Performance Evaluation of Cooperative Eigen value Spectrum Sensing GLRT Under Difference Impulsive Noise Environments in Cognitive Radio

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Abstract- *Spectrum sensing plays an important role in cognitive radio. Spectrum sensing with multiple receive antennas is addressed in the cognitive radio network under impulsive noise environments. Cognitive radio is a technology developed for the effective use of radio spectrum sources. The spectrum sensing function plays a key role in the performance of cognitive radio networks. The ever increasing demand for higher data rates in wireless communications in the face of limited or under-utilized spectral resources has motivated the introduction of cognitive radio. Various measurements of spectrum utilization have shown substantial unused resources in frequency, time and space. The concept behind cognitive radio is to exploit these under-utilized spectral resources by reusing unused spectrum in an opportunistic manner. The phrase "cognitive radio" is the idea of using learning and sensing machines to probe the radio spectrum was envisioned several decades earlier. Cognitive radio can be detecting unused spectrum. It shares this with no interference to the licensed spectrum. It makes viable communication in the middle of multiple users through co-operation in a self-organized manner. The proposed system evaluates the performance of cooperative eigen value under difference impulsive noise environments.*

Keywords- Cognitive radio, impulsive noise, spectrum sensing.

I. INTRODUCTION

Cognitive radio (CR) is a form of wireless communication in which a transceiver can intelligently detect which communication channels are in use and which ones are not. The transceiver then instantly moves into vacant channels, while avoiding occupied ones. These capabilities help optimize the use of the available radio frequency (RF) spectrum. A cognitive radio network (CRN) is split into two main networks, a primary network and a secondary network. The primary network owns the licensed band and consists of the primary radio base station and users. The secondary network shares the unused spectrum with the primary network. It consists of the cognitive radio base station and users. The secondary network shares the unused spectrum with the primary network. Spectrum sensing in Cognitive Radios is an energy-consuming task that also degrades the spectral efficiency of the SUs since they need to spend time and energy on a task that does not result in transmitted bits.It helps to avoid the interference between the primer user and the secondary user.

The Cognitive Radio Network has three basic components. They are Mobile station (MS),Base station/Access points (BS/Aps), Backbone networks. The machine learning-based sensing techniques aim at detecting the availability of frequency channels by formulating the process as a classification problem in which the classifier, supervised or unsupervised, has to decide between two states of each frequency channel are free or occupied. The main functions of cognitive radios are Power Control, Spectrum sensing, Transmitter detection, Wideband spectrum sensing, Null-space based. MATLAB allows matrix manipulations, plotting of functions and data, implementation of algorithms, creation of user interfaces, Interfacing with programs written in other languages and create models and applications. Application of CR networks to military action such as chemical biological radiological and nuclear attack detection and investigation, command control, obtaining information of battle damage evaluations, battlefield surveillance, intelligence assistance, and targeting.

II. RELATED WORK

Cooperative Spectrum sensing–CRNs have been performed by machine learning. The existing works can be classified into two main categories. The technique in the first category uses two steps. In the first step, unsupervised machine learning techniques are used to analyse data and discover the PU's patterns. In the second step, supervised machine learning techniques are used to train the model with the data labelled in the first step. For instance, a two-step machine learning model for Spectrum sensing can be constructed. In the first step, for instance, the K-means algorithm could be used to identify the state of the PU's presence. In the second step, support vector machine (SVM) or other types of classifiers can be used to attribute the new input data into one of the classes specified by the K-means method used in the first step. Techniques of the second category assume that the classes are known, and they are based on supervised machine learning to train models. For example, existing works in the literature that use only one step in which supervised machine learning classifiers, such as K-nearest neighbour, SVM, Naive Bayes (NB), and decision tree, are applied.

The task of determining the channel status based on Spectrum sensing is due to its nature a classification task, the use of machine learning models as inference tools. Comparison of the performance of several supervised and unsupervised machine learning techniques for cooperative Spectrum sensing purpose, such as SVMs, the K-means clustering algorithm and Gaussian mixture model, but do not provide a comparison of detection performance over different scenarios of interest, such as considering distinct training set sizes or different channel scenarios of practical interest. The use of machine learning algorithms for spectrum occupancy in CRNs, which include the Naive Bayesian classifier. Grouping algorithms to improve Spectrum sensing results and SVM training time and the pros and cons of several unsupervised and supervised machine learning techniques applied to Spectrum sensing, such as the requirement of data labelling for supervised models and the risk of over fitting. Shah and Koo proposed a centralised Spectrum sensing–CRN scheme based on K-nearest neighbour. In the training phase, each CR user produces a sensing report under varying conditions and based on a global decision either transmit or stays silent. The local decisions of CR users are combined through a majority voting at the fusion centre and a global decision is returned to each CR user, implying in a spectral overhead

The SVM-based cooperative Spectrum sensing model with the user grouping method. User grouping procedures reduce cooperation overhead and effectively improve detection performance. Hence, users in CRN are grouped before the cooperative sensing process using energy data samples and a proper machine learning model. The three grouping methods, the first divides normal and abnormal users into two groups, while the second grouping algorithm distinguishes redundant and non-redundant users, and the third grouping algorithm selectsusers within a subset that minimise average correlation. The performances of the three algorithms were quantified in terms of the average training time, classification speed, and classification accuracy.

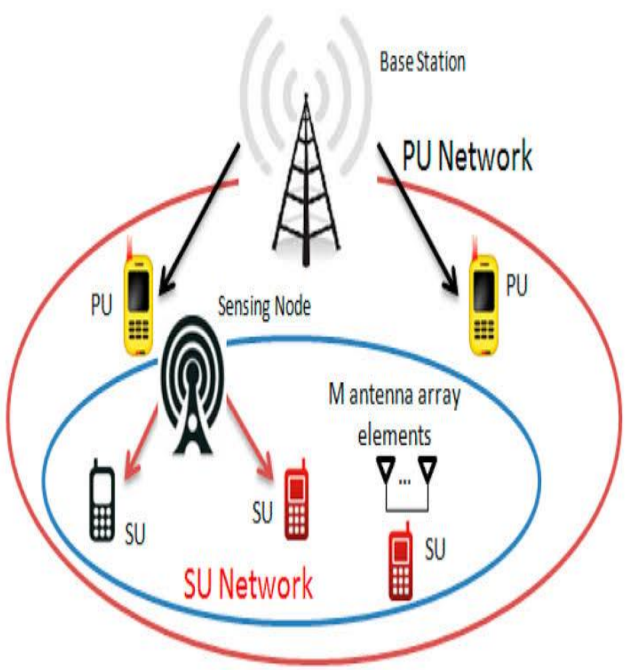
Finally, a low-dimensional probability vector is proposed as the feature vector for machine learning-based classification, instead of the high-dimensional energy vector in a CRN with a single PU and N SUs. Such a method down-converts a high-dimensional feature vector to a constant two-dimensional feature vector for machine learning techniques while keeping the same Spectrum sensing performance. Owing to its lower dimension, the probability vector-based classification requires a smaller training duration and a shorter classification time.

Table 1

1	APS	Access Points
2	APD’s	Accumulative Probabilities
3	BS	Base Station
4	BP-FLOM	Balance Parameter Flom
5	CR	Cognitive Radio
6	CRN	Cognitive Radio Network
7	CSS	Cooperative Spectrum Sensing
8	CFCPSD	Circular Folding Cooperative Power Spectral Density
9	CRSN’s	Cognitive Radio Sensor Networks
10	DSA	Dynamic Spectrum Access
11	DT	Decision Tree
12	DF	Decision Fusion
13	EGC	Equal Gain Combining
14	EISPACK	Eigen System Package
15	FDCR	Full Duplex Cognitive Radio
16	FLOM	Fractional Lower Order Moments
17	GLRT	Generalized Likelihood Ratio Test
18	KED	Kerenlized Energy Detector
19	LR	Linear Regression
20	LINPACK	Linear System Package
21	MS	Mobile Station
22	MLP	Multilayer Perceptron
23	ML	Maximum Likelihood
24	MRC	Maximal Ratio Combing
25	MATLAB	Matric Laboratory
26	NSS	Non Symmetric Stable
27	Non-CSS	Non Cooperative Spectrum Sensing
28	QOS	Quality Of Service
29	RF	Radio Frequency

30	ROC	Receiver Operating Characteristic
31	SS-CRS	Spectrum Sensing in Cognitive Radio
32	SVM	Support Vector Machine
33	SRN	Software Radio Network
34	SF	Sample Fusion
35	SS	Spectrum Sensing
36	SAS	Symmetric Alpha Stable
37	SU	Secondary User
38	VM	Virtual Machine

III. PROPOSED METHOD



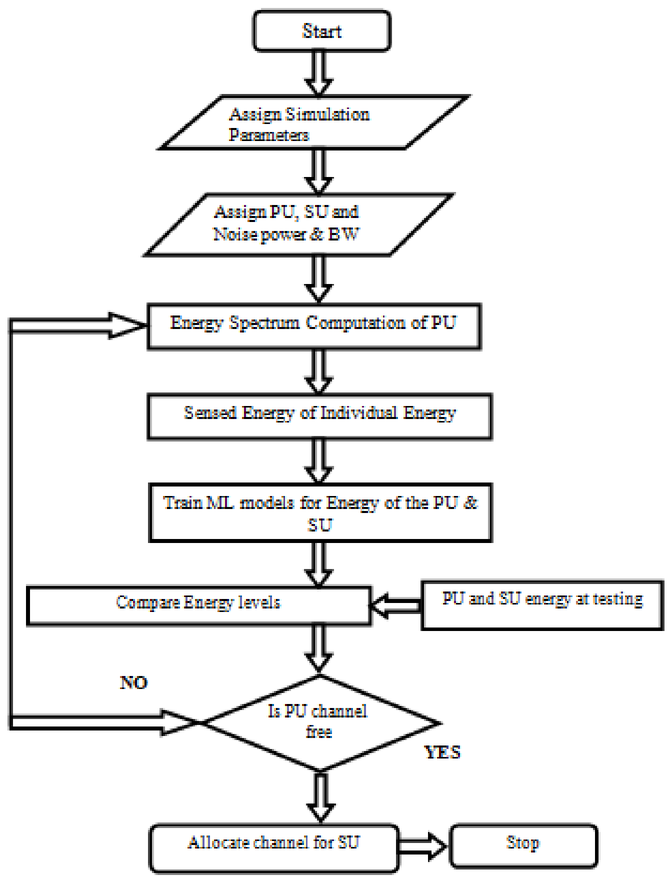
The mechanism that is proposed to detect and resolve the newly exposed security threat in the Cognitive Radio Network, called Cognitive User Emulation Area, by using a Coordinating Cognitive User. Whenever an New User enters the network, the first step of the Coordinating Cognitive User is to identify whether the New User is Cognitive User or Primary User.

This is done by measuring its behavioral characteristics such as the minimum threshold of the Primary User signals identified by Coordinating Cognitive User cell employing hypothesis testing. New User is identified as a Primary User.

The Coordinating Cognitive User stops all the communication within the Primary User transmitter range and searches for a new idle channel in the environment to resume its transmission. The Coordinating Cognitive User allows the initial transmissions and keeps recording the behavioral of the New User into its look-up table.

If the Trust Value of the New User is 1, then the New User is identified as a trusted Cognitive User and further transmission is allowed. Otherwise, the New User is considered to be a Malicious User and further transmission is blocked

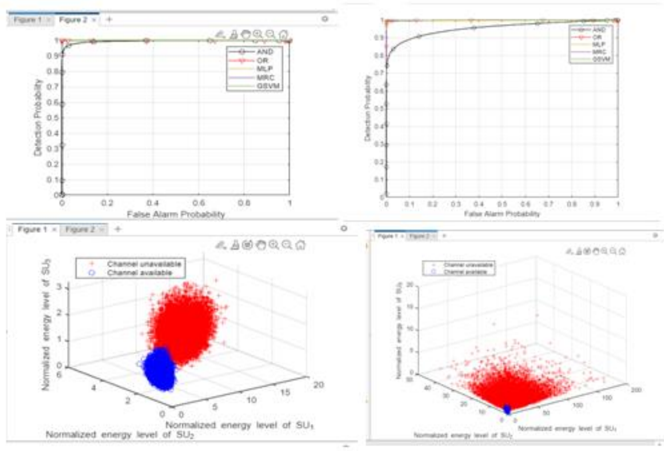
IV. FLOW CHAT



V. RESULT AND ANALYSIS

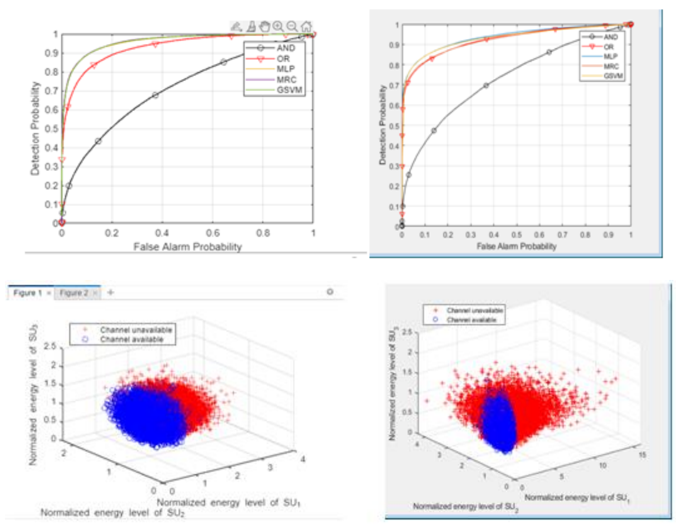
AWGN NOICE VARIENT a=3.6

RAYLEIGH NOICE VARIENT a=3.6



AWGN NOISE VARIENT a=4

RAYLEIGH NOICE VARIENT a=4



VI. CONCLUSION

The proposed system is designed with cooperative spectrum sensing (CSS) mechanisms for cognitive radio (CR) networks based on supervised learning techniques. The received energy level measured at the secondary users (SUs) is considered as a feature for determining the channel availability. The proposed MLP classifier achieves the highest detection performance compared to the other CSS algorithms by mapping the feature space into the higher dimensional space. Hence, the weighted MLP classifier is well suited for CSS which requires updating training energy vectors on-the-fly. In practical implementation, it is important to obtain accurate training energy vectors since inaccurate training of the classifier results in inaccurate decision. By using standard profiling tools, to obtain computational performance metrics for each machine learning model evaluated during the training and inference phases. For small CRNs context, the results demonstrated an advantage of MLP technique followed by Gaussian being the fastest model to train and infer the channel status, achieving great Area under the ROC Curve performance on channel status inference.

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