Artificial Neural Network Based Hybrid Spectrum Sensing Scheme for Cognitive Radio

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Abstract—Spectrum sensing is a key aspect of Cognitive Radio (CR). The main requirement in CR systems is the ability to sense the primary signal accurately and rapidly. In this paper, a novel hybrid spectrum sensing scheme in CR is proposed which considers the hypothesis problem as a binary classification problem. The proposed scheme is a combination of classical energy detection, Likelihood Ratio Test statistic (LRS-G^2) and Artificial Neural Network (ANN). The scheme utilises energy from energy detection and Zhang test statistic from LRS-G^2 as features to train the ANN while ANN provides the adaptive learning and stable performance to the scheme. The performance of proposed sensing scheme is evaluated on several real-world primary signals of various radio technologies and it has been found out that for all those radio technologies the proposed scheme outperforms the classical energy detection and the improved energy detection.

Index Terms—Cognitive Radio, Spectrum Sensing, Energy Detection, Likelihood Ratio Statistic, Artificial Neural Network.

I. INTRODUCTION

Cognitive Radio (CR) has emerged as one of the promising solutions that can mitigate the existing conflict between spectrum demand growth and spectrum underutilization [1], [2]. The key requirement for a CR is to sense the existence of licensed (primary) users in the spectrum and as a result of a sensing, CR decides the resource allocation for the unlicensed (secondary) users. One of the most important requisites for the allocation is to make sure that the secondary users should not cause any harmful interference to legitimate primary users. To guarantee the free-interference access it is required that the secondary users reliably identify the spectrum opportunities across frequency, time and space [3] and also vacate the allocated resources as soon as the primary user becomes active.

A number of different spectrum sensing schemes have been proposed in the literature to identify the presence of the primary users [4], [5]. Each sensing scheme provides different trade-offs for required time, complexity and detection capabilities. Generally, sensing schemes have been categorised into two categories, parametric sensing schemes and non-parametric sensing schemes. Parametric sensing schemes require CR to have some prior information on the primary users. However, in the most generic case, no prior information is available to a CR user. Due to this limitation, non-parametric sensing schemes are more promising for CR. One of the simplest and most popular sensing scheme in CR is energy detection [6], [7], which compares the received signal energy irrespective of the signal structure from a certain frequency band to a predefined threshold and makes a decision. However, perfect noise variance information is required in CR for energy detection to perform adequately. It has been shown that an imperfect knowledge of the noise power (noise uncertainty) may lead to the phenomena called SNR (Signal to Noise Ratio) wall [8], which is a SNR level below which the energy detection performance degrades drastically irrespective of the sensing time.

Considering this as a limitation for energy detection, researchers have proposed another class of algorithms in a non-parametric category which is based on the Goodness of Fit (GoF) test. A number of different GoF based sensing schemes have been proposed in the literature like Anderson Darling (AD) test [9], Ordered Statistics (OS) [10], Kolmogorov-Smirnov (KS) [11], [12] and Likelihood Ratio Statistics (LRS-G^2) [13], [14]. GoF based sensing schemes are good enough to provide good performance gain at lower SNR but the category is still struggling to provide overall desired performance gain.

In [15], authors have proposed an Artificial Neural Network (ANN) based sensing scheme which utilises the energy and cyclostationary features to train the neural network for the spectrum sensing, The scheme is more promising in terms of performance gain compared to the previous sensing schemes but again considering the fact that the cyclostationary feature detection scheme is a parametric sensing scheme, which requires a prior knowledge of the primary signal. It is hard to generalise the proposed sensing scheme for CR.

Considering all these limitations, a novel hybrid spectrum sensing scheme is proposed in this paper which not only gives a better performance gain but is also generic enough to embrace different primary user signal formats. The scheme utilises energy value and GoF based test for a non-parametric flavour with ANN to robustify the adaptive learning process. Recently, it has been shown in [14] that the Zhang statistic [16]

from LRS-G^2 gives the highest statistical power for the normality test in comparison with other GoF schemes. Thus, it has been concluded to use energy value from energy detection and Zhang statistic from likelihood ratio statistic scheme as sensing features for ANN in the hybrid scheme. It is also explored in this study that for a sensing event abrupt changes in features may lead to significant performance degradation. To mitigate this hurdle the proposed sensing scheme uses two extra features, energy and Zhang statistic of previous sensing event (under the assumption that sensing events are reasonably close in time) to make the learning scenario more robust.

The performance of the proposed scheme is evaluated based on various real-world primary signals using an experimental test setup and compared with Classical Energy Detection (CED) [7] and Improved Energy Detection (IED) [17]. The results obtained are promising as they show that the proposed mechanism outperforms both CED and IED sensing schemes.

The rest of this paper is organized as follows. First, Section II presents the proposed ANN-based hybrid spectrum sensing scheme. Section III describes the measurement and assessment procedure followed in this study to assess the performance of the proposed scheme. The obtained results are analysed and discussed in Section IV. Finally, Section V draws the main conclusions from the study.

II. PROPOSED ANN-BASED SPECTRUM SENSING SCHEME

Neural networks are very good at learning non-linear functions and can adapt the non-linear characteristics of primary signals. Considering this, the proposed sensing scheme utilises an ANN for the improvement of spectrum sensing. The proposed sensing scheme uses a Back Propagation Neural Network (BPNN), one of the simplest ANN architecture [18], which consists of an input layer, a hidden layer and an output layer with set of neurons as shown in Figs. 1 and 2.

The proposed sensing scheme incorporates classical energy detection and likelihood ratio statistics (LRS-G^2) into the ANN. It uses the energy value from energy detection and the Zhang statistic from the likelihood ratio statistic scheme as inputs to the ANN. Denoting the discrete version of a received signal as $y[n]$, the energy value E and the Zhang statistic Z_c are given as:

$$E = \sum_{i=1}^{N} |y[n]|^2 \tag{1}$$

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

where N is the sensing sample size and $F_0(y)$ is the known cumulative distribution function (CDF) of noise.

The scheme has three phases: ANN training, ANN model selection, and ANN testing. The first two phases are the pre-phases and are conducted before the actual
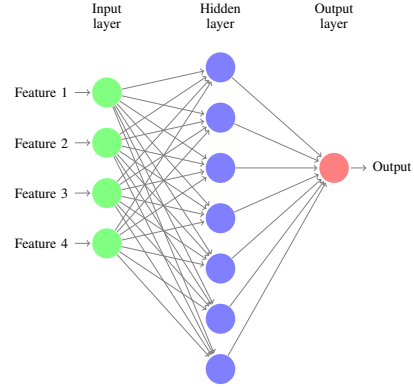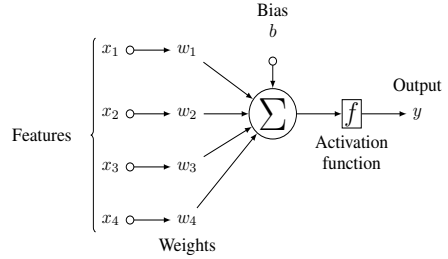

Fig. 1: ANN structure.

Fig. 2: Hidden layer neuron structure.

sensing starts. The scheme uses three data clusters training dataset, cross-validation dataset and testing dataset.

A. ANN Training

From the training data cluster, the primary user signal is acquired, the power level is measured and the obtained value is considered as the actual signal power σ_x^2 of the primary signal. Based on the desired SNR γ, the AWGN sequence with power level $\sigma_w^2 = \sigma_x^2/\gamma$ is generated and then added to the primary signal to have the desired SNR. To make the neural network bias free (neutral for the binary hypothesis problem), the training dataset consists of an equal amount of primary signal feature examples and AWGN feature examples.

Algorithm 1 illustrates the ANN training steps. First of all, based on the sample size (N), the features from the training dataset are computed and labelled as 0 for null hypothesis ($\mathcal{H}_0$ noise only) and 1 for alternative hypothesis ($\mathcal{H}_A$ existence of primary signal) using the prior knowledge of the training dataset. Afterwards, based on the batch size, random examples of features with their labels are extracted out and forward propagated to the ANN. The ANN predicts the output and based on the back-propagation mechanism, it improves its prediction. This process continuously takes place based on the number of iterations given to the ANN training mechanism. For each radio technology (see Table II) 200,018 examples are taken for ANN training. Out of all examples, 100,009 examples are maintained for AWGN and the other 100,009 examples are distributed into an SNR range from -20 dB to 4 dB, then

Algorithm 1 ANN Training

```
 1: function TRAINING(N, Epoch, Batch_size, Label, α, Data)
 2:     ANN Network ← Construct Network Layers ()
 3:     Network_weights & Bias ← Initialize (ANN Network)
 4:     size ← length (Data) / N
 5:     Samples ←  1ˢᵗ N Samples
 6:     E ← Energy (Samples)              ▷ Compute energy value
 7:     Z ← Zhang statistic (Samples)    ▷ Compute Zhang statistic
 8:     for j ← 2 to size do
 9:         Samples ←  (j)ᵗʰ N Samples
10:         E_P ← E                 ▷ Energy of previous sensing event
11:         Z_P ← Z       ▷ Zhang statistic of previous sensing event
12:         E ← Energy (Samples)
13:         Z ← Zhang statistic (Samples)
14:         Feature[j-1] ← {E, E_P, Z, Z_P, Label}
15:                                  ▷ Feature vector with labels
16:     end for
17:     for i ← 1 to Epoch do
18:         T_F & label ← Extract (Feature, Batch_size)
19:                         ▷ According to Batch_size random
20:                         features extraction with their labels
21:         output ← Forward Propagate (T_F, ANN Network)
22:         Error ← BackwardPropagateError (label, output)
23:         Weights ← UpdateWeights(label,output,ANN Network,α)
24:                              ▷ α is the Learning Rate
25:     end for
26:     return ANN Network
27: end function
```

the dataset is clubbed with all the radio technologies and forwarded to different ANN architectures as shown in Fig. 3. The batch size for the training examples is taken as 250 and around 350 iterations are used to train different artificial neural network architectures. The training data manipulation mechanism will be discussed later on.
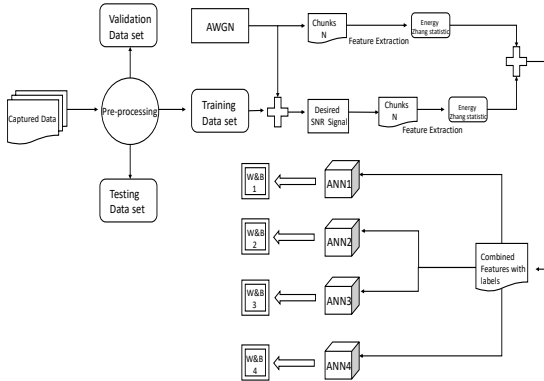

Fig. 3: ANN training.

B. ANN Model Selection

Once the different ANN architectures are trained with proper training dataset and proper iterations (Epoch), the ANN architecture that suits well overall needs to be identified. One way to figure this out is to define an architecture which fits best for the training set. However, in practice this will not always lead to a generalised model and for this reason the cross-validation dataset is used to find out an appropriate architecture for ANN as shown in Fig. 4. In the training process, different ANN architectures are trained with combined datasets of all

radio technologies with AWGN and the final weights and bias are stored for each ANN architecture. Using those weights and bias the cross-validation dataset is evaluated. In fact, the selection process not only focuses on the best fit but ensures that the model is simple enough to deal with the realistic sensing framework.

Notice that for a smaller number of layers the accuracy on cross-validation dataset remains almost similar irrespective of the number of neurons (see Table I). In order to have utility with real time systems, we are primarily concerned about the computational complexity of the proposed scheme, and that motivates to obviate an idea of increasing more number of hidden layers in ANN. Based on various experiments it was concluded that having only one hidden layer with only 7 neurons is sufficient for the proposed sensing scheme.
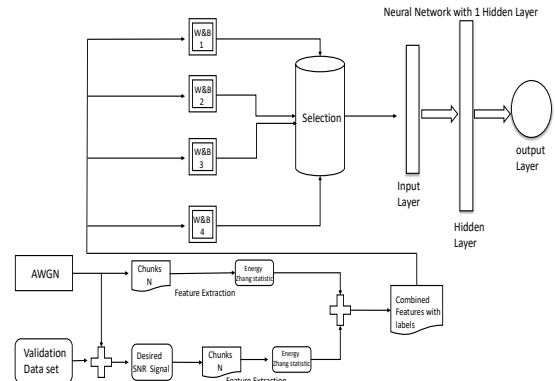

Fig. 4: ANN model selection.

TABLE I: Different ANN architectures with their accuracy on cross validation dataset

No. of hidden Layers	Nodes in each Layer	Accuracy Achieved
1	2	85.45%
1	7	87.79%
1	20	87.77%
2	5	87.85%

C. ANN Testing

The testing mechanism is the final phase to evaluate the sensing scheme. Fig. 5 illustrates the whole testing process. To find out the probability of detection (P_d) the test dataset is used and it is added with AWGN to adjust the desired SNR, then the dataset is divided into small chunks (e.g, $N = 100$) and features like energy and Zhang test statistic are extracted out. Afterwards, features are forwarded to the trained neural network. The number of times the neural network predicts its alternative hypothesis ($\mathcal{H}_A$) divided by the total examples is ultimately the detection probability for a given SNR. The probability of false alarm (P_f) is evaluated similarly but using AWGN sequences for feature extraction instead of test dataset. Algorithm 2 illustrates the final sensing steps, where the ANN takes the decision about the existence of the primary signal.
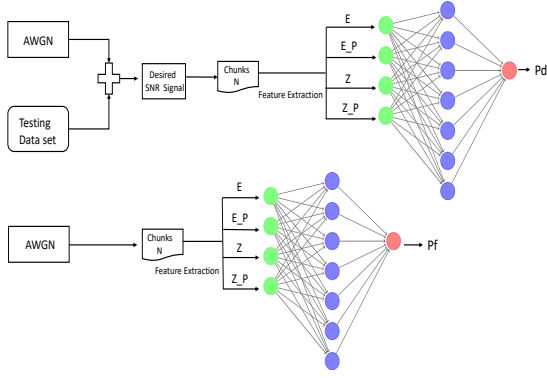
Fig. 5: ANN testing.

Algorithm 2 ANN Sensing

1: **function** SENSING(ANN Model, N, No. sensing event)
2:     weights & bias ← ANN Model
3:     **for** $i \leftarrow 1$ to No. sensing event **do**
4:         E_P ← Energy of $(i-1)^{th}$ N Samples
5:         Z_P ← Zhang statistic of $(i-1)^{th}$ N samples
6:         E ← Energy of $(i)^{th}$ N Samples
7:         Z ← Zhang statistic of $(i)^{th}$ N samples
8:         Features ← {E, E_P, Z, Z_P}
9:         output ← ANN Predict (Features, weights, bias)
10:        **if** $output == 1$ **then**
11:            $S_i \leftarrow \mathcal{H}_A$
12:        **else**
13:            $S_i \leftarrow \mathcal{H}_0$
14:        **end if**
15:    **end for**
16:    **return** S
17: **end function**

III. MEASUREMENT PROCEDURE

A. Measurement Platform

The measurement platform employed in this study includes both hardware and software parts (see Fig. 6) and is very similar to the one employed in [7]. The hardware part consists Universal Software Radio Peripheral (USRPS-N210) [19], WBX daughter board, RF-Explorer and D3000N Super Discone antenna. All these components are required to capture the primary user data.

The software part includes Gnu Radio [20] and Matlab. The host PC runs the Gnu radio's usrp_rx_cfile.py script to collect the digital samples from USRP. Once the data are captured, off-line processing is performed in Matlab and then the proposed scheme is applied on the stored data to evaluate the P_d and P_f. In this study BPNN is implemented using Python's library keras [21] backend with theano [22]. The implemented model uses Adam optimizer [23]. To adjust the loss, it uses binary_crossentropy and as activation function it uses rectified linear unit (ReLU) for hidden layer neurons and sigmoid for the output layer neuron. The reason for such consideration is its applicability for the binary classification problem.

B. Data Capturing and Pre-Processing

The measurement platform was placed on a SEAS building roof in India to have the direct line of sight from several transmitters with a minimum shadowing and reflection loss. With the help of RF-Explorer, some channels with high SNR were identified for various radio technologies (see Table II), which were afterwards used to capture primary signal data using the USRP (with appropriate centre frequency, decimation rate and gain factor, which are crucial to produce adequate signal data). The gain factor is selected such that the highest SNR is achieved in the received signal, while the decimation rate ensures that the received signal bandwidth is higher than or equal to the actual signal bandwidth. For each channel around 10^7 samples were captured. A pre-processing step was applied to filter the signals and remove any transient peaks in the initial samples. The pre-processed data are then partitioned into three groups for all radio technologies: training dataset (60%), cross-validation dataset (20%) and testing dataset (20%).

IV. RESULTS

Employing the presented measurement platform, the proposed spectrum sensing scheme is tested on four different radio technologies (see Table II). The performance for channels of the same radio technology was found to be very similar, thus a single channel from each radio technology is considered here to simplify the analysis. The obtained results are evaluated independently for all four radio technologies. In the evaluation procedure, four ANN architectures are used and they are assigned a specific radio technology. Afterwards, the training is applied to each of them independently and then using the test dataset the probabilities of detection (P_d) are computed. One can also uses single ANN and incorporate all the training set of different radio technologies together as in the model selection procedure, but doing this exercise one may miss the inherent effect of the technology dependency on P_d as mentioned in [7]. Moreover, the training time for the mentioned ANN architecture, epoch and batch size is around 10-12 Minutes (System: Intel I7, Quad Core Processor, 8GB RAM) mainly it depends on the system processor and RAM.

A. Validation

In general, in empirical setups it is not easy to get rid of the randomness factor, but to make sure the proposed setup and the captured data are valid, the captured data are used to reproduce the results of CED and IED mechanisms mentioned in [17]. By comparing the reproduced results we validate that our results are correct. The process of data capturing and sensing evaluation with proposed scheme was repeated more than 2 times and the performance remained unchanged in each repetition, which guarantees the statistical reliability of the results. The results follow basic theoretical expectations (e.g., increasing the SNR and/or the sample size N increases P_d).
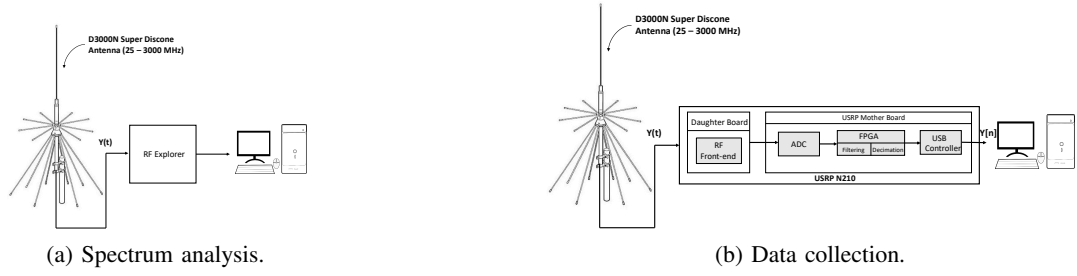
(a) Spectrum analysis.

(b) Data collection.

Fig. 6: Measurement platform employed in this study.

TABLE II: Channels measured in this study.

Radio Technology	Channel Number	F_{start}(MHz)	F_{center}(MHz)	F_{stop}(MHz)	Signal Bandwidth (MHz)	Gain (dB)	Decimation Rate (M)	Sampled Bandwidth (MHz)
FM Broadcasting		94.100 96.500 98.100	94.300 96.700 98.300	94.500 96.900 98.500	0.2	45	64	1
E-GSM(900) DL	27 77 120	940.2 950.2 958.8	940.4 950.4 959	940.6 950.6 959.200	0.2	45	64	1
DCS (1800) DL	527 690	1808.0 1839.6	1808.2 1840.8	1808.4 1841	0.2	45	64	1
UHF Television	U - 29 U - 33	534 566	538 570	542 574	8	45	8	8

B. ANN Training Analysis

1) Manipulation in training data: The proposed ANN-based mechanism includes an ANN architecture which requires a proper training to correctly classify the hypotheses. Another requirement in this study is to make the architecture as simple as possible so that the scheme can be implemented on a realistic sensing framework. Considering all of these aspects, we have done data manipulation on the training dataset. The manipulation scheme changes the percentage of higher and lower SNR examples in the training set while it does not affect the pure AWGN examples.

For this study, -20 dB to -6 dB SNR examples are categorized in lower SNR class, and the rest of -4 dB to 4 dB SNR examples are in higher SNR class. The manipulation is done such a way that we take some percentage of examples from lower SNR class, where each lower SNR like -20 dB, -18dB et cetera contributes equally with examples to that percentage and the remaining percentage of examples will be contributed by the higher SNR class. Here also each higher SNR like -4 dB, -2 dB et cetera contributes equally. Different combinations of training datasets were created by varying percentage combinations of higher and lower SNR class examples and afterwards, those combinations are used to train the ANN. Once the training is completed, the testing mechanism (sensing) is applied to the trained ANN, to compute P_d and P_f (see Fig. 7 and Table III).

Fig. 7 and Table III are evaluated using the training and testing dataset of the radio technology DCS 1800 (The same behaviour is found in other radio technologies too). Here, the data model represents the percentage portion of higher and lower SNR class examples in the training dataset. For example, 20-80 model represents that the 50% examples which contain a primary signal

in the training dataset has 20% examples from lower SNR class and 80% examples from higher SNR class, the remaining 50% are for the AWGN examples.

It is clear to note that the P_d and P_f values are the lowest for 20-80 model and highest for the 80-20 model. The fundamental reason behind this phenomena is at lower SNR the features become almost similar to the feature of noise examples. So, if the training dataset of primary signal consists more portion of lower SNR class examples compared with higher SNR class, then the neural network is likely to say presence of primary signal, when it identifies a slight increase in energy value and Zhang statistic (80-20 Model), while if the training set of primary signal have more examples of higher SNR class as compared with lower SNR class, then the neural network becomes more robust to identify the actual presence of primary signal (20-80 Model), ultimately everything depends on how the neural network is being trained. In order to moderate the P_d and P_f values, we have concluded to work on 40-60 model which consists 60% examples from higher SNR class and 40% examples from lower SNR class.

TABLE III: P_f for different training combinations (Radio technology is DCS-1800, N=100).

Training Models	False_Alarm
20-80	0.0166
30-70	0.0231
40-60	0.0352
50-50	0.0570
60-40	0.0795
70-30	0.0860
80-20	0.0988

2) Training with different features: We have also analysed the performance of the proposed architecture by taking different sets of features, such as only energy of current samples, only Zhang statistic of current
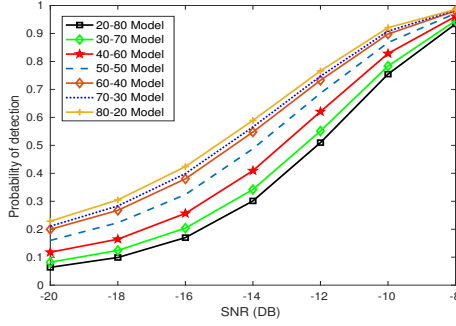
Fig. 7: P_d vs SNR for different training combinations (Radio technology is DCS-1800, N=100).

samples, energy and Zhang statistic of current samples and finally, all four features energy and Zhang statistic of the current samples and of the previous samples. The performance is evaluated on the basis of how cross-validation dataset fits on the trained ANN architecture. Here, features from cross-validation dataset are also extracted in the same way as for the training dataset, and then passed to the trained ANN.

It is clearly seen from Table IV that, using only the energy of the current sensing event as a feature for ANN training gives the worst performance compared to other feature combinations for all radio technologies. It is interesting to note that when ANN is trained using both energy and Zhang statistic of the current sensing event, the accuracy on cross-validation dataset remains almost similar as when only Zhang statistic is used as a feature, which shows the effectiveness of the Zhang statistic as a feature. Finally, it is worth to note that the combination of all four features provides the best accuracy among all four cases.

TABLE IV: Accuracy measurement on ANN using different radio technologies with different set of features ($N = 100$).

Radio Technology	Only Energy	Only Zhang Statistic	Energy and Zhang Statistic	All Four Features
FM Broadcast	76.66%	83.82%	84.15%	86.82%
GSM-900 DL	76.91%	83.93%	84.27%	86.88%
DCS-1800 DL	78.19%	86.49%	86.51%	89.04%
UHF TV	78%	85.97%	86.02%	88.55%

C. Performance Analysis

The proposed sensing scheme was evaluated for all radio technologies mentioned in Table II. Fig. 8 shows the performance curves (P_d vs SNR) for different radio technologies with different sample size. The results show that the proposed scheme outperforms the Classical Energy Detection (CED) and the Improved Energy Detection (IED) proposed in [17] for all radio technologies. Table V shows the associated P_f for the ANN model trained on different radio technologies with different sample sizes (N).

As the ANN dynamically learns from the features about the sensing problem, the associated false alarm

rate with ANN model remains almost static for a particular radio technology with sample size (see Table V). From Table V, it can seen that as N increases the false alarm rate decreases significantly. The reason for this phenomenon is that as N increases, the features become more robust, which leads to a better trained ANN model for the sensing decision (see Table VI). The same reasoning can be the cause for the P_d improvement as well.

In spite of the general operating principle of the energy detection method, it is shown [7] that certain technology-dependent inherent properties result in different detection performance for various radio technologies. The same phenomena occurs in our study as well, where the set of features (energy value and Zhang statistic) are affected by the technology dependent inherent properties and as a result, different detection performances are obtained for different radio technologies. The effect of the technology dependent inherent properties can be also understood by analysing the fitting accuracy of the training set on the same ANN architecture (see Table VI).

V. CONCLUSION

In this paper, a novel hybrid spectrum sensing scheme has been proposed. The performance has been evaluated based on various radio technologies using an experimental testbed setup. The obtained results demonstrate that the proposed scheme significantly outperforms the classical energy detection method and other improved energy detection methods for all the considered radio technologies. One aspect of the future work can be seen as to reduce the required training time, the other one can be thought of as incorporation of various other relevant features to gain higher performance accuracy. Certainly, greater the number of features, greater the computational complexity, both of these aspects cannot be simultaneously achieved.

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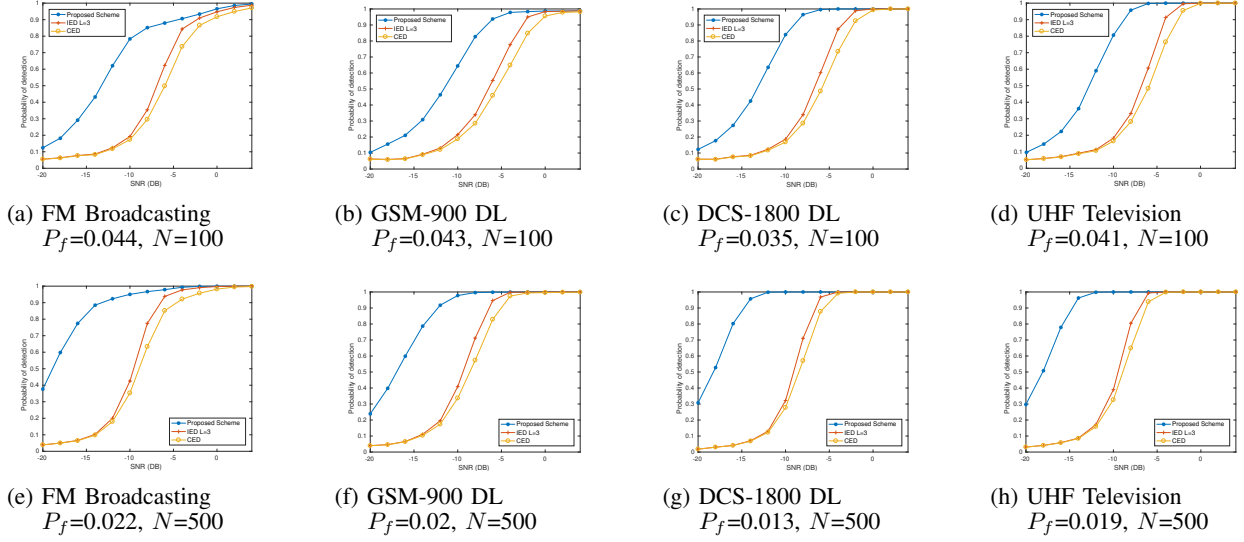
| (a) FM Broadcasting P_f=0.044, N=100 | (b) GSM-900 DL P_f=0.043, N=100 | (c) DCS-1800 DL P_f=0.035, N=100 | (d) UHF Television P_f=0.041, N=100 |
| (e) FM Broadcasting P_f=0.022, N=500 | (f) GSM-900 DL P_f=0.02, N=500 | (g) DCS-1800 DL P_f=0.013, N=500 | (h) UHF Television P_f=0.019, N=500 |

Fig. 8: Detection performance of the considered spectrum sensing methods (P_d vs SNR).

TABLE V: False alarm rate for the ANN model trained on different radio technologies with different sample sizes (N).

N=100		N=500	
Radio Technology	False_Alarm	Radio Technology	False_Alarm
FM Broadcast	0.0440	FM Broadcast	0.0220
GSM-900 DL	0.0434	GSM-900 DL	0.0200
DCS-1800 DL	0.0352	DCS-1800 DL	0.0137
UHF Television	0.0414	UHF Television	0.0191

TABLE VI: Fitting accuracy of training dataset for different radio technologies on ANN using different sample sizes.

N=100		N=500	
Radio Technology	Training Accuracy	Radio Technology	Training Accuracy
FM Broadcast	87%	FM Broadcast	94.90%
GSM-900 DL	86.46%	GSM-900 DL	93.67%
DCS-1800 DL	89.20%	DCS-1800 DL	95.86%
UHF Television	88.58%	UHF Television	95.37%

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