how SUs sense, decide, and access the spectrum to maximize long-term systemic efficiency while balancing high spectrum utilization, energy conservation, and minimizing conflict rates [20], [21].

A. DRL frameworks for strategic spectrum management

In DRL, SUs are agents that execute actions and receive cumulative rewards. DRL is excellent at formulating a comprehensive policy that integrates the decision when to sense with which channel to access and when to transmit. For example, the Deep Double Q-learning Spectrum Access (DDQSA) algorithm has been shown to learn policies that achieve near-optimal performance for the entire network [21]. Furthermore, Q-learning combined with mechanisms like discounted upper confidence bound (D-UCB) is able to dynamically select the optimal cooperation partners, minimizing scanning overhead and access delay [22].

B. Energy Efficiency and Overhead Minimization

DRL addresses the key challenge of keeping sensing and reporting overhead as low as possible. For instance, CQL is an influential offline DRL approach that detects the PU's presence for current and k-1 future timeslots [19]. In this way, by predicting future channel states, SUs do not have to perform any sensing for the subsequent timeslot(s) with comparable detection performance to state-of-the-art techniques while significantly reducing computation time and transmission overhead [15], [19].

C. Advanced DRL Architectures and Emerging Technologies

Most of the DRL architectures are now being developed with network complexity considerations. The DMRL algorithm provides solutions for multi-user access and cooperation by considering inherent spectrum sensing errors, leading to improved spectrum utilization with a lower conflict rate [20]. Other current thrust areas include integrating DRL with physical layer mechanisms, such as the optimization of RIS-assisted CSS, with agents adjusting dynamically the phase shifts at RIS and node selection [5].

IV. PERFORMANCE ANALYSIS, IMPLEMENTATION CHALLENGES AND SECURITY

A. Key Performance Indicators and Quantitative Benchmarking

Performance is measured in terms of the Probability of Detection (Pd) and the Probability of False Alarm (Pfa) [23]. The tradeoff between these probabilities is visualized using the ROC curve [24]. In AI-driven CSS, FPR is an empirical estimate of Pfa, and optimized clustering methods have attained FPR as low as 0.0083 [12]. For DRL systems, performance metrics are systemic efficiency metrics like throughput and conflict rate [15], [20].

B. Challenges of Computational Complexity and Energy Efficiency

The high computational complexity of DL models is one of the main challenges for their deployment. Large AI models, for training, require enormous computational resources and contribute a lot to rapidly increasing energy consumption [25]. Usually, model efficiency is evaluated using metrics such as the total number of trainable Parameters and the overall number of FLOPs (Floating-point Operations). For instance, one hybrid CM-CNN model had 1.19M Parameters and 7.11M FLOPs [26], [27]. Increased complexity provides better accuracy but, proportionally, increases latency and power consumption. Thus, research in lightweight and streamlined AI architectures is required [26], [28].

C. Security Vulnerabilities and Robust AI Defense

CSS is susceptible to security attacks such as the Byzantine attack, in which malicious SUs transmit forged sensing information to the FC [29]. Recently, this has developed into complex Adversarial Machine Learning (AML) attacks. The LEB attack framework proposed here works as a black-box attack that builds a surrogate model to construct malicious data which is optimized to mislead the fusion center [11].

The threats which require robustness, admist heavy-duty machine learning defenses. A non-intrusive method demonstrated to reduce the disruption ratio from the LEB attack by up to 80% which relates to influence limiting defense [11].In another approach, Fusion centers continuously evaluate the reported data to estimate their trust by using a real-time classifier, such as KNN or Decision Tree, which would spot the malicious sensor contributing towards machine learning based trust evaluation. Designs based on technologies such as the Tangle block chain offer a distributed learning technique, secure environment for recording and verifying sensing results while solving inherent trust issues in collaborative settings [3].

V. FUTURE DIRECTIONS AND OPEN RESEARCH ISSUES

A. Decentralized Intelligence: Federated Learning for 6G CSS

With future wireless communications, especially in 6G, researchers and telecomm industry intends to work towards a very scalable solution with a distributed control function. In current scenario rather than just being a central hub for everything does not seems to provide solutions because of immense communication requirements and increasing demands on personal and private information. Federated Learning is a perfect answer to this problem because it enables personal devices to learn and share parameters rather than sensor information.

Generalization, or sustaining strong performance in the face of environmental changes, continues to be a significant challenge in deep learning. Transfer Learning plays a vital role in tackling this issue without requiring any consideration of retraining. Methods like the Digital Tone-Coded Squelch System depend on sharing information at both domain and class levels to train an effective target detector that delivers excellent sensing capabilities with virtually no deployment expenses.

B. Pending Tasks & Research Inquiries

Certain fundamental questions require deep exploration:
1) **Data Scarcity and Generalization**: The absence of large datasets with significant diversity and precise annotations poses a challenge for deep learning techniques.
2) **Eco-friendly AI Frameworks**: The energy demands of deep learning create difficulties for its implementation on devices.
3) **The Cooperative AI Challenge**: To preserve information integrity, AI entities (SUs) must comprehend one another's beliefs and incentives, creating a need for establishing cooperative commitments to limit self-serving actions.

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