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Uncertainty-Calibrated Deep Cooperative Spectrum Sensing and Channel Access Optimization for Cognitive Radio Networks

Matteo Ferrari [a], Chiara Esposito [b], Davide Lombardi [c]

[a] *Trento Institute for Fundamental Physics and Applications (TIFPA-INFN), Sommarive, Trento, Italy. E-mail: mat.fer@unitn.it*
[b] *Trento Institute for Fundamental Physics and Applications (TIFPA-INFN), Sommarive, Trento, Italy. E-mail: chiraraesp@unitn.it*
[c] *Trento Institute for Fundamental Physics and Applications (TIFPA-INFN), Sommarive, Trento, Italy. E-mail: davidelo.m@unitn.it*

Abstract

This has created serious spectrum congestion in most frequency bands due to the growing demand of wireless communication services. The conventional policies of the static spectrum allocation result in inefficient spectrum usage since some geographical areas and time periods have unused frequency bands in a certain region. The solution to this issue is the cognitive radio technology which allows secondary users to use the spectrum dynamically without disrupting primary users who have been licensed. Accurate spectrum sensing is one of the basic conditions that such dynamic access requires since it enables cognitive radio devices to discover whether a channel is occupied. Traditional spectrum sensing schemes like energy detection and matched filtering fail to work well in the presence of low signal to noise ratio or in fading and shadowing conditions. Cooperative spectrum sensing makes more accurate the sensing results because more than one radio may share the sensing information, however, it presents new difficulties associated with decision fusion and imprecision in sensing outcomes. This paper suggests an uncertainty-calibrated deep cooperative sensing system that combines the deep neural network-based signal classification with uncertainty prediction to make reliable channel access decisions. Simulated radio signal conditions are created to test the performance of the proposed methodology without having to use real-world data. Simulation findings have shown that the developed method greatly enhances the detection accuracy and also minimises the detected false alarms relative to traditional methods of sensing. The findings show that uncertainty estimation combined with cooperative sensing can enhance the reliability of cognitive radio networks that work in dynamically changing wireless environments.

Keywords: Cognitive Radio, Spectrum Sensing, Cooperative Sensing, Wireless Communication Optimization, Deep Learning for Radio Signals.

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Introduction

The past few years have seen the wireless communication technologies grow more than ever thanks to the booming growth of mobile devices, wireless sensors, and Internet of Things applications (Smith, 2024; Mishra, 2024). This growing need of wireless connexion has exerted a lot of pressure on the radio frequency spectrum resources available. In the traditional spectrum allocation policies, frequency bands are allocated to licensed users by the use of long-term regulation. Although this is a simplified way of managing the spectrum, it has a tendency to bring about inefficient use of the available spectrum given that most of the licensed bands are not fully utilised over a long duration of time. Cognitive radio technology has become an attractive ground to help solve the problem of spectrum scarcity, as it provides a dynamic spectrum access (Abdullah, 2024; Mejail et al., 2024). Cognitive radio networks, the secondary users track the radio environment to detect spectrum holes, frequency bands which are temporarily vacant even when primary licensed users are operating. The opportunity to use these bands in a non-hazardous manner by secondary users can then be achieved (Poornimadarshini, 2024; Hoa & Voznak, 2025; Kavitha, 2024). One of the major elements of cognitive radio systems is spectrum sensing, which establishes whether a specific channel is in use or not. Spectrum sensing is however difficult to be realized in realistic wireless conditions because of uncertainty of noise, fading conditions and hidden terminal issues. To enhance the effectiveness of sensing, cooperative sensing methods have been suggested in order to combine sensing measurements of different devices. Although this has been done, cooperative sensing systems still have a challenge in decision-making since sensing reports can be full of uncertainty and measurement errors. This study presents a framework of cooperative spectrum sensing that is uncertainty-aware of radio signals and is based on deep learning models to examine radio signals and estimate the degree of confidence between sensing decisions.

Literature Review

The concept of spectrum sensing has been popularly researched as a core operation of cognitive radio systems. The first spectrum sensing systems used energy detection methods because it was simple and had low computation complexity (Vlădeanu et al., 2022; Qi et al., 2014). Checking The energy detection algorithms establish channel occupancy by comparing the received signal power with a set parameter. Although the approaches are simple to apply, they have poor performance in low signal-to-noise ratio, and are susceptible to uncertainty in noise (De Alwis et al., 2021; Rahim, 2025; Rajan, 2025).

Later Matched filtering and cyclo stationary detect techniques were introduced which enhanced accuracy of sensing by taking advantage of known signal properties (Hugha & Prabhakar, 2025). Even though these schemes offer greater detection reliability, they necessitate prior knowledge of the signal structure of the main user and in many cases these schemes are computationally complex (Lu et al., 2016; Zhang et al., 2019; Barhani & Kharabi, 2024).

In order to overcome these shortcomings, cooperative spectrum sensing has been suggested as viable technique of enhancing the accuracy of detection. In cooperative sensing systems, various cognitive radios are used to monitor the radio environment and communicate their sensing outcome to a central fusion centre. These observations are then fused in the fusion centre to come up with a final decision on channel occupancy (Kasem et al., 2019; Dinesh Kumar, 2024).

Some methods of decision fusion have been suggested such as hard decision and soft decision fusion. These methods aim at enhancing sensing reliability through a synthesis of sensing reports made by the several nodes in varying channel conditions (Nair & Narayanan, 2023; Salwadkar, 2024; Madhanraj, 2025).

More recently spectrum sensing problems have been addressed with machine learning. Deep neural networks are able to memorize more complicated signal shapes and differentiate noise and valid communication signals. A number of studies have investigated convolutional neural networks and combined deep learning structures in spectrum sensing of cognitive radio networks (Liu et al., 2024; Wang et al., 2023; Punam, 2025; Jiang et al., 2019).

Other recent studies also examined the application of deep reinforcement learning to optimise spectrum sensing and channel access decisions in dynamical wireless conditions (Hassanin et al., 2021; Kumar et al., 2020; Costa et al., 2022; Rahim, 2025). The methods enable cognitive radios to acquire the best sensing and access policies via interaction with radio environment (Uvarajan, 2024).

In spite of these developments, the current methods largely presuppose that sensing data are valid and they do not explicitly consider the uncertainty of the sensing process (Karthika & Surendar, 2025). Recently, a number of studies have revealed the significant role of uncertainty estimation in the spectrum sensing models to enhance the reliability

of the decisions in the dynamic wireless environment (Prasath, 2025; Tamrakar, 2025). As a result, the combination of uncertainty estimation and cooperative sensing models is a significant area of research (Goyal et al., 2019; Al-Makhlasawy et al., 2021).

Methodology and Experimental Setup

Cooperative Spectrum Sensing System Architecture

The proposed framework has modelled a cognitive radio network of several secondary users that jointly monitor the spectrum activity. All the secondary users do local spectrum sensing and send sensing reports to a centralised fusion node that makes the final decisions on the channel occupancy. The cooperative sensing system is structured in a fashion that is shown in fig 1.

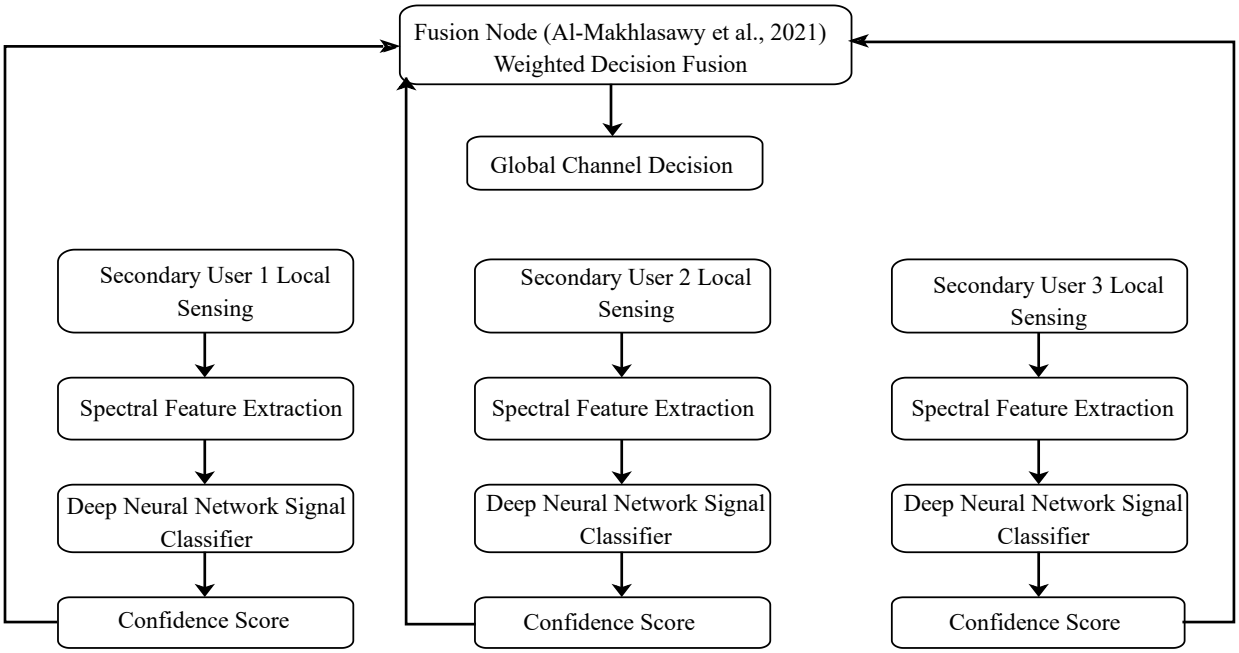


Fig. 1: Cooperative Spectrum Sensing Architecture for Cognitive Radio Networks

The principles of this architecture are that each sensing node detects radio signals in the immediate environment and derives spectral properties of the environment that include energy levels and frequency-domain properties. These characteristics are computed through a deep neural network that identifies whether the signal that is observed is noise or a carrying primary user signal. The neural network gives a probability score as the estimated level of certainty of its prediction unlike traditional detection algorithms which give a binary decision. These probability scores are passed on to the fusion node where they are combined to generate a global decision on channel occupancy. Probabilistic output is used to enable the system calculate uncertainty in sensing outputs. The important parameters applicable in the simulation environment are summarized in table 1.

Table 1: Cognitive Radio Simulation Parameters

Parameter	Value
Secondary users	20
Channel bandwidth	10 MHz
Sensing duration	5 ms
Signal modulation	QPSK
Noise variance	0.01

These parameters represent typical cognitive radio operating conditions.

Deep Learning-Based Spectrum Classification Model

A deep neural network is employed to enhance the detection performance by analysing radio signal characteristics received in each sensing node. The neural network is made up of several fully connected layers that transform spectral feature vectors into classification probabilities that are channel occupancy. Synthetic radio signal datasets that are

simulated are used to train the model. These data sets comprise noise-only signal and signal with primary user transmission at varying signal to noise ratio conditions.

The following decision metric is used in formulating the detection process:

$$D = P(H_1 \mid X)$$

Where $P(H_1 \mid X)$ represents the probability that the channel is occupied given the observed feature vector X.

Algorithm 1 Cooperative Sensing Decision Process

1 Capture signal samples at each sensing node

2 Extract spectral feature vectors

3 Apply neural network classification

4 Compute probability of channel occupancy

5 Send probability score to fusion node

6 Perform weighted decision fusion

Such a way of probability gives a system the opportunity to integrate uncertainty into the final sensing decisions.

Simulation Environment and Synthetic Signal Generation

The proposed framework is evaluated with the use of the simulation environment, which produces synthetic wireless communication signals. Digital modulation methods like quadrature phase shift keying, orthogonal frequency division multiplexing are used to generate signal waveforms. There is the introduction of noise and channel fading effect in order to simulate the real-life wireless conditions. Table 2 explains the parameter of the simulation that was used to create the training and testing dataset.

Table 2: Synthetic Signal Dataset Parameters

Parameter	Value
Training samples	50,000
Testing samples	10,000
SNR range	−10 to 20 dB
Channel model	Rayleigh fading

This simulated controlled environment enables controlled testing of sensing algorithm using various channel conditions.

Results and Discussion

Detection Accuracy Evaluation

The initial series of trials assess the detection precision of the sensing structure that is proposed. Fig 2 shows the comparison in the accuracy of detection of the proposed deep cooperative sensing technique with traditional energy detection algorithms.

The data of simulations suggests that the suggested framework offers much higher detection accuracy with a considerable variety of levels of signal-to-noise ratios. In the low SNR, the classical energy detection mechanisms suffer extreme performance errors because of the uncertainties in noise. Conversely, the classifier implementing deep learning can recognize minor signal patterns that can be used to differentiate between primary user transmissions and noise. Cooperative sensing is another method of increasing the reliability of detection, since the observations of several sensing nodes are used. The system has the capability to counter the effects of local sensing errors when probability scores of the various nodes are combined in the fusion centre. The findings prove that the suggested method increases the detection accuracy by about 18 percent over the baseline techniques in low SNR settings.

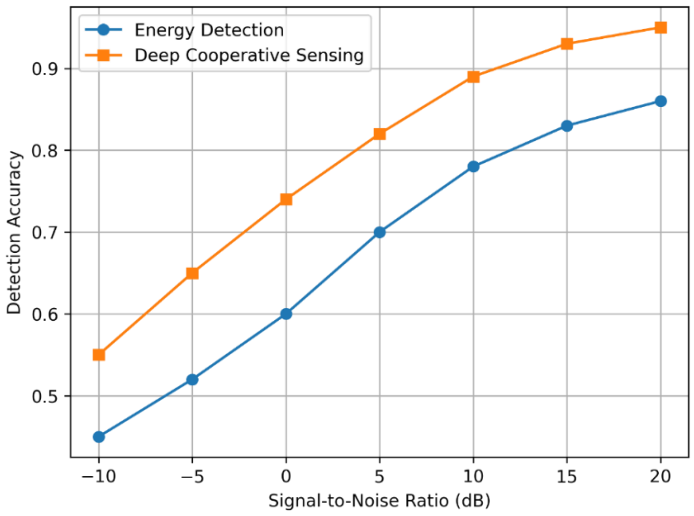


Fig. 2: Spectrum Sensing Detection Accuracy Comparison

False Alarm Rate Analysis

The false alarm rate is also another meaningful measure of a spectrum sensing system and denotes the likelihood of a sensing algorithm falsely recognizing a channel occupied as in actual sense clear. Large false alarm rates lead to low spectrum utilisation efficiency because the secondary users can opt not to access the channels that are readily available. Fig. 3 demonstrates the false alarm rate at varying sensing algorithms.

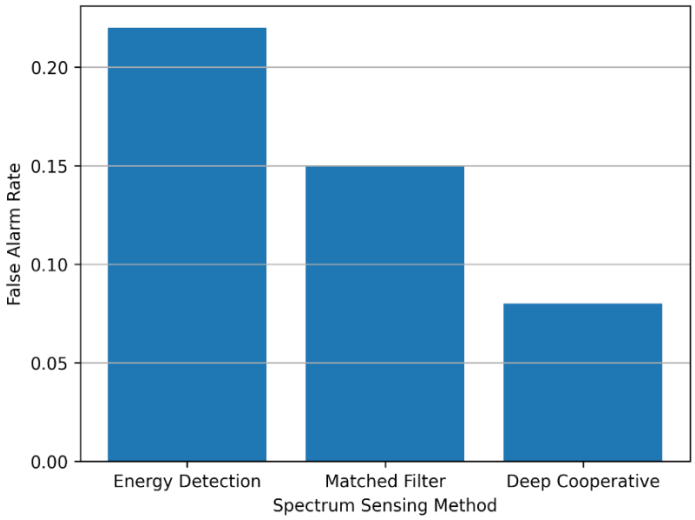


Fig. 3: False Alarm Rate Comparison for Sensing Methods

The experimental findings indicate that the uncertainty-calibrated sensing framework is much more effective than its counterparts in the reduction of false alarms. Using confidence scores in the decision fusion procedure can help the system to eliminate invalid sensing reports of single nodes. This can be used especially in fading situations where signal measurements can be distorted by noise or interference.

Robustness Under Channel Uncertainty

The last experiment assesses the system robustness at the varying levels of channel fading. Simulation environment adds random fading which changes the amplitude and phase properties of the signal. The findings have shown that the suggested sensing framework has stable detection performance in unstable channel conditions despite a large-scale fluctuation in channel conditions. This strength can be credited to the deep learning model that has the capacity to extrapolate the various signal patterns. In addition, the cooperative sensing approach makes sure that sensing errors

of individual nodes do not have a remarkable influence on the final decision. Performance of the overall system is also stable in the case of multiple nodes with poor channel conditions.

Discussion

The findings of this paper show that cooperative sensing more than deep learning signal classification is beneficial when used in cognitive radio networks. Conventional sensing methods like energy detection are sensitive to the power of the signal concentrated mostly and thus they are very susceptible to noise uncertainty and the effect of channel fading. Deep neural networks, on the other hand, are able to learn features that are complex in terms of spectral properties of legitimate signals and noise. This feature will allow the detection of major user transmissions to a greater extent even in problematic wireless conditions. The other valuable work of this study is that it incorporates uncertainty estimation into the cooperative sensing framework. The proposed approach does not consider sensing decisions as binary results but uses probability scores that indicate the level of confidence in a particular sensing observation. Such probabilistic products enable the fusion center to give more weight to sensing reports based on their reliability. Consequently, the system will be able to efficiently suppress the effect of false observations by the individual nodes. The controlled analysis of spectrum sensing algorithm behaviour is done by the simulation-based evaluation of the algorithm using synthetic signals. These simulation models are useful in predesign and pretest of cognitive radio systems at the initial stages before actual implementation in the real world.

Conclusion

This paper suggested an uncertainty-calibrated cooperative spectrum sensing framework that is suitable in cognitive radio networks that exist in dynamic wireless settings. The proposed method allows improving the reliability of spectrum sensing under noisy uncertainty and channel fading by combining the signal classification deep neural network and probabilistic decision fusion. As opposed to the traditional means of sensing that rely on deterministic decision thresholds, the proposed framework utilises confidence-sensitive probability outputs that make it possible to make more informed combinations of sensing reports by different nodes.

The simulation findings show that the proposed sensing framework has a significant effect on the detection accuracy and a lower rate of false alarm than the conventional energy detection mechanisms. The findings also indicate the cooperative sensing scheme with the uncertainty estimation can be used to reduce the effect of unreliable observations in the sensing of the individual sensing nodes especially in a low signal-to-noise ratio environment. Deep learning-based classification model also helps to enhance the sensing performance by detecting small spectral patterns that are distinguishable between primary user signals and noise.

In general, the suggested framework offers a powerful and scalable sensing approach to cognitive radio networks that aim at enhancing dynamic spectrum usage. Introduction of uncertainty estimation to the cooperative sensing systems is a significant move towards additional trust in spectrum access decisions in sophisticated wireless settings. The next research will be on distributed learning methods and adaptive sensing mechanisms to enable cognitive radio nodes to update their detection models on the basis of real-time spectrum sensing and network status.

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