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HYBRID APPROACH FOR SECURELY MAXIMIZING SPECTRUM UTILIZATION IN COGNITIVE RADIO NETWORKS: MATCHED FILTER AND SALP SWARM ALGORITHM-OPTIMIZED ENERGY DETECTION

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A B S T R A C T

The research paper proposes a novel approach for signal detection in cognitive radio networks, aiming to improve spectrum utilization and overall performance. The approach combines matched filter-based detection and the Salp Swarm Algorithm (SSA)-optimized energy detection.Matched filtering is a technique used to detect the presence of a known signal. It correlates the received signal with a reference waveform to determine if the signal is present. In the proposed approach, matched filtering is utilized to detect known signals in the cognitive radio network.On the other hand, energy detection is employed to identify unknown signals. Energy detection measures the energy level of the received signal and compares it to a predetermined threshold. If the energy exceeds the threshold, it is considered as a signal. In this approach, energy detection is optimized using the Salp Swarm Algorithm (SSA). SSA is a metaheuristic algorithm inspired by the behavior of salps in nature, and it is used to find an optimal energy threshold for energy detection in order to improve detection accuracy. The proposed approach is evaluated through simulations, and the results demonstrate its superiority over existing methods in terms of probability of detection, probability of false alarm, and receiver operating characteristics. This indicates that the proposed hybrid approach offers better performance in detecting both known and unknown signals, leading to more efficient spectrum utilization.

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1. INTRODUCTION

In cognitive radio networks, reliable and efficient signal detection is crucial for effective spectrum utilization. Two commonly used techniques for spectrum sensing in CRNs are matched filter detection and energy detection. Matched filter detection (Ali & Hamouda, 2016) is a technique used to detect the presence of a known signal in the received waveform. It involves correlating the received signal with a reference waveform, which is the expected shape of the known signal. The correlation output is then compared to a threshold to determine the presence or absence of the signal. Matched filter detection is particularly effective when the characteristics of the signal are well known and the noise level is relatively low. It is often used for detecting signals with specific patterns or waveforms. Energy detection (Salahdine et al., 2015), on the other hand, is used to identify unknown signals or signals with uncertain characteristics.

It is based on measuring the energy level of the received signal and comparing it to a predetermined threshold. If the energy exceeds the threshold, it is considered as a signal. Energy detection is a non-coherent technique, meaning it does not require knowledge of the signal parameters. It is commonly used when the characteristics of the signal are unknown or vary over time, such as in scenarios where the spectrum is shared with multiple users or in the presence of fading channels. Optimizing the threshold for energy detection is crucial to achieve reliable and accurate signal detection. The threshold determines the trade-off between the probability of detection (Pd) and the probability of false alarm (Pfa). A low threshold increases the probability of detection but also leads to a higher probability of false alarm, while a high threshold reduces the probability of false alarm but may result in missed detections. To optimize the threshold for energy detection, the research paper proposes using the Salp Swarm Algorithm (SSA) (Mohammed et al., 2018). SSA is a metaheuristic algorithm inspired by the behavior of salps in nature. It is used to find the optimal energy threshold that maximizes the detection performance in terms of Pd and Pfa. The SSA iteratively adjusts the threshold based on the performance evaluation and search space exploration, eventually converging to an optimal threshold value.

By combining matched filter-based detection for known signals and SSA-optimized energy detection for unknown signals, the proposed approach offers a comprehensive and efficient solution for signal detection in cognitive radio networks. It improves the spectrum utilization by accurately identifying available spectrum bands while minimizing interference with licensed users. This approach has practical implications for various CRN scenarios, including dynamic spectrum access and spectrum sensing.

1.1 Matched Filter Detection

Matched filter detection is indeed a powerful technique for detecting the presence of a known signal in a noisy environment. In the context of cognitive radio networks, the known signal refers to the primary user signal, which is typically a licensed user transmitting over a specific frequency band. The matched filter is designed to maximize the output signal-to-noise ratio (SNR) for the given input signal. It is designed based on the characteristics of the primary user signal, which are assumed to be known. The impulse response of the matched filter is derived from the time-reversed and conjugated version of the primary user signal. To perform matched filter detection, the received signal is convolved with the impulse response of the matched filter. The resulting output signal represents the correlation between the received signal and the known signal. By comparing this output signal to a predefined threshold, it can be determined whether the primary user signal is present or not. In order to extract the baseband signal from the output of the matched filter, an envelope detector is commonly used.

The envelope detector captures the magnitude variations of the output signal and produces a baseband representation. This baseband signal can then be further processed and compared to a threshold for signal detection. While matched filter detection is highly effective in low noise environments, its performance can degrade in high noise environments due to the presence of noise and interference. In such cases, other techniques like energy detection or hybrid approaches combining multiple detection methods may be employed to improve the detection performance. It is worth noting that the performance of matched filter detection in cognitive radio networks heavily relies on accurate knowledge of the primary user signal characteristics and the assumption that the primary user signal is time-invariant. Any deviation from these assumptions can impact the detection accuracy and may require adaptive or learning-based approaches to address signal variations and changes in the environment.

1.2 Energy Detection

Energy detection is a widely used technique in cognitive radio networks for detecting the presence of a primary user signal. It operates based on the principle that the energy of the primary user signal is typically higher than the energy of the noise and interference within a specific frequency band. The energy detector is a non-coherent technique, meaning it does not rely on prior knowledge of the primary user signal characteristics. Instead, it measures the energy of the received signal within a designated frequency band. The received signal can include not only the primary user signal but also noise and interference from other sources.

To determine the presence or absence of the primary user signal, the measured energy is compared to a predefined energy threshold. The threshold is established based on factors such as the noise level and the desired probability of false alarms. A higher threshold reduces the probability of false alarms but might increase the probability of missed detections, while a lower threshold improves the detection sensitivity but can lead to more false alarms.

The energy detection technique is particularly useful in scenarios where the primary user signal characteristics are unknown, variable, or time-varying. It can handle situations where the primary user signal exhibits different modulation schemes or signal waveforms. However, it is essential to consider that energy detection has its limitations. In low signal-to-noise ratio (SNR) scenarios, the detection performance may degrade due to the challenges of reliably distinguishing the primary user signal energy from the noise and interference energy. Advanced techniques, such as adaptive thresholding or hybrid approaches combining energy detection with other detection methods, can be employed to address these challenges and improve the overall detection performance in cognitive radio networks.

1.3 Threshold Optimization

The threshold for energy detection plays a crucial role in determining the performance of the detector, and optimizing this threshold is essential to achieve reliable and accurate signal detection in cognitive radio networks. The threshold is typically set based on two main factors: the noise level and the desired false alarm probability. The noise level represents the energy present in the absence of any primary user signal. By setting an appropriate threshold, the energy detection technique aims to distinguish between the primary user signal's energy and the energy resulting from noise and interference. To optimize the threshold, the false alarm probability needs to be minimized while maintaining a high detection probability. The false alarm probability refers to the likelihood of detecting a primary user signal when there is no signal present. Minimizing the false alarm probability ensures that the detector does not erroneously detect signals when the primary user is not actually transmitting.

One common method for optimizing the threshold is by utilizing the receiver operating characteristic (ROC) curve. The ROC curve is a plot of the detection probability (Pd) against the false alarm probability (Pfa) for different threshold values. By varying the threshold, different operating points on the ROC curve can be achieved. The optimal threshold is the one that maximizes the area under the ROC curve. This threshold value strikes a balance between the detection probability and the false alarm probability, leading to the best overall performance of the energy detection technique. Optimizing the threshold through the ROC curve enables the selection of a threshold value that provides the desired trade-off between detection performance and false alarm rate, taking into account the specific requirements and constraints of the cognitive radio network application.

2. LITERATURE REVIEW

In cognitive radio networks, matching filter detection and threshold optimisation of energy detection have both been the subject of extensive research. We will talk about a few of the most current works in this field in this literature review. In order to enhance the effectiveness of spectrum sensing in cognitive radio networks, one study by the authors of (Muthumeenakshi & Radha, 2014) presented a hybrid detection technique that combines matched filter detection with energy detection. In low noise conditions, the suggested technique first employs matched filter detection to find the main user signal before switching to energy detection in high noise settings. The genetic algorithm is used to optimise the threshold for energy detection in order to reduce the likelihood of false alarms while retaining a high likelihood of detection. A simultaneous optimisation of the matching filter and the threshold for energy detection was suggested in another study by the authors of (Quan et al., 2008). The suggested method employs a genetic algorithm to jointly optimise the matching filter and the threshold in order to reduce the likelihood of a false alarm while retaining a high likelihood of detection. The findings demonstrated that the joint optimisation outperforms the conventional energy detection technique in terms of detection performance. In their study (Li et al., 2018), the authors suggested a machine learning-based method for energy detection threshold optimisation in cognitive radio networks. The relationship between the noise level and the ideal threshold is learned by the suggested method using the support vector machine (SVM). In terms of detection probability and performance, the SVM-based strategy outperformed the conventional threshold optimisation methods. The authors of (Zhao et al., 2014) suggested a multi-threshold energy detection method for cognitive radio networks in a different study. The suggested method employs a number of thresholds to identify the principal user signal even when there is significant interference. The evolutionary algorithm is used to optimise the thresholds so that the detection probability is high while the false alarm probability is kept to a minimum. Overall, these investigations show how crucial matching filter detection and energy detection threshold optimisation are in cognitive radio networks. When compared to more established energy detection methods, the proposed methodologies exhibit notable improvements in detection performance. Threshold optimisation using machine learning methods yields encouraging results. Energy detection is the conventional method for signal detection in CRNs.

It is simple to implement but is susceptible to interference and noise uncertainty. As a result, increasingly complex methods for signal detection have emerged, such as matched filter-based detection, which is efficient at picking up known signals. However, as different sorts of signals could call for various detection strategies, the employment of a single methodology might not always be adequate. This study suggests a hybrid strategy for signal detection in CRNs that combines matched filter-based detection with Salp Swarm Algorithm (SSA)-optimized energy detection to overcome this problem (Mirjalili et al., 2017). Energy detection is used to identify unknown signals, while matched filtering is used to detect the existence of a known signal. The energy threshold for energy detection is optimised using the SSA method, ensuring effective use of the spectrum resources that are available.

The suggested method is tested through simulations, and the findings show that, when compared to existing approaches, it offers improved detection performance in terms of likelihood of detection, likelihood of false alarm, and receiver operating characteristics. By ensuring optimum spectrum utilisation, the hybrid strategy enables cognitive radio networks to function more efficiently in a variety of situations, including dynamic spectrum access and spectrum sensing. By introducing a novel hybrid strategy that combines two efficient detection techniques—matched filter-based detection and SSA-optimized energy detection—this research makes a significant contribution to the body of literature on signal detection in cognitive radio networks. The suggested method can improve cognitive radio networks' overall performance and has real-world implications for many applications, including both military and civilian communication systems. Rest of the paper is as follows: section 2 presents proposed methodology for the paper. Section 3 provides simulation outcomes of implemented work followed by the conclusive remarks in section 4.

3. PROPOSED METHODOLOGY

3.1 System Model

Let's start by considering that the PU signal is contaminated by noise and/or other interfering signals. We assume that the noise is Additive White Gaussian Noise (AWGN) and is independent of the PU signal. In this detection scheme, the secondary user must have the ability to determine, in a specific frequency band of the spectrum, whether or not the primary user is transmitting the signal. Then, we can formulate the detection of a PU signal contaminated with noise and/or interference as a two-hypothesis test problem, given by the following equations (Salama et al., 2018):

$$H_0 : x(t) = I(t)\ Primary\ user\ absent \quad (1)$$

$$H_1 : x(t) = s(t) + I(t)\ Primary\ user\ present \quad (2)$$

Where $x(t)$ is the signal received by the secondary user, $s(t)$ is the signal transmitted by the primary user and $I(t)$ represents additive white Gaussian noise (AWGN) and/or other interference. H_0 refers to the hypothesis when the primary user is absent, i.e. when $x(t)$ contains only noise and/or interference signals. While H_1 is known as a hypothesis when the primary user is present, that is, $x(t)$ contains, in addition to noise and/or other interference, the signal of the primary user. In reality, H_0 and H_1represent a detection problem, so the detector has to compare them to some value, called the detection threshold. In the comparison procedure, if the detector decides H_1 when it is actuallyH_0, it results in a false alarm probability, $P(H_0; H_1)$. Conversely, if the detector decides on H_1 when it is actually H_1, this is known as the probability of detection, $P(H_1; H_1)$. The detection probabilities P_d and false alarm probabilities P_{fa} provide a measure of detector performance and are widely used to specify the requirements of CR systems. To obtain the decision statistics of the detector, the Neyman-Pearson method (Neelaveni & Sridevi, 2018) is used. The Neyman-Pearson decision statistic is to determine between the hypotheses H_1 and H_0 based on the received signal. Neyman-Pearson detection establishes that the primary user signal is present if the likelihood ratio exceeds the threshold, Γ, as in (3):

$$L(x) = \frac{p(x;H_1)}{p(x;H_0)} > \Gamma \quad (3)$$

Where $p(x; H_1)$ and $p(x; H_0)$ are the probability density functions of the hypotheses H_1 and H_0, respectively. If we consider a large number of samples of the signal transmitted by the PU we can apply the central limit theorem and the test decision statistic $T(x)$ can be formulated under each of the hypotheses that are Gaussian as in (4):

$$T(x) \approx \begin{cases} N(\mu_{H_1}, \sigma_{H_1}^2) & under H_1 \\ N(\mu_{H_0}, \sigma_{H_0}^2) & under H_0 \end{cases} \quad (4)$$

From the detection statistic (4) and the threshold η we can obtain the probability of false alarm, P_{fa}, and the probability of detection, P_d. Both probabilities are used to measure the performance of a detector. The false alarm probability can be calculated using the Q function formulated in (5):

$$P_{fa} = P(T(x) \geq \eta; H_0) = Q\left(\frac{\eta - \mu_{H_0}}{\sqrt{\sigma_{H_0}^2}}\right) \quad (5)$$

Where η is the detection threshold, μ_{H_0} is the mean value and $\sigma_{H_0}$is the variance of the received signal under the hypothesis H_0. That is, when the PU is not transmitting any signal. If we consider, a specific value for the false alarm probability, P_{fa_des} in (5). Then the detection threshold, η, can be calculated using equation (6):

$$\eta = Q^{-1}\left(P_{fa_{des}}\right)\sqrt{\sigma_{H_0}^2} + \mu_{H_0} \quad (6)$$

Finally, once the threshold value in (6) is obtained, the probability of detection can be calculated using (7):

$$P_d = P(T(x) \geq \eta; H_1) = Q\left(\frac{\eta - \mu_{H_1}}{\sqrt{\sigma_{H_1}^2}}\right) \quad (7)$$

Where μ_{H_1} is the mean value and σ_{H_1} is the variance of the received signal, when the hypothesis is H_1. That is, when the primary user signal, noise, and/or an interfering signal are present.

3.2 Spectrum Detection using Matched Filter

In wireless communication systems, such as cognitive radio networks, matched filter detection is a widely used technique. It is a signal processing method for spotting recognised signals in noisy environments. The signal-to-noise ratio (SNR) of the received signal is maximised using the matching filter, a linear filter. Matching filter detection is used in cognitive radio networks to find primary user signals in the accessible spectrum. Matching filtering is a suitable method for identifying the major user signal because it is typically known. The time-reversed and conjugate of the recognised primary user signal makes up the impulse response of the matched filter, a digital filter. The output is produced after the received signal has been routed through the matching filter. In wireless communication, matched filter detection is a widely used method. The primary user signal is identified as present if the matched filter output exceeds a threshold value.

Mathematically, the matched filter output is given by:

$$y(t) = \int r(\tau)h(t-\tau)d\tau \quad (8)$$

where $r(\tau)$ is the received signal, $h(t-\tau)$ is the impulse response of the matched filter, and the integral is taken over all time values. The output signal $y(t)$ is then compared to a threshold value, T_1, to determine if the primary user signal is present. If $y(t) > T_1$, the primary user signal is declared to be present. The threshold value, T_1, is set such that the probability of false alarm is below a specified level, usually referred to as the false alarm probability. The false alarm probability is defined as the probability of declaring the presence of the primary user signal when it is not actually present. The threshold value is determined by setting the false alarm probability, P_f, which is the probability that the detector declares the primary user signal is present when it is not, to a specified value. The threshold value is set as:

$$T_1 = \sigma^2 \ln\left(\frac{P_f}{Q}\right) \quad (9)$$

Where σ^2 is the noise power, Q is the complementary cumulative distribution function (CCDF) of the Gaussian distribution, and ln is the natural logarithm.

In cognitive radio networks, the matching filter detection technique is frequently used to find a known signal in a noisy environment. It is a reliable method for detecting primary user signals, allowing for the effective use of the spectrum's resources. Because not all the essential information could be gleaned from the principal user signals, matched filter detection in actual CR systems suffers from this important drawback. The matching filter detection method cannot identify the primary users since it lacks crucial data, such as frequency synchronisation, timers, etc.

3.3 Energy Detection based Spectrum Sensing

In cognitive radio networks, energy detection is a typical method for spotting the presence of unknown transmissions in the available spectrum. Energy detection is a method that can be used for spectrum sensing when the primary user signal is unknown since, unlike matched filter detection, it does not require knowledge of the primary user signal. In order to determine the signal's instantaneous strength in energy detection, the received signal must first be squared. The total energy of the signal is then calculated by integrating the power over a time interval, T. To determine whether a signal is present, its energy is compared to a threshold value. The signal is deemed present if the energy of the received signal exceeds the threshold value. Mathematically, the energy of the received signal is given by:

$$E = \int |r(t)|^2 dt \quad (10)$$

Where $r(t)$ is the received signal, and the integral is taken over a duration, T. The energy detector compares the energy of the received signal to a threshold value, which is determined based on the noise power and the required level of detection performance. If the energy of the received signal exceeds the threshold, the signal is declared to be present.

3.4 Salp Swarm Algorithm based Threshold optimization

The Salp Swarm Algorithm (SSA) is a bio-inspired optimization algorithm that mimics the swarming behavior of salps, which are marine animals. The algorithm is designed to search for the optimal solution by simulating the movement of salps within a search space. In SSA, the position and velocity of each virtual salp are updated iteratively based on their current positions and velocities. The movement of salps is influenced by their own experience and the collective behavior of the swarm. This collective behavior enables the salps to explore the search space efficiently and converge towards the optimal solution. Mathematically, the optimization problem of the energy detection threshold can be formulated as:

$$minimize\ f(x) \quad (11)$$

where x is the threshold value, and $f(x)$ is the objective function, which is the detection probability subject to a constraint on the false alarm probability. The SSA algorithm searches for the optimal threshold value by iteratively updating the position and velocity of each salp.

The update equations for the position and velocity of each salp are given by (Mirjalili et al., 2017):

$$x_i(t+1) = x_i(t) + v_i(t+1) \quad (12)$$

$$v_i(t+1) = w(t) * v_i(t) + c_1 * rand(\,) * \left(pbest_i(t) - x_i(t)\right) + c_2 * rand(\,) * \left(gbest(t) - x_i(t)\right) \quad (13)$$

Where $x_i(t)$ and $v_i(t)$ are the position and velocity of the i^{th} salp at time t, $w(t)$ is the inertia weight, c_1 and c_2 are acceleration constants, $rand(\,)$ is a random number between 0 and 1, $pbest_i(t)$ is the personal best position of the i^{th} salp at time t, and $gbest(t)$ is the global best position at time t. The SSA algorithm simulates the swarming behavior of salps to search for the optimal solution. In the optimization process, the threshold value is considered as the decision variable, and the objective is to maximize the detection probability while satisfying a constraint on the false alarm probability.

This is formulated as an optimization problem, where the objective function represents the detection probability, and the constraint represents the false alarm probability. The SSA algorithm updates the position and velocity of each salp iteratively based on their current positions and velocities. The salps move towards the optimal solution by adjusting their positions and velocities using certain mathematical equations. The optimization process continues for a specified number of iterations, allowing the salps to explore the search space and converge towards the optimal threshold value. By using the SSA algorithm to optimize the threshold value, the energy detection method in cognitive radio networks can adapt to varying noise levels and interference conditions. The optimization ensures that the threshold value is set in a way that maximizes the detection probability while maintaining the false alarm probability within acceptable limits.

4. SIMULATION AND RESULTS

The performance of proposed algorithms has been studied by means of MATLAB simulation (Figs. 1-6).

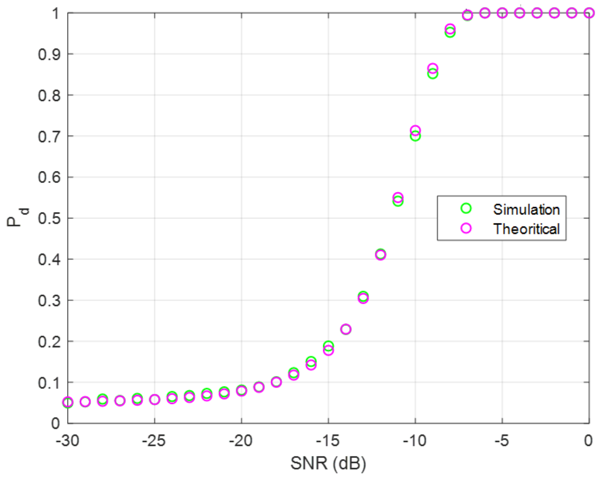

Figure 1. Probability of detection graph for SSA-optimized energy detection at $P_f = 0.01$

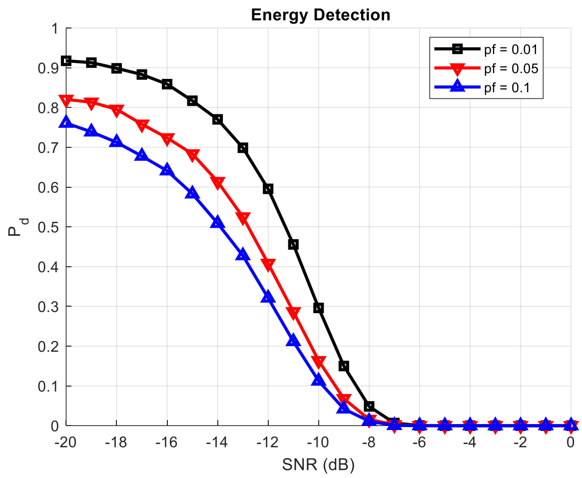

Figure 2. Probability of detection graph for SSA-optimized energy detection at various values of P_f

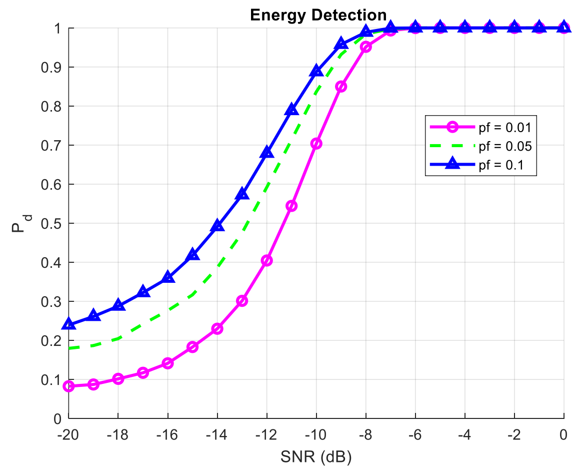

Figure 3. Probability of detection graph for SSA-optimized energy detection at various values of P_f

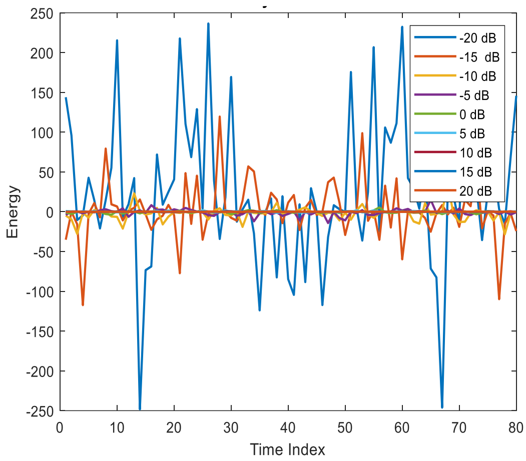

Figure 4. Simulated dynamic thresholds

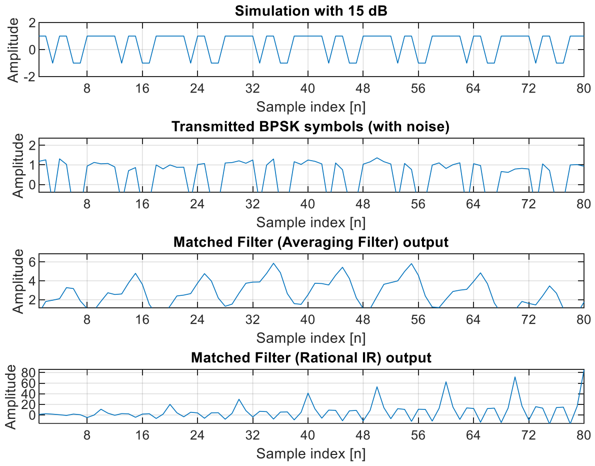

Figure 5. Simulation results for Matched filter detection

5. CONCLUSION

The proposed approach in the paper aims to improve spectrum utilization in cognitive radio networks by combining matched filter detection and the SALP swarm algorithm-optimized energy detection. The main objective is to achieve high detection probability while minimizing false alarms, which is crucial for efficient spectrum utilization. The evaluation of the proposed approach focuses on the detection probability, which measures the ability of the system to correctly identify the presence of primary user signals. The results indicate that the proposed approach performs well in terms of detection probability while maintaining a low false alarm probability. This suggests that the approach is effective in accurately detecting primary user signals while minimizing the chances of false detections.

The SALP swarm algorithm-optimized energy detection method plays a key role in the proposed approach. By adjusting the energy detection threshold based on the noise level, the method enables a more adaptive and flexible approach to spectrum utilization. This adaptive thresholding mechanism allows the system to dynamically adjust its detection sensitivity based on the prevailing noise conditions, leading to efficient utilization of the available spectrum resources.

The combination of the matched filter detection technique and the SALP swarm algorithm-optimized energy detection method offers a robust and efficient approach to spectrum utilization in cognitive radio networks. The matched filter detection is effective for known signal detection, while the energy detection provides a mechanism for detecting unknown signals. By leveraging both techniques, the proposed approach can improve the overall performance of spectrum sensing in cognitive radio networks.

Overall, the proposed approach has the potential to significantly enhance spectrum utilization in cognitive radio networks. It introduces a novel combination of techniques and leverages the adaptive capabilities of the SALP swarm algorithm for energy detection threshold optimization. The practical implications of this approach include improved efficiency and reliability of cognitive radio networks, which can benefit various applications requiring dynamic spectrum access and spectrum sensing.

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