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Spectrum Sensing In Cognitive Radar System with SVM Classifier

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Abstract
Spectrum sensing is one of the most important and challenging tasks in cognitive radio. To develop methods of dynamic spectrum access, robust and efficient spectrum sensors are required. In this project , the performance of support vector machine (SVM)-based classifier is applied for spectrum sensing in cognitive radio (CR) networks, is analyzed. A single observation given input to classifier is composed of three statistical features extracted from the primary user (PU) sensing signal and residual energy in percent of the secondary user (SU). The trained classifier predicts PU's presence based on the input signal. The SU starts transmission if PU is predicted absent, otherwise continues sensing other frequency bands. The performance of classifiers is examined in terms of accuracy results. The signal-to-noise (SNR) ratio from PU to SU is varied to investigate effect on classifier's performance. Furthermore, the receiver operating characteristics (ROC) is presented for more evaluation. The simulation results show the efficiency of proposed features with SVM Based classifier for spectrum sensing in CR applications.

Keywords: Spectrum Sensing, Cognitive Radio, Support Vector machine, Signal to Noise Ratio

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I. INTRODUCTION

Wireless networks and information traffic have grown exponentially over the last decade, which has resulted in an excessive demand for the radio spectrum resources [1][2]. The radio spectrum is a limited resource controlled by regulations and the recognized authorities, such as the federal communications commission (FCC) in the US. The current radio spectrum allocation policy consists of assigning the channels to specific users with licenses for specific wireless technologies and services. Those licensed users have access to that spectrum portions to transmit/receive their data, while others are forbidden even when those spectrum portions is unoccupied [3].

Recent studies reported that the spectrum utilization ranges from 15% to 85% in the US under the fixed spectrum allocation (FSA) policy [4]. FCC measurements also show that some channels are heavily used while others are sparsely used as illustrated in Figure 1 [5].

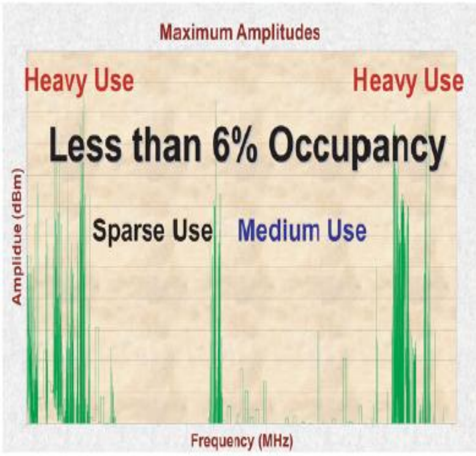

Figure 1: Radio spectrum occupancy [5]

Allocated spectrum portions are not used all the time by their owners, called primary users (PUs), which creates spectrum holes. A spectrum hole, also called white space, is a frequency band assigned to a PU, but it is not being used at a particular time and at a particular location. Therefore, the radio spectrum is inefficiently exploited [8][9]. Thus, the scarcity and inefficiency of the spectrum management require an urgent intervention to enhance the radio spectrum access and achieve high network performance. A better way to overcome the spectrum scarcity issue is dynamically managing it by sharing unoccupied channels with unlicensed users, called secondary users (SUs), without interfering with the PUs signals. The opportunistic spectrum access (OSA), also called dynamic spectrum access (DSA), has been proposed to address the spectrum allocation problems. In contrast to the FSA, DSA allows the spectrum to be shared between licensed and non-licensed users, in which the spectrum is divided into numerous bandwidths assigned to one or more dedicated users [10].

In order to advance the use of the OSA, several solutions have been proposed, including cognitive radio [11]. According to Mitola [12], cognitive radio is an intelligent radio frequency transmitter/receiver designed to detect the available channels and adjust its transmission parameters enabling more communications and improving radio operating behaviour [13]. A cognitive radio system can observe and learn from its environment, adapt to the environmental conditions, and make decisions in order to efficiently use the radio spectrum. It allows SUs to use the PU assigned radio spectrum when it is temporally not being utilized as illustrated in Figure 2.

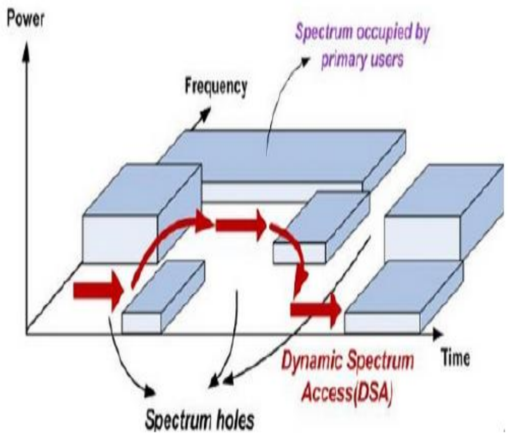

Figure 2: Dynamic spectrum access

Cognitive radio is considered as the future technology to solve the resource allocation problem that the requirements of the 5th generation of the wireless communication raised. With these 5th generation of the wireless communication systems, the wide wireless will be interconnected offering high quality of service and data rates.

Some reference researched SVM method in spectrum sensing. The reference [4] investigated grade criterion to judge output result and update SVM algorithm. In [5], the combination of SVM classification machine and SVM regression machine were studied to obtain intelligence in CR. In this paper, we present a methodology that exploit SVM learning theory in time domain to achieve the spectrum sensing. Compared with the energy detection, the SVM measured results show high performance and low error detection probability by simulation experiments.

Table 1: Comparison of different sensing techniques

Sensing Technique	Narrowband(NB)/ Wideband(WB) Sensing	Prior signal information	Reliability & accuracy	Computational Complexity	Sensing time	Cost	Power consumption
Energy Detection	NB/WB	No	Very very poor	Very very Low	Very Very less	Very Very low	Very Very low
Matched Filter	NB	Yes	Very good	Very low	Very less	Very low	Medium
Waveform based	NB	Yes	poor	Medium	Medium	Low	Very low
Eigen value based	NB	Yes	Very poor	Low	Less	Medium	Low
Wavelet Based	WB	Yes	Medium	Very high	Very large	Very high	Very high
CycloStationary	NB	Yes	Good	High	Large	High	High

II. COGNITIVE RADIO CYCLE

As illustrated in Figure 3, a cognitive radio system performs a 3-process cycle: sensing, deciding, and acting [14]. The first process is critical since it is the stage where the measurements are taken and the spectrum sensing is performed. Due to multipath fading, shadowing, or varying channel conditions [15], uncertainty affects this first process.

In the observation process, measurements taken by the SUs are also uncertain. In the next process, SUs make a decision based on what has already been observed using their knowledge basis, which may have been impacted by the uncertainty in the detected measurements, leading to the wrong decisions. In the last process, uncertainty spreads over the cognitive radio cycle, and sometimes the wrong actions are taken [1].

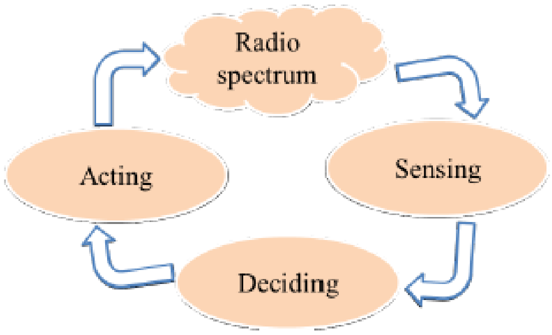

Figure 3: Cognitive radio cycle

Thus, uncertainty propagation impacts all the radio spectrum processes, which degrades the cognitive radio performance [16]. Therefore, it is necessary to address these uncertainty problems in the cognitive radio cycle by sensing the spectrum correctly, making the correct decision, and taking the right action.

III. PROPOSED SVM BASED SPECTRUM SENSING

The idea of support vector machines (SVM) was proposed by Vladimir N.Vapnik. It works on the basis of structural risk minimization principle. SVM can provide better generalization and improve performance for small number of training samples. The SVM was basically designed for the solution of classification problems and it belongs to the class of supervised learning algorithm.

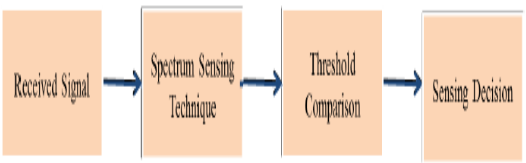

Fig 4. General Spectrum Sensing Model

In SVM, a mapping function Imown as kernel is used to map the input space to high dimensional feature space. The Performance of SVM depends on both support vectors and selection of kernel function that makes kernel a key part of SVM. Autocorrelation kernel function successfully detects the signals at very low SNR values. This technique is efficient for the signal detection at very low SNR values but it is computationally complex spectrum sensing technique.

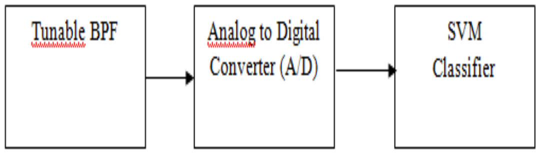

Fig 5. Spectrum Sensing Based SVM Block Diagram

Figure 5 shows the Block diagram of SVM Classifier. The input successive composite signal includes signal with noise and noise which are independent and not overlapping in time domain. Then they pass a Tunable BPF which is used diagram of spectrum sensing by SVM detection. The input successive composite signal includes signal with noise and noise which are independent and not overlapping in time domain. Then they pass a band-pass filter. An A/D converter is followed for sampling in time domain to achieve training data. Each of them can be two or multi dimensional and send into SVM classification. After two class separated hyperplane conducting, SVM system will randomly take samples for testing. Finally, SVM classifier could able to decide testing datatype is the main user or noise.

Processing of SVM

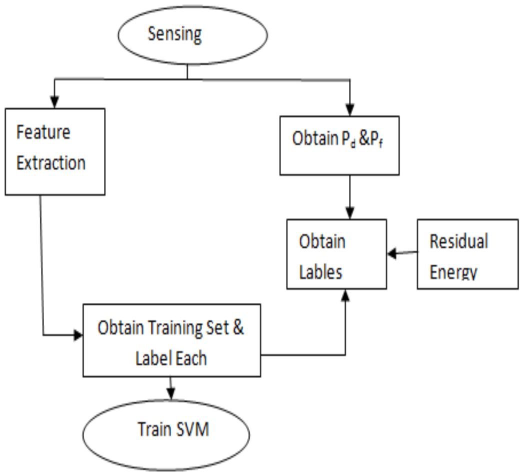

Fig 6. Flow chart of the proposed algorithm of SVM-based classifier Training

The flowchart of proposed algorithm is presented in Fig 6. The three features are extracted from the PU signal sensed by SU. The P_d and P_f values are obtained from the same signal. The randomly generated residual energy levels and P_d and P_f values are used to define the classes of the sensing signal. The final training dataset is obtained by labeling the features extracted from

PU signal with residual energy of node as fourth feature. Finally, the feature pool is consisted of five columns with the signal and residual energy features in first four columns and the corresponding class label in the last column. The training phase of SVM-based classifier is shown in Fig 6. The test observation is given input to the classifier in form of four features, three statiscial features extracted from the sensing signal and residual energy of the SU node as fourth features.

The system model assumes a pair of SU transmitter and receiver operating in the transmission range of PU transmitter. The SU sense the spectrum to detect PU presence and takes a decision to transmit or not based on the sensing signal. If the PU signal is absent, the SU transmitter will start transmission and this case is considered as hypothiesis $H0$. If the PU signal is present the SU will keep silent and this is hypothesis $H1$. The sensing signal under hypothesis $H0$ and $H1$ is given as

$$\begin{cases} H_0{:}Y_i = n_i \\ H_1{:}Y_i = S_i, +n_i \end{cases}$$

Where S_i, n_i for i=1,2,....,M ,represents the PU signal and white Gaussian Noise ,respectively. Let M be the total sensing samples in single sensing slot.

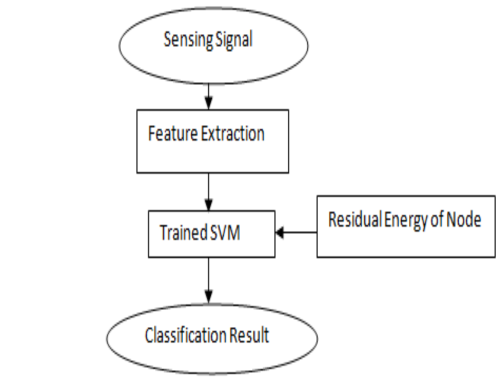

Fig 7: Flow chart of the proposed algorithm of SVM-based classifier Testing Phase

The probability of detection and false alarm are given as:

P_d=(PY>λIH$_1$)=Q $\frac{\lambda-M(\gamma_p+1)}{\sqrt{2M}(2\gamma_p+1)}$

P_f=P(Y>λIH$_0$) = Q($\frac{\lambda-M}{\sqrt{2M}}$)

i.e Q(n)=1/$\sqrt{2\pi}\int_{\lambda}^{\infty} e^{-t^2/2}$

Where Q is Quality function That is that defined Predifined Threshold and γ_p is the SNR of Primary User sensed by Secondery User.

IV. EXPERIMENTAL RESULTS

The spectrum sensing outputs are shown below.

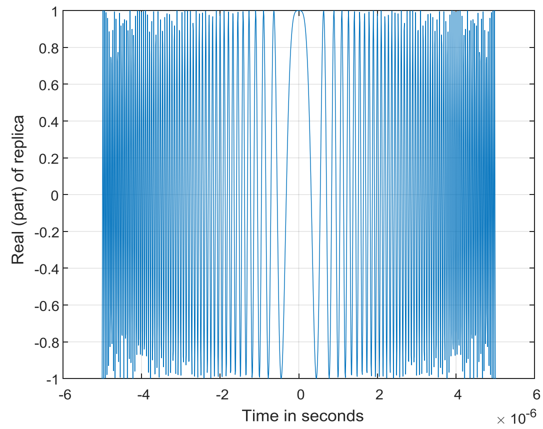

Figure 8: RF Input Signal

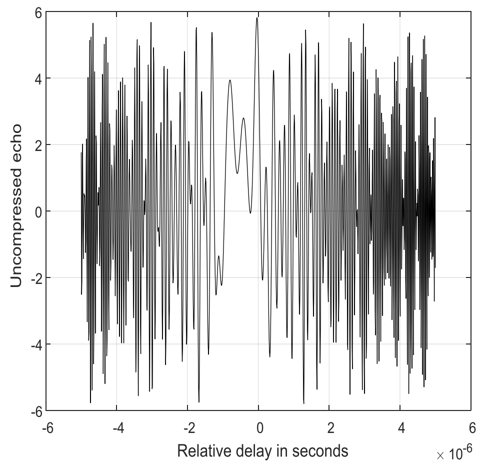

Figure 9: Uncompressed Echo Signal

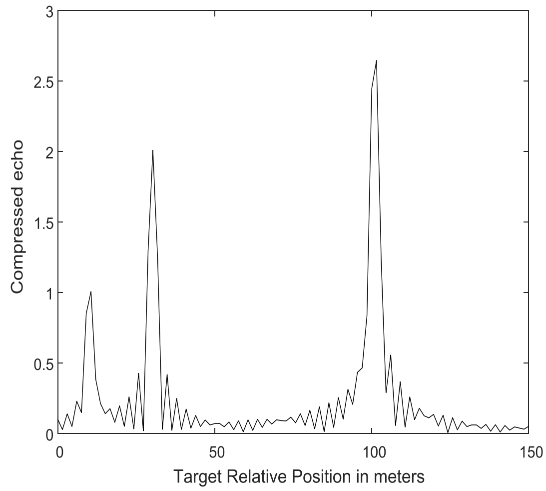

Figure 10: Matched Filter FFT Output Signal

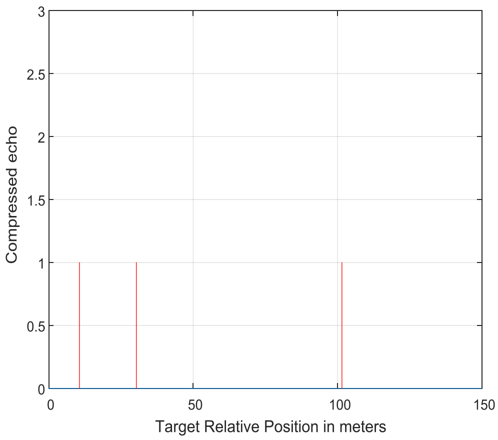

Figure 11: Matched Filter Discret Sampled output signal

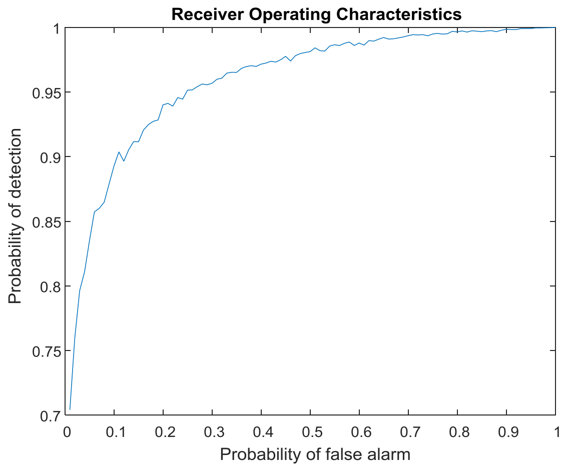

Figure 12: Spectrum Sensing Output Signal with Energy Detector

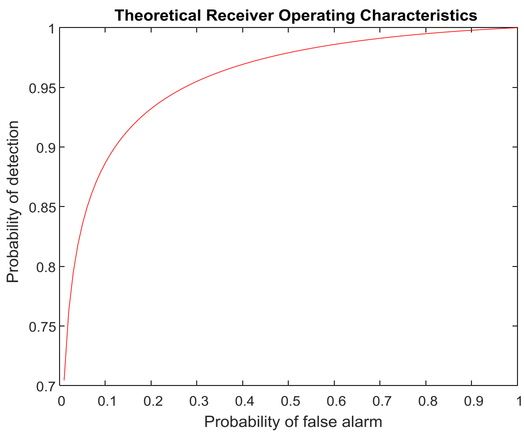

Figure 13: Spectrum sensing theoretical Signal with Energy Detector

Next we need to apply characteristics of sensor based outputs to the classifier like SVM . Take the data set, train the data set to identify the similarity functions. Monitoring of the data and finding different values. The experiments where performed on the data. After this, for the trained data different other functions have been added for testing. After testing the data, the features were achieved and formed into a data matrix. This data is used to identify the regions and locations.

Here in this paper we consider 75 samples in which 23 samples are used for testing and 52 samples are used for training i.e 70 % is used for training and 30% is used for testing. The results obtained using two classifiers one is support vector machine classification and other is random forest classifier. The performance of the classifiers is compared using parameters like precision, Sensitivity, Specificity, Accuracy and Overall Time.

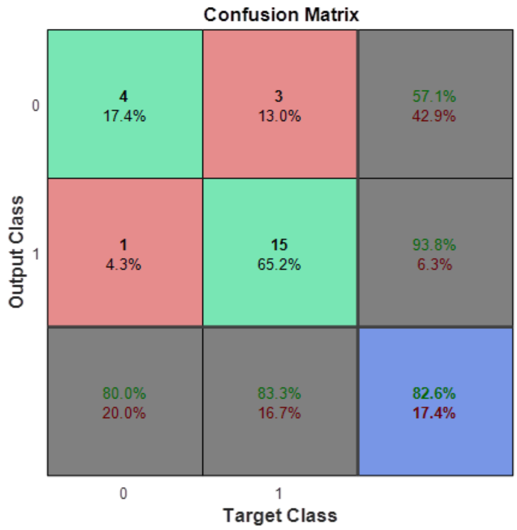

Fig 14: Confusion Matrix for SVM classifier

The parametric values obtained using SVM classifier are shown in below table 2.

Parameter	Value
Precision	83.3 %
Sensitivity	93.7%
Specificity	57.14%
Accuracy	82.61%
Overall Time	0.157 sec

V. CONCLUSION

Spectrum sensing is the first step in the cognitive cycle to detect a spectrum hole. Many spectrum sensing techniques are available in the open literature. Each technique has its own advantages and disadvantages. For example, the performance of the cyclostationarity based feature detection is better and robust spectrum sensing as compared to energy detector. Energy detector is easy to implement and simple coarse sensing technique. The matched filter technique is optimal but it needs the prior information about the transmitted signal. Eigen value based spectrum sensing performs well in case of highly correlated signals but its complexity is high. Wavelet based spectrum sensing provides a better solution for the detection of wide band signals but it needs more samples for processing as compared to energy based detector. SVM based signal detector can detect the signals at very low SNR values with good computational complexity. The rate of accuracy obtained is 82.6%

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