ANALYSIS OF HYBRID SPECTRUM SENSING IN COGNITIVE RADIO USING HYBRID APPROACHES

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Resume

Cognitive radio (CR) technology enables dynamic spectrum access to meet the growing demand for wireless communication. This study investigates spectrum sensing methods, specifically energy detection (ED) and matched filter detection (MFD), within hybrid strategies. A novel hybrid MFD method was developed and evaluated via MATLAB simulations, analyzing factors like sample size, signal-to-noise ratio (SNR), and false alarm probability. Results reveal that ED has a higher miss-detection rate compared to MFD and the proposed hybrid method, which performs particularly well under low sample counts and SNR conditions. This research enhances spectrum sensing techniques in cognitive radio systems, paving the way for more reliable wireless communication networks.

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1 Introduction

The CR is a viable approach for more effective spectrum usage, notably in the worldwide wireless network market. It addresses the challenge of limited radio channels, primarily allocated to licensed users like television, radio, and cellular network providers. The CR technology allows DSA, allowing secondary users (SU) to use underutilized spectrum lacking interference. This approach not only alleviates spectrum scarcity but optimizes wireless communication networks, as well, driving innovation and improving connectivity across various applications. As demand for wireless communication grows, CR adoption and advancement are crucial for sustainable and efficient spectrum management [1-2].

Mitola developed cognitive radio in 1999-2000 to enable unlicensed users to reuse licensed spectrum. This technology, known as dynamic spectrum access (DSA) [3], uses an intelligent radio system called Cognitive Radio (CR) to identify frequencies, identify available spectrum gaps, and adjust transceiver features based on the radio environment data [4]. The CR addresses spectrum scarcity by allowing unlicensed users to access the channel of a licensed user when the primary user is not present [5-6]. The CR adapts to the current spectrum background, identifies gaps, and communicates opportunistically within these gaps with minimal interference [7].

The CR, although being a wireless technique, offers the ability to increase the spectrum space for wireless communication (WC). It differs from traditional wireless technology by taking advantage of multidimensional electromagnetic (MDEM) potential. This phenomenon opens up new opportunities in the MDEM space. Furthermore, multidimensional spectrum (MSD) options include frequency, time, location, code, power, angle of arrival, and polarization of wireless transmissions [8]. The CR can effectively address the spectrum shortage issue in VANET. The CR-based VANET, also known as CR-VANET, is an assuring mechanism that addresses road security, crowding, and infotainment concerns. It also serves as a foundation for next-generation transportation systems, particularly automobiles that are autonomous [9]. The increasing number of vehicles on the road has highlighted the need for Intelligent Transportation Systems (ITS) to prevent collisions, monitor traffic, and assure road safety. The VANET technology enables vehicle-to-vehicle (V2V) communication, making it suitable for new vehicular applications. The vehicle nodes have onboard modules for detecting, transmitting, and receiving communications. The vehicle's on-board system makes decisions depending on traffic conditions, vehicle speed, and other factors to prevent accidents. Furthermore, CR-enabled vehicular networks are expected to improve communication efficiency compared to existing VANETs [10].

Three crucial tasks are carried out by a cognitive radio when it is used in broadcasting environments: spectrum sensing (SS), spectrum analysis, and spectrum decision [11]. The SS is a vital factor of the CR network, involving the detection of unoccupied spectrum spaces to establish communication channels for SUs without interfering with the transmissions of primary users (PU) [12]. The spectrum sensing stage of the CR life cycle is the most sensitive [13]. This procedure continuously scans the frequency spectrum for vacancies using a chosen bandwidth or channel. Spectrum holes are the vacancies that are present in the channel. We increase the spectrum's usage by making use of these gaps in the spectrum [14]. Therefore, the spectrum sensing approach must operate effectively to identify these spectrum gaps so that CR technology may use them to support the new devices that need to communicate. Two types of bands are assumed by CR technology: licensed bands and unlicensed bands. Those who possess a band within the spectrum are referred to as main (PU) users since they are granted permission to use the band whenever they like. The second-class users are those users who attempt to utilise any available bandwidth. Although the principal users don't always use their licenced band, the secondary users can still communicate by utilising these bands. SS techniques might be utilized to find these shortfalls in these licensed bands. To identify gaps and make the most use of the channels that are not being used by the principal users, the spectrum sensing algorithm's performance becomes vital [15]. Different signal properties, including ED, MFD [16], cyclo stationary detection, and so on, are used in traditional spectrum sensing techniques [17-18]. The most often utilized SS technology is ED [19-20]. Greater reliability is achieved with matched filtering, although needs previous awareness of the signal of the PU [21-22]. Therefore, CFD-based SS achieves well in the negative SNR zone as related to matched filter and ED-based approaches, given that CFD sensing has some understanding of PUs [23].

Though every spectrum sensing methodology has advantages and disadvantages, no single approach is always the best choice. To tackle this obstacle, scholars have suggested hybrid spectrum sensing methodologies that merge various sensing approaches to capitalize on their complimentary benefits. Improved detection robustness, adaptability to a variety of environmental circumstances, and dependability are possible with hybrid spectrum sensing.

Hybrid techniques are included in cognitive radio systems by employing different fusion procedures to integrate the outputs of individual sensing methods. Compared to independent methods, hybrid spectrum sensing can perform better by cleverly merging the outputs of ED and matching filter feature detection. They assess how well various fusion strategies perform in terms of improving detection precision, lowering false alarm rates, and simplifying calculation. We illustrate the potential advantages of combined spectrum sensing to improve the effectiveness of spectrum usage and facilitate smooth cohabitation with main users through simulations and performance evaluations. Our results give useful insights for constructing robust and adaptable spectrum sensing techniques and advancing modern spectrum sensing for CR systems. The primary contributions to the analysis are as follows:

1. The hybrid spectrum sensing method combines techniques for matching filter detection and ED. This hybrid strategy is intended to maximize the benefits of each method while correcting for their unique limits, resulting in improving overall SS performance.
2. Performance of the suggested hybrid technique will be thoroughly evaluated using MATLAB simulations in a variety of scenarios with varying SNR levels, false alarm probability, and sample counts.
3. Furthermore, it suggests hybrid spectrum sensing strategies that enhance detection robustness and adaptability to varying environmental conditions by combining several sensing techniques.

The review of the literature for several types of research related to ED and matched filter detection was summarized in Section 2; the system model, its types and the suggested technique were explained in Section 3, and Section 4 provides graphs illustrating the stimulation and effect, a conclusion in section 5, and the list of references for this work is given in the part that follows.

2 Literature review

The ED method's low implementation complexity makes it a well-liked signal-sensing strategy in spectrum sensing. Nevertheless, uncertainty arises because noise variance uncertainty is frequently computed. This study [24] suggests an ED-based sensing technique that integrates signal samples from several antennas to produce a decision threshold independent of noise variation. According to simulation data, this method outperforms the ED method without noise variance estimations, approaching 1 even at SNRs of -15 dB. However, the noise characteristics could vary depending on the environment or operating conditions, the method claim to be noise-independent might not always hold true.

In cognitive radio, spectrum sensing is essential, and ED is the most commonly utilized kind. Because of their predetermined thresholds, conventional double-threshold ED approaches have a poor detection probability. An adaptive double-threshold cooperative spectrum sensing method is presented [25], which aggregates detection results using the "or" condition and the average energy of prior sensing moments. When compared to alternative double-threshold methods, this method considerably enhances detection performance. However, it might function well in a steady environment, and some sudden changes in the environment could cause it to malfunction. It might not respond fast enough to cope with the signal's frequent shifts.

The utilization of wireless systems has risen due to the growing need for apps on tablets, mobile phones, IoT, and WSNs. To enhance throughput in wireless networks, it is necessary to comprehend spectrum scarcity [26]. By borrowing spectrum from cognitive networks, networks can work together to achieve lower error rates at lower SNR values and longer sharing procedures. However, the evaluation, which evaluates ED probability with false alarm rates and signal-to-noise ratio, may not fully capture the performance and efficacy of spectrum-sharing mechanisms in cognitive networks.

In the present research [27], a novel ED method for cognitive radio system spectrum detection is introduced. Using Newton's method with forced convergence, the three-event ED (3EED) approach approximates the optimum decision threshold with high accuracy. The method represents a breakthrough in tracking primary users' actions, outperforming conventional ED (CED) in spectrum sensing. However, false positives and false can still occur despite the efforts to reduce the chance of decision errors. Careful consideration should be given to how these faults may affect the overall performance of the system.

The 5G technology uses more energy but also demands higher receiver sensitivity. 5G technology is anticipated to provide large data traffic volumes and minimum latency [28]. It also highlights the potential advantages of cognitive radio and 5G by implying that MIMO can increase radiated energy and spectrum efficiency. However, when cognitive spectrum sensing and power harvesting are used together, there may be mismatches with current devices and infrastructure, necessitating major upgrades or changes.

The paper [29] focuses on applying a novel method based on matched filter identification to find effective channels in cognitive radio networks at low SNR. The ED in different SNR conditions is compared with the matching filter detection with 10 samples using MATLAB. The findings indicate that matched filter detection performs better in terms of sensing since it has a higher chance of detection at low SNRs (-30 dB) than ED (-10 dB). However, not all situations or signal types will lend themselves to matched filter detection. Various elements, like multipath propagation, interference types, and signal modulation, may affect its effectiveness.

Dynamic spectrum allocation is required due to the growing number of wireless applications and consumers. A radio system called Cognitive Radio takes advantage of its environment to determine vacant spectrum to increase efficiency. For systems based on Cognitive Radio, spectrum sensing is essential. This work [30] employs simulations to assess several spectrum sensing techniques and determines the best way based on real-world application results. However, system efficiency might be decreased by false positives or lost opportunities to utilize the available spectrum.

As a result, the method's noise characteristics can change based on the surroundings and how it is used, therefore its claim that its noise-independent is not necessarily valid. It is possible that spectrum-sharing processes in cognitive networks are not fully captured by the assessment of ED probability and false alarm rates. There is still a chance of false positives and false negatives, which could impact system performance. Mismatches may arise when cognitive spectrum sensing and power harvesting are combined, requiring updates or modifications.

3 System model

Spectrum sensing is the process of detecting available frequency bands in wireless communication. It allows cognitive radios to opportunistically access unused spectrum, enhancing efficiency.

a) Energy detection

A secondary user tracks the energy content in a particular frequency band to verify its occupancy using energy-detecting technology. When the primary users are present in the spectrum, energy levels rise significantly over the noise floor. To determine the spectrum occupancy, when detecting energy, the incoming signal energy is compared to a predetermined threshold [31].

b) Cyclostationary (CS) detection

Cyclostationary detection is the most important spectrum sensing technique for advanced radio that is available. It is a promising algorithm because it can identify the spectrum at low SNR without being affected by noise. By calculating the mean and autocorrelation of the signal, it takes advantage of the periodicity characteristics of the data. The identification of PU without a discernible interference between PU and SU is another important feature of CS. The CS algorithm has been used recently to identify the spectrum under different circumstances [32].

c) Matched filter detection

It is a viable method for spectrum sensing in CR networks, particularly when comprehensive prior information of the primary user signal's parameters is available, including its center frequency, bandwidth, modulation scheme, and the wireless channel's response. This technique entails comparing the received signal with pilot samples obtained previously from the same radio transmitter. By leveraging these stored pilot signals, the matched filter computes a test statistic, enabling precise detection of the primary user's presence [33].

3.1 Mathematical model for current spectrum sensing methods

The efficiency of this algorithm is dependent on several factors, including noise uncertainty, sample size, and SNR ratio. One of the two hypotheses H_0 or H_1 is chosen by spectrum sensing using Equation (1) and (2) by the signal that is received.

$$H_0 : x(n) = w(n), \tag{1}$$

$$|H_1 : x(n) = y(n) + w(n). \tag{2}$$

In this study, a spectrum sensing technique is employed to ascertain the presence or absence of a PU within a particular frequency band. The hypothesis H_0 suggests the absence of the primary user, while H_1 signifies the presence of the primary user's signal. In addition, $x(n)$ is the n^{th}sample of the signal received by the secondary user and $y(n)$ is the transmitted signal. The detection statistic S is then compared with a predefined threshold λ, and the detector's performance is assessed using the probability of detection (P_d) and the probability of false alarm (P_{fa}).

P_{fa} is a probability of H_0, and is provided by Equation (3),

$$P_{fa} = P_r\left(S > \lambda / H_0\right). \tag{3}$$

P_d denotes a probability of H_1, and is given by,

$$P_d = P_r\left(S > \lambda / H_1\right). \tag{4}$$

The possibility that a sensing algorithm may detect a PU presence even in the absence of PUs is known as the false alarm probability. A low false alarm probability makes it more likely that SUs will use the sensed spectrum, which raises the secondary network's feasible throughput. The number of times the sensing approach properly determines the existence of PU is known as the probability of detection. The PU controls how well the system performs. Enhancing PU spectrum utilisation can maximise PU priority by recognising more PUs and minimising interference through longer sensing distances and interference-prevention limits.

A successful sensing approach achieves a high probability of detection while maintaining a low probability of false alarms.

Another challenging task is figuring out the threshold that will be utilized to compare to the probability. As a result, practical conditions must be followed when doing theoretical analysis and numerical computations.

Techniques for spectrum sensing are based on the problem of binary hypothesis testing. The theoretical formulation is in equation (5):

$$x(n) = \left\{\begin{cases} w(n) & under\ H_0 \\ y(n) + w & under\ H_1 \end{cases}\right. . \tag{5}$$

a) Energy detection

Energy detection is highly preferred for its simplicity and its capability to operate without prior knowledge of the primary signals [34-35]. The detection statistic for ED was derived by computing the average energy of N experimental samples, y(n), as equation (6):

$$S = \frac{1}{N}\sum_{n=1}^{N} |x(n)|^2 . \tag{6}$$

Equation (7) defines the average signal-to-noise ratio:

$$SNR = \frac{P}{\sigma_n^2} \tag{7}$$

and σ_n^2 denotes the noise variance.

The received signal power is defined in equation (8):

$$P = \lim_{N \to \infty} \frac{1}{N}\sum_{n=1}^{N} |y(n)|^2 . \tag{8}$$

The probability of a false alarm was determined as equation (9),

$$P_{fa} = \left(\frac{\lambda - \sigma_n^2}{\sqrt{2\sigma_n^2 / N}}\right). \tag{9}$$

The probability of detection is determined by equation (10),

$$P_d = \left(\frac{\lambda - (P + \sigma_n^2)}{\sqrt{2(P + \sigma_n^2)^2 / N}}\right). \tag{10}$$

Equations (9) and (10) are substituted to give the criteria for the chance of false alarm in Equations (11) and (12).

$$\lambda = Q^{-1}(P_{fa}) \cdot \sqrt{2\sigma_n^4 / N} + \sigma_n^2 , \tag{11}$$

$$\lambda = Q^{-1}(P_d) \cdot \sqrt{2(P + \sigma_n^2)^2 / N} + P + \sigma_n^2 . \tag{12}$$

From Equation (7), (11), (12), it is possible to determine the correlation between N, SNR, P_{fa}, and P_d using equation (13):

$$P_d = Q\left(\frac{Q^{-1}(P_{fa}) \cdot \sqrt{2/N} - SNR}{\sqrt{2/N} \cdot (SNR + 1)}\right). \tag{13}$$

Further, the probability of missing a recognition is equation (14):

$$P_{mr} = 1 - P_d . \tag{14}$$

b) Matched filter detection

As explained in [36], the Matched filter is used for coherent detection. This method is extensively employed in spectrum sensing due to its ability to optimize the SNR. When the characteristic unknown signal aligns with those of a known signal, it is inferred that a PU is present in the spectrum. By correlating the received signal with a reference pilot signal, y_p, the presence of the PU can be detected using equation (15):

$$S = \frac{1}{N}\sum_N x(n) * y_p(n). \tag{15}$$

Corresponding to Neyman-Pearson criteria, P_d and P_{fa} are, stated as

$$P_d = Q\left(\frac{(\lambda - E)}{\sqrt{E\sigma_n^2}}\right), \tag{16}$$

$$P_{fa} = Q\left(\frac{\lambda}{\sqrt{E\sigma_n^2}}\right), \tag{17}$$

where:

$$E = \sum_{n=1}^{N} y(n)^2, \tag{18}$$

where E represents the energy signal.

By manipulating Equations (16) and (17), the following formulas can be used to get the thresholds:

$$\lambda = Q^{-1}(P_d) \cdot \sqrt{E\sigma_n^2} + E, \tag{19}$$

$$\lambda = Q^{-1}(P_{fa}) \cdot \sqrt{E\sigma_n^2}, \tag{20}$$

$$P_d = Q\left(Q^{-1}(Pfa) - \sqrt{\frac{E}{\sigma_n^2}}\right). \tag{21}$$

3.2 Model of the hybrid matched filter detection technique

Figure 1 illustrates the block diagram for the recommended “Hybrid Matched Filter Detection”. This approach integrates the conventional Matched Filter Detection methodology with the double Matched Filter Detection (MFD). Given its hybrid nature, it manifests two distinct responses contingent upon the probability of a false alarm. When the probability of a false alarm is below 0.5, the second part of the detector, representing a double-matched filter detector, is activated. This innovative double-matched filter detector functions by multiplying the thresholds and detection statistics derived from two standard-matched filter detectors. Conversely, when the probability of a false alarm equals or exceeds 0.5, a standard-matched filter detector is employed.

Equation (22) is the detection statistics of the detector for $P_{fa} < 0.5$

$$S = \frac{1}{N}\sum_N x(n) * y_p(n) \cdot \frac{1}{N}\sum_N y(n) * y_p(n). \tag{22}$$

Equation (15) provides the detection statistics of the detector corresponding to P_{fa} >= 0.5. The detector’s cutoff for P_{fa} < 0.5 is provided by equation (23):

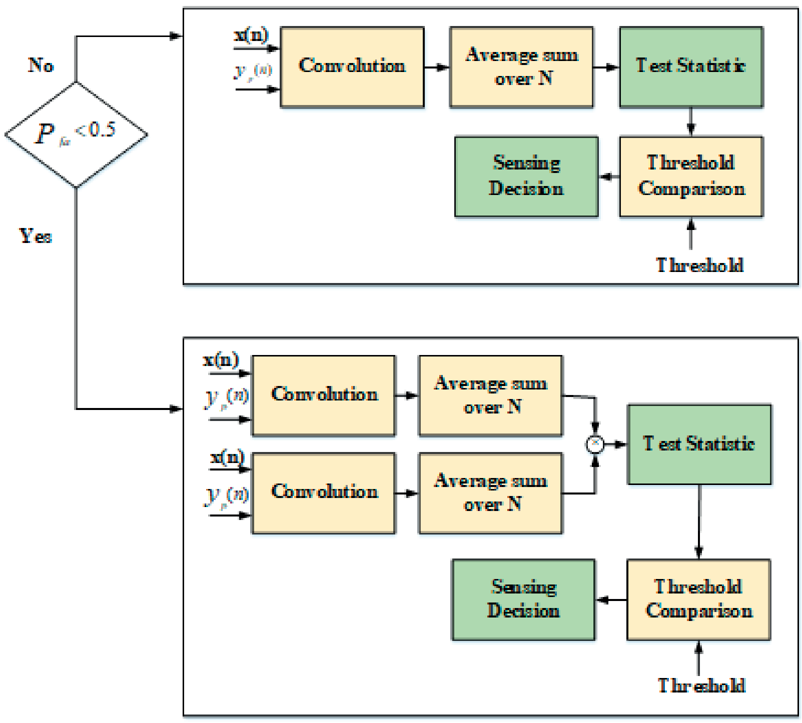


***Figure 1** The hybrid matched filter detection technique’s proposed model*

$$\lambda = \left(Q^{-1}(P_{fa}) \cdot \sqrt{E\sigma_n^2}\right)^2. \tag{23}$$

Equation (20) gives the threshold of the detector corresponding to P_{fa} >= 0.5.

When the false alarm probability is less than 0.5, the double-matched filter detector works better than the conventional matched filter detector. The probability of missed detections rises with the false alarm probability, up to 0.5 or higher, however, there comes a tipping point where the double-matched filter detector is outperformed by the conventional matched filter detector.

The probability of miss-detection was calculated utilizing a flowchart in Figure 2, with variables N_t, N_d, and P_{fa} representing Monte-Carlo simulations, iterations, and false alarm probability, respectively. The approach for both the ED and MFD involves setting the sample count, SNR, and several Monte Carlo runs. The loop was implemented to cover false alarm probabilities in increments of 0.01 from 0 to 1, with another cycle increasing the number of Monte Carlo simulations. A new variable, i, was used to determine the number of Monte-Carlo simulations completed and remaining. The transmitted signal and additive white Gaussian noise are randomly generated for each Monte-Carlo simulation utilizing the randn function with a mean of zero, allowing signals to have both positive and negative values.

This is how the detection statistic is computed: Equation (6) is utilized for the Energy Detection, and the detection statistic's outcome is always positive. The Matched Filter Detection uses Equation (15), and the result could be positive or negative.

When calculating the risk of false threshold for ED, Equation (11) is taken into account, but for Matched Filter Detection, Equation (20) was employed. One finding is that the value in the equation's second component is always higher than the value in the first portion. When these values are added together, as per Equation (11), the threshold for Energy Detection always yields a positive result. On the other hand, a null, positive, or negative threshold can be used for Matched Filter Detection. This phenomenon is explained by the Q^{-1} function's fluctuating behaviour.

- it is positive for a P_{fa} < 0.5;
- it is negative for a P_{fa} > 0.5;
- it is zero for a P_{fa} = 0.5.

To ascertain whether the detection statistic surpasses the threshold, confirmation is required. If the detection statistic is smaller than the threshold, it can be used to interpret whether the variable i equals N_t. This requirement is satisfied when every Monte-Carlo simulation for every value of the false alarm chance has been finished. $1 - N_d/N_t$ provides the likelihood of miss-detection. The false alarm likelihood simulation terminates at that point.

The variable i will be increased and a new Monte-Carlo simulation will begin by randomly generating the signals if the variables i and N_t differ. We shall increase the variable N_d if the detection statistic exceeds the threshold. The next step is to confirm that, as previously mentioned, the variable i equals N_t. In the last step, the completion of all the Monte Carlo simulations for the present false alarm probability is confirmed. If this is the case, it is possible to determine the probability of miss-detection for the current false alarm probability; if not, one must run additional Monte-Carlo simulations until all the false alarm probabilities have been run and a plot is produced. The Double MFD scenario‘s method for determining the chance of miss-detection is quite parallel to the MFD method. The alterations are in the MFD‘s threshold and squared values of the detection statistic.

The Double MFD‘s detection statistic and threshold are established as follows:

- The detection statistic is calculated using Equation (22) and the outcome is always positive.
- The threshold is calculated using Equation (23) and is always positive, except P_{fa} = 0.5, where the value is zero.

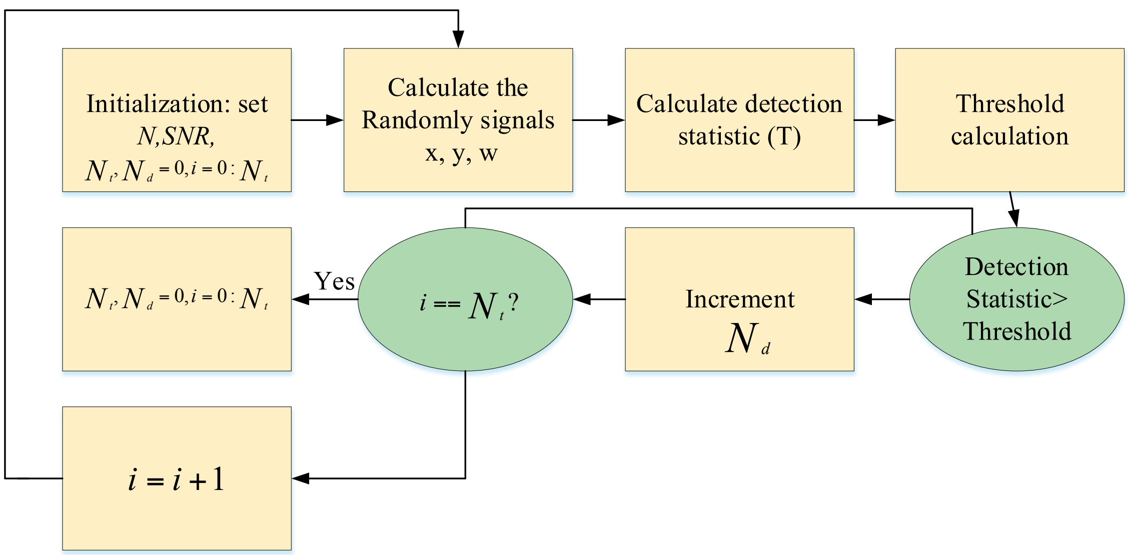
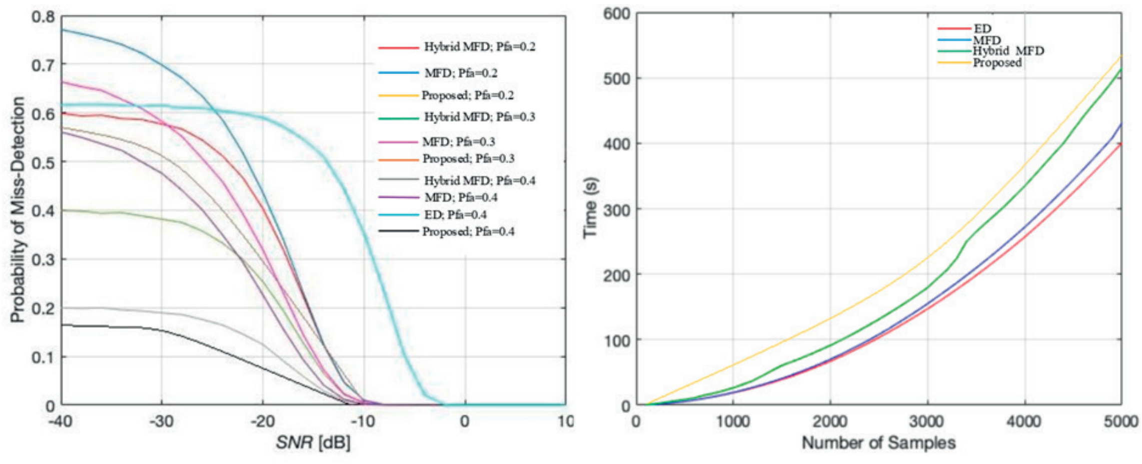


Figure 2 *The algorithm that computes the miss-detection probability*



(a) *(b)*

***Figure 3** Comparison between techniques for the probability of miss-detection vs SNR for* (a) Pfa = 0:3, (b) N=100

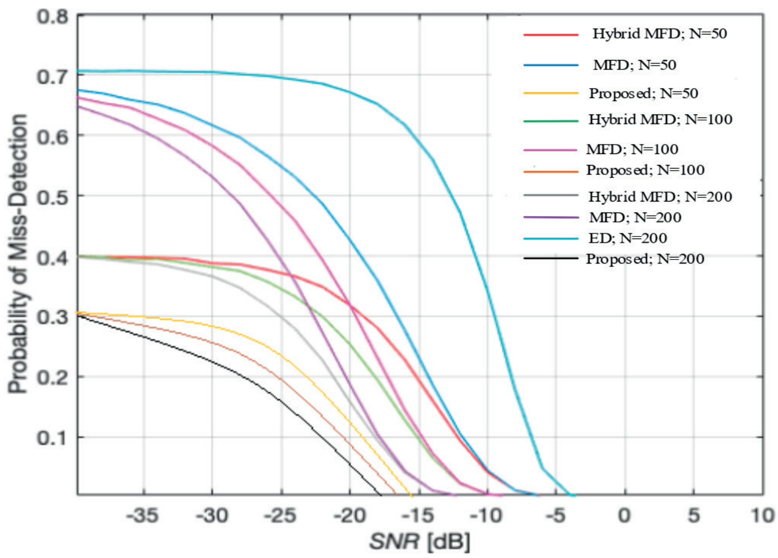


***Figure 4** Comparison of the time vs number of samples with P_{fa} = 0:3 and SNR D -25 dB*

4 Stimulation and results

MATLAB is used to simulate and analyse various strategies while changing the parameters to assess the impact of the number of samples, chance of false alarm, and SNR on the probability of miss-detection. Figures 3 and 4 display the consequence for the probability of miss-detection as a function of SNR when comparing different spectrum sensing approaches. P_{fa} = 0.3 is taken into account in Figure 3.

In Figure 3, we consider N = 100 while varying the probability of false alarm (except the ED sensing approach, which only took P_{fa} = 0.4 into account). Compared to the MFD, the Hybrid MFD (or HMFD) in Figure 3 exhibits a lower probability of missed detection for N = 50, N = 100, and N = 200, up to the SNR of -10 dB, -12 dB, and -16 dB, correspondingly. Under these SNR settings, the proposed hybrid technique performs better.

When comparing Figure 4's P_{fa} = 0.2, P_{fa} = 0.3, and P_{fa} = 0.4 values to the MFD, the probability of miss-detection decreases until the SNR reaches -14 dB, -12 dB, and -10 dB, in that order. Increasing SNR is analogous to the HMFD and MFD behaviours. As an indicator of computational difficulty, Figure 4 contrasts the approach simulation running time for a given N across several spectrum sensing techniques. Figure 4 takes into account SNR of -25 dB and P_{fa} of 0.3. O(N^{-2}) is the computational complexity for all spectrum sensing methods under consideration. As N increases in Figure 4, so does the running time. The disparity between the three spectrum sensing methods increases with increasing N. MFD and HMFD need 431 and 515 seconds, respectively, to mimic 5000 samples, also the ED sensing approach requires 401 seconds. Compared to the traditional sensing method the proposed hybrid sensing takes 520 seconds to complete the task. In contrast to current methods like ED, MFD, and

HMFD the suggested HMFD sensing methodology will undoubtedly enable the SUs to identify spectrum gaps more effectively in a variety of situations, all the while gaining unhindered access to major licensed bands.

5 Conclusion

The study's findings highlight the critical role of efficient spectrum sensing in cognitive radio (CR) technology to meet the burgeoning demand for wireless communication in transportation systems. By exploring energy detection (ED) and matched filter detection (MFD) methods, and developing a novel hybrid-matched filter detection approach, the research addresses the need for reliable spectrum access in vehicular communication networks. The MATLAB simulations revealed that ED, although simpler, has a higher miss-detection rate compared to MFD and the hybrid MFD method. Notably, the hybrid MFD method demonstrated superior performance, especially in challenging conditions characterized by low sample counts, low signal-to-noise ratios (SNR), and false alarm probabilities slightly below 0.5. This advanced method ensures more accurate detection of primary users, thereby preventing interference and ensuring seamless communication. The enhanced spectrum sensing techniques proposed in this study not only improve the reliability and efficiency of cognitive radio systems but significantly contribute to safer and more connected vehicular environments, as well. As transportation systems increasingly rely on robust wireless communications, the advancements in CR technology underscore a pivotal step towards achieving dynamic, resilient, and high-performance communication networks essential for modern transportation infrastructures.

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Conflicts of interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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