Hybrid Spectrum Sensing Techniques in 5G Cognitive Radio Networks in Soft Computing: A Review

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Abstract

This paper describes an updated and efficient method for Hybrid spectrum sensing in cognitive radio (CR) system utilizing soft computing paradigms. The suggested soft computing approach utilizes an artificial neural network and for learning and decision making as a solution to the problems when a new product is subjected to the CR framework, developed the ability for unlicensed cognitive users to access radio frequencies through a spectrum hole and understand its implications through mechanisms spectrum sensing. The suggested soft computing approach could then be referred to as the Neuro technique. The need for higher bandwidth is important with the rise in the number of communication devices. Usage of cognitive radio for the fifth generation 5G communication network of the next generation Consider the fact that CR technology will efficiently optimize the use of much of the unused communication spectrum bands for the future 5G of wireless network and beyond.

Keywords

5G Cognitive Radio (CR), ANN technique, Hybrid spectrum sensing.

INTRODUCTION

Spectrum services are becoming increasingly limited with the exponential development of wireless networking technology and the introduction of 5 G large multiple-input multiple-output (MIMO) systems[1]. The total use of spectrum varies from 7 to 34 percent, as per the spectrum occupancy campaign in 2016, indicating substantial under-use of spectrum resources[2]. For the spectrum band's effective utilization and opportunistic use, the spectrum distribution has to be complicated. Cognitive Radio (DSA/CR) is intended to be a promising alternative to reduce this emerging controversy between the competition for spectrum and the under-use spectrum[3]. CR schemes seek to improve the effectiveness of the use of spectrum by enabling unlicensed or secondary users (SUs) to enter momentarily unlicensed or primary users (PUs) licensed spectrum bands in a non-interfering manner[4]. Precisely, CR takes advantage of radio spectrum components that are not populated in certain specific positions at certain specific times and transfer its activity to these components called spectrum holes or white spaces for opportunistic access[5]. The literature has indicated a variety of various spectrum sensing schemes[6]. Several spectrum sensing techniques have been explained in [7, 8], particularly matched philter identification, adaptive spectrum sensing, and cyclostationary based sensing. Energy detection[9, 10], which contrasts the obtained signal energy with a predefined threshold and decides the PU state, either busy or idle, is one of the most basic and commonly popular non-parametric sensing schemes. It is easy to incorporate energy detection, but it is susceptible to signal and noise uncertainty[11, 12]

LITERATURE SURVEY

In particular, by following the characteristics of CUs without disrupting the behaviors of PUs, the efficiency of the wireless communication device can be increased. The researchers have suggested numerous spectrum control tasks, except spectrum detection, spectrum detection, and spectrum determination for the CUs. Various techniques such as energy detection, matched philters, cyclostationarities, and wavelet detections have been widely used in spectrum sensing to recognize the radio frequency channel status.

The next generation's network connection will be listed as the Fifth Generation (5 G) and is planned to be commercialized in the next few years[13,14]. With a minimum of 1 ms latency and greater usage power and battery life, the estimated data rate for the 5 G network is about 100 Gbps[15,16]. Different future options include the use of the millimeter-wave frequency band, are in the process to achieve the required level of service (QoS)

Spectrum sensing is among the most complicated CR systems tasks because it needs high precision and high efficiency for dynamic spectrum entry.

Higher detection possibility ensures more excellent safety of primary users (PUs), and lower possibility of false alarm assures more probability of secondary users (SUs) using the channel. For all the sensing algorithms, a false alarm probability of 10 percent and a detection probability of 90 percent were seen as the aim specifications.

Venkatesan et al.[19], who suggested studies on artificial neural networks and optimized real radio output under a cognitive radio system, implemented a learning scheme. He provided specific examples, including industrial virtual hardware systems that are not widely accessible to the public and simulated hardware/software goods that are mobilized to access output work, and the performance of suitable prototypes to be used for the proper structure of the neural network.

A few studies, including the Multilayer Perception and Secret Markov Model, have preferred to use neural network models as they do not require established expertise to use numerical networks. It was suggested by Tumuluru et al.[21], who showed critical benefits of using a channel stage predictor for spectrum sensing activities, which would essentially save the SU's output from sensing energy. Researchers have analyzed channel status prediction systems and their potential reliabilities for qualitative performance measurement.

To use better particle swarm optimization (PSO) techniques, Tang developed a method to solve non-convex optimization problems. Via integrated simulated annealing (SA), he suggested methods to address the main problems of individual components and PSOs to form a PSOSA algorithm. His algorithm's results demonstrate that the solution obtained was considerably more effective than current methods.

Similarly, in the current study, the authors suggested a spectrum of an intelligent radio that conducts vision, comprehension, and analysis spatially. Therefore, these concepts have also been extended to CR networks. The Naive Bayesian Classifier (NBC) dependent multi-class spectrum sensing detection was suggested. At the same time, the authors proposed a random forest classifier-based solution to eliminate unlicensed user interaction with licensed users in the CR network, thus significantly increasing network throughput.

The authors suggested a sensing scheme that uses energy and cyclostationary characteristics to train the spectrum sensing neural network. We used energy and Zhang statistics as a training function for ANN in our previous work[22]. The multi-slot spectrum projection based on ANN and the selection of adaptive mode in the full-duplex CR network were suggested in [10]. In recent work, the systematic analysis of machine learning-based spectrum sensing in CR can be identified[24].

Several researchers have discussed different simulation algorithms[24-27] and have researched various artificial neural network tools, interpretation, and modeling[28-19].

Encouragement

The collection of hyperparameters in an ANN for CR network is extensively analyzed and studied to achieve a better ANN classification performance, leading to higher detection efficiency at low SNR. There is a systematic analysis of the effect of the lower and higher SNR regime on ANN results. Research studies indicate ANN's superior efficiency across lower and higher SNR regimes relative to current CED and IED algorithms. ANN's tuned hyperparameters such as activation function, optimization algorithms, and learning rate are validated based on observational data sets of different radio technology. Besides, the effect of the number of epochs for which the neural network is trained on the loss function is explored for various optimizers. Current outcomes show that the proposed ANN architecture for spectrum sensing outperforms CED and IED algorithms by identifying the best hyperparameters.

HYBRIDE SPECTRUM SENSING

Energy Detection

There are several issues with low SNR that limit the efficiency of the energy detection method [32], such as the method of energy detection.

Noise, mentoring, and channel fading ambiguity, and the significant difficulty in this strategy is quantifying the noise.

In the classic form, we see that a static threshold is used, but as we realize that the detection threshold is used, the threshold depends on the ambient noise. In this work, we suggest a complicated threshold to maximize the noise Sensing probability.[33]

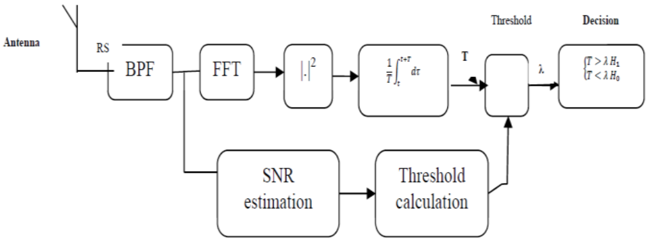

Fig 1: Energy Detection Model

The execution was performed in the Matlab software. The energy detector model is split.

In two bits. In the first part, at 100, the primary consumer emits an FM signal. Simulating a real one

In communication, we add Gaussian noise to the signal. We notice the secondary consumer in the second section, which

This includes an algorithm for energy detection to indicate the presence or absence of a primary signal.[34]

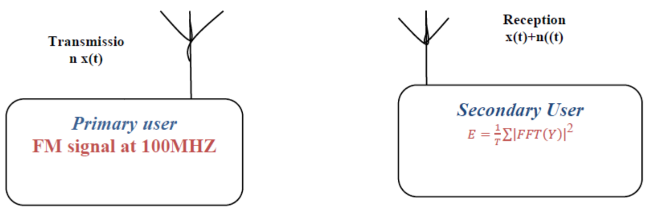

Fig 2: A simulation model

Match Filter Spectrum Detection

A matched philter (MF) is a linear philter configured for a given input signal to optimize the output signal to noise ratio. Matched philter recognition is implemented because secondary users have advanced experience of the primary consumer signal. The function of the matched philter is analogous to a similarity in which the unidentified signal is transformed to the philter whose frequency response is the variant of the transmitted signal mirror and time-shifted Matched philter detection operation is expressed as:

$$Y[n] = \sum_{k=-\infty}^{\infty} h[n-k]x[k] \tag{1}$$

Where 'x' is the unknown signal vector and is combined with 'h', the matched filter's impulse response is matched to the reference signal to maximize the SNR. Monitoring using the matched filter is useful only in cases where cognitive users are informed by primary users[35]

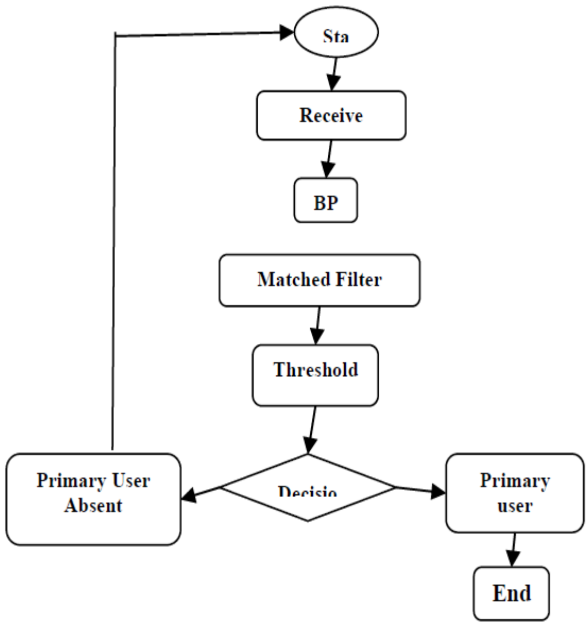

Fig 3: flow diagram of Matched filter Detection

Cyclostationary Feature Spectrum Detection

The To assess the involvement of primary users (PU), it takes advantage of the rate of change in the provided primary signal. In sinusoidal carriers, pulse trains, distributed code, hopping sequences, or cyclic prefixes of the primary signals, the periodicity is typically embedded. These cyclostationary signals display repetitive statistical and spectral similarity properties that are not observed in stationary noise and interference due to their periodicity [36]. Cyclostationary function detection is also resistant to noise uncertainties and performs better in low SNR regions than energy detection. Although it needs a priori awareness of the parameters of the signal, the identification of cyclostationary features will differentiate CR outputs from different types of PU signals. In cooperative sensing, this reduces the synchronization requirement of energy detection. Besides, during cooperative sensing and thereby enhance the overall CR throughput, CR users might not be needed to remain silent. Due to its high computational sophistication and long sensing time, this approach has its deficiencies. This method of detection is less common than spectrum sensing in cooperative sensing due to these problems [37].

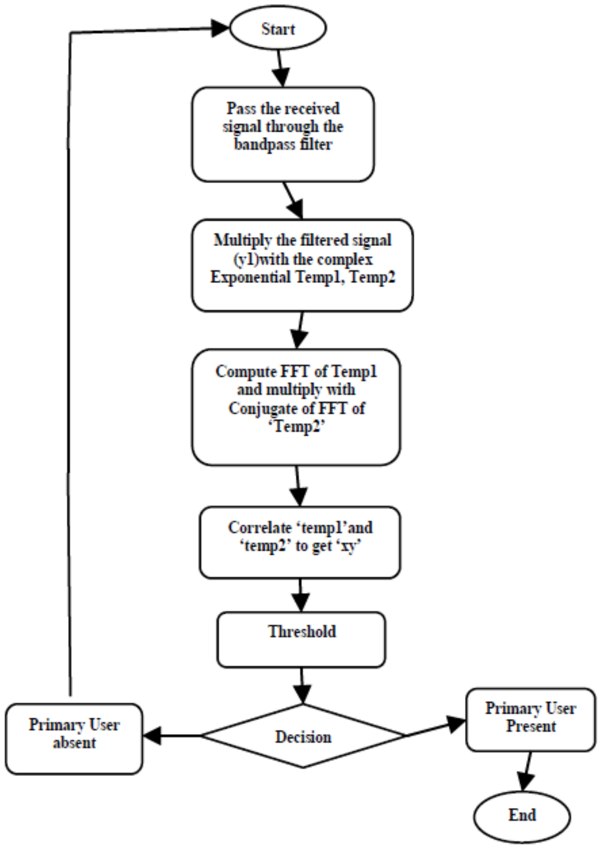

Fig 4: Flow diagram of Cyclostationary feature Detection.

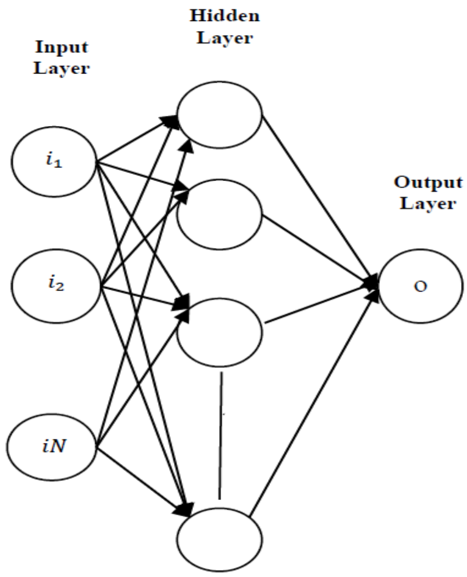

Fig 3: : ANN structure

ARTIFICIAL NEURAL NETWORK

Model of the Framework

A standard neural network architecture with one hidden layer and one single output is shown in Fig. 5. We presume that in a CR network, an SU detects only a single PU channel activity signal using the spectrum sensing algorithm consequently proposed. Here the SU is expected to regularly sense the PU's channel to decide

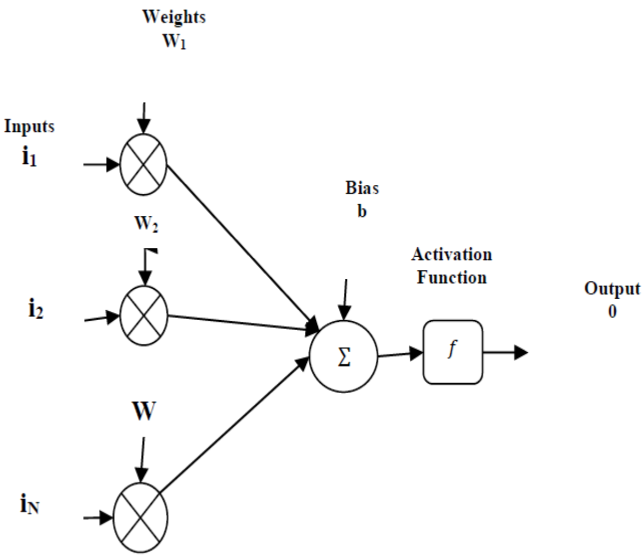

Fig 4: Hidden layer neuron structure

Whereas the hypothesis H_{i-1} suggests that the PU is current and the probability of spectrum is inaccessible at the SU stamp. Based on the observations captured, $y1, y2, \ldots, y_i, \ldots, y_K, \ldots, yK$, The primary aim is to predict if the channel will be idle or busy in the next 1st timestamp, i.e.$(k+1)$ th. The goal is to measure, mathematically, the following probability distribution:

$$P\,r\left(H_{k+1,j}|y^1, y^2, \ldots, y_k\right), \quad (2)$$

Where Remember that the null hypothesis is suggested by, while suggests the alternative hypothesis. To compute this probability, there are various mathematical models. After all, given the extraordinary potential to suit complex non-linear functions, an ANN-based method was carried out in this work.

Further, we extract four characteristics of the received signal as defined in Sect. 3, represented as X, to be supplied to the ANN as data. The neural network is then used to learn the mapping of

$$P\,r\left(H_{k+1,j}|X_{k'}\right), j \in \{0,1\} \quad (3)$$

Hyperparameter ANN-based Hybride Spectrum Sensing Scheme

The far more significant aspect of neural networks is that they are excellent in understanding non-linear functional mapping between input and output and thus respond to PU signals' non-linear features. A back amplification neural network (BPNN) is used in the suggested sensing system. Our proposed method is aimed at determining/classifying whether the PU channel is active or idle. We use a supervised learning environment in this article, where the classifier is trained with characteristics and associated marks. The ANN mainly integrates classical statistics of energy detection and probability ratio as its characteristics. For situations where the channel is idle and busy, the labels in this classifier are 0 and 1, respectively. The energy value E is given by denoting the discrete version of the obtained signal as y_i aS:

$$E = \sum_{i=1}^{N} |y_i|^2 \quad (4)$$

The Zhang Statistic $Z_c Z_c$ is given as:

$$Z_c = \sum_{i=1}^{N}\left[log\left\{\frac{F_0(y_i)^{-1}-1}{\frac{N-\frac{1}{2}}{i-\frac{3}{4}}-1}\right\}\right]^2 \quad (5)$$

The established sampling distribution (CDF) of noise is where N is the sample size and $F0$ሺyሻ(y)is the first step is to collect data. The first function is the signal energy, denoted as x1 (l) where l denotes the lth training sample. The second function is the preceding sensing event's energy value, denoted as x1(l). Also, we consider this function to prevent a sudden decrease in energy values caused by minor errors caused by experimental configuration leading to miss-classification. Likewise, the third and fourth characteristics are respectively denoted by the Zhang statistics of the present and previous sensing cases.

Similarly, the labels for the training sample are denoted by l. Here, l is the function vector index, separate from k, which is the number of the row index Uh Mode. In terms of machine learning, validation is a significant step. There may be a situation in which the classifier recalls all the training data set characteristics and may work amazingly on the training data set, but then fails when practically implemented introduced to real-life structures. One patent explanation for such cases is that the ANN has remembered and did not read or appreciate the training data[40]. This problem is known as data over-fitting. Data sets are commonly split into three separate sets to avoid this issue: preparation, validation, and verification. The validation data set uses all the models that have been learned to test the algorithm's output using the training data set. Also, to verify how many times the classifier incorrectly predicts the names, an indicator function is used. Also, the model is chosen which achieves the lowest value of the indicator function

Development with ANN

The primary aim of ANN development is to mitigate the value feature described in (11). There are two steps designed to train each ANN model sequentially, namely forward amplification and backward amplification, which are described below:

- **Forwards Amplification**

The function vector is provided as an input to the ANN, and specific weight values are allocated to each neuron. The neuron weights are multiplied with extracted features in the forward pass and applied to a bias value, which is ultimately passed to hidden layers as an input. For an ANN with n_H hidden layers, mathematically,

$$net_j = \sum_{i=1}^{p} x_i w_{ji} + w_{j0} \quad (6)$$

Where f is the value of the i_{th} function, is the j_{th} hidden layer's weight,w_{j0} is the bias value, and is the hidden layer's net activation. You can obtain the output of the hidden layer of jth by:

$$y_j = f(net_j) \tag{7}$$

where represents the activation function. Equally, for the output layer of the ANN;

we measure the net activation and output:

$$net_k = \sum_{j=1}^{n_H} y_j w_{kj} + w_{kC,} \tag{8}$$

$$z_k = f(net_k) \tag{9}$$

Here, the activation function maps input R →[0,1] . That's one of the hyperparameters that can be tailored for better performance to be obtained. The best activation function can be used for checking the ANN model after analyzing different activation activation functions on actual-world signals.

• Back Amplification

This measures the expense parameter gradient. The error in the output to the input neurons is then determined using the separation following equation as follow:

$$\frac{\partial J}{\partial w_{ji}} = \frac{\partial J}{\partial z_k}\frac{\partial z_k}{\partial net_k}\frac{\partial net_k}{\partial y_j}\frac{\partial y_j}{\partial net_j}\frac{\partial net_j}{\partial w_{ji}} \tag{10}$$

$$\frac{\partial J}{\partial w_{ji}} = \frac{\partial J}{\partial z_k}\frac{\partial z_k}{\partial net_k}\frac{\partial net_k}{\partial y_j}\frac{\partial y_j}{\partial net_j}\frac{\partial net_j}{\partial w_{ji}} \tag{11}$$

By going in the maximum margin range, the neural network weights are modified using such gradients, reducing the objective functions. There are various assessment methods, such as Adam optimizer, to change the weights, momentum-based gradient descent, etc.

The different hyperparameters, the best of which are used after analyzing their output on different real-world signals in testing the ANN model

Methods of Simulation

The solution methods used to achieve higher accuracy with each radio technology are discussed in this section.

1. Stochastic gradient descent (SGD): This algorithm improves the value function j(w) parameters was:

$$w := w - \eta.\nabla wj ਨ,w ਨ \tag{12}$$

For those changes, the simulation time g remains unchanged. Often to prevent overheating the saturation stage, the back amplification for SGD is usually lower than batch gradient descent.

2. AdaGrad: This algorithm is a useful tool for successful learning rate adjustment[39]. Compared to having a similar training set with all the weights, it preserves the information gain per parameter. One of the disadvantages of AdaGrad is that the training error gets slightly lower as it gets closer to the target. Still, even after several tests, it can not achieve the very minimum.
3. Adam: It's possible to use this optimization technique rather than and after several variations, it gets slightly smaller, so it does not meet the exact minimum classical SGD for filling gaps weight values regarding the training results. " Adaptive Moment Estimation " (ADAM)[43] is the term that comes. A focus on addressing is retained for each network weight (parameter) and adapted individually as testing unfolds, unlike the classical SGD that retains a single training set for all the weight changes. Adam knows the advantages of both AdaGrad and RMSProp (another optimization algorithm), including the use of regression periods of the first (mean) and second (uncensored variance).

The ADAM optimizer is used to achieve quicker optimization. Though, the highest performing compiler is subject to the data set that it is educated and checked on. In the case of spectrum sensing, Nesterov's rapid differential performing the skill, owing to its ability to acquire velocity and prevent dependence on other state space, yields minimal model loss.

The option of the activation function is yet another significant hyperparameter to be calibrated efficiently. For that, to evaluate the efficiency of the suggested ANN architecture, we include the following activation functions:

1. Activation feature of Sigmoid:

$$f(a) = \frac{1}{1+e^{-a}}, \tag{13}$$

2. Activation feature of ReLU:

$$f(a) = \max(0, a), \tag{14}$$

3. Activation feature of Tanh:

$$f(a) = \frac{e^{a}-e^{-a}}{e^{a}+e^{-a}}, \tag{15}$$

Sigmoid and Tanh are typically haven't used due to the neural network issues, which essentially reduces the accuracy rate. However, in spectrum sensing, because the network used is not large, all activation functions yield the same precision of the segment on numerical effects.

The validity of Data Captured

Although the randomness factor and its implications are difficult to remove from the empirical setup, the data collected was used to replicate the results of the CED and IED equations given in[41]. Furthermore, to guarantee the quality of the information set, the data collection and sensing validation were replicated numerous cycles for the proposed method, and the quality barely changed. These experiments were also taken to ensure no unusual or erroneous patterns that violated basic theoretical expectations (e.g. rise in the SNR and sample size N, increase in Pd).

Summary of various features

Taking into account various sets of functions, we evaluate the efficacy of the suggested architecture as follows:

(1) just present measurements of energy,
(2) only new samples of Zhang statistics,
(3) recent comparisons including both energy and Zhang statistics, and
(4) various state samples of both energy and Zhang statistics. More precisely, we test the performance of how qualified ANN suits the information of standard error.

OUTCOMES

The suggested spectrum sensing scheme based on ANN was checked and analyzed on scientific evidence. Rather than using channels from just a single cognitive radio, we selected channels with different radio technologies. The average efficiency of single radio technology for multiple channels was considered quite equal. Therefore, four ANN architectures have been used, and particular radio technology is assigned, as mentioned earlier. The identification frequency Pd and the false alarm rate Pf are calculated, having received separate training and certification results for each radio technology. A single ANN may also be used to combine all radio technologies combined, but in doing so, as per [42], the intrinsic impact of technology reliance on Pd can be ignored. For each radio technology, a comparative evaluation of the project method with current CED and IED algorithms on collected data is made. The findings indicate that the suggested scheme outperforms.

ANN SCHEME REVIEW

The suggested ANN-based sensing system was evaluated as evident by including all radio technologies with various strengths of sample sizes and false alarm frequencies. Even the detection efficacy of the suggested scheme is comparable to CED and IED sensing schemes. SNR correlation with NBC in [32] and BPNN for the current proposal. In our case, the spectrum data is obtained through the configuration of the analytical testbed. However, we have created the data through the parameter values given in [32] for a fair comparison. We could see that our suggested methodology behaves very similarly with the NBC at low SNR regime relative to the BPNN scheme without hyperparameter. This is relative to the learned model without hyperparameter tuning; the suggested methodology learns faster whenever the hyperparameters are tuned.

CONCLUSIONS

A new hybrid spectrum sensing device in this paper implemented is already. The analysis has been checked utilizing an innovative proof of concept setup based on different radio technologies. The researchers acknowledged that for all regarded radio technology, the suggested scheme greatly surpasses traditional energy detection methods and other new methods of energy detection. One part of the potential work should be seen as reducing the learning time needed; the other can be considered as integrating various other related features to achieve greater consistency in results. Definitely, the larger the number of functions, the larger the computing efficiency; it is difficult to satisfy all of these things at the time.

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