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Advanced Spectrum Sensing in Cooperative Cognitive Radio Networks Using Data Fusion for Military Application

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Abstract: To increase demand for wireless communication spectrum, cognitive radio (CR) technology has arised as a promising solution to efficiently utilize the available radio frequency bands. This paper presents a novel architecture for data fusion in cooperative cognitive radio networks and designed to address the critical challenges of spectrum sensing and management. The proposed architecture supports advanced data fusion techniques and cooperative spectrum sensing to enhance accuracy and speed while maintaining efficient utilization of the spectrum. Simulations provide significant improvements in both accuracy and speed of spectrum sensing.

Keywords: Cognitive Radio Networks (CRNs), Cooperative Spectrum Sensing (CSS), Data Fusion, Military Communication, Soft and Hard Decision Fusion, Energy Detection, Simulation in MATLAB, Spectrum Detection Accuracy.

1. Introduction:

In military communications, efficient utilization of the radio frequency spectrum is crucial to ensure reliable and secure transmissions. A cognitive radio network (CRN) enables secondary users (SUs) to opportunistically access unused spectrum without interfering with primary users (PUs). The main goal of this paper is to create a cooperative spectrum sensing (CSS) to improve spectrum utilization by lowering noise and raising the accuracy of detection using methods like matched filter detection, cycle-stationary feature detection, and energy detection. The CSS collects local sensing information from distributed SUs to make a global decision regarding spectrum availability through advanced data fusion architecture. The paper explores data fusion methodologies, enabling the network to make informed decisions based on gathered from distributed spectrum sensing. The objective is to develop a simulation environment in MATLAB to evaluate the performance of the proposed framework. This environment will simulate various real-time signal scenarios, aiming to minimize false alarm rates and improve the probability of detection. The system will be designed to adapt to dynamic spectrum and efficient spectrum sensing for military applications.

2. Related Works

R. B. Chaurasiya and R. Shrestha [1] have analyzed SU signals using 16-QAM modulation in a fading channel with the help of the cooperative spectrum sensing method. In the health care mechanism [2], Kaschel has to enhance the projected energy usage that resulted in node mobility patterns useful for detecting energy efficiency. Y. Zeng and Y.-C. Liang [3] have investigated cooperative operations to enhance sensing performance and reduce sensing time in cognitive radio networks. It deals into data fusion and decision algorithms that contribute to efficient spectrum sensing. G. Ganesan and Y. Li [4] have explored cooperative spectrum sensing based on energy detection in cognitive radio networks, focusing on soft combination methods and their performance in fading channel conditions. S. M. Mishra, A. Sahai, and R. W. Brodersen [5] have discussed the practical aspects of implementing cooperative spectrum sensing strategies that utilize soft fusion techniques, emphasizing the challenges and potential solutions. S. Mishra, A. Sahai, [6] have examined various data fusion schemes implemented at the fusion center in cooperative spectrum sensing. It provides a comparative analysis of hard and soft fusion techniques, highlighting their performance in different scenarios. Ning, W, Huang [7] have selected the best SU by performance of nodes to detect probability dynamically by using the discounted upper confidence bound (D-UCB) based cooperation partner selection algorithm.

3. Cooperative Spectrum Sensing

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Cooperative sensing has been proposed as an important technique to enhance the spectrum sensing for cognitive radio networks (CRNs) in order to deal with specific sensing issues like fading, shadowing, and receiver uncertainty issues. The main objective collaboration is to enhance detection performance by using spatial diversity to more effectively protect primary users and minimize false alarms while making better use of the idle spectrum.

The cooperative spectrum sensing involves three steps.

a. The fusion center (FC) allows each cooperating CR user to perform local sensing on themselves while identifying a channel or frequency spectrum of interest for sensing.

b. Through the control channel, each cooperating CR user provides the results of their sensing.

c. The FC then sends them back to the CR users before combining the received local sensing information in order to determine whether a signal is present or not.

As shows in Fig 1, CR1 can receive signals from primary network easily. CR2 can receive signals from primary network suffers from multipath and shadowing caused by buildings and trees. CR3 suffers from the receiver uncertainty problem because it is located outside the transmission range of the primary transmitter.

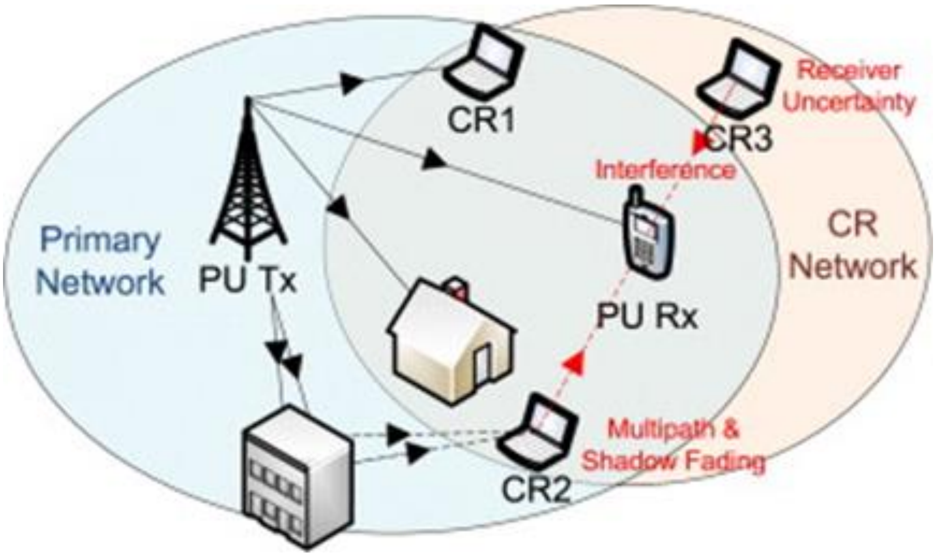

Figure-1 Cooperative Spectrum Sensing in Cognitive Radio Network

Above all these problems can be overcome with cooperative spectrum sensing if secondary users share information.

4. Data Fusion Method

Consider a peak at the cognitive radio network where K cognitive users (detected by k = {1, 2... K}) sense the spectrum to find the PU. Assume that N samples of the received signal are used by each CR to separately carry out local spectrum sensing. With two potential hypotheses, H0 and H1, a spectrum-detecting problem can be expressed as a single hypothesis-testing problem.

$$H0 = xk\ (n) = wk\ (n) \tag{1}$$

$$H1 = xk\ (n) = hk\ s(n) + wk\ (n)$$

For the kth CR user, where wk (n) is the receiver noise, and s(n) are samples of the sent signal (PU signal). This is supposed to be an i.i.d. random process with zero mean and variance. The channel between the PU and the kth CR user has a complicated gain of σn2 and hk. The absence or presence of the signal is indicated by H0 and H1, respectively. In order to determine the received energy, the kth CR user will employ an energy detector.

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$$\text{Ek} = \sum_1 x_k^2(n) \tag{2}$$

Each CR user sends the whole energy result E k to the FC in the event of a soft decision. However, to make a hard decision, the CR users compare the received energy Ek with a predetermined threshold λk to arrive at the one-bit decision provided by Δk. The CR user k of detection probability Pd, k and false alarm probability Pf, k of are defined as,

$$Pd, k = Pr\,\{\Delta k = 1|H1\} = Pr\,\{Ek > \lambda k|H1\}$$

$$Pf, k = Pr\,\{\Delta k = 1|H0\} = Pr\,\{Ek > \lambda k|H0\}$$

The following expressions can be used to represent the detection probability, false alarm probability, and miss detection probability Pm, k across AWGN channels, respectively, if $\lambda k = \lambda$ for all CR users,

$$Pm, k = 1 - Pd, k \tag{3}$$

where m=TW is the temporal bandwidth product, η is the signal to noise ratio (SNR), QN (.,.) is the generalized Marcum of function, and Γ(.) and Γ (.,.) are the full and incomplete gamma functions, respectively.

FUSION RULES

This section involves a fusion rules that can be used for comparison.

Hard Decision Fusion

In this method, each user detects the presence or absence of the primary user and sends a one-bit decision-making to the data fusion center. The key advantage of this technology is the simplicity to operate and the fact that it requires low bandwidth. When binary decisions are transmitted to the common node, three decision rules can be applied: "and," "or," and the majority rule. Assume the individual statistics Δk are quantized to one bit with $\Delta k = 0, 1$; is the difficult decision from the kth CR user: 1 indicates that the signal is present, whereas 0 indicates that it is absent. The AND rule determines if a signal is present if all users detect it.

The OR rule identifies that a signal occurs if any of the users detects a signal.

$$\text{H}_1 = \sum_{k=1} \quad \Delta_k \geq 1 \tag{4}$$

H_0 =otherwise

The third rule is the voting rule and indicates a signal is present if at least M of K users have identified a signal (1 ≤ M ≤ K). The test is formatted as

$$\text{H}_1 = \sum_{k=1} \quad \Delta_k \geq 1 \tag{5}$$

H_0 =otherwise

A majority decision is an individual case of the votes rule for M=K/2, like the AND and OR rules, which are special cases of the voting rules for M=K and M=1, respectively. The terms of cooperative detection probability Qd and cooperative false alarm probability.

Soft Data Fusion

In soft data fusion, CR users transmit the entire sensing result Ek to the center fusion without making any local decisions, and the decision is made at the fusion center using suitable combining rules. Soft combination improves hard combination, although it requires more bandwidth for the control channel. It also creates greater expenses than the hard combination scheme.

Square Law Combining (SLC): SLC is one of the most fundamental linear soft combining algorithms. In this way, the assumed energy in each node is delivered to the central fusion and combined. The summation is then compared to a threshold which determine the presence or absence of the PU, and a decision statistic is supplied by

$$Eslc \; = Ek \tag{8}$$

Where E_k represent the statistic from the k^{th} CR user.

Maximum Ratio Combining (MRC): MRC differs from SLC due to the fact that considers the energy obtained in the center of the fusion from each user with a normalized weight before adding. The weight is determined by the received SNR of each CR user. This scheme's statistical test is provided by

$$Emrc \; = \sum_{k=1} \; wk \; Ek \tag{9}$$

Selection Combining (SC): the fusion center chooses the branch with the highest SNR.

$$\boldsymbol{\gamma sc} \; = max(\gamma 1, \gamma 2, \ldots.., \gamma K\,) \tag{10}$$

The probability of false alarm and detection over AWGN channels using the SC diversity method

5. Review of Literature:

Extensive simulations were conducted using MATLAB to evaluate the performance of the proposed data fusion architecture under various scenarios. In this paper implementation, secondary users (SUs) can overcome fading and shadowing effects, and also individual SUs can sense for shorter durations, saving energy while maintaining high accuracy through data fusion at the fusion center (FC). The data fusion architecture enabled efficient spectrum allocation, reduced interference, and enhanced communication reliability and effectively combined information from multiple CRNs, leading to more reliable and accurate spectrum estimations.

Power Spectrum Of Primary User

Figure 2 represents the Periodogram of the original primary user signal. The Periodogram is a tool for visualizing the power spectral density (PSD) of a signal which shows how the signal's power is distributed over various frequencies. The presence of PU indicates at the peak of the power spectral density which is above 15db.

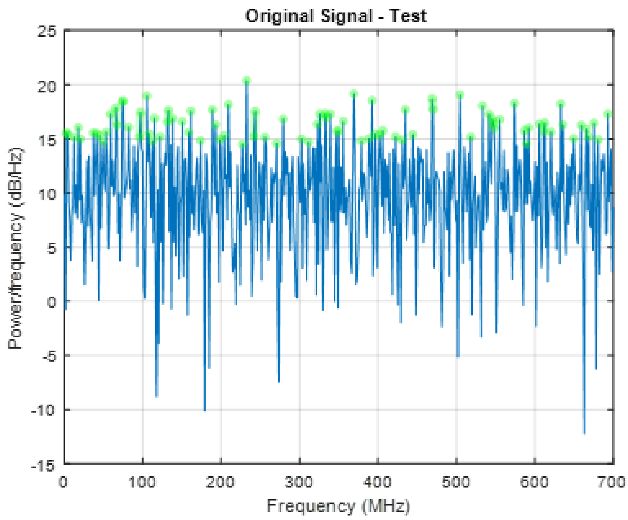

Figure-2 PSD of Primary user

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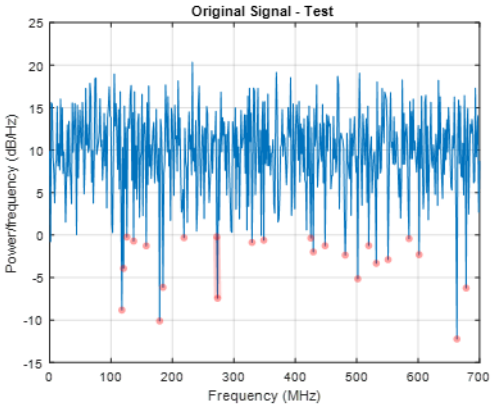

Figure-3 PSD of noise floor

The power spectral density of noise floor can be identified as below 0db as shown in figure 3.

Local Decision Of PU

If the local decision value is 1, it represents a state where the primary user is used, and the spectrum is busy, so the channel cannot be used by SU. If the local decision value is 0, it means the primary user is unused spectrum, and the channel is available for SU as shown below figures 4 and 5.

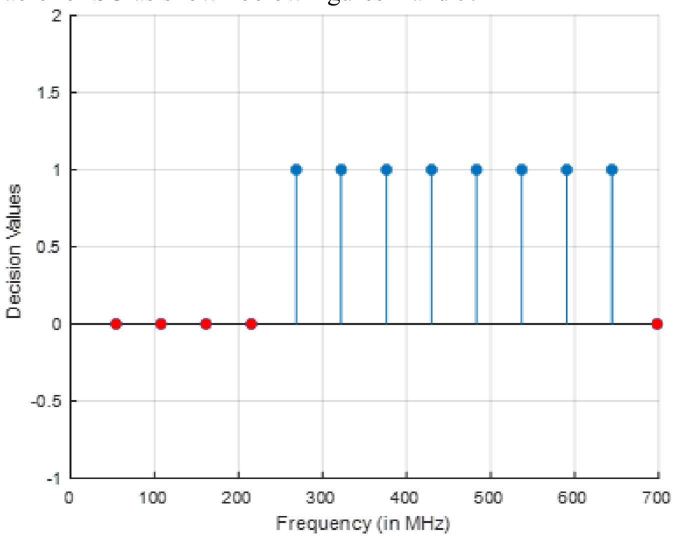

Figure-4 Local decision of PU at node 1

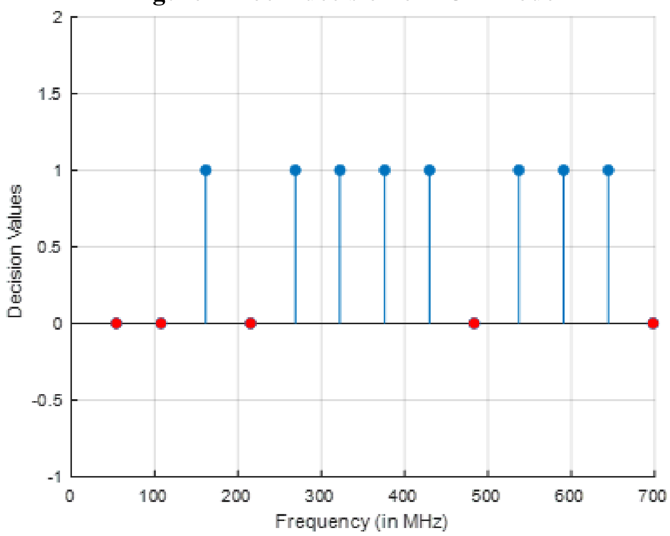

Figure-5 Local decision of PU at node 2

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Probability Of Detection And False Alarm Rate

As shown in above figure 6, the probability of detection is the probability of correctly declaring the signal is present. On the other hand, if all decisions have an equal risk of error, it is considered a false alarm rate. High Qd means the system is effective at detecting signals when they are present. Low of indicates the system has fewer false positives, meaning it is reliable in not raising false alarms.

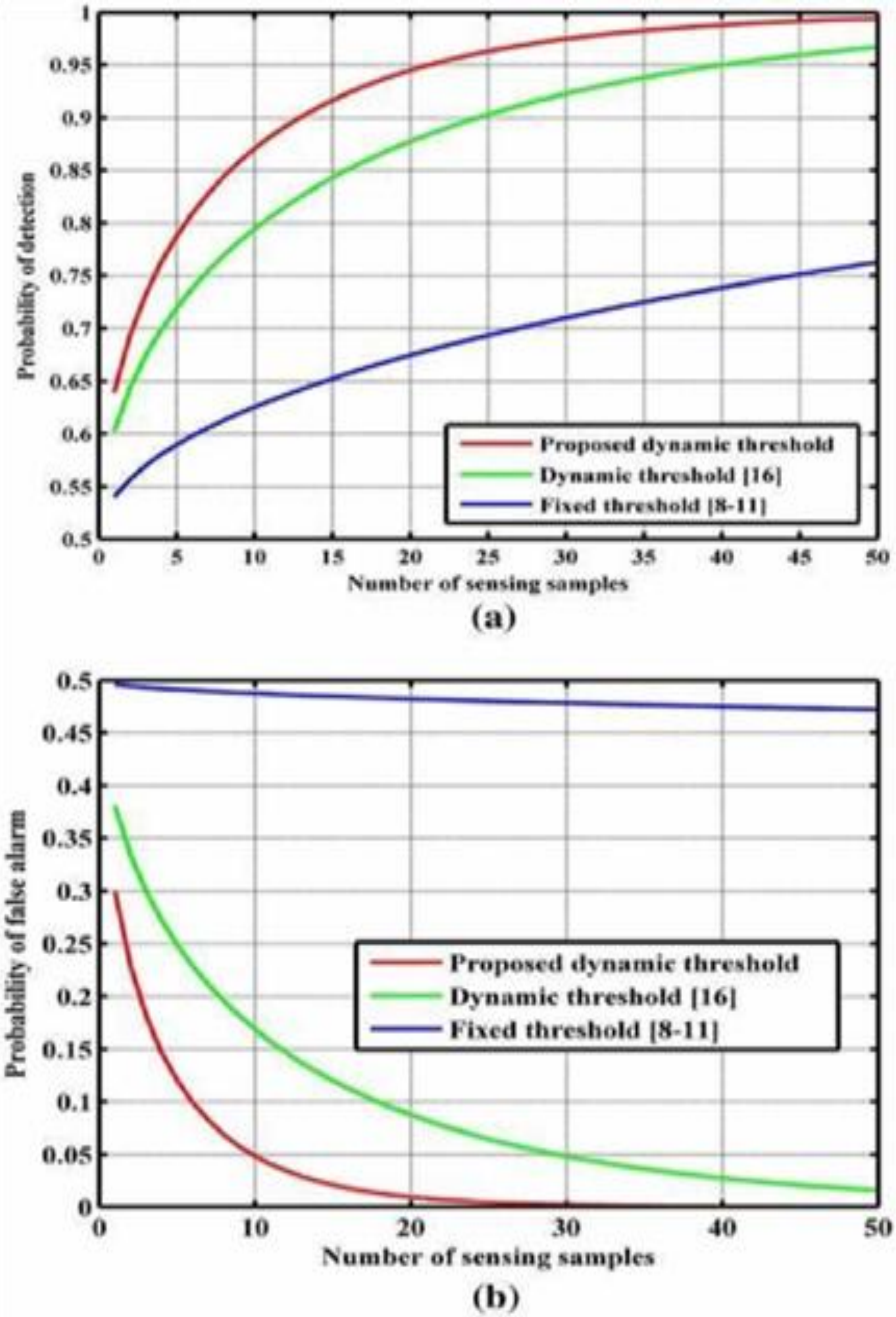

Figure-6 Probability of detection and false alarm rate

Node Location Plot

The plot illustrates the spatial configuration of all nodes in the simulation, including the primary user (PU), the fusion node, and secondary users (SUs) as shown in figure 7. This visualization helps analyze how nodes move dynamically in the simulated environment and interact with the primary user.

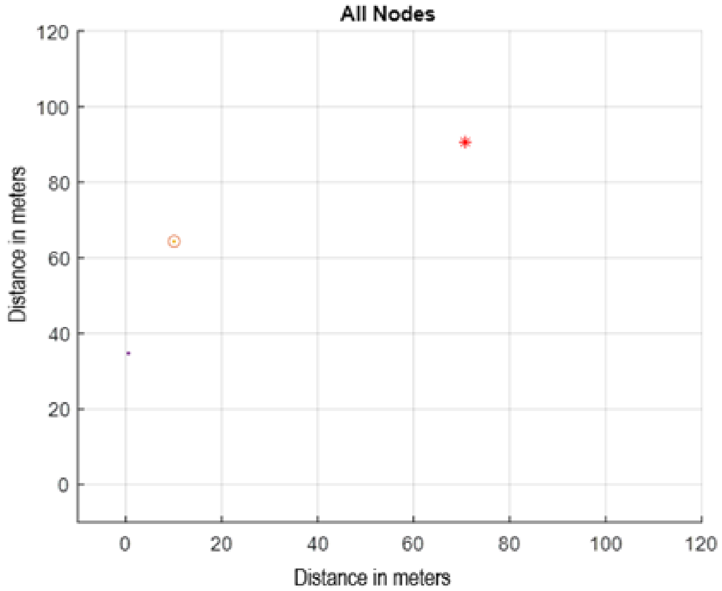

Figure-7 Node location

Red star (*): Primary user's location

This is represented by a red asterisk (*) at a fixed location (PX, PY). The PU broadcasts a signal that SUs attempt to detect.

Circles (o): Fusion center node

This is represented by a circle (o) among the secondary nodes. It serves as the central point for collecting decisions and data from other nodes.

Dots (.): Locations of other secondary users

This is represented as dots (.), scattered across the area, with their positions changing over time.

6. Conclusion

The proposed work for real-time cooperative spectrum sensing in cognitive radio networks (CRNs) exhibits exceptional potential for enhancing military communication systems. By supporting advanced data fusion techniques, this paper effectively addressed critical challenges such as network heterogeneity and spectrum scarcity in dynamic environments. Simulation results achieved an impressive spectrum detection accuracy of 97%, a high probability of detection at 98%, and a low false alarm rate of 3%. These results highlight the system's suitability for implementation in essential military applications, which ensure reliable and effective communication in limited-resource conditions.

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