Improving Energy Detection in Cognitive Radio Systems Using Machine Learning

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Abstract —Research has shown that a huge portion of the electromagnetic spectrum is underutilized. Over the years, cognitive radio has been demonstrated as an efficient dynamic spectrum management technique. Energy detection is one of the widely used spectrum sensing techniques. However, its performance is limited by factors such as multipath fading and shadowing, which makes it prone to errors, particularly in low signal-to-noise ratio conditions. Yet, it still has a low computational cost, which reduces communication overhead. This paper aims to improve the detection accuracy of the energy detector through the use of machine learning (ML) techniques. In this research, ML models were trained using the energy characteristics of the primary user and other users present within the system. Weighted KNN produced the highest overall accuracy with an average of 91.88% accuracy at various SNR conditions. However, complex tree algorithm gave the most accurate detection (99% accuracy) of the primary user across all the channel conditions tested. This detection also helped to differentiate between the identity of the primary or secondary user from interference.

Index Terms—Cognitive radio, energy detection, detection accuracy, machine learning

I. Introduction

The status of the electromagnetic spectrum presently reveals a high degree of under-utilization [1]. It was observed that some portions of the radio spectrum are already overcrowded (3GHz – 300GHz region) [1] due to the very many telecommunication applications and services that perform better in the very high frequency. However, there are some spectrum spaces between 30MHz and 3GHz that are not as crowded. These portions are still part of the radio spectrum (3MHz – 3THz) that can be effectively utilized for telecommunication services [2]. This status is rapidly deteriorating such that efficiently using the spectrum to empower the increasing wireless devices and services is slowly becoming almost infeasible [3].

The regulations that were put in place by the Radio Communication Sector of ITU (ITU-R) to ensure efficient spectrum allocation and to avoid interference between users cannot effectively manage the upsurge of existing and upcoming bandwidth-demanding wireless technologies. At the end of 2016, the worldwide population of mobile phone subscriptions was 7.5 billion, with each subscriber individually contributing an average data usage of 2.1GB to worldwide 8.8EB total mobile data traffic [2], [4]. On average, more than 1 million mobile phone subscribers will be added to the annual mobile device subscription database until 2022 to make a huge 9 billion mobile subscribers worldwide [2].

These new radio access technologies are limited by the shortage of the useable available radio spectrum. This is because the present regulations possess fixed radio functions, static spectrum allocation, and limited network coordination [5]. This situation calls for an urgent need to improve the utilization of the spectrum, and cognitive radio is a dynamic spectrum management application that can suffice as a workable solution [6].

The spectrum utilization statistics in Africa as a case study shows that the continent alone contributed 13% to the world wireless technology users and 10% of the total internet subscribers worldwide as at the end of the first quarter of 2017 [4], [7]. There were 985 million subscriptions from Africa alone, out of the global 2.1 billion LTE subscribers in the first quarter of 2017. Despite this huge growth in network connectivity demand, the continent is still limited by low telecommunication connectivity quality which is depicted in measurable parameters such the overall Internet Service Provider (ISP) subscriptions, Internet Exchange Point (IXP) traffic and available bandwidth compared to the rest of the world [8]. Bridging this digital divide, which would entail an improved broadband wireless access technology requires more efficient use of spectrum opportunities such as the GSM white space through dynamic spectrum management [9], [10].

Cognitive Radio (CR) technology has been proven through research to be an efficient dynamic spectrum management technique [10], [11]. This software-defined radio can effectively manage the spectrum by exploiting spectrum holes and permitting the deployment of diverse wireless devices and services [6]. It can sense the status of the spectrum channels to determine the possibility of utilizing the channels. It is thus able to tune the usage of the spectrum dynamically based on certain factors such as

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number and type of radios requiring bandwidth allocation, location of the radios, time of the day, etc. [12].

Spectrum sensing is very crucial in cognitive radio operations to avoid interference and channel misallocation. This is particularly very sensitive because interfering with the channel of a licensed user has legal implications [13]. There are several techniques that can be used in spectrum sensing. Energy detection-based sensing is one of the least resource-demanding and yet effective methods in spectrum hole detection [14], [15]. Cognitive radio is one of the solutions to the problem of spectrum overcrowding, and it does this by opportunistically allocating unoccupied frequency bands of licensed users to unlicensed users. It is necessary for unlicensed users to have cognitive radio capabilities, such as reliable spectrum sensing in order to check if a particular channel is in use by a licensed user at a specific point in time [13].

II. Literature Review

Authors in [16] worked on the evaluation of an improved version of the energy detection algorithm. The aim was to improve the detection quality of energy detectors in cognitive radio systems. The method proposed outperformed the classical energy detection scheme and at the same time, maintaining a similar level of algorithm complexity and computational cost. Detection time was reduced in comparison to other, more sophisticated methods of sensing.

Authors in [17] examined different spectrum sensing schemes amongst which is an adaptive threshold energy detector. Performance and lower hardware requirements were used to suggest new schemes. The results were then used to confirm the theoretical basis of these techniques. The work in [18] improved energy detection spectrum sensing by using an optimum power operation instead of the squaring operation in the classical energy detector. The best power operation was achieved based on the probability of false alarm, the probability of detection, the average signal-to-noise ratio, or the sample size.

Authors in [19] developed an improved energy detector for wideband spectrum sensing in cognitive radio networks. The aim was to determine the detection thresholds for non-overlapping sub-bands. This resulted in improved spectrum sensing and opportunistic access for secondary users.

In [20], an augmented spectrum sensing algorithm for cognitive radio systems was proposed. Cyclostationary detection was used to augment the energy detector's detection. However, this method needs some knowledge of the primary users' transmission characteristics.

Authors in [21] used multiple antenna techniques to improve the performance of energy detection and cyclostationary feature detection-based spectrum sensing systems for cognitive radios. Cooperative spectrum sensing was used together with various combining techniques. Equal Gain Combining (EGC) gave the highest gain when used with different modulation schemes.

Reference [22] used a cyclostationary detection based cooperative spectrum sensing in a cognitive radio network consisting of multiple antennas and a fusion center. The method used was able to perform well in low signal-to-noise ratios (SNR) conditions. The paper also showed that the probabilities of detection in low SNR conditions can be increased with an increasing number of secondary users.

Authors in [23] proposed a scheme where cognitive users can use different channels, even without any information about the environment. This paper was able to improve on the usage of the idle spectrum and at the same time considering fairness in channel selection. In [24], the authors developed an improved energy detection algorithm with the aid of a p-norm energy detector. This improved the sensing of each cognitive radio used in cooperative spectrum sensing thus affecting the performance gain positively in AWGN and generalized κ-μ fading channels.

III. Methodology

A. System Model

Energy detection is a non-coherent detection method that is used to detect the operation of a licensed user within a particular communication channel [9]. In energy detection, the energy detected in the channel being sensed is measured and compared with a predefined threshold to determine the presence or absence of the primary user (PU) signal [10]. An energy detector is largely employed in ultra-wideband communication to utilize an idle channel when not in use by a licensed user.

In the implementation of the energy detector, the received signal $x(t)$ is filtered by a bandpass filter (BPF) in line with the bounds of the frequency channel being sensed. This signal detected is then squared with a square-law device. The bandpass filter serves to reduce the noise bandwidth. Hence, noise at the input to the squaring device has a band-limited flat spectral density. The output of the integrator is the energy of the input to the squaring device over the time interval T. Afterward, the output signal from the integrator (the decision statistic), Y, is compared with a threshold to decide whether a primary (licensed) user is present or not. A decision regarding the usage of the band will be made by comparing the detection statistic to a threshold [24].

The mathematical model for energy detection is given by the following two hypotheses [11]:

H_0: PU absent

$$y(n) = u(n) \quad n = 1,2, \dots N \tag{1}$$

H_1: PU present

$$y(n) = s(n) + u(n) \quad n = 1,2, \dots N \tag{2}$$

where $u(n)$ is noise and $s(n)$ is the PU's signal

The energy detector performs optimally in spectrum sensing if the noise variance is known. This is required to define the threshold which helps in deciding spectrum is occupied or not [25]. The challenge with the spectrum sensing of the energy detector is that it is unable to accurately detect the PU when the signal is weak, i.e. at low SNR. The detection accuracy further deteriorates when the noise characteristics cannot be defined due to varying noise uncertainties [26], [27].

This study is aimed at managing interference which may occur in energy-detection based cognitive radio by introducing supervised machine learning. This is expected to help the cognitive radio system (CRS) learn the patterns in the unknown noise characteristics through a clustering algorithm. The specific properties of the PU were used as training data in a supervised learning technique to serve a feature detection algorithm in the CRS. This scheme intends to improve the detection accuracy of the energy detector in scenarios when the SNR falls to the SNR wall level.

Equation (3) shows the normalized test (decision) statistic for the detector and this was developed based on [28] as:

$$T' = \left(\frac{1}{N_{02}}\right)\int_0^T y^2(t)dt \tag{3}$$

where:

T'= test statistic in during sensing session

y = received signal input

T = sampling instant

N_{02} = two-sided noise power density spectrum

If the test statistics exceed a fixed decision threshold then it results in H_1 hypothesis. However, when the test statistics is less than the decision threshold then H_0 hypothesis occurs.

As shown in [16], λ is the decision threshold which in the number of samples $N \gg 1$, can be expressed as a Gaussian distribution:

$$\lambda = \sqrt{\frac{2}{NQ^{-1}}}(P_{fa}^{CED} + 1) \tag{4}$$

where:

$$P_{fa}^{CED} = Q\left(\frac{\lambda - 1}{\sqrt{\frac{2}{N}}}\right) \tag{5}$$

$$P_d^{CED} = Q\left(\frac{\lambda-(1+\gamma)}{\sqrt{\left(\frac{2}{N}\right)(1+\gamma)^2}}\right) \tag{6}$$

$$\gamma = \frac{\sigma_s^2}{\sigma_w^2} \tag{7}$$

σ_s^2 is the received average primary signal power

σ_w^2 is the noise variance.

B. Machine Learning Improved Solution

The operating characteristics in the network can be assessed in frames (N). The energy test statistic ($Y^{\alpha}_{p|s|x,i}$) at the i^{th}frame of the user's transmission operations can be extracted as input data. Similarly, $Y^{\beta}_{p|s|x,i}$ and $Y^{\gamma}_{p|s|x,i}$can be extracted at specific points in the channel and receiver respectively.

Energy test statistics for the primary user ($Y_{p,i}$) is represented as:

$$Y_{p,i} \in (Y^{\alpha}_{p,i}, Y^{\beta}_{p,i}, Y^{\gamma}_{p,i}) \tag{9}$$

Energy test statistics for a secondary user ($Y_{s,i}$) is represented as:

$$Y_{s,i} \in (Y^{\alpha}_{s,i}, Y^{\beta}_{s,i}, Y^{\gamma}_{s,i}) \tag{10}$$

Energy test statistics for an interfering user ($Y_{x,i}$) is represented as:

$$Y_{x,i} \in (Y^{\alpha}_{x,i}, Y^{\beta}_{x,i}, Y^{\gamma}_{x,i}) \tag{11}$$

The labels identifying these input data in specific frames as primary user (U_p), a secondary user (U_s) or interfering user (U_x) based on their respective energy test statistics can be represented as decisions (d_i).

Both classes of data (energy test statistics and labels) are expected to be inputted as training data. The resulting ML classifier should be able to identify an unknown user ($U_?$) occupying the channel based on its energy test statistics as follows:

$$d_i = \begin{cases} U_p, & Y_{n,i} \in Y_{p,i} \\ U_s, & Y_{n,i} \in Y_{s,i}\ U_p, \quad 1 \le i \le N \\ U_x, & Y_{n,i} \in Y_{x,i} \end{cases} \tag{12}$$

This machine-learning enabled energy detection process can be represented in the form of a block diagram as shown in Fig. 1.

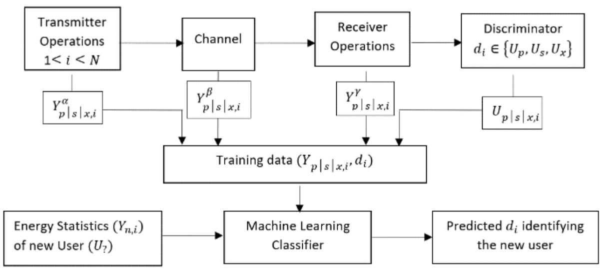

Fig. 1. Block diagram representing the machine-learning enabled energy detection process

The block diagram in Fig. 1 was implemented with MATLAB Simulink on MATLAB 2017a software. The model consisted of transmitters with an energy detector based cognitive radio through an additive white gaussian noise (AWGN) channel. The noise variance of the channel was set to -15dB to -25dB. The single sensing technique was employed using a frequency of 936MHZ and a bandwidth of 200 kHz and the threshold set to 0.2. Setting up the cognitive radio spectrum sensor (energy detector) in Simulink. Details of the simulation parameters are presented in Table I. The cognitive radio was tested through simulations in scenarios such as the

PU utilizing the channel, the PU not utilizing the channel, the secondary user (SU) utilizing the channel and interference in the channel. Afterward, machine learning was introduced to mitigate interference.

SNRs were varied in order to access the performance of the Energy Detector (ED) in very low SNRs. Machine Learning (ML) algorithms, particularly tree algorithms and KNN were harnessed to enable the ED to learn the characteristics of the network for better sensing. The sample size was varied between 300 and 300,000 samples using holdout validation. This helped to determine the best accuracy for the system. The simulations carried out compared the output of a conventional energy detector with an ML-enabled energy detector. The best 5 ML algorithms were selected based on their overall prediction accuracy.

TABLE I: SIMULATION PARAMETERS

Parameters	Values
SNR Variation	-25 dB to -10 dB
Channel	AWGN
Frequency of PU	936 MHz
Bandwidth	200 kHz
Threshold	0.2

IV. SIMULATION AND RESULTS

The energy levels of the primary user (PU), a Secondary User (SU), and interference (IU) were collected. Samples collected were fed into the Classification Learner of MATLAB. The problem under consideration is a classification problem thus, it is required of Machine Learning (ML) to predict the PU, SU, and IU correctly.

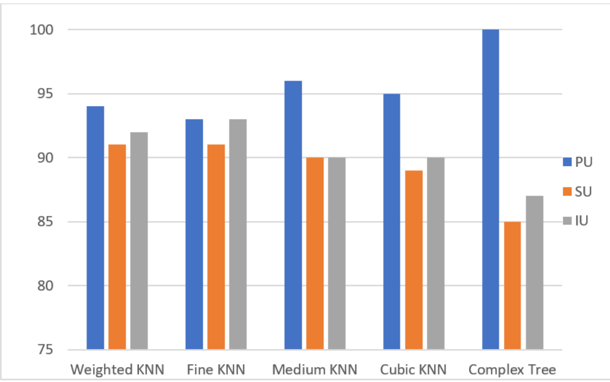

Fig. 2. Bar chart showing the accuracies for five classifiers at -15dB

Quick-to-train classification algorithms were used to train the data. The best five algorithms namely: Complex Tree, Fine KNN, Weighted KNN, Cubic KNN, and Medium KNN were selected and ranked based on the accuracy. These algorithms performed well during testing. The accuracies across different dB levels are presented in Table II-V. In , results for the output of the ML at -15dB were presented with the complex tree algorithm having the highest accuracy for the prediction of a PU. Thus, Table VI shows the accuracy of different sample sizes using the complex tree algorithm at -25dB.

Fig. 3-6 show the receiver operating characteristics (ROC) of the CR for varying dB levels. Comparisons were made between the output of the conventional energy detector (CED) and the ED with ML incorporated within.

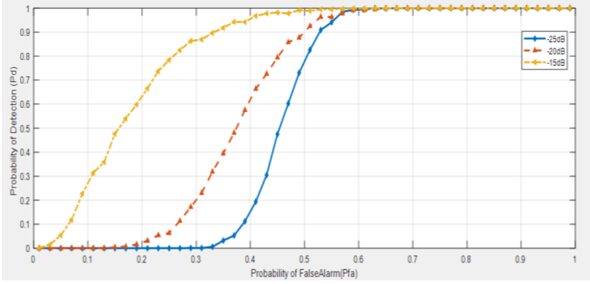

Fig. 3. ROC curves across four dB levels using CED

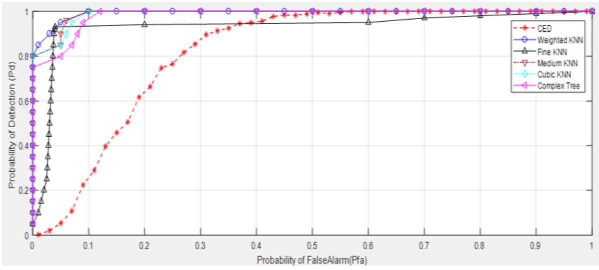

Fig.4. ROC curve comparing five classifiers at -15 dB

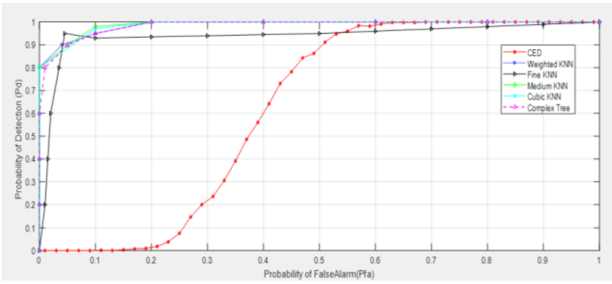

Fig. 5. ROC curve comparing five classifiers at -20 dB

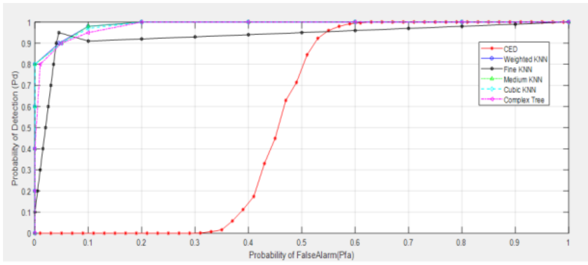

Fig. 6. ROC curve comparing five classifiers at -25dB

TABLE II: ACCURACY OF CLASSIFIERS AT -10DB

	PU		SU		IU		
CM	TPR (%)	FNR (%)	TPR (%)	FNR (%)	TPR (%)	FNR (%)	OA[1] (%)
WKNN	95	5	91	9	92	8	92.5
FKNN	93	7	91	9	93	7	92.6
MKNN	96	4	89	11	90	10	91.8
CKNN	96	4	89	11	90	10	91.7
CTree	>99	<1	85	15	87	13	90.4

TABLE III: ACCURACY OF CLASSIFIERS AT -15DB

	PU		SU		IU		
CM	TPR (%)	FNR (%)	TPR (%)	FNR (%)	TPR (%)	FNR (%)	OA[1] (%)
WKNN	94	6	91	9	92	8	92.2
FKNN	93	7	91	9	93	7	92.1
MKNN	96	4	89	11	90	10	91.5
CKNN	95	5	89	11	90	10	91.3
CTree	>99	<1	85	15	87	13	90.4

TABLE IV: ACCURACY OF CLASSIFIERS AT -20DB

	PU		SU		IU		
CM	TPR (%)	FNR (%)	TPR (%)	FNR (%)	TPR (%)	FNR (%)	OA[1] (%)
WKNN	94	6	90	10	91	9	91.7
FKNN	92	7	90	10	92	8	91.7
MKNN	96	4	89	11	89	11	91.2
CKNN	95	5	89	11	89	11	90.9
CTree	>99	<1	84	16	86	14	90.3

TABLE V: ACCURACY OF CLASSIFIERS AT -25DB

	PU		SU		IU		
CM	TPR (%)	FNR (%)	TPR (%)	FNR (%)	TPR (%)	FNR (%)	OA[1] (%)
WKNN	93	7	89	11	91	9	91.1
FKNN	91	9	89	11	92	8	90.8
MKNN	95	5	88	12	89	11	90.7
CKNN	95	5	88	12	89	11	90.4
CTree	>99	<1	85	15	87	13	90.5

TABLE VI: EFFECT OF TRAINING SAMPLE SIZE ON ACCURACY AT -25DB USING COMPLEX TREE ALGORITHM

	PU		SU		IU		
Training Samples	TPR (%)	FNR (%)	TPR (%)	FNR (%)	TPR (%)	FNR (%)	OA[1] (%)
300	52	48	48	52	44	56	48
3000	99	1	50	50	58	42	69.1
30000	100	0	78	22	74	26	83.9
300000	>99	<1	85	15	87	13	90.5

OA[1]: Overall accuracy
CM: Classification methods
WKNN: Weighted KNN
FKNN: Fine KNN
MKNN: Medium KNN
CKNN: Cubic KNN
CTree: Complex tree
TPR**:** True positive rate
FNR: False-negative rate

V. DISCUSSION

Fig. 3 revealed that detection sensitivity reduces as SNR reduced from -15 dB to -25 dB. It exposed the weakness of ED in low SNR operating conditions. It confirms the need for improved sensitivity detection in low SNR operating conditions. The improvement effort was made with the incorporation of ML algorithms to learn the network operating characteristics. The results presented in Fig. 4-6 show a reduction in the probabilities of false alarm and missed detections. In Fig. 4, the ROC for -15 dB using ML was compared with that of the CED. Fig. 5 showed the ROC for -20dB while Fig. 6 displays the ROC at -20dB. It was observed from these results that the detection sensitivity improved using ML when compared to CED.

Results from Table VI showed that the detection sensitivity and accuracy of the CR improved with an increased sample size. The overall accuracy of detection for the PU remained steady at 3000 to 300000 samples. However, the TPR of the other classes improved as the sample size increased.

These results reveal that the detection sensitivity of ED-based CRS can be improved upon by incorporating the ML algorithms while preserving the low computational complexity and requirements of the CRS. The CRS could thus be sensitive enough to differentiate between the signals of the PU in the channel being sensed, SU's signals, other random transmissions, and noise even in low-SNR conditions.

Authors in [29] used ML to determine if the channel is occupied or not. This work enabled the CR to detect and differentiate between channel users. It gave a clearer discussion of channel occupancy. Furthermore, it is an improvement on other studies that utilize ML it does not just focus on sensitivity. Instead, it helps to act as a discriminator to differentiate between PU, SU, and a potential interferer.

This, therefore, fulfills the aim of minimizing interference without compromising the sensitivity of an ED-based CRS. It is a further step towards the improvement of energy detectors in CRS using ML.

VI. CONCLUSIONS

This study provides a solution to the demand for improved detection sensitivity in areas of low SNR conditions for CRS without increasing the computational complexity and overhead of the communication system. This was carried out with the incorporation of ML algorithms in ED-based CRS. The ML-improved CRS learns the patterns in unknown noise characteristics as well as other operating characteristics of the network in a semi-supervised form of learning. This makes it robust enough to perform efficiently in different noisy channels. On the whole, it contributes significantly to better interference management.

The limitation of this work is that it was carried out only in an AWGN channel. Future work will evaluate the development in other noisy channels with varying noise characteristics.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

AUTHOR CONTRIBUTIONS

The conception and design of this work were carried out by all three authors. Temitope Fajemilehin handled the data collection, analysis, and interpretation, with manuscript drafting. Prof. Yahya and Dr. Langat supervised the whole research. Prof. Yahya critically reviewed the manuscript. All authors approved the final version to be published.

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