IMPLEMENTATION OF MACHINE LEARNING SPECTRUM SENSING FOR COGNITIVE RADIO APPLICATIONS

Mohamed El-Tarhuni[1], Khaled Assaleh[2], and Firas Kiftaro[1]

[1]American University of Sharjah, UAE

[2]Ajman University, UAE

ABSTRACT

In this paper, a cognitive radio system is implemented using National Instruments (NI) Universal Software Radio Peripheral (USRP) devices. The implemented system provides a working prototype based on real data generated and collected by an experimental laboratory setup to compare the performance of spectrum sensing algorithms based on energy detection and polynomial classifier channel sensing techniques. For a sensing time interval ranging from 0.05 ms to 5ms, the experimental results show that the polynomial classifier has a better performance compared to the conventional energy detector in terms of the misclassification rate, especially at lower SNR values.

KEYWORDS

Cognitive Radio, Spectrum Dynamic Access, Spectrum Sensing, Polynomial Classifier, Energy Detection, USRP

1. INTRODUCTION

Many spectrum measurement campaigns at different parts of the world have indicated that the radio spectrum is significantly underutilized [1] – [5]. This represents a major issue as there is virtually no space to accommodate new allocations of the radio spectrum, especially in the sub-gigahertz frequency range, while there is a lot of spectrum that is licensed to users who are not utilizing its full capacity. To overcome this challenge, Dynamic Spectrum Access (DSA) has been proposed to allow secondary users to use the underutilized spectrum licensed to primary users without causing major degradation to the primary users operation.

Cognitive Radio (CR) is a technology that was developed to implement DSA and allow for sharing the radio spectrum in an opportunistic manner. Figure 1 shows the basic principle of a CR, where it uses an intelligent radio system that has the ability to sense the radio spectrum and decide when there is a spectrum hole (spatially or temporarily unoccupied frequency channel). The secondary user data is sent over the vacant radio channel when the primary user is not transmitting. The CR has to continue monitoring the activities of the primary users and as they become active, the CR will cease transmission to avoid causing interference to the primary user data. In order to provide seamless communication quality of service to the secondary user, the CR needs to also look for other vacant channels in order to transfer the secondary user transmission in case the primary user becomes active. All these operations need to be done almost in real-time and within very short time interval. In [6], the cognitive radio cycle has been developed to include the following steps: spectrum sensing, spectrum analysis, and spectrum decision. In spectrum sensing, the cognitive radio monitors the frequency spectrum to capture the frequency bands' information and detect the frequency spectrum holes. While in spectrum analysis, the cognitive radio estimates the characteristics of the detected frequency holes. In spectrum decision, the

cognitive radio system will determine the appropriate frequency band based on the required transmission bandwidth, transmission mode, and transmission rate.
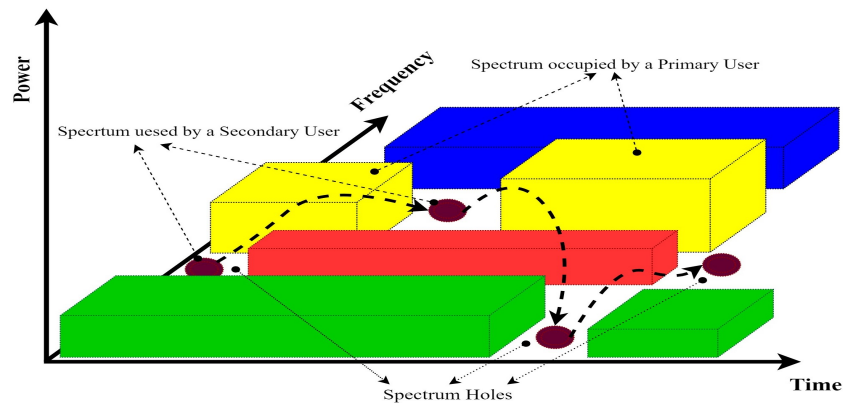

Figure 1. Cognitive radio principle

One of the key steps in CR is spectrum sensing to allow for successful utilization of the free spectrum and avoid causing interference to the primary user that might cause performance degradation. There are many techniques developed for spectrum sensing such as that using energy detection, matched filter detection, and cyclostationary detection [7] [8]. Machine learning based spectrum sensing schemes were introduced in [9] – [11]. These schemes could be implemented in a centralized mode where a central node makes the sensing and decides on the availability of the channel; or a non-centralized mode where the availability of the channel is decided by each node independently. There has been a significant number of simulation and analytical studies published by the research community analyzing different CR scenarios, especially the spectrum sensing part. However, there has been little efforts in reporting prototype or real-world implementation of CR systems.

In this paper, we present an experimental implementation of a CR system using the National Instruments (NI) Universal Software Radio Peripheral (USRP) devices. We have implemented the conventional energy detector spectrum sensor in addition to a machine learning based spectrum sensor using polynomial classifiers. We would like to remark that the use of a polynomial classifier for cognitive radio applications has been introduced in [9] – [11]. However, these investigations were based on computer simulation only. In this work, we present a real-world hardware implementation of a cognitive radio system while deploying both polynomial and energy classifiers for spectrum sensing.

The rest of the paper is organized as follows: Section II describes the CR system experimental setup; sections III and IV describe the implemented spectrum sensing schemes using energy detection and polynomial classifier; section V presents the results and section VI presents the conclusion of the work.

2. COGNITIVE RADIO EXPERIMENTAL SETUP

The cognitive radio experimental setup is shown in Figure 2. It consists of a primary user that is implemented using a USRP device operating at 2.8 GHz. This frequency was used for illustration purposes and it was ensured that there were no other signals present at that frequency except from the primary user. The secondary user is implemented by another USRP device that performs spectrum sensing to decide if the primary user is present or not. The primary user sends random data at an intermittent pattern unknown to the secondary user. The primary user device is

positioned at a fixed location during the experiment, while the secondary user is moved to different locations around the coverage area to investigate the performance of the spectrum sensing algorithms under different distances.

Figure 2. Cognitive radio experimental setup

The USRP is a device developed by National Instruments (NI) that can be used for implementation of Software Defined Radio (SDR) systems. It has the capabilities of altering the RF operating parameters such as the center frequency, frequency range, modulation scheme, etc. by software. Figure 3 shows a block diagram of the basic structure of an SDR system [12]. The system implemented in this work uses the USRP-2922 SDR that covers a range for 400 MHz to 4.4 GHz. The USRP-2922 can be remotely controlled through LabVIEW programming environment.
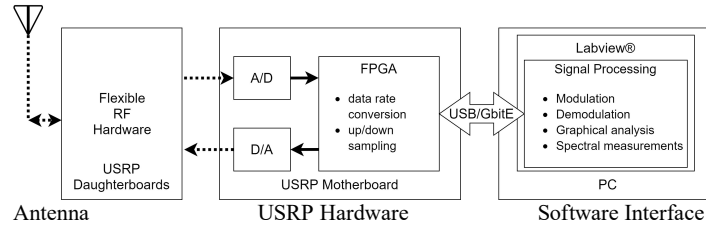

Figure 3. USRP structure

3. SPECTRUM SENSEING WITH ENERGY DETECTION

Figure 4 shows the energy detector implemented in the secondary user USRP device after down conversion to baseband. This is a conventional scheme that consists of a low pass filter to remove the adjacent signals and to limit the noise captured by the sensing device, an analog-to-digital converter to convert the continuous time signal, s(t), to discrete time signal samples, $s[n]$, a squaring law device and an integrator. Basically, the energy detector measures the energy associated with the sensed signal over a defined time period and frequency band. The measured energy value is then compared to a threshold value selected properly to determine the presence state of the primary user.

Depending on the presence state of the primary user and the decision statistic obtained from the energy detector, the primary user presence state can be modelled as a binary hypothesis testing problem and given as:

$$\mathcal{H}_0 : \text{The primary user is absent}$$
$$\mathcal{H}_1 : \text{The primary user in present}$$

where hypothesis ($\mathcal{H}_0$) represents the absence of the primary user at a given time interval and only noise is sensed at the receiver input, however, hypothesis ($\mathcal{H}_1$) represents the presence of

the primary user and the receiver is sensing both the transmitted signal $x(t)$ and the background noise $w(t)$. The continuous time signal $s(t)$ received at the receiver end is given by:

$$s(t) = \begin{cases} w(t) & \text{Under } \mathcal{H}_0 \\ x(t) + w(t) & \text{Under } \mathcal{H}_1 \end{cases}$$

(1)

For the discrete time signal $s[n]$, The decision statistic T for a received frame of N samples is given by:
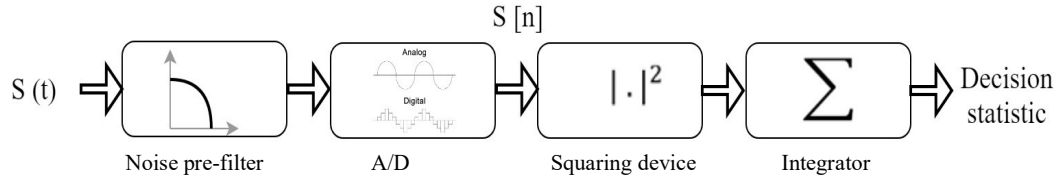
$$T = \sum_{n=1}^{N} |s[n]|^2$$

(2)

Figure 4. Energy Detector

To characterize the performance of the energy detector or any detector, the probability of false alarm (P_{fa}), classifying a signal as present while the true state is absent ($\mathcal{H}_0$), and the probability of missed detection (P_{md}), classifying a signal as absent while the true state is present ($\mathcal{H}_1$), are considered. The lower the probability of false alarm results in a higher spectrum usage by the secondary user. Similarly, the larger the probability of missed detection the more the interference caused to the primary user. Mathematically, these probabilities are represented as follows:

$$P_{fa} = P(T > \lambda | \mathcal{H}_0)$$

(3)

$$P_{md} = P(T < \lambda | \mathcal{H}_1)$$

(4)

where λ is the decision statistic threshold value used to classify primary user presence for a specific frequency channel. In our data analysis process, we calculated the threshold value based on fixed false alarm probability for a given number of samples per received data frame. The threshold values presented in Table 1 are calculated only when noise was present (the primary user transmission was switched off). The variations in the false alarm probabilities with the threshold values are shown in Figure 5 for N = 100 samples.

Table 1. Threshold values for the energy classifier

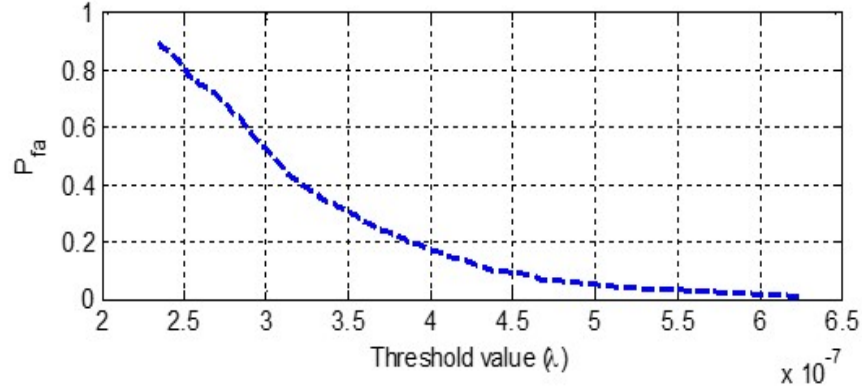| P_{fa}	Threshold value (λ)		
	$N = 10$	$N = 100$	$N = 1000$
0.05	$6.3625e - 8$	$5.009e - 7$	$4.019e - 6$
0.10	$5.3362e - 8$	$4.374e - 7$	$3.868e - 6$
0.15	$4.7719e - 8$	$4.083e - 7$	$3.558e - 6$

Figure 5. False alarm probability for the energy classifier

4. SPECTRUM SENSING USING POLYNOMIAL CLASSIFICATION

A polynomial classifier is a special case of single-hidden layer neural network that uses the input patterns and the input polynomial patterns [13]. A polynomial classifier can be easily implemented and has been shown to achieve good recognition performance in different applications [14] [15]. A polynomial classifier works by expanding the neural network input feature vector into a higher dimensional space to produce a number output feature vectors that are linearly separable [16]. These output vectors are used to compute a score for each class and the class with the highest weight is selected. Figure 6 demonstrates the basic blocks forming the polynomial classifier.
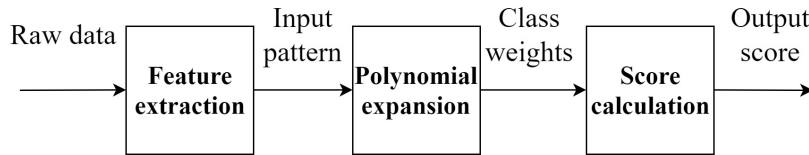

Figure 6. Polynomial classifier block diagram

In the context of the spectrum sensing application at hand, we have two classes (binary hypothesis problem) to be identified of either the primary user is active (channel is occupied) or primary user is not transmitting (channel ideal and can be used by the CR network). A polynomial classifier can be designed to classify the two classes, $\mathcal{H}_i$ for $i \in \{0,1\}$. The design of the polynomial classifier involves two stages: training stage and testing stage. Given the input training sequence arranged as the $M \times N$ matrix $\boldsymbol{D_{train}}$, the input feature vectors are expanded into polynomial terms to form the $M \times L$ matrix $\boldsymbol{Y_{train}}$, where M is the number of feature vectors, N is the dimensionality of the feature vectors and L is the dimensionality of the expanded feature vectors (the number of expansion terms). For demonstration purposes, we use a second order polynomial classifier for the feature vectors in $\boldsymbol{D_{train}}$ that can be expressed as [16]

$$\boldsymbol{Y_{train}} = \begin{bmatrix} 1 & x_1 & x_2 & x_3 & \dots & x_N & x_1^2 & x_1x_2 & x_1x_3 & \dots & x_N^2 & x_1x_N & x_2x_N & \dots \end{bmatrix}^T \qquad (5)$$

where $(.)^T$ is the transpose operator and N is the dimensionality of the feature victors in $\boldsymbol{D_{train}}$.

The polynomial classifier can be trained to obtain the class weights given the target vector $t_{train_i} = \begin{bmatrix} t_{i_1} & \dots & t_{i_k} & \dots & t_{i_M} \end{bmatrix}^T$, where

$$t_{i_k} = \begin{cases} 1 & , & \text{if feature vector } k \in \text{class } i \\ 0 & , & \text{if feature vector } k \notin \text{class } i \end{cases} \quad (6)$$

In order to train the classifier, the weights vector can be obtained by minimizing the mean square error (MSE) function to obtain [16]

$$w_i^{opt} = \underset{w_i}{\arg\min} \left\| Y_{train} W - t_{train_i} \right\|_2 \quad (7)$$

where Y_{train} is the expanded feature vector whose rows are the training features and t_{train_i} is the training target vector corresponding to the ith class. The solution to (7) is given by

$$w_i^{opt} = Y^+ t_{train_i} \quad (8)$$

where Y^+ is the pseudoinverse function of Y and given by

$$Y^+ = \left(Y_{train}^T Y_{train} \right)^{-1} Y_{train}^T \quad (9)$$

Finally, in the testing stage we are given a testing input sequence D_{test} to determine its class. At first, this input sequence will be expanded similar to (5) generating the sequence Y_{test}. Then, the output score from the polynomial classifier can be obtained using Y_{test} along with the trained models w_i^{opt}, the output score s_i is given by

$$s_i = Y_{test} w_i^{opt} \quad (10)$$

The polynomial classifier implemented in this work is shown in Figure 7 with detailed LabVIEW implementation for presented in [17]. The complex baseband signals are measured by the USRP devices and then stored in the computer. The data was divided into two sets: training data set and testing data set. At first, the training set was divided into frames each of size N samples and the states of each frame were used to define the frame state vector t_{train}. A frame state of 1 indicates the presence of the primary user and a frame state of 0 indicates the absence of the primary user. For each frame of data, the variance (2nd moment), skewness (3rd moment) and kurtosis (4th moment) were calculated in order to define the feature vector D_{train}.

Next, the feature vector D_{train} can be expanded through a second order polynomial expansion block to obtain Y_{train}. Using equation (8), the weight vector W can be obtained from the expanded feature vector Y_{train} and the frame state vector of the training data t_{train}. The testing data set was also divided into frames of size N samples and the features for each frame were extracted forming the feature vector D_{test} which then expanded through the second order expansion block to obtain the feature vector Y_{test}. Finally, using the weight vector W obtained from the training step and the new expanded feature vector Y_{test}, equation (10) used to estimate the testing data set frame states vector t_c. Finally, this vector can be converted into a binary number by comparing the score to a threshold to obtain a score of 1 or 0 indicating the presence or the absence of the primary user during each frame. The threshold is set to have a fixed probability of false alarm, similar to the procedure used for energy classifier. Table 2 and Figure 8 show the threshold values for the polynomial classifier and the false alarm probability variations with the threshold for N = 100 samples, respectively.
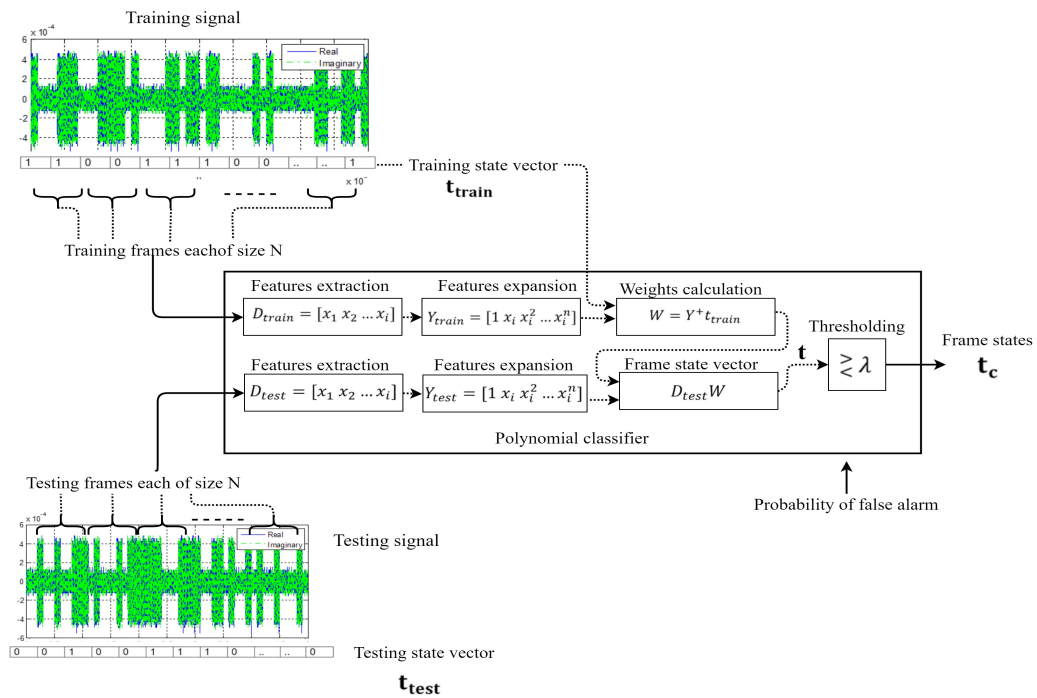
Figure 7. Overall operation of polynomial classifier

Table 2. Threshold values for the polynomial classifier

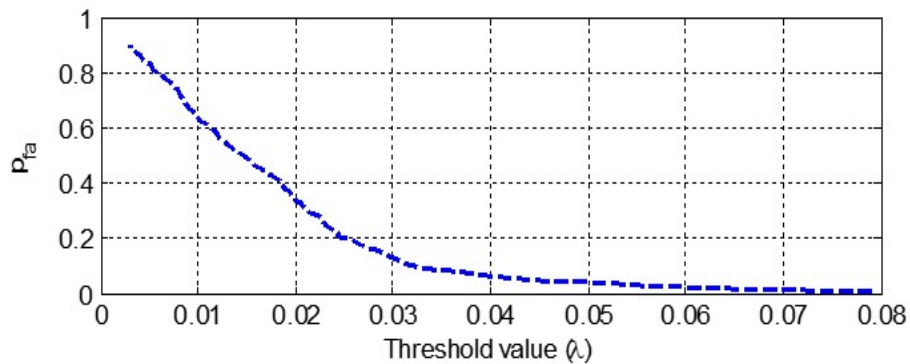| P_{fa}	Threshold value (λ)		
	$N = 10$	$N = 100$	$N = 1000$
0.05	0.0922	0.0455	0.0209
0.10	0.0794	0.0324	0.0169
0.15	0.0725	0.0289	0.0152

Figure 8. False alarm probability for the polynomial classifier

5. EXPERIMENTAL RESULTS

In this section, we present the misclassification rate for a spectrum sensing scheme using either the energy or polynomial classifiers. The misclassification rate is calculated as the overall error in

classifying the primary user as present while it was not transmitting or the error in classifying the primary user as off while it was actually transmitting. The calculations are based on real world data that was collected using the USRP devices.

Figures 9, 10, and 11 show the misclassification rate ε as a function of the signal-to-noise ratio (SNR) and a frame size (N) of 10, 100, and 1000 samples, respectively. The sampling rate was set to 200,000 samples per second resulting in a frame duration varying from 0.05 to 5 milliseconds. Each figure shows the performance for different false alarm probabilities (P_{fa}) of 5%, 10%, and 15%. The results show that the polynomial classifier has a lower misclassification rate compared to the energy classifier for all frame sizes. It is noticed that both schemes have good performance with more than 90% correct classification when the SNR is large. However, a smaller frame size would result in a larger floor for the misclassification rate (worse performance). Finally, it is observed that the larger the false alarm probability allowed (more conservative in using the spectrum), the lower the difference in performance between the energy detector and polynomial classifier.
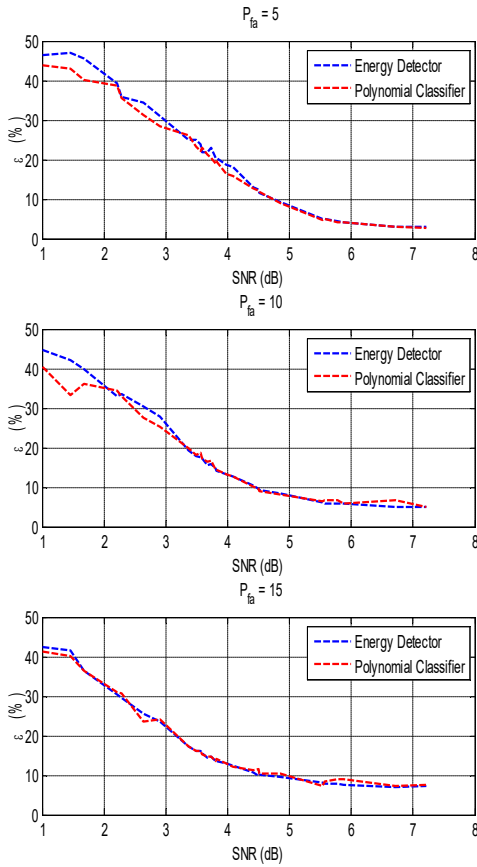
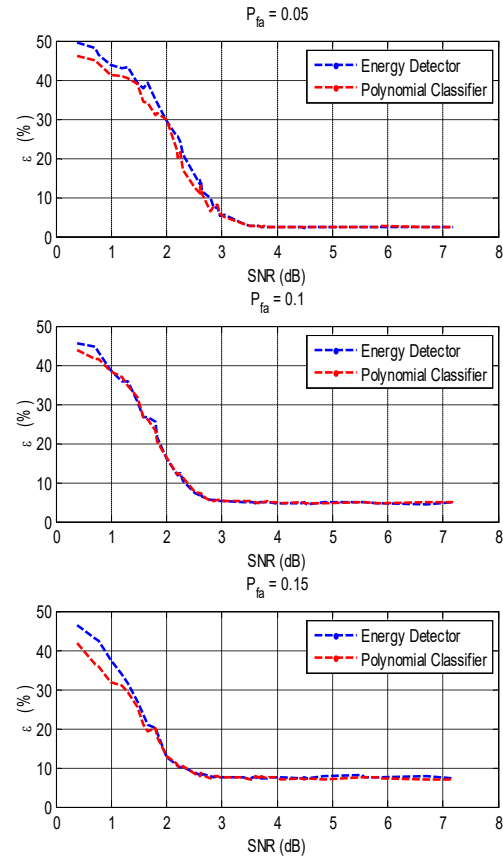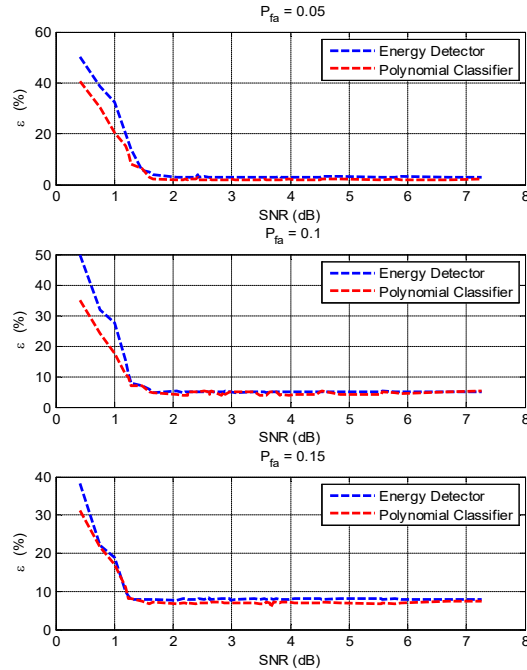Figure 9. Misclassification rate at frame size N = 10 samples

Figure 10: Misclassification rate at frame size N = 100 samples

Figure 11: Misclassification rate at frame size N = 1000 samples

6. CONCLUSION

In this paper, we present experimental results for the performance of two spectrum sensing schemes used in cognitive radio systems. The experimental work is done using NI USRP software defined radio devices to implement an energy detector based spectrum sensing scheme and a machine learning polynomial classifier spectrum sensing scheme. The misclassification rate for the two schemes under different SNR conditions and different sensing periods is presented.

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AUTHORS

Mohamed El-Tarhuni is currently a Professor of Electrical Engineering and Vice Provost for Graduate Studies at the American University of Sharjah in the United Arab Emirates. His research interests include mobile radio systems, cognitive radio, 5G, and physical layer issues.

Khaled Assaleh is currently a Professor of Electrical Engineering and Vice Chancellor for Academic Affairs at Ajman University in the United Arab Emirates. His research interests include bio-signal processing, biometrics, speech and image processing, and pattern recognition

Firas Kiftaro is currently working with the Ministry of Education in the United Arab Emirates as a Senior Creative Design and Innovation subject training lead. His research interests are in the area of wireless communications and cognitive radio.