Proceedings of CONF-SPML 2026 Symposium: The 2nd Neural Computing and Applications Workshop 2025
DOI: 10.54254/2755-2721/2026.TJ30887

A Survey of Collaborative Spectrum Sensing under Non-Ideal Conditions

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Abstract. Cooperating Spectrum Sensing(CSS) is the cornerstone of dynamically shared spectrum access in CRN. But it's hampered by subpar conditions like noise that's not right, a lack of data, and hardware issues too. These defects distort sensing data and cause the "SNR wall" effect, seriously degrade the performance of traditional sensing algorithms. To solve those issues this article gives a comprehensive review on CSS, the survey is started with creating a common analysis platform which will isolate the key problems then we will be taking a look at them from 3 points of view: noisiness, Data Integrity, Hardware Impairment Based on the aforementioned framework, we do a comprehensive overview and comparison of 3 major categories of mainstream solutions - statistical learning method based on the generalized Gaussian mixture model and meta-heuristic optimization; deep learning approach integrated with Convolutional Neural Networks (CNN) and Transformer architecture; and Deep Reinforcement Learning-based communication-sensing co-design strategy. The evaluations cover several areas like the kind of deformities it addresses, use of prior knowledge, complexity in processing, and whether it can work in actual situations. This complete examination leads to a good plan that covers finding things, missing them accidentally, and doing well even if there's some trouble. our analysis tells us how good each method is, what trade-offs they have, and when they work best. This gives us simple rules about which methods to use and how to make them. In the end, we give potential directions for future research, which are new paradigms for adaptive and privacy-preserving CSS in the dynamic spectrum-sharing, heterogeneous network integration, and increasing privacy-security environment.

Keywords: Collaborative Spectrum Sensing, Non-Ideal Conditions, Deep Learning, Robustness, Privacy-Preserving Sensing

1. Introduction

Due to the swift progress in wireless communication technologies and intelligent terminals, although a large portion of the spectrum has been authorised for usage, its utilisation rate over spatio-temporal dimensions is still very low. The problem of spectrum shortage becomes even more severe. The problem of spectrum shortage has become the main bottleneck affecting the development of future wireless communication systems. Cognitive radio (CR) does it by means of dynamic spectrum

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access (DSA), which allows for smart sharing and effective utilization of idle frequency bands. Spectrum sensing is a key part of CR, it has poor reliability at a single-node level when there are unfavorable conditions like multipath fading, shadowing, and hidden terminals. But with Collaborative spectrum sensing (CSS), the spatial diversity advantage is enabled by sharing out the observations amongst the multi-cognitive nodes who then fuse their decisions, so that the sensing is substantially improved in accuracy and robustness.

In actual CSS applications, complex and dynamic wireless en-vironments, different types of heterogeneous devices, and limited resources lead to non-ideal observations with many uncertainties and im- perfects [1]. Noise power is uncertain, data trans-mission may have errors and omissions, quantization errors, and errors and distortions caused by poor-quality hardware. Clock and sampling time asynchronization between different nodes. All these messes make it hard for the collaborative system to get a good look at the spectrum state. These troubles don't just ruin the idea of seeing things close up and over time — they also cause that pesky "the more you listen, the less you can hear" feeling. This causes detection probabilities to plummet and false alarm rates to surge under low SNR conditions, severely compromising the system's overall robustness and practicality. These problems arise when traditional collaborative sensing approaches that assume ideal data have to face engineering deployment. Robust CSS methodologies specifically tuned up for non-ideal data conditions are urgently required, especially concerning robust techniques spread over detector architecture level, local pre-processing procedure, link error control strategy, fusion approach and even thresholds tuning to improve adaptation and perception performance when handling noise uncertainty and reported channel bit errors in complex wireless environments [2], which can pave the way to practical realisation of cognitive radio Recent work also tried to reduce the affect of noise uncertainty and reported channel bit errors on CSS by introducing clustering models and changing thresholds to report [1], bettering the reporting and fusion procedures [2]. But we can still do better at modeling non-ideal factors uniformly and having a simple approach for robust design and large scaling up.

CSS related works from the beginning generally adopted ideal system assumptions such as accurate observation statistics, perfect reporting links, and precise node synchronization which led the researchers to focus mainly on sensing algorithm development and increasing the collaborative gain. Ghasemi and Sousa presented an initial architecture for energy fusion among multiple nodes operating under Rayleigh fading and proved that collaboration can result in a greater detection probability. Subsequent works have extensively improved hard decision fusion like k out of N rule, soft decision fusion like weighted average, maximum likehood fusion, etc., on top of this the real-world constraint of diverse node heterogeneity and resource constraint led to the development of solutions like signal to noise ratio weighted fusion, adaptive threshold adjustment, cluster structure perception, and compressed sensing assisted fusion. They try to have both good performance and not use too much extra power in big networks with lots of channels [3,4]. Though the methods show great performance under ideal data situation but most of the time ignore the interference and imperfect situations occurring in real world.

As CSS Engineering grows, study focus now rests on robustness under less-than-ideal situations – noise power drifts, link bit miscalculations, omitted viewings, node oddities, and sync differences – which disrupt fusions and bring quick degradation at low SNR or high-perturbation settings – thus, researchers have added robustness mechanisms by many techniques: Gong et al. introduced threshold adjustment methods to match noise uncertainty [5]; Wang et al. used Dempster-Shafer evidence theory with node credibility for identifying and reducing unreliable nodes [6]; Jia et al. reduced performance reduction caused by missing parts of the reported data through weighted

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completion and linearly interpolated filling [7]; Song et al. adopted a lightweight correction method according to multi-source interference modeling in the end-to- en robust fusion frame work [8]. But the current methods are still limited: they mostly deal with a single source of disturbance, do not have modeling and optimization frameworks for different sources of interference, and some need complex computation processes or rich prior information, which makes it difficult to use them on devices with limited resources. Simultaneously achieving robustness, efficiency, and scalability within large-scale perception networks is still a key problem in need of a breakthrough. This shows that developing a robust CSS methodology that is more applicable in practical deployment scenarios and can better adapt to and stabilize in complex wireless scenarios remains an important future research direction.

The primary innovations and contributions of this work are as follows:

• This paper systematically identifies the three major sources of distortion caused by non-ideal conditions, mainly including noise uncertainty factors, incomplete data factors, imperfect hardware and synchronization factors, investigates how they affect the detection statistics consistency and stability under these circumstances, as well as how they cause "SNR wall" phenomena. For which reason I define unifying analytic frames for systematic and mechanism analysis

• We offer a multi-lev- el examination model spanning statistical models to deep learning. It is a multi-dimensional one, evaluating it with respect to the kinds of distortions that are manageable, how much prior knowledge is required, computational and engineering complexities. It points out that any trade-off, if any exists at all, between performance, robustness and cost will be methodology-specific.

• This paper describes an integrated evaluation system (e.g., robustness gain, performance degradation rate) to clarify algorithm performance boundaries in real-world applications. Also thinking about the adaptive methods based on online learning, so as to accommodate dynamic surroundings and privacy preserving paradigms with federated learning, and map out potential growth routes for the next generation of smart sensing systems..

2. Related work

2.1. Fundamental architecture of cooperative spectrum sensing

Cooperative Spectrum Sensing(CSS) is reliable spectrum state determination made possible through the collaborative detection of primary user signals by multiple cognitive users. According to system architecture as well as information fusion methods, the CSS could be roughly classified as two typical architecture, centralised architecture and distributed architecture.

2.1.1. Centralised architecture

When we use a centralised CSS architecture,we will build up a Fusion Centre(FC)in the system,which is usually served by a base station,or an access point,or a user. The FC coordinates the uploading of the information from multiple sensing nodes and manages the fusion decision-making process, each cognitive user performs local spectrum sensing to obtain observational statistics or preliminary detection results Transmit this info to the FC by way of an uplink reporting channel. The FC is processing all nodes' sensing data for the final detection decision. Fusion processes that are more concentrated tend to give centralized model more advantages through complex statistics such as weight soft fusion, likelihood ratio detecting etc. to get better performance on detection. The system is also more easily controlled and managed by one person. However, like any system, it also

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has its disadvantages. On the one hand, it depends on the FC and if the FC fails, the sensing system will be paralyzed. But, on the other hand, a centralised approach to uploading has the downside of communication delays, as well as a bit error rate. Also, large scale node integration has an inherent drawback in terms of communication and computational bottlenecks at the fusion centre. Also when deploying a centralized one, there are many problems with the resource limited or the non-homogeneous network settings.

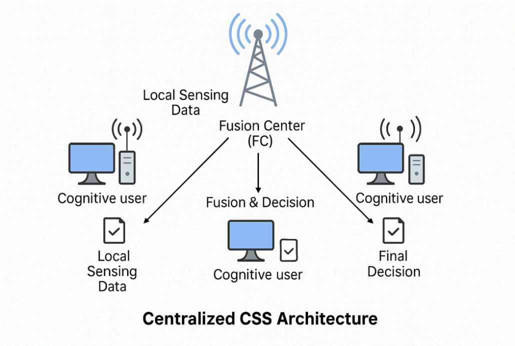

Figure 1. Centralised architecture

2.1.2. Distributed architecture

The disperse CSS architecture does without a central merger centre. Each cognitive user, independently, makes local fusion decisions after the exchange of perception information with neighboring nodes. In general, it would choose a P2P network architecture and use graph structures, adjacency matrixes, or consensus-based algorithms to do information sharing and collaborative inference. The greatest strength of the distributed structure is robustness and scalability, because there isn't any single point of failure, so the system is quite tolerant of faults in nodes and communication linkages. This makes it well-suited for use in mobile, unmanned regions or as a temporary network. Also it's better for heterogeneous networks also for privacy-sensitive apps. But distributed fusion needs much information exchange, needing much knowledge on network topology and inter-node synchronisation. Its converging and identifying speed is greatly determined by the number of network node points and how well they connect up.

Overall, Centralized architecture is best in static or well-infrasctructure environment, decentralized/architectures best in dynamice or complex or edge deployment environment. The two should be selected for the actual deployment situation, network scale and performance, or these two can be combined to form combined perception systems .

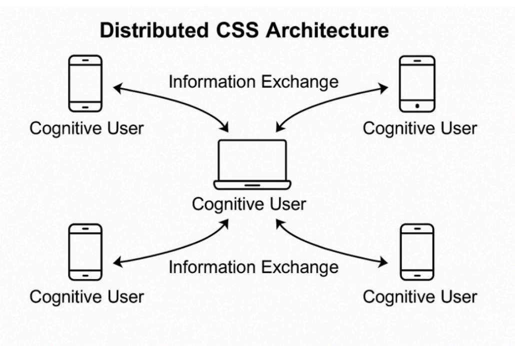

Figure 2. Distributed architecture

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2.2. Non-ideal data

2.2.1. Noise uncertainty

For energy-based cooperative spectrum sensing, the detection performance hinges on correct estimation of receiver noise power. However, in actual deployments noise levels see sporadic changes because of things like temperature, electromagnetic interference and amplifier gain drifting around. which results in erroneous threshold value setting and is a classic noise uncertainty problem.

Noise estimation bias hinders performance: under-estimation can lead to increased false-alarm rate (primary user signal might be wrongly detected); over-estimation, on the other hand, can miss a detection for the primary user signal Moreover, there might come an “SNR wall” where even adding more samples doesn’t get us past that minimum SNR thing. And heterogenous distribution of noise among nodes degrades the accuracy of weighted fusion and decreases the collaborative benefits.

2.2.2. Data incompleteness

Data loss or corruption can happen during the CSS whole life process of observation to upload, it can appear as missing terminal samples, missing transmission packets or bit error. These kinds of events mostly come as a result of restricted hardware means, unstable transmission channels, or severe interference settings.

Data incomplete messes up the smoothness and steadiness of numbers, so when we find cool features and pick a proper score to spot them, it turns strange and doesn't match up, making the finding not very good. Especially in soft fusion, it is because bit errors have made the observation date skewed, so the traditional fusion rules are no longer suitable. Even at low bit error rate, system performance degraded more than 20% which is very bad for CSS.

2.2.3. Hardware non-idealities and synchonisation non-idealities

In a collaborative network, nodes that collaborate mostly come from a different hardware which ADC saturations, quantization errors, and I/Q imbalance are typical issues in these different hardware platforms. At the same time, independently operating node clocks are easy to cause sampling time offsets and frequency drift, and synchronization is reduced.

These non-idealities add up and cause amplitude and phase errors in what we see, making it hard to make good joint time-frequency domain models for working together to find things. This results in degraded fusion statistics, reversed collaborative effects, and even overall performance inferior to single-node systems. While self-calibration and compensation is mitigated by current self-calibration and compensations but at the same time the cost is still too high for resource limited systems.

3. Cooperative spectrum sensing methods under non-ideal data conditions

In CR network, cooperative spectrum sensing(CSS) senses primary user signal. But the observed data often has non-ideal factors like noise uncertainty, missing data, quantization mistakes, and being out of sync, which makes traditional methods not work very well anymore. To make sure sensing is reliable in these types of environments, different strong CSS ways have been made over the past few years. These mainly consist of statistical model-based algorithms, deep learning techniques, and communication-sensing co-optimization strategies.

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3.1. Cooperative spectrum sensing based on adaptive gaussian mixture models

Srinivas Samala et al. [9] in 2022 proposed a CSS method based on AGMM in 2022. This approach uses the local energy detection result of each SU to generate a feature vector and applies AGMM to adaptively model different statistics with respect to the changing noise and channel conditions and thus improves the perception robustness in real non-ideal scenarios like noise uncertainty.Simulation results show an improvement over traditional K-means clustering algorithms in terms of detection probability, recall rate and F1 score but also maintains very high detection accuracy at very low noise SNR scenarios.

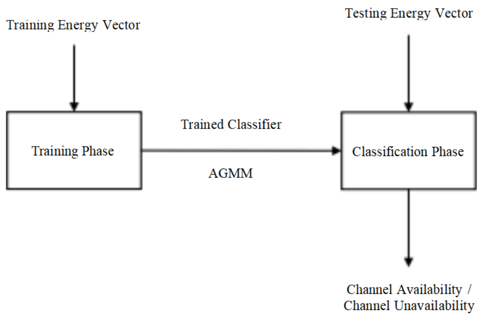

Figure 3. Modular structure of the CSS framework

3.2. Collaborative spectrum sensing based on clustering and meta-heuristic optimisation

V. Srivastava et al. [1] introduced a CSS approach in 2023 that blends clustering with meta-heuristic optimization. This method first groups cognitive users with the same or similar energy detection results and noise level data to improve intra-group data homogeneity. Then, it uses algorithms like Support Vector Machine (SVM) and Random Forest (RF) for nodes to optimally collaborate. This method can better reduce false alarms and increase detection probabilities in multi-channel and changeable environments. But its clustering success can still be limited in presence of highly diverse nodes, so better models for clustering might also be good to make it even easier. Adding smarter cluster stuff with deep-learning might too be useful to help it resist mistakes better.

3.3. Deep learning method based on CNN and transformer

E.V. Vijay et al. [10] proposed a CNN- Transformer integrated DL- CSS method in year 2024. Using the approach of CNN to extract the local spatio-temporal signal features, and then using the Transformer to learn the long-term dependency and global channel environment information. The results show that this approach still has high detection accuracy under low SNR, multipath, and strong interference; the model achieves better adaptability and robustness for the complex channel and interference model compared with traditional approaches.

3.4. Communication awareness co-awarement based on deep reinforcement learning

A. Paul et al. [11] present a communication sensing collaborative optimisation framework based on deep reinfrocerment learning (DRL) in 2023. It jointly optimizes sensing scheduling and D2D comm strategies, which achieves a balance between sens acc and sys throughput in dynamic envs. This method shows high robustness in situations where there are many changes to netw topo and SSDF. but its training process is complicated and requires lots of data, it isn't real time. Need future

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development on model compression, online training, lightweight model to reach practical deployment.

4. Performance analysis

4.1. Performance evaluation metrics

Collaborative spectrum sense system need to evaluation in overall from various perspectives, such as Pd, Pfa, cooperative gain and resiliency. Pd, Pfa represent whether the system makes right decision, respectively. The relationship between Pd and Pfa is a typical trade-off relation which can be presented by ROC/DET curves. Collaborative gain is expressed with the quantity reduction of minimum SNR requirement when compared to single-node sensing under the condition of same Pd and Pfa. It indicates the spatial diversity and information fusion that comes from collaborative sensing. In order to achieve practical application, robustness becomes a key metric to measure CSS. It looks into how the system manages to keep its work the same even when there’s noise uncertainty and problems with link bits, not enough information coming through, or nodes acting up. By checking if Pd/Pfa at various degrees of distortion changes or by using the performance degrading rate (the robustness gain metric) metric.

4.2. Comparative analysis

Table 1. Qualitative analysis

Algorithm	Advantages	Limitations
[9]	1) Parameters adapt automatically to environmental conditions; 2) Suitable for processing non-linear data; 3) Demonstrates robust detection performance under noisy uncertainty and heterogeneous nodes	1) Default reporting is reliable, disregarding packet loss/error rates; 2) Relies on high-quality data
[1]	1) Clustering reduces redundancy and optimises node collaboration; 2) Meta-heuristic algorithms (SVM, RF, etc.) adapt to heterogeneous environments; 3) Effective in multi-channel scenarios	1) Clustering effectiveness diminishes with high node heterogeneity; 2) Significant computational overhead
[10]	1) Strong feature extraction capability, adaptable to complex channels; 2) Transformers capture long-term dependencies, enhancing global awareness	1) Requires substantial training data with prolonged training duration; 2) Complex models entail high computational resource consumption
[11]	1) Adaptively optimises perception scheduling and communication strategies; 2) High robustness and throughput in dynamic environments; 3) Resistant to SSDF attacks	1) Computational complexity, requiring substantial data for training; 2) Demanding real-time requirements, posing significant engineering implementation challenges

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Table 2. Quantitative analysis

Algorithm	Pd (Ideal)	Pd (Non-ideal)	Pfa (Ideal)	Pfa(non-ideal)	Collaborative Gain	Robustness
[9]	98.2%	94%	1.5%	2.8%	5 dB	High
[1]	95.4%	90%	3.0%	5.5%	4.5 dB	Medium
[10]	97.5%	94%	1.2%	2.5%	6 dB	High
[11]	94.0%	90%	2.5%	4.0%	7 dB	Very high

We can comprehensively examine the performance of different collaborative spectrum sensing methods under non-ideal data conditions using qualitative and quantitative comparative evaluations to comprehend it well. Qualitative analysis looks at the strengths, weakness and the applicable situations of each algorithm, showing how they work well with or against non-ideal issues like noise, lack of data, and different hardware. An example is AGMM which does great with noisy stuff, but deep reinforcement learning works better when things change suddenly and when trying to outsmart something. Quantitative comparison takes this practicality one step further using concrete results like Pd, Pfa, collaborative gain, and robustness, and shows that deep reinforcement learning algorithms yield the largest gain and robustness, so they're well suited for complicated, dynamic environments. In contrast deep learning performs better in low signal to noise and multipath Combine all of those results, I think it is right that we should pick different algorithms at different places. In the future, we could try using a combination of these techniques to combine their relative strengths, so as to improve the systems ability to work under all conditions for the best result (and the worst result).

5. Future research directions and outlook

5.1. Adaptive spectrum sensing requirements in dynamic environments

Under fast-changing spectrum occupancy conditions and constantly varying time-varying factors include interference, multipath effect, and node state drift, etc., it is required for the cooperative spectrum sensing system to have adaption features which include online learning, real-time updating, rapid feedback, and so on. Model parameters can also be optimized in an active model through incremental learning, adaptability based upon thresholds, and reinforcement learning based scheduling. With fragmentary spectra and different devices, task-aware scheduling and model truncation should be used to balance performance and computation.

5.2. Federated collaboration mechanisms under privacy protection

In terms of privacy risks caused by uploads and sharing of observation data, federated learning can be used for local training, where only gradients or parameters are uploaded to achieve collaboration. but data distribution is uneven, missing data, delay in communication, and node noise and failures still exist. We need strong parameters aggregate, node credit evaluate, adaptive local update frequency methods for stronger stability in cognitive radio. And they also have to work with security policies so as to defend against the model being inferred back and inference attacks.

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5.3. Future wireless systems multi-layer collaborative perception framework

In future wireless systems that are open, smart, and highly dense, we need a multi-layered cooperative perception framework that can do real-time learning, make strong decisions, and protect people's privacy. It is an important developmental direction for the realization of intelligent spectrum sharing and for promoting the practical application of cognitive radio technology. .

6. Conclusion

This paper conducts a comprehensive analysis on key problems in collaborative spectrum sensing under non-ideal situations, examining how noise uncertainty, data deficiency and synchronization deviation affect collaborative spectrum sensing. Through a comprehensive taxonomy of the robust methods, we will review a range of important techniques, from generalized gaussian mixture models to deep reinforcement learning, and identify inherent trade-offs between computational efficiency, generalization capacity, and ease of implementation.

To solve the problem that the adaptability of current algorithms is limited, we put forward an integrated framework of online learning, federated learning and cross-layer optimization to overcome the privacy and resource constrained sensing problem. So we have set up a theoretical basis for the following generation of smart frequency range cognition, and also provided some useful instructions for how to take cognitive radio from an idea to reality.

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