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Wireless Standard Identification Based on Extended Radial Basis Function Neural Network in Cognitive Radio Het Nets

Monika Tulsyan, Seemanti Saha, Rajarshi Bhattacharya

Abstract**:** *This paper presents a novel scheme for the automatic identification of primary user (PU) signal with respect to known wireless standards like GSM, Bluetooth, WLAN a/b/g/af, Zigbee, LTE etc. in a heterogeneous Cognitive Radio Network. The Secondary users (SUs), aware of the coexisted PU signal standard, can better exploit the available spectrum with coexisting PUs. Hence, in the proposed work, an Extended Radial Basis Function (ERBF) neural network (NN)) is used to classify PU signals of various standards using relevant explicit and implicit features (extracted from the detected PU signal), as the input to the classifier. The proposed method also involves automatic classification of digital modulation format used by the PU signal without a prior knowledge of the signal parameters. The proposed method can recognize single carrier modulation schemes like MPSK, MFSK, MASK, and MQAM, along with multicarrier modulation scheme like OFDM. The recognized modulation format is utilized further as an implicit feature given as an input to the signal classifier. Extensive simulation in MATLAB has been carried out for various signal-to-noise ratio (SNR) ranging from -20 dB to 20 dB. Simulation studies show that the proposed classification method is giving excellent detection and classification performance of 98% for most of the wireless standards, even in very low SNR of -20 dB.*

Index Terms**:** *Cognitive HetNet, feature extraction, modulation classification, radial basis function, wireless standard classification.*

I. INTRODUCTION

With the development in the emerging wireless technologies and communication systems, the intensive hunger for speed and bandwidth is increasing manifolds, leading to the enormous spectrum requirements. To cater the tremendously increasing demands for higher data rate, various radio access technologies (RATs) are applied in 5G communication systems, which may share the same wireless resource, constituting a heterogeneous network (HetNet) [1]. As the fixed spectrum allocation results in inefficient spectrum utilization, the cognitive radio (CR) technology is applied in HetNets as well, resulting in cognitive heterogeneous networks, which incorporates several international standards, e.g. LTE-U, IEEE 802.11 af, IEEE 802.22, etc [2]. In a heterogeneous cognitive radio network (CRN), wireless standard identification, when employed with proper network management, helps CR to exploit the same wireless resources

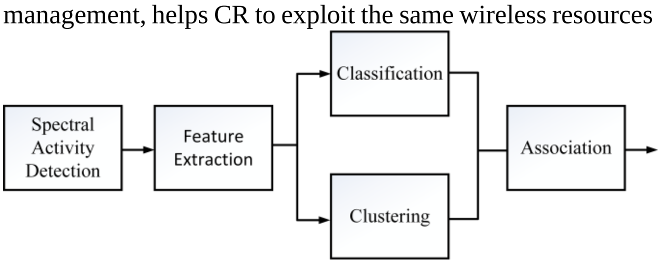

Fig.1. Spectral activity identification in a cognitive radio.

more efficiently while maintaining the quality of service (QoS) to the PUs who are using the same resource at some time instant [3], [4].

In other words, it could be said that signal identification helps in reducing the interference to the coexisting Pus, which use the same resource with the SU, but communicating in different standard than the SU [5]. Employing Cognitive radio, the SUs should lessen interference to the Pus in cognitive channels, which are the licensed channels with white spaces, such as TVWS and also take care of the interference, caused in unlicensed channels like unlicensed Wi-Fi network [6], [7]. Thus, channel sensing and monitoring followed by wireless standard technology identification are among the main operation of a CRN to meet the requirements of the next generation 5G communication systems and networks.

The signal identification problem in CR can be formulated as three step problem as depicted in Fig. 1 [8]. The first step is to extract feature vector for signal detection. The second step is to classify the extracted feature vector into some known classes. The classification module classifies feature vector into some set of known classes based on supervised learning. The final step is to associate the resulting classes with known standards.

In some of the early works, authors have proposed an HMM based signal classification algorithm using a cyclostationary based feature extraction module [9]. However, the requirement of prior training makes it less adaptive for a CR operating in unknown environment. An automatic recognition method for the classification of Wi-Fi and Bluetooth transmissions has been devised in [10].

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***** Correspondence Author (s)
Monika Tulsyan, Department of ECE, NIT Patna, Patna, India.
Seemanti Saha, Department of ECE, NIT Patna, Patna, India.
Rajarshi Bhattacharya, Department of ECE, NIT Patna, Patna, India.

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Other signal classification methods include fuzzy logic approach [4], neural network model [11], support vector machine model [12], Dirichlet process mixture model [13] etc. Recently, an unsupervised learning method based on sparse coding has been proposed for RF signal classification [14] that requires no prior knowledge about the signal. To make the CR system fast and efficient, work has been done towards the cooperative signal classification in which pre-processed measurements are fused linearly [15].

Signal modulation type is one of the important characteristic used in signal monitoring and classification, determined from automatic modulation classification. For instance in [16], authors have chosen radial basis function (RBF) for classification of many RATs e.g. GSM, UMTS, DECT, DAB, DVB-T, etc., based on the apriori knowledge of the channel bandwidth. But due to the scalability of channels, low classification performance was achieved. For high dimensional data vector, RBF network shows non monotonic interpolation behavior of RBF for smaller standard deviations and extrapolation behavior tending to zero, which is unavoidable. Also, with increase in data dimensionality, the number of RBF required for classification increases, which in turn increases the total number of unknown parameters and results in enhanced complexity. Hence, we opt for extended radial basis function (ERBF) network, which can be used to model dynamic process with reduced complexity [17].

In this work, we have classified the incoming digital modulation based PU signals into different wireless standards and technologies e.g. GSM, IEEE 802.15.4 (ZigBee), IEEE 802.15.1 (Bluetooth), IEEE 802.11.a, b, g (WLAN), LTE and IEEE 802.11.af (White Fi) using ERBF based signal classifier. This network is able to overcome the abovementioned problem associated with scalability, interpretability and complexity [18]. The remainder of the paper is organized as follows: Section II gives a detailed description about the signal features and the methodology adopted for extraction. The RBF node and network structure is discussed in section III. Section IV introduces the proposed ERBF NN based signal classifier having non-linear classification algorithm. Results and discussion are presented in Section V and Section VI concludes the paper.

II. FEATURE EXTRACTION

Signal classification can be grouped into two types of approach: Decision-based (DB) approach and feature-based (FB) approach. Considering FB approach in this work, our prime objective is to extract relevant implicit features (modulation format, spectral correlation function (SCF) etc.) and explicit features (bandwidth, center frequency, hopping behavior etc.) of the received PU signal. In this paper, explicit features are extracted using power spectral density (PSD). For implicit feature, an algorithm is developed to decide the type of modulation of the intercepted signal reliably. The detailed description of these features is further discussed below [19]:

A. Explicit Features

(a) Spectral Features

The average power distribution of a signal with respect to frequency represents PSD of the signal. Mathematically, it is the average of squared magnitude of Fourier Transform over a large time interval, given by

$$S_X(f) = \lim_{T\to\infty} E\left\{ \frac{1}{2T} \left| \int_{-T}^{T} x(t) e^{-j2\Pi ft} dt \right|^2 \right\} \quad (1)$$

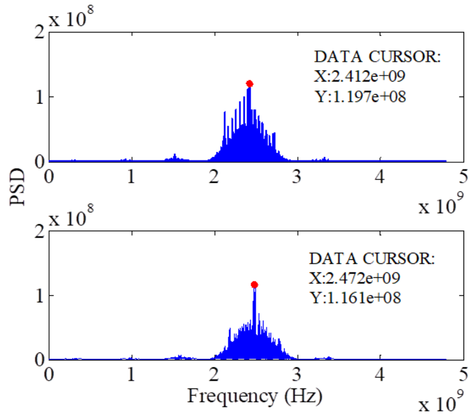

Fig. 2. Spectral peak in the power spectra of channel 1 and 13 of 2.4 GHz band.

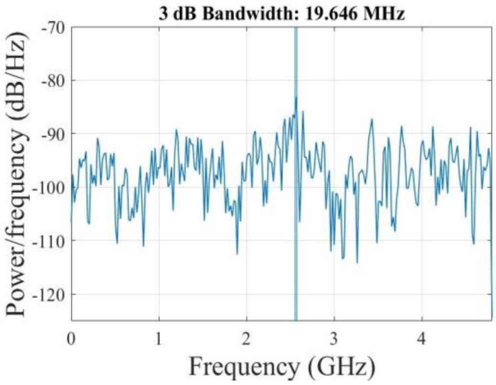

Fig. 3. 3dB bandwidth of 2.4 GHz band of WLAN system.

The WLAN signal is simulated in MATLAB and the carrier frequency and bandwidth of the signal is determined from the PSD characteristics. The frequency in the power spectra at which the corresponding power is maximum, represents the carrier frequency and the frequency range centered at f_c, containing half the maximum power, gives the approximate bandwidth information of the received PU signal. Fig. 2 shows the power spectra of channel 1 and 13 of 2.4 GHz band under WLAN system. The carrier frequency could be clearly identified with the help of maximum power spectral peak. It can be seen from Fig. 3 that the 3dB bandwidth comes out to be 19.646 MHz, which is almost equal to the theoretical value.

B. Implicit Features

(a) Spectral Coherence Function

The second order statistical periodicity (e.g. autocorrelation) can be used to determine the symbol rate of the received signal. The cyclic autocorrelation function is given as:

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$$R_X^{\alpha}(\tau)=\frac{1}{T}\int_{-\frac{T}{2}}^{\frac{T}{2}} R_X\left(t+\frac{\tau}{2},t-\frac{\tau}{2}\right)e^{-j2\pi Xt}dt \tag{2}$$

where, α is the cyclic frequency which is equal to integral times of the fundamental frequency, $\alpha = k/T_O$. The fourier transform of cyclic autocorrelation function is known as Spectral Correlation Density and could be expressed by Cyclic Wiener relation [20] as:

$$S_x^{\alpha}(\mathrm{f})=\int_{-\infty}^{\infty} R_x^{\alpha}(\tau)e^{-i2\pi f\tau}d\tau. \tag{3}$$

Further from (3), spectral coherence (SC) function [21] can be defined as:

$$C_x^{a}(f)=\frac{S_x^{a}(f)}{\left[S_x(f+a/2)S_x(f-a/2)\right]^{1/2}} \tag{4}$$

whose value lies between 0 and 1. The spectral coherence for BPSK and QPSK modulation schemes is computed using (4). We have taken N=100 frames consisting of T=500 digitally modulated samples each. To reduce the data handling complexity, the classifier can use only the peak values of SC, which is termed as cyclic domain profile (CDP), given as:

$$CDP(\alpha)=\max_f \left|C_x^{\alpha}(\mathrm{f})\right| \tag{5}$$

The CDP of QPSK and BPSK have two and three peaks respectively, as can be seen from Fig. 4 and Fig. 5. The first peak determines the symbol rate (f_r) of the corresponding modulation format, second corresponds to carrier frequency (f_c), and the last one corresponds to $(f_c + f_r)$. The algorithm for the estimation of SC and CDP is detailed in Algorithm 1.

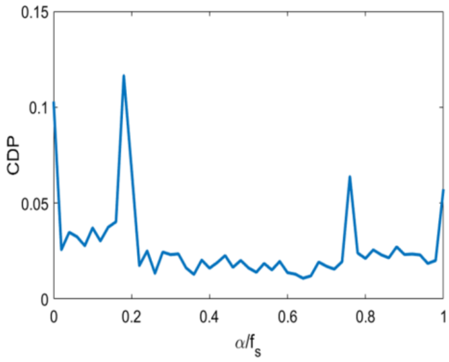

Fig. 4. CDP of QPSK

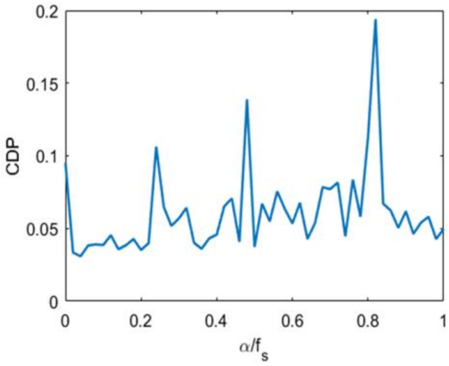

Fig. 5. CDP of BPSK

Algorithm 1 Pseudo code for estimating CDP

Initialization: Divide δt samples of modulated signal number of frames such that $T = \frac{\delta t}{N}$
Obtain FFT of each frame $X_T = fft(x)$
Shift FFT of each frame by $+\alpha/2$ and $-\alpha/2$
Calculate $S_{x_t}^{\alpha}(f) = \frac{1}{T} X_T\left(f + \frac{\alpha}{2}\right) X_T^*\left(f - \frac{\alpha}{2}\right)$
Take average of all N frames
Repeat For each value of α
Until SCF is obtained
Normalize SCF using equation 4 and Obtain $C_x^{\alpha}(f)$
Obtain CDP using equation 5
End

(b) Modulation Format

In a HetNet, systems with different priorities have different protection requirements and operating parameters. A CR should be able to recognize and adapt accordingly with respect to different coexisting systems, which necessitates the need of automatic modulation recognition (AMR). Various types of features can be used for modulation classification such as instantaneous frequency, amplitude and phase, wavelet transforms, timing information, phase offsets etc. Some features used in this work are amplitude and phase level information and spectral coherence. The identification of multicarrier (MC) signal such as OFDM from single carrier (SC) signal becomes a normality test [22], as the amplitude distribution of a OFDM can be approximated with a gaussian distribution (according to the central limit theorem) due to the presence of large number of orthogonal subcarriers. For SC/MC classification, we have chosen Kolomogrov-Smirnov gaussianity test which can perform accurately even at low SNR scenario as seen from Table I. This test results in 0 and 1 for MC and SC signals respectively. The complete AMR process is described using flowchart shown in Fig. 6.

Table I: Result of KS test for various modulation formats

Mod	OFDM	BPSK	QPSK	16 QAM	4 ASK	4 PSK
KS-test	0	1	1	1	1	1

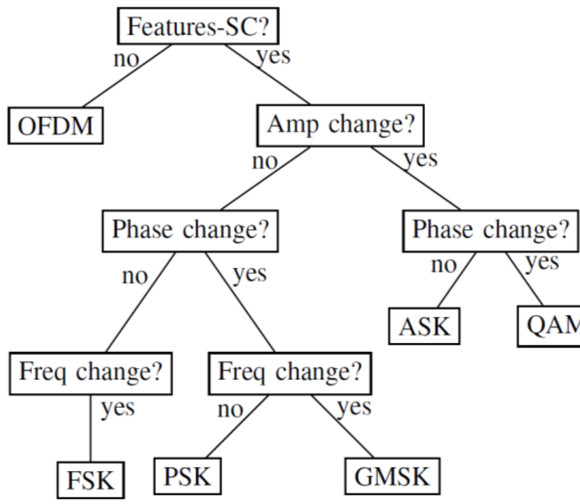

Fig. 6. Modulation Classification

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III. RADIAL BASIS FUNCTION NETWORK

An artificial neural network is a powerful tool for information processing, learning and adaptation of the system and is closely related to mathematics, statistics and optimization in engineering domain. In this work, we have used RBF based neural network, utilizing a non linear activation function to design a signal standard classifier. A standard RBF network has a feed-forward structure consisting of three layers: an input layer, a nonlinear hidden layer and a linear output layer. This network utilizes a radial construction mechanism which gives a better interpretation of the hidden layer parameters and hence allows faster training

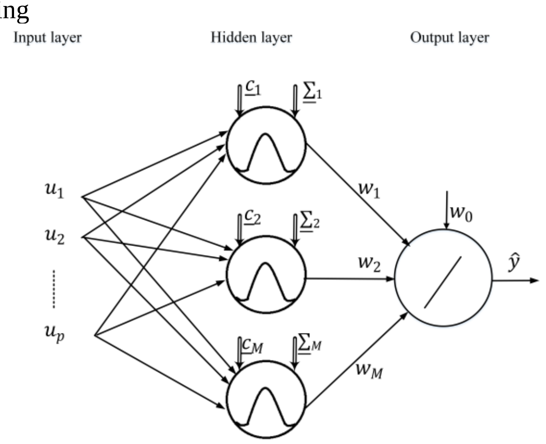

Fig. 7 Radial basis function network.

methods. The outputs are weighted linear combinations of the basis function responses as illustrated from Fig. 7.

The hidden layer parameters of the ith RBF node contain the centre vector c_i, representing the position and the norm matrix Σ_i, representing the widths and rotation of the ith basis function. The node calculates the distance x_i of the input vector $u=[u_1\ u_2,\ldots,u_p]^T$ to the centre vector $c_i=[c_{i1}\ c_{i2},\ldots,c_{ip}]^T$ with respect to the norm matrix Σ_i, followed by its transformation through a nonlinear basis function $\phi(x)$, which can be expressed as

$$\phi_i = \exp(-\frac{1}{2}x_i^2) \qquad (6)$$

where,

$$x_i = \|u-c_i\|_{\Sigma_i} = \sqrt{\sum_{j=1}^{p}\left(\frac{u_j-c_{ij}}{\sigma_{ij}}\right)^2} \qquad (7)$$

p is the input data dimension and σ_{ij} denotes the standard deviation of ith element in jth dimension. RBF neural network is obtained by arranging several RBF nodes in parallel and connecting to the network output node, which can be mathematically formulated as

$$\hat{y} = \sum_{i=0}^{M} w_i\phi_i(\ \|u_i-c_i\|_{\Sigma_i}\ ) \qquad (8)$$

with $\phi_0(\cdot)=1$ and output layer weights w_i. Radial basis functions (RBF) and normalized radial basis function (NRBF) networks can be used for the interpretation of static models. But in real time scenario, we have dynamic processes to be modeled. So, we opt for extended radial basis function (ERBF) network, which is the extension of NRBF, in which constant weights w_i is replaced by a function $\beta_i = w_{i0}+w_{i1}u_1+w_{i2}u_2+\cdots+w_{ip}u_p$, which is the linear combination of weights with the inputs. The output of the ERBF system can be written as [17],

$$\hat{y} = \frac{\sum_{i=1}^{M}\beta_i\phi_i(\|\underline{u}-\underline{c}_i\|_{\underline{\Sigma}_i})}{\sum_{i=1}^{M}\phi_i(\|\underline{u}-\underline{c}_i\|_{\underline{\Sigma}_i})} \qquad (9)$$

The resulting output vector is given to a hard limiter to obtain the label of the classified class. The Global estimation approach is used to estimate all linear parameters simultaneously using LS optimization. In this approach, the parameter vector contains all $n=M(p+1)$ parameters of the model with M nodes and p inputs.

IV. PROPOSED ERBF BASED MULTISTAGE CLASSIFIER

From the previous discussions, it is obvious that the ERBF based system will be much more efficient compared to the other mode of RBF. The wireless standard classification task is accomplished using an ERBF based neural network, which is discussed in this section. Network training is done in a supervised fashion and consists of determining the network centers using K-means clustering algorithm. In this technique, each observation point is assigned to its nearest centroid, based on the squared Euclidean distance. If c_i is the collection of centroids in set C, then each data point u is assigned to a cluster based on

$$\arg\min_{c_i\in C} dist(c_i,u)^2$$

where dist(·) is the standard (L2) Euclidean distance. The output layer weights optimization is done with the help of LS estimation and can be mathematically written as

$$w=(X^TX)^{-1}X^Ty \qquad (10)$$

Where y is an n dimensional output layer vector and X is regression matrix given as

$$X=\left[X_1^{sub}\ X_2^{sub}\ldots X_M^{sub}\right] \qquad (11)$$

Each regression submatrix is expressed mathematically as:

$$X_i^{sub}=\begin{bmatrix}\phi_i(u(1)) & u_1(1)\phi_i(u(1)) & \cdots & u_p(1)\phi_i(u(1))\\ \phi_i(u(2)) & u_1(2)\phi_i(u(2)) & \cdots & u_p(2)\phi_i(u(2))\\ \vdots & \vdots & & \vdots\\ \phi_i(u(N)) & u_1(N)\phi_i(u(N)) & \cdots & u_p(N)\phi_i(u(N))\end{bmatrix} \qquad (12)$$

Each standard differ from each other in some or other way. Ideal features used for the classification of various wireless standard signals are listed in Table II.

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Algorithm 2 Pseudo code for signal Classification

1: **Initialization (Training):** Load training feature vector $F_i = [Fc_i, BW_i, M_i, MC_i, H_i]$, $i = 1, 2....no.of training samples.$
2: **Obtain** center vector, C_i and standard deviation, σ_{ij} using K-means clustering and compute basis function.
3: **Obtain** Weights $[w_{ij}]$ using least square optimization
4: **Obtain** Classification performance for train feature vector.
5: **Initialization (Testing):** Load testing feature vector $F_{test} = [Fc_{test}, BW_{test}, M_{test}, MC_{test}, H_{test}]$,
6: **Obtain** Classification performance for test feature vector.
7: **End**

A simplified block diagram representation of the proposed classification procedure is illustrated in Fig. 8. It can be seen that the signal classifier is fed with explicit features, extracted from the received PU signal having some unknown wireless standard, along with the digital modulation format, which is identified through AMR with the help of implicit features. Implicit feature set consists of features namely instantaneous amplitude and phase of the modulated signal and SCF. Explicit feature set consists of features such as carrier frequency, bandwidth and hopping characteristics. The Implicit features are given to an ERBF based modulation classifier to obtain the digital modulation format of the received signal. Here, modulation format is considered as one of the feature and is fed as an input to the ERBF based signal classifier along with the explicit features. After association of the input feature vector with the known classes and clusters, we get the desired classification based on various wireless standards.

Table II: Feature set of various signals of known wireless standards

Standard	f_c (MHz)	BW (MHz)	Modulation	SC/ MC	Hop
GSM	900	0.2	GMSK	SC	Yes
802.11a	5000	20	OFDM/16QAM	MC	No
802.11b	2400	22	DSSS/QPSK	SC	No
802.11g	2400	20	OFDM/64QAM	MC	No
802.11af	790	8	OFDM/256QAM	MC	No
802.15.1	2400	1	FHSS/GFSK	SC	Yes
802.15.4	868	2	BPSK	SC	No
LTE	2300	0.005	OFDM/QPSK	MC	No

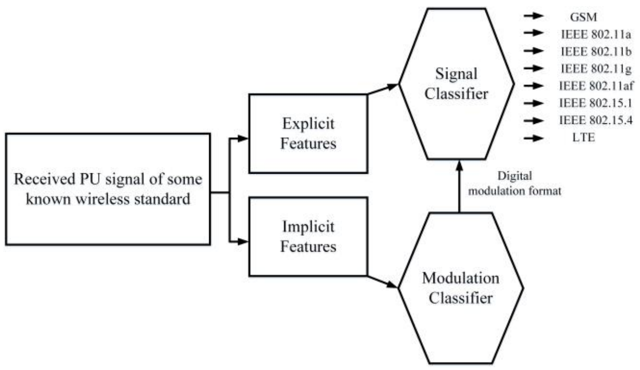

Fig. 8. RBF Classifier

V. RESULTS AND DISCUSSIONS

All the simulations for feature extraction and classification process were carried out in MATLAB, with 1000 samples of each wireless standard in training phase and 3000 samples in testing phase. In all simulations, noise was taken into account by varying the SNR from -20 dB to 20 dB. Hard limit thresholding was done to label the resulting output vector into known classes. In high SNR scenario, the training accuracy of the proposed classifier was 100%. At very poor SNR, i.e. -20 dB, the training error was found to be 0.08%.

Table III: Classification results of various wireless standards.

Wireless Standards	SNR -20 dB	SNR -10 dB	SNR 0 dB	SNR 10 dB	SNR 20 dB
GSM	89.52	97	100	100	100
802.11a	99.12	100	100	100	100
802.11b	99.16	98.25	100	100	100
802.11g	95.56	98.11	99.28	100	100
802.11af	98.25	94.76	100	100	100
802.15.1	98.82	100	100	100	100
802.15.4	98.75	100	100	100	100
LTE	95.86	100	100	100	100

It can be seen that KS test is very much accurate in classifying Single and Multiple carrier modulation formats as the success rate is 100%, which is evident from Table I. It can be observed from Table III that for high SNR scenario, the proposed classifier gives 100% successful classification rate for all the wireless standards considered in this paper. Our classifier gives almost 98% success rate for most of the wireless standards at -20 dB SNR as shown in Table III. The minimum achieved accuracy in terms of percentage is 89.52% for GSM at -20dB SNR. Overall classification rate in differentiating signals is above 98% for all formats, whereas it is 95.86% and 89.52% for LTE and GSM respectively. Therefore the performance of the proposed classifier is excellent even in low SNR scenario upto -20 dB.

VI. CONCLUSION

In this paper, we have presented a wireless standard identification method based on Extended Radial Basis Function, which employs the extraction of implicit and explicit features of the received PU signal, as well as the automatic modulation recognition of PU signal. Classifier was tested at various SNR values in the range of -20 dB to 20 dB. The classifier results in 100% accuracy upto 0 dB SNR. The success rate is above 98% for most of the standards, except for GSM and LTE, for which the accuracy is 89.52% and 95.86%. Hence our proposed classifier gives excellent overall performance in very poor SNR scenario as well.

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AUTHORS PROFILE

Monika Tulsyan Ph.D Student**,** Department of Electronics Engineering, National Institute of Technology Patna, Patna, Bihar, India.

Seemanti Saha Assistant Professor, Department of Electronics Engineering, National Institute of Technology Patna, Patna, Bihar, India.

Rajarshi Bhattacharya Assistant Professor, Department of Electronics Engineering, National Institute of Technology Patna, Patna, Bihar, India.

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