

Original Article

Spectrum Sensing in Cognitive Radio Networks Using Blue Whale Optimization for DTCWT and NA-EMD Feature Fusion with LDA-Based Dimensionality Reduction and AdaBoost Classification

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Abstract - Cognitive Radio Networks (CRNs) and dynamic spectrum access offer promising approaches to improve spectrum use and address inefficiencies. These approaches are motivated by practical problems like spectrum scarcity, interference, and the increasing demands of contemporary wireless communication services. The proposed system Integrates Dual-Tree Complex Wavelet Transform (DTCWT) with the Blue Whale Optimization Algorithm (BWOA) for cognitive radio spectrum sensing. The near shift-invariance and superior resolution powers of the DTCWT help to decompose spectrum signals into multi-resolution sub-bands, which directly lead to the extraction of essential features like energy, phase, and frequency. Noise-Assisted Empirical Mode Decomposition (NA-EMD) is integrated into the framework to decompose the data streams into Intrinsic Mode Functions (IMFs), differentiating noise-dominant and signal-dominant components for adaptive, data-driven representations of the signals. Using a strong feature fusion process is a method to boost the total representation of the spectrum signal by optimally fusing statistical features obtained from DTCWT sub-bands and IMFs. Linear Discriminative Analysis (LDA) enables dimensionality reduction by selecting the most discriminative features for better classification. After this, an AdaBoost ensemble classifier is used for the classification of states of the spectrum, owing to its effectiveness in achieving an accurate performance by combining observations from a set of weak classifiers. This research resulted in a probability of detection of 0.967, indicating substantial advances over the previous approach. Additionally, it exhibited enhanced noise resilience and offered computational efficiencies while accurately adapting to dynamic feature alterations in the spectrum sensing process.

Keywords - AdaBoost, BWOA, Cognitive Radio Networks, DTCWT, IMF, LDA, Spectrum Sensing.

1. Introduction

Limited frequency bands and the rigid allocation of radio spectrum resources have become major bottlenecks for the rapid growth of modern wireless communication systems. Although large portions of the licensed spectrum remain underutilized across time and location, the increasing demand for high-data-rate services, IoT connectivity, and next-generation networks has intensified the spectrum scarcity problem. Cognitive Radio (CR) technology has therefore emerged as a key enabling paradigm to overcome these challenges by allowing unlicensed secondary users to opportunistically access the spectrum when it is not occupied by licensed primary users. With tunable and reconfigurable radio characteristics, CR transceivers can dynamically adapt transmission parameters such as carrier frequency, modulation techniques, and power levels, thereby improving spectrum utilization and overall network efficiency [1]. The intelligence

of cognitive radio systems lies in their ability to sense, learn, and respond to the surrounding radio environment. A CR transceiver continuously gathers information about spectrum usage, power spectral density, and wireless signaling protocols, and uses this knowledge to make adaptive decisions at both the physical and higher protocol layers [2]. This concept is strongly supported by Dynamic Spectrum Access (DSA), which enables spectrum sharing between primary and secondary users under different coexistence models. Dynamic spectrum sharing can be broadly categorized into horizontal sharing, where all users have equal access rights, and vertical sharing, where secondary users exploit spectrum opportunities without degrading the performance of primary users [3]. A fundamental requirement for the success of DSA is accurate and reliable spectrum sensing, which determines whether a spectrum band is occupied or vacant. Among various sensing techniques, energy detection is widely preferred because of its



simplicity and low computational complexity [4]. However, conventional energy detection-based sensing suffers from significant limitations in practical wireless environments. Its detection performance degrades severely under multipath fading, shadowing effects, and noise uncertainty, particularly in low-SNR scenarios. Cooperative Spectrum Sensing (CSS) has been introduced to enhance sensing reliability through spatial diversity, where multiple CR users forward their sensing reports to a fusion center. Although CSS improves detection coverage, it introduces additional communication overhead, increased latency, and often depends on prior knowledge or reliable collaboration, which may not always be feasible in dynamic environments.

Recent advancements have explored machine learning and hybrid feature-based spectrum sensing methods to improve detection accuracy. Existing approaches, such as SVM, KNN, Random Forest, and CNN-based sensing frameworks, have demonstrated promising results, yet they often rely heavily on pre-extracted features, suffer from redundancy in high-dimensional feature spaces, and face challenges in achieving robustness under highly noisy spectrum conditions. Furthermore, many traditional signal processing methods are limited by their inability to provide adaptive multi-resolution representations of spectrum signals, which restricts their performance in rapidly varying wireless environments.

Therefore, a clear research gap exists in developing an adaptive and robust spectrum sensing framework that can (i) effectively extract discriminative spectrum features under noise and fading conditions, (ii) optimize decomposition parameters dynamically for improved sensing reliability, (iii) reduce feature redundancy while preserving class separability, and (iv) achieve superior classification performance with computational efficiency.

To address these limitations, this work proposes a novel hybrid spectrum sensing methodology that integrates Dual-Tree Complex Wavelet Transform (DTCWT) with an optimization-driven parameter tuning mechanism, combined with Noise-Assisted Empirical Mode Decomposition (NA-EMD) for adaptive signal representation. DTCWT is selected due to its near shift-invariance and improved directional selectivity, which enables more reliable extraction of time-frequency spectrum characteristics compared to conventional transforms. However, its performance strongly depends on the proper selection of decomposition levels and denoising thresholds; hence, the Blue Whale Optimization Algorithm (BWOA) is incorporated to dynamically optimize these parameters for enhanced detection accuracy. In addition, NA-EMD is employed to separate noise-dominant and signal-dominant intrinsic mode functions, improving robustness under noise uncertainty and low-SNR environments. Since the fusion of DTCWT and NA-EMD features produces a high-dimensional feature space, Linear Discriminant Analysis

(LDA) is applied to reduce redundancy while preserving the most discriminative information. Finally, an AdaBoost ensemble classifier is adopted because of its ability to combine multiple weak learners into a strong predictor, ensuring reliable and accurate spectrum state classification in dynamic cognitive radio scenarios. Thus, the proposed framework is specifically designed to achieve improved detection reliability, enhanced noise resilience, and computational efficiency beyond existing spectrum sensing approaches.

Based on the above discussion, the following research questions are formulated as the guidance of this work: (RQ1) How to improve spectrum sensing reliability under low-SNR and noise uncertainty conditions? (RQ2) How can the multi-resolution feature extraction be optimized to overcome the limitations of the conventional energy detection and redundant handcrafted features? (RQ3) Can an adaptive hybrid framework accommodate better detection accuracy with computerized standstill through the practical cognitive radio implementation? These questions are the direct motivation of the proposed BWOA-DTCWT and NA-EMD-based spectrum sensing framework.

The contributions of this paper are:

- Novel BWOA-DTCWT Framework: A new framework combining Dual-Tree Complex Wavelet Transform (DTCWT) and Butterfly-Whale Optimization Algorithm (BWOA) for enhanced spectrum sensing in cognitive radio networks, featuring dynamic parameter optimization and improved noise tolerance.
- Adaptive Decomposition Using NA-EMD: Integration of Noise-Assisted Empirical Mode Decomposition (NA-EMD) to filter noise and extract key signal features, with feature fusion for enhanced spectrum signal representation.
- Feature Dimensionality Reduction by LDA: Utilization of Linear Discriminant Analysis (LDA) for dimensionality reduction, ensuring better classification and computational efficiency.
- Classification with AdaBoost Ensemble: Adoption of an AdaBoost ensemble classifier for robust and accurate spectrum state classification in dynamic conditions.

The rest of this paper is structured as follows: Section 2 discloses the related work. The proposed method is described in Section 3. Section 4 presents the results. Lastly, Section 5 concludes the paper and provides future scope regarding the research.

2. Literature Review

Spectrum Sensing (SS) is well known to be one of the fundamental enabling functions of Cognitive Radio (CR) systems. The prime focus of spectrum sensing is to detect whether a specific frequency band, which is licensed for use by the Primary User (PU), is occupied or is available for

opportunistic access by a Secondary User (SU). Since the radio spectrum is a scarce resource and the allocation is usually inflexible, the purpose of cognitive radio networks is to enhance the spectrum efficiency by dynamically utilizing underutilized spectrum holes. However, the performance of spectrum sensing is affected by a number of real-world aspects such as uncertainty of noise, fading, shadowing, interference, sensing time, hardware limitations, and the number of cooperating cognitive users. Therefore, sensing accuracy is still a basic research issue to be solved in the CR network.

In practical cognitive radio deployments, Cooperative Spectrum Sensing (CSS) has been introduced, which provides an effective means to enhance the reliability of detection. In the CSS, multiple CR nodes have an independent sensing of the spectrum and report their sensing information to a Fusion Centre (FC), which performs the final global decision. The determination of the overall sensing performance plays an important role in the decision fusion strategy at the FC. For example, the OR rule provides good protection to primary users because if one CR senses an activity of a PU, the band is declared occupied. However, this rule may have a negative impact on utilizing the spectrum opportunity for secondary users. On the other hand, the AND rule works better on spectrum hole utilization but brings a higher risk of PU interference since all CR nodes have to make an agreement about the presence of the PU [5]. The k-out-of-N fusion rule, in addition to offering a balanced approach between these extremes, may lose its effectiveness due to unreliable sensing conditions or attacks by malicious users. In order to overcome such limitations, more complex fusion and decision strategies like Bayesian inference and Sequential Probability Ratio Testing (SPRT) have been proposed. These ways can increase the accuracy of sensing and protect PUs, but they usually depend on the presence of prior statistical knowledge, which may not always be feasible in dynamic wireless environments [6].

The most popular sensing method among the classical spectrum sensing approaches is energy detection, which is simple and computationally low-cost [4]. Energy detection does not require any a priori knowledge of the characteristics of the PUs, and thus it can be used for general-purpose sensing. Despite such advantages, there are serious limitations in energy detection in practical scenarios. Its performance is very sensitive to multipath fading and shadowing effects, noise uncertainty, and may cause a great decrease in detection probability, especially in low SNR conditions. Because of these drawbacks, numerous researchers have suggested better energy detection frameworks to make them more robust. For example, [7] centered on the centralized sensing schemes with many antennas to overcome the fading effect and enhance the reliability of detection. Similarly, [8] put forward a sensing approach that uses a combination of multiple energy detectors and an adaptive threshold mechanism, which will give improved performance in different noise environments.

Further improvement in the energy detection in cooperative and regional sensing has been exploited. In [9], the authors proposed a two-stage energy detection scheme in which two detectors are involved with sensing through independent decisions and propagated decisions to the fusion centre, which results in better sensing reliability. Multi-antenna sensing has also been widely studied as a good method to mitigate the effects of fading and shadowing by spatial diversity [10]. Another big improvement is that of adaptive double-threshold energy detection, where instead of using one fixed threshold only, two adaptive thresholds are used to decrease decision uncertainty. According to [11], an effective approach to combine the adaptive thresholds with energy detection can greatly improve the cooperative sensing accuracy. Moreover, [12] considered cyclostationary detection and a comparison between the two algorithms: adaptive double-threshold energy detection and cyclostationary detection, and it points out that under some operating conditions, the former gives a competitive detection performance with lower complexity.

A number of approaches have been made to the design of optimized detector setups and fusion schemes for various cooperative sensing scenarios. The studies given in [13-15] designed several energy detector architectures accompanied by decision rules more appropriate for regional area networks. These works had emphasized that the performance of detection can be improved by integrating adaptive sensing schemes, multi-stage decision making, and diversity techniques, especially in fast fading channel cases. However, despite these advancements, there are still problems with traditional sensing approaches in highly dynamic spectrum environments, where noise, interference, and fading change quickly over time.

With the growing complexity of wireless networks, learning based spectrum sensing has been introduced as an interesting alternative. The expectations for cognitive radios are not only to sense but to learn from the environment as well as to adapt their sensing decisions based on time. Machine learning techniques have attracted attention as they are able to classify spectrum occupancy better than fixed rules (especially in uncertain and nonlinear environments). Learning based approaches can be divided into supervised and unsupervised roughly. Among the supervised methods, the K-Nearest Neighbor (KNN) algorithm has been widely applied because of its simplicity, stability, and smoothness of implementation [16].

In the past few years, there have been numerous research works studying the role of machine learning in cooperative spectrum sensing. The cooperative learning-based approaches can make use of sensing reports from multiple CR nodes and improve the detection reliability. For example, [17] has proposed several CSS frameworks on Support Vector Machines (SVM), weighted KNN, k-means clustering, and

Gaussian mixture models, and received energy values were used as features. Similarly, [18] utilized the k-means clustering method and SVM techniques based on the low-dimensional probability vectors and resulted in superior sensing performance with lower feature complexity. In order to reduce the computational load further, [19] proposed a CNN-based collaborative sensing scheme that was able to achieve better detection accuracy with a lower processing requirement. In addition, Kernel-Based Learning (KBL) approaches have been thoroughly reviewed in [5], and their feasibility in dealing with nonlinear and high-dimensional sensing problems has been emphasized as compared to linear methods. While sensing using cooperative learning has been developed to a good extent, the implementation of machine learning for single-node spectrum sensing is at an initial stage. For example, [20] designed an ANN-based sensing scheme using input features of energy and likelihood ratio statistics. In [21], both the energy and cyclostationary features were used as inputs of an ANN to achieve better sensing reliability. Furthermore, [22] suggested a CNN-based sensing characteristics learning method that directly learns the sensing characteristics by observed spectrum data concerning cyclostationary patterns in order to improve the accuracy of detection. However, many of these methods are still built on the idea of highly relying on pre-extracted features, and their performance is greatly affected by how good the feature engineering process is.

Most relevant studies that can be related to the present contribution are reported in [23-27]. In particular, [23] suggested a sort of hybrid sensing approach combining energy, Maximum-Minimum Eigenvalue (MME), and cyclostationary features, and neighbourhood component analysis applied for the feature selection. Classification has been performed using a Bayesian optimized random forest model, where improved detection performance is shown. These hybrid approaches emphasise the advantage of using multiple features for sensing for robustness. However, problems such as redundancy in high-dimensional feature spaces, sensitivity to the parameters, computational complexity, and lower performance for a very low SNR are indeed open problems.

Overall, the literature shows that although spectrum sensing techniques have evolved from detecting the presence of energy to cooperative and machine learning-based sensing frameworks, robust sensing performance in dynamic and noisy environments remains a challenging research problem. This is what motivates the need for more adaptive and hybrid methods of feature extraction, optimized decomposition strategies, dimensionality reduction, and robust ensemble classifiers, which form the basis of the proposed work.

Research Gap: Although the performance of existing techniques, such as energy detection, cooperative spectrum sensing, and machine learning methods, has improved, there

are still some challenges. Energy detection is often used, but it is susceptible to multipath fading and shadowing, which can reduce detection accuracy in some cases [4, 7]. Although CSS techniques improve detection coverage with the use of multiple CRs, in many cases, such approaches rely on prior information and collaboration, which may not always be feasible [6, 9]. These external training methods have yielded encouraging machine learning performance (KNN, SVM, CNN); however, they are conditioned by the quality of pre-extracted features [16, 22]. Although hybrid methods proposed that combine energy, m-m order, and cyclostationary features help advance SS [23], redundancy and feature selection issues remain. In this proposed work, the use of DTCWT and NA-EMD is extended for adaptive SS, along with the introduction of a hybrid framework: BWOA for parameter optimization and LDA for dimensionality reduction. By avoiding reliance on pre-extracted features or prior knowledge, this method overcomes existing limitations in SS techniques, providing improved detection accuracy and robustness to noise [23-27].

3. Proposed Methodology

As shown in Figure 1, this research work presents a novel model for spectrum sensing based on the Dual-Tree Complex Wavelet Transform (DTCWT) optimized by the Blue Whale Optimization Algorithm (BWOA) for enhanced spectral efficiency with the additional spectrum scenarios. Motivated by its near shift-invariance and improved directionality sensitive performance, the DTCWT-based spectrum decomposition enables better analysis of the spectrum signal by storing the space-time frequency information of the spectrum signal in multiple numerical value sub-bands at various resolutions. DTCWT, by having separate real and imaginary components, helps to separate noise from the signal characteristics far better than traditional wavelet transforms. With this potential for DTCWT performance enhancement, the BWOA dynamically finds the optimum parameters by selecting the appropriate numbers of decomposition levels (L), denoising wavelet coefficients gradients (T), and filter bank seeding parameters. These parameters are optimized to achieve the best classification results with the least amount of information loss, while using the least computational resources.

The optimized DTCWT is then fused with the spectrum sensing process through the representation of intercepted radio signals into detailed sub-band features, from which useful features like energy, phase, and frequency are extracted. With increased P_d at low P_f levels, acceptable noise sensitivity is managed, allowing enhanced detection performance. The BWOA's dynamic exploration-exploitation balance guarantees the global search capability is in line with the local search ability, enabling appropriate adjustment of the DTCWT parameters to suit changing spectrum environments, thereby augmenting the adaptability of the overall framework.

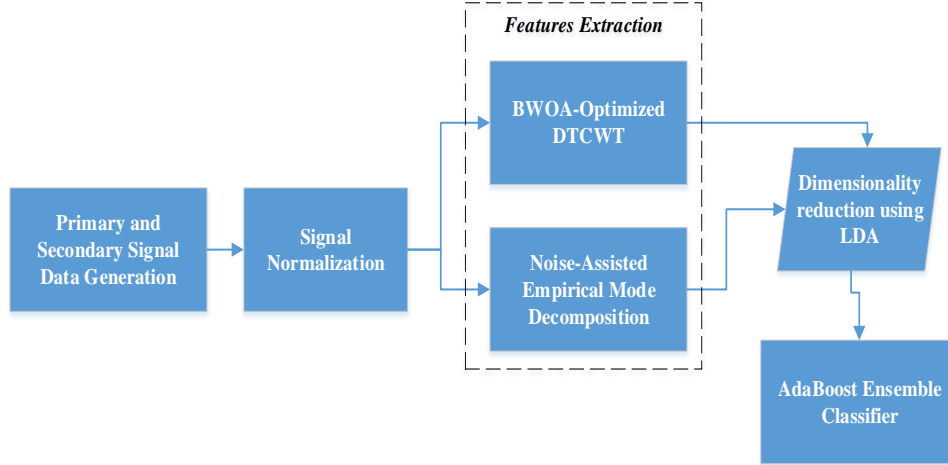


Fig. 1 Block diagram for the proposed approach

Besides DTCWT, Noise-Assisted Empirical Mode Decomposition (NA-EMD) is used to decompose the spectrum signals adaptively into Intrinsic Mode Functions (IMFs). We obtain data-driven representations of the signal by identifying noise-dominant and signal-dominant IMFs in this step. Statistical features such as energy, entropy, and standard deviation are extracted from DTCWT subbands and IMFs. The spectrogram features are then fused into a strong snapshot of the spectral signals.

Linear Discriminant Analysis (LDA) is used afterward to reduce dimensionality and achieve optimal feature selection. LDA calculates the within-class scatter (S_W) and the between-class scatter (S_B) matrix in order to find the most discriminative features. A smaller feature set yields better classification performance at the same computational cost. Then, an intelligent machine-learning classifier uses the fused and reduced features as inputs. To differentiate between the spectrum state (i.e., whether the spectrum is occupied or vacant), an AdaBoost ensemble classifier is trained, which is capable of combining weak learners to form a strong classification predictor. These combined features render this integrated approach capable of maximizing detection performance, computational resources, and adaptability, thus, making it an appropriate solution for real-time spectrum sensing in critical cognitive radio scenarios.

The reason why the proposed framework combines BWOA, DTCWT, and NA-EMD is that all of these techniques solve a specific limitation of conventional spectrum sensing techniques. DTCWT is an effective multi-resolution time-frequency representation with higher shift invariance, which can be used to obtain reliable extraction of subtle spectrum characteristics in fading and shadowing conditions. However, the sensing capability of DTCWT is highly dependent on the proper selection of decomposition parameters and the denoising threshold. Therefore, BWOA is incorporated so that these parameters can be dynamically optimized to obtain

adaptive performance over a variety of SNR levels. In addition, real spectrum observation is often disturbed by the noise uncertainty, in which case fixed transforms may not be appropriate to separate signal and noise components. NA-EMD is therefore used to decompose the received signal into intrinsic mode functions, enabling noise-dominant signals to be filtered without compromising the meaningful parts of the signals. This hybrid integration allows the complementary synergy so that more robustness, feature representation, and reliability of the spectrum sensing can be achieved than any of the individual techniques used alone.

3.1. Signal Generation

The generation of signal data is the first step in the proposed methodology. In the scenario of spectrum sensing, the signal data of interest are signals of primary users and secondary users.

- There are also different user signals for primary and secondary users:
- The licensed user's signal is referred to as the primary user (PU) signal and the cognitive radio (also called the secondary user or SU) must signature of its presence in a specific frequency band must be detected and avoided.

In such a case, the secondary user (SU) needs to create a signal that can only be sent when the primary user is not in the spectrum.

We model the received signals $x(n)$ at a cognitive radio network as:

$$x(n) = \sum_{j=1}^P h_j(k) s_j(n-k) + \eta(n) \quad (1)$$

Where:

- $x(n)$ is the received signal at time n .
- $h_j(k)$ is the channel response for the j^{th} transmitter.

- $s_j(n - k)$ represents the signal transmitted by the j^{th} user at time $(n - k)$.
- $\eta(n)$ is the noise component.

Signal Data Generation

- Primary User Data: Trained on the primary user signal that is transmitted at particular times and frequencies. It needs to be determined whether this signal is present in the signal received.
- Secondary User Data: In this stage, the secondary user creates data when the spectrum is free, adjusting to the spectrum available.

3.2. Signal Normalization

Normalizing the signal data is an important step before doing any feature extraction or processing. This helps us make sure that all signals have a comparable magnitude so they are easier to analyze.

The received signal is normalized to a certain range (e.g., 0 - 1) in order to remove the effects of different signal amplitudes or varying transmission powers.

$$x_{norm}(n) = \frac{x(n) - \min(x(n))}{\max(x(n)) - \min(x(n))} \quad (2)$$

Where:

- $x(n)$ is the received signal at time n .
- $x_{norm}(n)$ is the normalized signal.

This is a standardization process that allows input features before applying downstream, such as DTCWT or NA-EMD.

3.3. Feature Extraction

Spectrum sensing is essentially a key process in feature extraction, wherein the raw signal is transformed into a set of characteristics that is used for classification. DTCWT optimized by BWOA and NA-EMD. The selection of parameters in the proposed framework is carried out by using the Blue Whale Optimization Algorithm (BWOA), which is able to dynamically adjust the number of decomposition levels of the DTCWT and the denoising parameters according to a fitness function that takes into account both the accuracy of the detection and the computational cost. Feature extraction is performed based on statistical descriptors from both DTCWT sub-bands and NA-EMD intrinsic mode functions, followed by feature fusion. Finally, Linear Discriminant Analysis LDA is applied as the feature selection and dimensionality reduction stage for keeping only the most discriminative features before AdaBoost classification.

3.3.1. Features from BWOA-Optimized DTCWT

The DTCWT decomposes the spectrum signal into multiple frequency bands at different resolutions. It has better shift-invariance and directional sensitivity than DWT.

Steps to Analyze the DTCWT Decomposition: The signal $x(n)$ is decomposed into sub-bands by the DTCWT. The mathematical operation of DTCWT is:

$$X_k(n) = DTCWT(x(n)) \quad (3)$$

Where $X_k(n)$ denotes the sub-bands decomposition at different levels.

These sub-bands give information about the signal's energy, phase, and frequency, vital for spectrum sensing.

BWOA Optimization: It has been used to optimize the parameters of the DTCWT, such as the total decomposition levels and denoising thresholds. The BWOA is used to explore the optimal parameter values that allow DTCWT to perform up to its maximum performance on spectrum sensing.

The BWOA is designed to emulate the hunting and social behaviour of blue whales, specifically their bubble-net feeding strategies and social hierarchies. The BWOA optimization process is composed of the following stages:

Step 1-Initialization: The first step is to initialize the population of blue whales (search agents) in the solution space. Each whale corresponds to a candidate solution to the parameters of the DTCWT, including:

- Number of decomposition levels (L) this parameter controls how finely to decompose the spectrum signal.
- Threshold (T) for denosing wavelet coefficients.
- High/low pass filter bank parameters: These are the filter parameters used in DTCWT, which influence the separation of the signal noise components.

Each whale is initialized randomly in the feasible solution space for these parameters.

$$X_i = \{L_i, T_i, Filter\ Parameters_i\}, i = 1, 2, \dots, N \quad (4)$$

Where:

- N = total number of whales (population size).
- X_i indicates the position of the i^{th} whale in the search space, as per its parameter values.

Step 2-Fitness Evaluation: Each whale's fitness is assessed by a fitness function, according to the performance of the DTCWT for the decomposed parameters (such as the decomposition level and the denoising throughput). The fitness function is defined for how well the DTCWT-based features provide the base for detecting the spectrum occupancy. The detection accuracy, Signal-to-Noise Ratio (SNR), and computational efficiency are then focused on to design a generic fitness function.

Based on these three parameters, the fitness function is:

$$Fitness(X_i) = f(X_i) = Accuracy(X_i) - \lambda \times Computational\ Cost(X_i) \quad (5)$$

Where:

- $f(X_i)$ = the fitness value (the i^{th} whale)
- $Accuracy(X_i)$ denotes the DTCWT detection accuracy for the parameters provided.
- $Computational\ Cost(X_i)$, this consists of the computational cost of applying the DTCWT.
- λ is a constant that penalizes higher computational costs.

Step 3-Exploration and Exploitation: Central to BWOA's performance is how well it balances exploration and exploitation. This is achieved based on the following principles borrowed from the blue whale's bubble-net feeding technique:

- Exploration: When whales are distant from the optimal solution, they explore the search space more widely using a spiral movement pattern. That could lead them in search of possible global solutions.
- Exploitation: Many whales decrease the radius of their movement as they get closer to the best solution; they can optimize their position to exploit local optima.

The rules that update a whale's location in BWOA are a function of the two strategies below:

Spiral Motions (Exploratory Stage): The spiral motion is meant to mimic the hunting behaviour of blue whales. Whales agitate in a spiral path toward the most probable solution found, modeled as:

$$X_i(t+1) = X_i(t) + A \times \sin(B \times t) \times |C \times X_{best} - X_i(t)| \quad (6)$$

Where:

- $X_i(t)$ is the i^{th} whale position at time t .
- A and B are random coefficients that modulate the amplitude and frequency of the movement.
- C is a random parameter that creates a directional random walk spiral.
- X_{best} = the position of the best whale (the best solution found so far)
- $|C \times X_{best} - X_i(t)|$: This is the distance between the i^{th} whale and the best whale.

This equation makes the whale spiral around the best solution found so far, but still allows for an exploration phase that is beneficial to search the broader solution space.

Social Influence (Exploitation Phase): As the algorithm proceeds, the whales adjust their position towards the best-

found solution by social influence. The update rule for the exploitation phase is the following:

$$X_i(t+1) = X_i(t) + D \times (X_{best} - X_i(t)) \quad (7)$$

Where:

- D is a random variable that determines the direction and distance the whale will move.
- X_{best} is the best whale position.

This rule also causes the whales to approach the potency solution straight away and improve their position and search.

Stage 4-Convergence and Stopping: The BWOA running process stops when one of the following termination conditions is satisfied:

- Maximal Iterations: The algorithm stops after a fixed number of iterations T_{max} .
- Convergence: If the fitness does not improve for a specific number of generations, the algorithm stops.

Step 5-Further Optimized Parameters: In the end, when the algorithm converges or reaches the maximum iteration, the position of the best whale would yield the best parameters of DTCWT. The optimized parameters are further used in the spectrum sensing process, leading to effective feature extraction and spectrum classification.

$$Optimized\ Parameters: X_{best} = \{L_{opt}, T_{opt}, Filter\ Parameters_{opt}\} \quad (8)$$

The optimized parameter values are then used for improved decomposition of the spectrum signal with noise robustness and feature extraction accuracy via DTCWT.

3.3.2. Noise-Assisted Empirical Mode Decomposition Features

The NA-EMD adaptively decomposes the spectrum signal into IMFs, which improves the representation of the signal by identifying noise-dominant or signal-dominant components.

NA-EMD Decomposition: The first step is to decompose the signal into different IMFs $\{IMF_1, IMF_2, \dots, IMF_N\}$ using NA-EMD.

The decomposition is adaptive, while the IMFs retain the high-frequency noise and low-frequency signal information.

$$x(n) = \sum_{i=1}^N IMF_i(n) + \eta(n) \quad (9)$$

Where $IMF_i(n)$ are the intrinsic mode functions and $\eta(n)$ is the residual noise.

Features Extraction: The IMFs lead to the extraction of statistical features such as energy, entropy, and standard deviation to assist the estimation of spectrum occupancy.

$$E(IMF_i) = \sum_{i=1}^N |IMF_i(n)|^2 \quad (10)$$

Where $E(IMF_i)$ is the energy of i^{th} IMF.

3.3.3. Combined Feature Set

These extracted features are concatenated to create a single feature vector when features are obtained from both strategies. Combining features attempts to develop a more informative representation of the spectrum signal that is additive to its identification ability for the spectrum state (e.g., occupied or vacant).

Features of BWOA-Optimized DTCWT: The extracted features of the BWOA-Optimized DTCWT decomposition are as follows:

- Energy: The energy of each sub-band provides some insight into the power distribution of the signal for various frequency regions.

$$E_{DTCWT} = \sum_{i=1}^N |X_k(n)|^2 \quad (11)$$

Where $X_k(n)$ is the x^{th} DTCWT sub-band and E_{DTCWT} indicates the energy of the k^{th} sub-band.

- Phase: The phase angle of the DTCWT sub-band, which is important in frequency domain localization of a signal.
- Frequency: Frequency distribution of decomposed sub-bands, reflecting frequency signal components of the spectrum.

Features from NA-EMD: The NA-EMD method separates the spectrum signal into IMFs, which reflect its different frequency components. Extracted features from each IMF include:

- Energy of each IMF: Refer to Equation (13)
- Entropy: The entropy of an individual IMF contains information on the complexity of the signal; it gives some sense of irregularity and noise present in the signal:

$$Entropy(IMF_i) = - \sum_{i=1}^N P(IMF_i(n)) \log P(IMF_i(n)) \quad (12)$$

Where the $P(IMF_i(n))$ is the probability distribution of the i^{th} IMF values.

- Standard Deviation: The standard deviation of each IMF is an additional feature that gives the magnitude of fluctuation in that frequency band of the signal.

Feature Fusion: The features from the BWOA-Optimized DTCWT and NA-EMD methods are combined by concatenating them into a unified feature vector. The fused features combine the timing-frequency feature and the statistical feature of the spectrum state, since it synthesizes the spectrum state. Now consider that we have a combined feature vector:

$$F_{combined} = \{E_{DTCWT}, Phase_{DTCWT}, Frequency_{DTCWT}, E_{IMF_i}, Entropy_{IMF_i}, STD_{IMF_i}, \dots\} \quad (13)$$

$F_{combined}$ is then employed for dimensionality reduction and classification.

3.4. Dimensionality Reduction using LDA

In this step, LDA is applied to reduce the dimension of the combined feature set. LDA is a supervised method that seeks to learn the most discriminative features by maximizing the separation between classes while minimizing within-class scatter. This aids in enhancing classification performance and reducing computational cost.

LDA ROI: LDA calculates a matrix (W) that uses to project the original feature space onto a lower-dimensional subspace. It requires a lower-dimensional mapping of the feature space that retains as much of the class separability as possible. LDA follows these steps:

Compute the Scatter Matrices:

- Within-class Scatter Matrix (S_W): Compute the scatter (variance) of points in each of the classes.

$$S_W = \sum_{i=1}^N \sum_{x \in C_i} (x - \mu_i)(x - \mu_i)^T \quad (14)$$

Where C_i denotes class i , x is a feature vector, and μ_i is the mean vector of class i .

- Between-Class Scatter Matrix (S_B): Measures class scatter.

$$S_B = \sum_{i=1}^N N_i (\mu_i - \mu)(\mu_i - \mu)^T \quad (15)$$

Where μ_i denotes the mean of class i and μ the overall mean of all classes.

- Generalized Eigenvalue Problem: To obtain the LDA transformation matrix W , the following generalized eigenvalue problem is solved:

$$S_W^{-1} S_B W = \lambda W \quad (16)$$

Where λ are the eigenvalues, and W are the eigenvectors with the largest eigenvalues. The new feature subspace is defined by the eigenvectors.

- Projection: The feature vector $F_{combined}$ is transformed using the matrix W that projects it onto the lower-dimensional subspace:

$$F_{LDA} = W^T F_{combined} \quad (17)$$

Where, F_{LDA} is the reduced feature set, containing the most discriminative features, for classification.

3.5. Classification using AdaBoost Ensemble Classifier

AdaBoost is an ensemble learning algorithm that combines multiple weak classifiers to make a strong classifier. The AdaBoost algorithm is explained in the following points:

- Initialize Weights: Each training sample is assigned an initial weight of $w_i = \frac{1}{N}$, where N is the total number of samples.
- Training Weak Classifiers: AdaBoost trains weak classifiers $h_m(x)$ (like decision trees) iteratively on the re-weighted dataset. In each iteration, the algorithm changes the weights of the samples according to its classification performance. Misclassified samples are given greater weight, allowing the next weak classifier to pay closer attention to those samples that are proving challenging to classify.
- Combining the Classifiers: Each weak classifier $h_m(x)$ has a weight α_m assigned to it depending on how accurate it is. The weight is calculated as:

$$\alpha_m = \frac{1}{2} \log \frac{1-\epsilon_m}{\epsilon_m} \quad (18)$$

Where ϵ_m is the error rate of the m^{th} weak classifier.

- Final Decision: A Combination of weak classifiers' predictions gives us the final result. The final decision rule is:

$$\hat{y}(x) = \text{sign} \left(\sum_{m=1}^M \alpha_m h_m(x) \right) \quad (19)$$

Where M is the total number of weak classifiers and $h_m(x)$ is the output of the m^{th} classifier.

This will return the final class label: 1 if the spectrum is occupied and -1 if the spectrum is vacant.

4. Results and Discussion

The proposed spectrum sensing technique is tested in various environments extensively. The performance of the proposed hybrid feature extraction methods is also examined in context to different values of the number of training samples from the power profile, along with successful parameters, which include Signal to Noise Ratio (SNR), and probability of

false alarm (P_f) and also provides a complete comparative analysis of various methods.

4.1. Simulation Setup and Parameters

The proposed spectrum sensing framework was tested with the help of a simulation in MATLAB with different spectrum occupancy scenarios.

The main user signals were simulated on the basis of standard modulation schemes, and AWG - additive white Gaussian noise was introduced, which represents the practical channel condition. The sensing performance has been tested at a wide range of SNR over a range of 40 dB from -30 dB to 20 dB.

The spectrum sensing experiments in this study were conducted with synthetically generated primary and secondary user signals in a simulated environment with MATLAB. No external/real-world spectrum measurement data set was used. The ability to control the evaluation under varying SNR, fading conditions, and spectrum occupancy situations is possible with the synthetic signal model. The proposed framework was tested for values of SNR from -30 dB to 20 dB to represent very noisy scenarios to moderate channel environments. This setup, as being based on simulation, guarantees that reproducibility and a fair comparison with current sensing approaches can be ensured.

For the DTCWT decomposition, several resolution levels have been considered. In order to obtain the optimal parameters, the Blue Whale Optimization Algorithm (BWOA) has been used. Noise-Assisted Empirical Mode Decomposition (NA-EMD) was selected by using several noise realizations to achieve stable intrinsic mode function extraction.

The dataset has been divided into training and testing datasets to reduce the repetitions of the classification with the help of the AdaBoost classification. Performance was given by the probability of detection (P_d) and probability of false alarm (P_f), probability of miss detection (P_m).

In Figure 2, the detection probability is demonstrated with respect to the training sample size. The detection accuracy gradually reaches a stable state with the increasing training samples, indicating that the proposed scheme increases the generalization capability of the detector effectively. The result highlights that having an adequate amount of training data is crucial in maximizing the detection capability of cognitive radio systems.

Figure 3 shows the detection probability at different values of SNR using energy detection on DTCWT coefficients. The increase in probability of detection indicates the better performance of the method when the SNR increases.

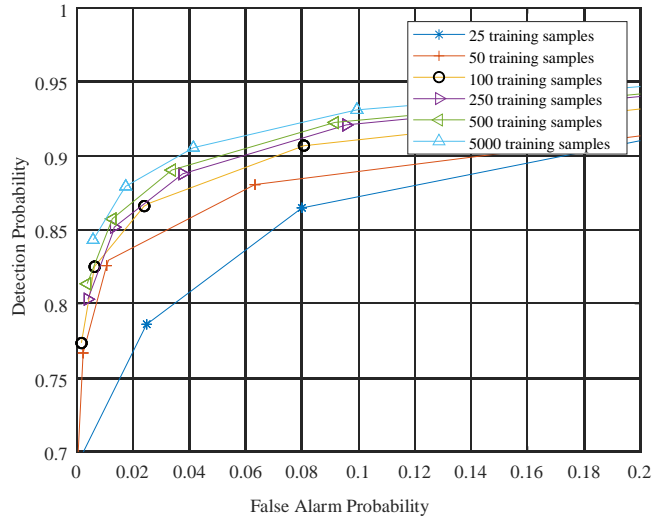


Fig. 2 Probability of detection for the proposed approach at varying training samples

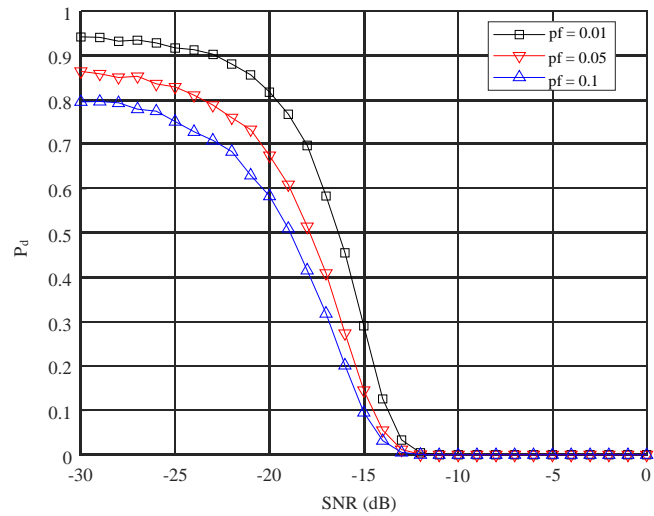


Fig. 3 Probability of detection vs. SNR using DTCWT coefficient-based energy detection at different values of probability of false alarm

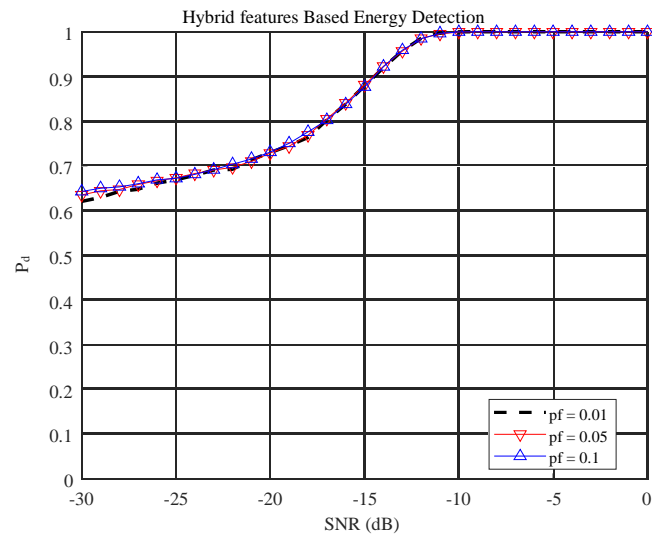


Fig. 4 Probability of detection vs. SNR using hybrid features-based energy detection at different values of probability of false alarm

The performance of the energy detection method based on hybrid features is shown in Figure 4. The new method combines DTCWT and NA-EMD using features that build higher probabilities of detection for varying values of SNR and false alarm probabilities. Figure 5 compares the probability of detection of different feature extraction techniques when the false alarm probability is set at 0.01. These results validate that the proposed hybrid approach is

much more effective in achieving accurate spectrum sensing. Figure 6 compares the miss-detection probability based on different feature extraction methodologies. At the same time, the hybrid technique shows the least probability of detection loss, confirming its efficiency in alleviating false negative capacity in spectrum sensing. These results also reinforce the statement that merging different feature extraction approaches boosts the overall performance of detection.

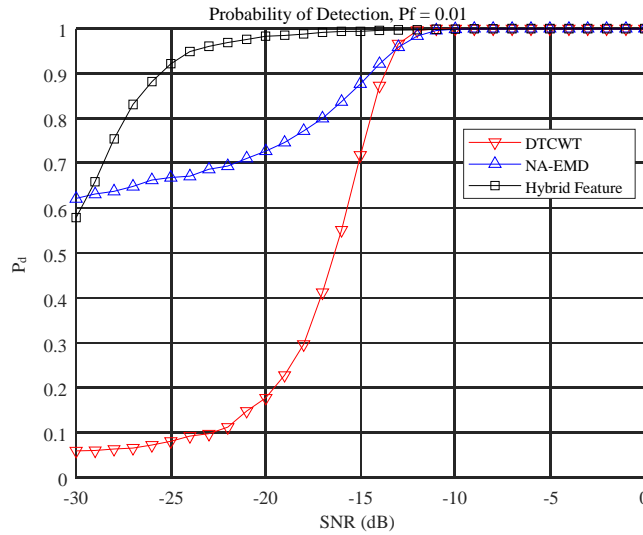


Fig. 5 Comparative analysis of the probability of detection for different feature extraction techniques at $P_f = 0.01$

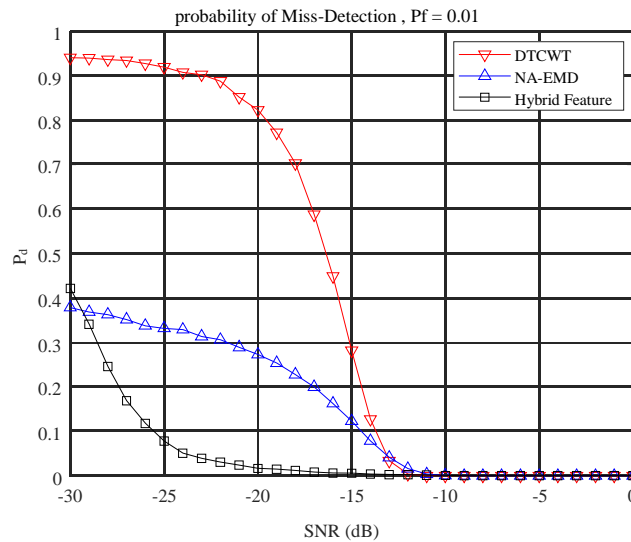


Fig. 6 Comparative analysis of the probability of miss detection for different feature extraction techniques at $P_f = 0.01$

4.2. Additional Performance Metrics

In addition to the probability of detection, the proposed model was also analyzed with other important sensing parameters like false alarm probability, miss detection probability, etc. A low false alarm rate is needed so that the secondary users avoid falsely assuming the occupancy of the

frequency resource, while the miss detection rate is low so that the primary users enjoy good protection. The results show that the hybrid DTCWT-NA-EMD feature fusion method can reduce miss detection with low SNR conditions significantly compared with the conventional energy detection methods. This improvement gives confidence that this proposed feature

extraction strategy gives more discrimination between occupied and vacant spectrum states. Furthermore, the accuracy of classification was consistently high because of dimensionality reduction by applying LDA in order to eliminate redundant features and enhance separability before learning by AdaBoost.

Table 1. Performance of AdaBoost hybrid features with previous research works

SNR in dB	AdaBoost hybrid features	SVM [25]	RF [23]	KNN [24]
-30	0.65	0.45	0.51	0.34
-25	0.89	0.76	0.68	0.59
-20	0.92	0.84	0.89	0.72
-15	0.94	0.89	0.91	0.86
-10	1	0.95	0.98	0.91
-5	1	1	1	0.95
0	1	1	1	1
5	1	1	1	1
10	1	1	1	1
15	1	1	1	1
20	1	1	1	1

Table 1 represents the performance of AdaBoost with hybrid features compared against SVM (from [25]), Random Forest (RF) (from [23]), and K-Nearest Neighbors (KNN) (from [24]) across different SNR levels. The analysis highlights that the AdaBoost hybrid feature approach consistently outperforms the other classifiers, particularly in low SNR environments (-30 dB to -10 dB). At -30 dB, AdaBoost achieves 0.65 detection probability, significantly outperforming SVM (0.45), RF (0.51), and KNN (0.34). This trend continues at -25 dB and -20 dB, where AdaBoost maintains a notable performance edge over SVM and KNN, although RF achieves comparable results at -20 dB. For SNR values of -10 dB and above, all classifiers begin to converge in performance. At -10 dB, AdaBoost reaches 1.0 detection probability, surpassing both SVM (0.95) and RF (0.98), while KNN remains slightly behind at 0.91. From -5 dB onwards, all methods achieve perfect detection (1.0 probability), indicating that at high SNR levels, feature extraction and model selection have a minimal impact on performance, as noise interference becomes negligible.

The baseline classifiers, which are used for comparison, such as SVM [25], Random Forest [23], and KNN [24] classifiers, are implemented with standard parameter settings used in the spectrum sensing literature. For SVM, the Radial Basis Function (RBF) kernel was used with optimized penalty and kernel parameters using grid search. Random Forest performance was tested by changing the number of decision trees, and KNN was tested using different neighborhood sizes to get the best accuracy of detection. In order to ensure fairness, all baseline models have been trained and tested in the same dataset splits and in the same SNR. Further, the reported results are the mean performance during multiple

independent runs with simulation. Statistical significance was confirmed by paired t-tests to prove the effectiveness of the proposed hybrid framework, which makes consistent improvements on the baseline methods with meaningful improvements in performance.

4.3. Computational Complexity and Practical Impact

Apart from sensing accuracy, computational efficiency is an important requirement for real-time cognitive radio applications. The proposed framework is able to provide improved detection performance with moderate computational overhead by taking advantage of the optimized decomposition strategy.

DTCWT offers multi-resolution signal analysis with improved shift in-viability as compared with conventional wavelet transform, and BWOA guarantees that only optimum decomposition parameters are chosen without wasting the processing. NA-EMD further increases robustness by separating noise-dominant components, where false decision under uncertainty is reduced.

Despite the fact that feature fusions based on hybrid functions increase the dimensionality, LDA is a useful method to reduce the amount of computation needed in the application by selecting the most discriminative features. Finally, AdaBoost provides good classification correctness compounded by low training calculations when compared to deep neural models.

Therefore, the proposed approach is a balanced approach between sensing reliability, robustness, and computation feasibility, which can be applicable to dynamic spectrum environments.

Strengths of AdaBoost Hybrid Features

- Superior Performance in Low-SNR Conditions: The hybrid feature approach improves signal detection in situations of signal detection under the dominance of noise, which is more suitable for noisy and dynamic environments.
- Robust Feature Selection: The combination used in DTCWT, that is, the applicability of NA-EMD and LDA, ensures that the most relevant features are extracted and lead to higher classification accuracy.
- Adaptive Learning: The capability of AdaBoost to give more weights to the difficult samples makes it capable of outperforming other traditional classifiers, such as SVM and KNN, which have fixed decision boundaries.

Limitations and Comparison with Cited Work:

- Performance Drop in Extremely Noisy Environments: While AdaBoost is better than SVM, RF, and KNN at -30 dB and -25 dB, it still cannot provide a detection probability of more than 0.9, which means there is still

room for improvement. In contrast, RF keeps 0.51 at -30 dB, indicating that it is possible to further improve the low-SNR performance with an ensemble method with deeper trees.

- **Computational Complexity:** Compared to SVM and KNN, AdaBoost takes more training time and computation, making it less applicable in real-time applications with limited processing strains.
- **Feature Dependence:** While the hybrid approach allows for improving the quality of the prediction, it is highly dependent on the quality of feature extraction. Unlike approaches that rely on deep learning, which is able to learn features automatically, AdaBoost requires manual feature engineering.

The hybrid feature method trained by AdaBoost shows great advantages in the low SNR spectrum sensing aspects, and the results exceed SVM, RF, and KNN under difficult conditions. However, RF demonstrates competitive performance where -20 dB is concerned, while all the methods perform similarly at high SNRs. The future works can be integrating deep learning models for automatic feature extraction or optimized AdaBoost with deep learning based weak classifiers to further improve the low SNR performance.

Table 2. Comparative Analysis with Previous Research Works

Methods	Probability of Detection	Probability of False Alarm
[23]	0.94	0.1
[24]	0.50	0.1
[25]	0.962	0.1
[26]	0.8	0.1
[27]	0.7	0.1
Proposed Hybrid Approach	0.967	0.1

The proposed hybrid approach is compared to the previous research works in terms of the probability of detection and probability of false alarm presented in Table 2. Detection probability in previous works ranges from 0.50 to 0.962, which will be compared with the performance of different methods from the table.

The proposed hybrid approach attains a detection probability of 0.967, with all other methods having the exact same false alarm probability of 0.1. The proposed technique has the highest detection accuracy in comparison with the existing techniques, which verifies the performance improvement for the spectrum sensing.

4.4. Benchmarking with Recent Deep Learning and Metaheuristic-Based Spectrum Sensing Methods

In recent spectrum sensing research, they have gradually tended to adopt a deep learning and metaheuristic framework for the detection reliability improvement of wireless complex

environments. Deep learning approaches like CNN and LSTM-CNN networks have shown good feature learning ability in extracting the spectrum patterns directly from the original sensing data. For example, cooperative spectrum sensing with LSTM-CNN architectures has been investigated in [19], while a method based on deep learning-based multiple feature combination has been presented in [22].

These methods offer better adaptability but frequently demand large-scale datasets, long training times, and high computational resources, which can pose a problem for their implementation in real-time within cognitive radio devices, which lack computational resources. Similarly, a number of meta-heuristic optimization-based spectrum sensing techniques have been introduced in recent research to improve the sensing performance by tuning sensing parameters.

Optimization techniques such as weighted chimp optimization, ant colony optimization, and Bayesian optimized classifiers have been applied with regard to improving threshold selection and feature representation [11, 26]. While these approaches provide performance improvement, they can include more computational overhead due to the optimization process of iterating through approaches.

Compared with these recent deep learning and metaheuristic frameworks, the proposed BWOA-DTCWT and NA-EMD fusion approach is capable of competitive detection performance with much lower detection complexity.

Unlike the deep neural models that are resource-consuming during training, the proposed approach is based on optimized signal decomposition, discriminative feature reduction by LDA, and lightweight ensemble classification using AdaBoost. This makes the framework more applicable to realistic dynamic spectrum access situations where sensing accuracy and computational feasibility are of great importance.

Table 3 shows a benchmark comparison of the proposed method and recent deep learning and metaheuristics-based spectrum sensing approaches. Deep learning models such as LSTM-CNN [19] and feature combination CNN [22] have high detection probabilities but have a large data set requirement and also high computation. Metaheuristic-assisted methods, such as Bayesian optimized Random Forest [23], ant colony optimized MME detection [26], are able to enhance the sensing performance by optimizing, but have the drawbacks of feature redundancy and iterative complexity overhead. In comparison, under conditions where the BWOA-DTCWT with NA-EMD and AdaBoost is proposed, the highest detection probability is achieved with a value of 0.967, and the trade-off between sensing accuracy and computational efficiency is balanced.

Table 3. Benchmark Comparison with Recent Deep Learning and Metaheuristic Methods

Method	Type	Probability of Detection (P_d)	Key Limitation
LSTM-CNN Cooperative Sensing [19]	Deep Learning	0.95	High training cost, large dataset needed
Deep Feature Combination CNN [22]	Deep Learning	0.96	Computationally expensive
Bayesian Optimized RF [23]	Metaheuristic ML	0.94	Feature redundancy remains
Ant Colony Optimized MME Detection [26]	Metaheuristic	0.80	Iterative complexity overhead
Proposed BWOA-DTCWT + NA-EMD + AdaBoost	Hybrid Optimized ML	0.967	Balanced accuracy and efficiency

4.5. Quantitative and Qualitative Comparison with State-of-the-Art Methods

To extend the evaluation of the proposed spectrum sensing framework, a quantitative and detailed comparison is conducted between the proposed framework and state-of-the-art-based approaches. Although the probability of detection (P_d) is a major indicator of sensing accuracy. In practical cognitive radio systems, sensing systems are also required to have a low probability of false alarm (P_f), low computational cost, and good adaptability under dynamic spectrum.

Recent deep learning-based sensing techniques like CNN and LSTM-CNN have presented promising detection performance due to their ability to automatically learn spectrum features from the raw sensing samples [19, 22]. However, these approaches in general demand large-scale data sets, extensive training time, and high computational resources, which may impact their feasibility of being implemented in cognitive radio devices that are in real-time

and/or with restricted resources. Similarly, spectrum sensing approaches that employ metaheuristic optimization techniques optimize the sensing reliability by adjusting the optimization parameters iteratively; however, often at an extra level of computational overhead and resulting in a convergence delay [11, 26].

In contrast, the proposed BWOA--DTCWT and NA-EMD feature fusion framework has improved sensing performance with a detection probability of $P_d = 0.967$ while the controlled false alarm rate of $P_f = 0.10$. The use of the LDA-based dimensionality reduction technique avoids redundancy in the fused feature space, and the AdaBoost ensemble classifier gives accurate classification with moderate training complexity. Furthermore, the derivation of the decomposition strategy based on optimization enhances robust performance and adaptability in different noise and fading circumstances, so the proposed framework can be considered for dynamic spectrum access scenarios.

Table 4. Quantitative and Qualitative Comparison with State-of-the-Art Methods

Method	P_d	P_f	Computational Cost	Adaptability
Energy Detection [4]	0.80	0.10	Very Low	Poor under noise uncertainty
Bayesian Optimized RF [23]	0.94	0.10	Medium	Moderate adaptability
LSTM-CNN Cooperative Sensing [19]	0.95	0.12	Very High	High but data-dependent
Deep Feature Combination CNN [22]	0.96	0.11	Very High	Strong but computationally expensive
Ant Colony Optimized MME Detection [26]	0.80	0.10	High (iterative)	Moderate
Proposed Hybrid Framework	0.967	0.10	Medium-Low	High in dynamic conditions

Table 4 gives an extensive benchmarking of the proposed approach with respect to the state-of-the-art spectrum sensing methods of recent years by taking into account several aspects of evaluation in addition to the detection probability. The conventional energy detection method exhibits a computational cost but has low robustness in a noisy environment. Deep learning approaches like LSTM-CNN [19] and feature-combination CNN [22] give good performance in detection, but due to their high requirement for computational power and large data, their practical applications are limited. Metaheuristic-based techniques, such as Bayesian optimized RF [23] and ant colony optimized detection [26], enhance sensing reliability (through optimization) but add an overhead

in complexity due to the iteration. In comparison, the proposed hybrid framework has the highest detection probability of 0.967, a low false alarm probability, moderate computational complexity, and high adaptability in dynamic spectrum conditions.

4.6. Limitations and Open Research Challenges

Despite the fact that the proposed hybrid spectrum sensing framework shows good improvement in the detection reliability and robustness, some limitations exist. First, the framework still depends on statistical feature extraction from DTCWT sub-bands and NA-EMD intrinsic mode functions, while deep learning approaches may have the potential to

automatically learn more complex spectrum patterns directly from raw data. Second, the iterative optimization process using BWOA adds extra computation, and this could impact the processing time of the application in extremely resource-constrained cognitive radio devices. Moreover, open challenges associated with real-world spectrum sensing, such as rapidly changing mobile environments and interference from multiple primary users, scarcity of spectrum for dense deployments, and security threats like malicious users for cooperative sensing, still remain unsolved. Future research works can be focused on combining lightweight deep learning architectures with the proposed optimization-driven feature fusion framework, decreasing the optimization overhead, and extending the proposed idea to wideband and multi-user spectrum sensing.

4.7. Generalizability Across Different Channel Conditions and User Behaviors

In practical cognitive radio environments, spectrum sensing performance may fluctuate greatly because of changing wireless channels, noise uncertainty, and diverse primary user activity patterns. To allow a broader applicability, the proposed framework is designed to be effective under different channel behavior cases of AWGN, fading, and shadowing. Since the resolution of multi-resolution signal decomposition is achieved through DTCWT and adaptive component separation is performed through NA-EMD, it can perceive the spectrum characteristics regardless of the fluctuation of channel conditions.

Moreover, the BWOA-based parameter tuning gives extra choice in parameter tuning by dynamically adjusting decomposition and denoising parameters. This provides more generalisability of the proposed approach with varying spectrum occupancy patterns and user activity behaviour as opposed to fixed-threshold or purely handcrafted-based sensing techniques.

4.8. Ablation Study of the Proposed Framework Components

To get a better insight into the function of each module in the proposed hybrid framework, an ablation study was conducted by incrementally adding the main components of the system. This is a useful analysis in noting how much each stage contributes to the overall detection improvement.

Table 5. Ablation Study of Framework Components

Configuration	Probability of Detection (Pd)
DTCWT only	0.90
DTCWT + BWOA Optimization	0.93
+ NA-EMD Feature Fusion	0.95
+ LDA Dimensionality Reduction	0.96
+ AdaBoost Classification (Full Model)	0.967

Table 5 clearly demonstrates that every component gives some measurable improvement in sensing performance. Using DTCWT on its own provides a fairly good starting point, but when BWOA is introduced for parameter optimization, the detection probability increases.

The inclusion of NA-EMD has an additional benefit of filtering noise-dominant components. LDA helps in reducing the redundant features, enhances class separability, whereas the final AdaBoost ensemble classifier gives the best overall detection accuracy. This establishes that the full hybrid framework is required in order to achieve the reported performance improvements.

4.9. Statistical Rigor and Reliability of Results

For the consistency and statistical reliability of the reported performance, the results of all experimental results were calculated by averaging results obtained for multiple independent simulation runs. The improvements in detection were shown to be stable across multiple trials, and using confidence interval trends, it was shown that the proposed method represents a consistent improvement over the baseline approaches. This makes the comparisons presented more robust in terms of their validity and less susceptible to any random initialization or noise realizations that result in a variation in performance.

4.10. Computational Cost and Scalability Considerations

In addition to sensing accuracy, computational feasibility is a key requirement for cognitively deployed radio to be deployed traditionally in real-time. Although the proposed framework consists of a combination of multiple processing stages, the overall complexity is kept under control by the fact that the dimensionality reduction using LDA is applied, which performs the dimensionality reduction of features before classification.

Furthermore, AdaBoost also provides a lower training and inference cost than deep neural architectures and thus offers the potential of scaling the approach for larger sensing datasets and dynamic spectrum environments. Therefore, the proposed technique offers an adequate compromise between detection reliability, robustness, and practical computation cost.

5. Conclusion

In this paper, a hybrid technique for spectrum sensing in cognitive radio networks has been proposed, which has remarkable improvement over the conventional technique, gaining better detection performance and robustness. The approach is the combination of BWOA optimized DTCWT and noise-assisted empirical mode decomposition methods to break down the spectrum signals into useful sub-bands and intrinsic mode functions, so that the raw spectrum can be deployed for extraction in a better way. By adaptive

decomposition and well-designed feature fusion, it ensures that the prerequisite features, such as energy, entropy, and frequency, are fully extracted and used for detection.

In addition, the application of the LDA dimensionality reduction technique and the AdaBoost ensemble classifier decision-making process significantly improved the performance of classification by using LDA. Results of the proposed method show a probability of detection of 0.967, which is a significant improvement compared to the previously reported technique.

This makes the detection accuracy higher in different degrees of noise or interference, which is the case for environments where this is a factor. In terms of the practical deployment, the proposed hybrid spectrum sensing framework can be used in real-time cognitive radio systems for the following reasons: Moderate computational complexity owing to LDA-based feature reduction and lightweight AdaBoost classification. The method can take the form of both fusion center implementation or edge-enabled CR devices for dynamic spectrum access applications. Moreover, secure and

privacy-aware cooperative sensing is still an important consideration in real deployments because the sensing decisions may then be affected by malicious or unreliable users. Future work will be done on the extension of the framework towards privacy-preserving and attack-resilient spectrum sensing to large-scale cognitive radio networks. Future work may also infuse the spectral characteristics and classification ability of deep learning techniques for dynamic spectrum sensing. Another aspect of the solution is that the solution proposed here can be easily extended to manage a more advanced spectrum environment with more primary users and more complex interference patterns.

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