Radio Access Technology Classification for Cognitive Radio Networks

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***Abstract*— In spectrum bands where spectrum sharing is allowed by national regulators, radio access technology recognition is an important technique for reducing interference and facilitating cooperation among cognitive radios. Unlicensed users (secondaries) need to be able to differentiate between transmissions of licensed users (primaries) and other unlicensed users. Furthermore, secondaries should only free a band when the licensed primary user starts to transmit. In this regard, secondary users' transmission technology classification will have a vital role for coexistence/cooperation purposes in such shared spectrum bands. For the purpose of this work, a practical testbed made up of software defined radio transceivers and a set of computing units was put together. A classification neural network was trained in a supervised learning method. Testbed results demonstrate the efficiency of the classification in differentiating among different radio access transmissions.**

***Keywords*– cognitive radio, signal classification, supervised learning, spectrum sharing, DSA, testbed, coexistence.**

I. INTRODUCTION

The huge demand to access information wirelessly and ubiquitously in the past decade in conjunction with the scarcity of radio resources [1] has resulted in intensive research towards the concept cognitive radio networks (CRNs) [2]. Nonetheless, only a small subset of published works have found their way into implementation and standardization. This is due to many factors; among them are the ambiguity of the cognitive radio concept for which many definitions exist, and the lack of complete implementable solutions.

Spectrum Sensing is one of the key enablers of cognitive radio networking. Cognitive Radios need to observe what type of transmissions are inhabiting specific spectrum bands in order to make decisions. These intelligent radios may want to find coexistence opportunities with other compatible devices, screen different frequency bands for white spaces, and detect occupied bands by primary users and try to avoid them.

In this article we propose an experimental testbed for radio access technology (RAT) recognition in cognitive radio networks, where there could be concurrent transmissions from Primary Users (PUs) owning a frequency band usage license and Secondary Users (SUs) who operate on a license-exempt basis. Primary and secondary users' signal recognition by SUs will help in accommodating the SUs' transmissions adequately – which might be considered as interference to the PUs otherwise. In [3], the authors have studied the classification of many RATs e.g. GSM, UMTS, DECT, DAB, etc. The recognition was based on the a priori knowledge of these RATs' channel bandwidths. This approach will have a low classification performance, since most of the current RATs use scalable channel bandwidths, e.g., Scalable-OFDMA, and thus one RAT could be mistakenly classified for another. In [4], an automatic network recognition method was devised for the classification of WiFi and Bluetooth transmissions. However, these two radio communication protocols use inherently different multiplexing techniques, namely, Direct Sequence Spread Spectrum (DSSS) and Frequency Hopping Spread Spectrum (FHSS); where the former is using a fixed and wider channel bandwidth than the latter, and the latter is using pseudo-randomly hopping transmissions of very short duration, i.e., 625µsec. Furthermore, Bluetooth is not as versatile as other RATs in handling high data rates, and thus its use in sub-GHz shared spectrum bands is not predicted for the near future.

This research paper aims to be a good demonstration of the suitability of learning algorithms for classification of various RATs, especially for the foreseen case of primary-secondary cooperation in shared spectrum bands - a highly regarded scenario in the ITU's World Radio Conference (WRC) 2012 [5].

The rest of this paper is organized as follows. In section II, a brief description of the testbed is given along with the data collection process. In Section III the architecture of the network is described with a brief explanation of the underlying training algorithm. Section IV unveils the results of the neural signal processing. In section V, use cases of this technique and its application to Radio Environmental Maps (REMs) are discussed. Section VI, concludes the work and briefly discusses the research in progress.

II. TESTBED SETUP AND DATA COLLECTION

In order to examine the performance of the RAT classifier in a more realistic scenario than PC-based simulation, a practical testbed was assembled. The testbed, consisting of two Universal Software Radio Peripherals (USRPs) from Ettus Research, namely, the N210 and USRP2 models, were

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connected to two PCs over a gigabit Ethernet local area network resembling an indoor scenario. Figure 1 indicates a schematic of the testbed network.

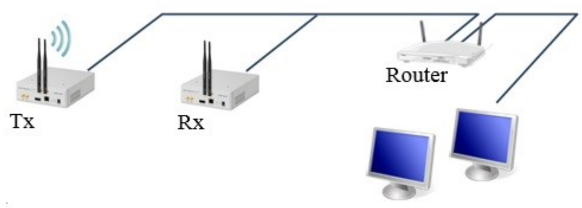

Figure 1 RAT Recognition Testbed

Taking advantage of the software defined nature of how USRPs can be reconfigured, different types of RATs were built in Simulink software package and then were fed into the transmitting USRPs through the connecting Gigabit Ethernet local area network. In order to demonstrate the potential of neural network classification technique in opportunistic spectrum access scenarios, three RATs were taken into account: DVB-T to exemplify Digital TV signals, WCDMA to represent a primary mobile network signal, and IEEE 802.11a WiFi to represent an unlicensed secondary transmission. Three experiments were set up; on each experiment one of the aforementioned RATs was transmitted from one of the USRPs and received through the receiving USRP. Time series data was collected for the duration of one second on each experiment for the training, testing and validation of the neural network.

III. Supervised Learning Neural Network for Classification

The trained neural network was structured as a Multi Layer Perceptron (MLP) network and it comprised of two layers: a hidden layer and an output layer. Through trial and error experimentation, the number of nodes in the hidden layer was set to 20. DVB-T, WCDMA and WiFi signals were fed into the network seperately. The traffic generator was operating on full-buffer bases. The received packets from the receiving USRP were cut into chuncks of 11120 samples representing the features that are input to the neural network. The number of samples was chosen based on observing the duration of a single packet. 747 signal examples each of 11120 samples for the three classes were parsed together to form the design matrix (input data). A schematic depicting the 2-layered neural network is shown in figure 2.

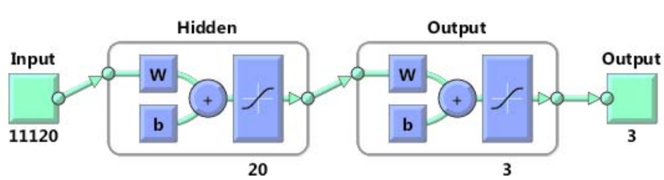

Figure 1 A 2-Layer Neural Network with 20 hidden nodes

The Transfer functions on the output of both of the Hidden and Output Layers taken each layers total weighted input and passes them through a Hyperbolic Tangent Sigmoid (tansig) functions. The weights are initialized according to Nguyen-Widrow layer initialization method [7]. Back propagation is used to calculate derivatives of the performance function, or in other words the cost function, with respect to the weight and bias variables. Scaled conjugate gradient algorithm [6] implemented in Matlab was used to apply the conjugate gradient updates. This algorithm can train any network as long as its weight, net input, and transfer functions have derivatives [7]. The implemented algorithm in Matlab also takes care of the preprocessing and post-processing steps, e.g. data normalization.

The scaled conjugate gradient algorithm is based on conjugate directions but this algorithm, unlike other versions of the conjugate gradient back propagation algorithm, does not perform a line search at each iteration to find the learning rate *η(n)* that minimizes the cost function [7]. Instead, as stated in [11] *η(n)* is given by

$$\eta(n) = 2\left(\eta(n) - P^T H(n)P + \eta(n)\frac{\|P\|^2}{\|P\|}\right)^2 \qquad (1)$$

where n is the step index, H is the Hessian of the gradient and P is given by

$$P = \left(\frac{\partial E(n)}{\partial \boldsymbol{w}}(n)\right). \qquad (2)$$

E(n) is the Minimum Square Error function, and $\boldsymbol{w}$ is the neuron weight vector [8]. For a more detailed observation of the scaled conjugate gradient back propagation algorithm the reader is kindly referred to [11]. The data is divided randomly into three datasets: 70% for training, 15% for testing and 15% for validation.

For many of the optimization algorithms used for network training, such as conjugate gradients, the error is a non-increasing function of the iteration index. Nevertheless, the error generated by test dataset, which is not used in the training process, decreases in the beginning, and then starts to increase when the neural net starts over-fitting the data. In this regard, in order to avoid the neural network to over-fit the training data, alongside the training data, a validation dataset is used as a test dataset so that it validates the performance of the training as it proceeds. Training will be discontinued at the point of smallest error after it has not decreased for a certain number of iterations (called Maximum validation failures) with respect to the validation dataset. This is done in order to obtain a neural network having a good generalization performance and avoid over-fitting the training dataset. This method is called Early Stopping approach [8].

There are other practical guidelines one could take to reach a better performance. In our case of RAT Classification, training stops when any of the following conditions occurs [7]:

- Validation error has been equal or increased more than a specific maximum number of failing times since the last time it decreased.
- The maximum number of epochs (repetitions) is reached before reaching some acceptable level of classification error.
- The maximum amount of time set to reach the performance levels is exceeded.
- Performance is minimized to the goal, which is usually set to zero.
- The performance gradient falls below the minimum specified gradient value.

The above discussed neural network parameters and their corresponding values are indicated in Table 1.

TABLE I
NEURAL NETWORK PARAMETERS

Parameter	Value
Maximum validation failures	6
Maximum Epochs	1000
Maximum Training Time	Inf
Performance Goal	0
Minimum Gradient	10^{-6}
Transfer Function	Tan-sigmoid

IV. RESULTS

The confusion matrices shown in Figure 3 clearly demonstrate the potential of this learning classification method.

Figure 2 Training, Testing and Validation Confusion Matrices

A confusion matrix is typically used to indicate the performance of a supervised learning classification algorithm where the number of correct guesses of the neural network outputs is shown along their diagonals, and the misclassification are displayed outside the diagonal according to the classes correspondingly. Here class 1 is DVB-T, class 2 is WCDMA and class 3 is WiFi.

Regarding the high performing neural network as indicated by the confusion matrices above, to avoid misperception it is necessary to mention the close proximity of the USRPs which was ranging between 2 to 3 meters of horizontal distance. This has certainly led to a strong reception of the transmitted signals at the receiver and henceforth a better classification.

The lower section of the figure 4 displays the errors made in the validation set versus epoch index. At epoch 93, where the best validation performance was reached – which is equal to 0.073434, the neural network fails to optimize its performance for 6 consecutive epochs and thus comes to a halt as it was programmed to do so according to Early Stopping method.

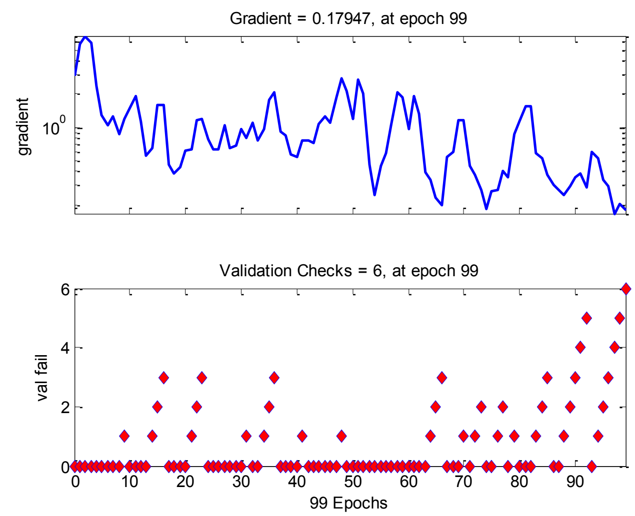

Figure 3 (upper) gradient at each epoch, (lower) validation error count.

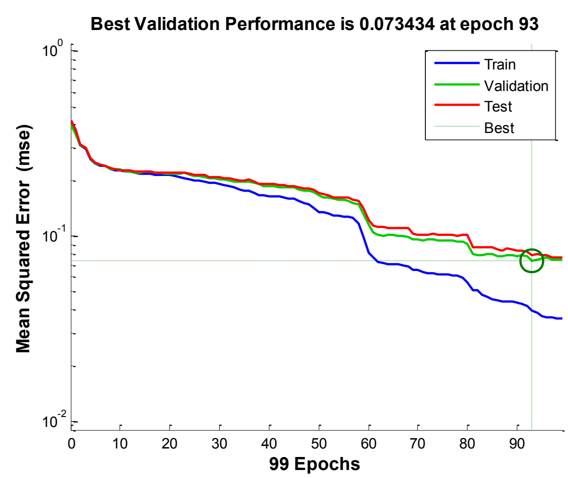

Figure 4 Training, testing and validation MSE graphs

Figures 3-5 only shows the results of one training experiment only. In order to avoid an optimistic and biased result, it is advisable to *cross-validate* a neural network design by performing many training experiments and averaging over the number of experiments. In this regard, the designed neural net was trained 100 times and the resulting confusion matrix was generated as shown in figure 6.

Throughput in terms of misclassification could be explained as follows. Looking at the throughput of generic primary system communication link from a Signal to Interference plus Noise Ratio (SINR) perspective and using the throughput definition used by the authors of [9], it can be shown that the throughput of a link is a cascaded multiplication of several probabilities as indicated by equation (3).

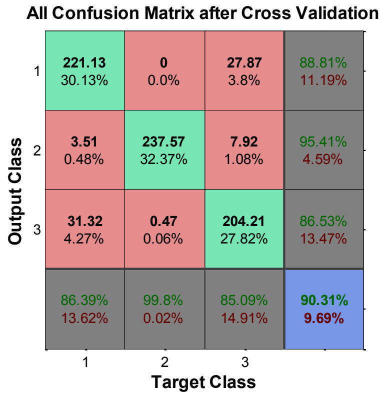

Figure 5 All Confusion Matrix after Cross Validation

Namely, the probability whether the transmitting node is actually transmitting at a particular moment, whether the receiver is silent and is not transmitting at this moment, and, finally, the probability for the communication channel to be regarded as a reliable link.

$$T = P\{probe\ transmits\}\, P\{receiver\ silent\}\, P\{no\ outage\} \quad (3)$$

The latter term is fundamentally meaning,

$$P\{no\ outage\} = P\{SINR \geq \gamma^*\}. \quad (4)$$

Where γ^* is a tolerated threshold that ensures reliability over a communication link. The SINR at the receiver needs to exceed γ^* for the received signal to be successfully recovered [9]. In the case of secondary-secondary cooperation working in an underlay scenario the misrecognition of a signal, i.e. a primary user to be classified as secondary user, will lead to an increased outage in the primary system, and hence a lower throughput.

The down side of this technique is that security aspects could be exploited by adversaries. Primary User Emulation, Connection attack, and Random Noise attacks are a few to name. For this reason, unsupervised learning techniques, and specifically K-means clustering and Self-organizing maps (SOMs), has been researched to do the signal classification; in which case the classifier will have to tolerate little availability of *a priori* information [10]. Nevertheless, this technique from implementation point of view was very simple and straightforward. There was no need to detect and get synched to the beginning of the received frames; it can easily be implemented for online mode operation. It is fast, where new inputs are just passed through the trained network and are classified with a class immediately.

V. Potential Appplications

In what follows we will discuss use cases of this technique in the context of cognitive mobile spectrum sharing and enriching Radio Environmental Maps.

A. Cognitive collaboration in overlay CRNs

Considering adaptation mechanisms in overlay CRNs, when SUs recognize the type of the access technology used by the PUs they have the privilege of exploiting their traffic pattern so that they can fill up the gaps/silent instances of the PUs that they usually produce by using a particular Radio Access Technology.

B. Secondary-secondary cooperation in shared spectrum

Another application is to reduce interference generated by the SUs affecting other SUs. In most of the published papers, authors assume that there are only PUs in a certain frequency band, e.g. TV Bands, and they try to fill up the white space in between PU channels while one can have more than one secondary network trying to transmit in the same white space band. To counteract situation alike, through RAT recognition an SU may observe the RAT used by another SU currently occupying a certain band, e.g. detection of a WiFi transmission (which is inherently a contention based multiple access scheme), and would want to contend for bandwidth. Even if the working SU is not currently using a contention based multiple access, both SU can negotiate a multiple access scheme, e.g. WiFi, so that both can use the band simultaneously.

C. Radio Environmental Maps (REMs)

REMs are seen as a fundamental facilitating technology to the emerging cognitive radio networks. They can represent knowledge base storing, managing and on-the-fly updating and extending the radio environment knowledge. Since the radio environment is dynamic in nature, the continuous tracking of the cognitive radio network events, such as the PUs or the SUs appearance or changes in the propagation conditions, is essential for the proper operation and optimal resource allocation in the cognitive environments.

A general and broad REM data model should consider at least one of the following three types of information, tightly correlated between each other:

1. Information on the present transmitters and the receivers in the area of interest. This can include information on their locations, capabilities, as well as their current configurations in terms of used frequency, power, bandwidth, employed technology etc. This information can be either pre-known, obtained from the regulator bodies or the operators, or can be dynamically estimated from the spectrum measurements executed by mobile terminals or dedicated spectrum sensors. This information is important since it can assist the decision making process and provide more optimal devices operation in the cognitive networks.
2. Information on the underlying propagation environment. This type of information can refer to statistical propagation models, terrain information, building plans, walls, obstacles etc. It is also vital information for the proper operation of the cognitive networks, since it relates to the propagation characteristics of the radio environment in the region of interest.
3. Radio Interference Fields (RIFs) are also an important component of the REM data model. The spatial distribution of the received signal strength (RSS), the signal-to-noise ratio (SNR), the summary interference, and other metrics can help in identifying coverage areas, evaluating the optimality of the conveyed strategies etc. The RIF data can be either empirically derived, using the results of the practical spectrum measurements or statistically modeled using the information from the previous two points.

With respect to the required REM data model, a general REM architecture should be able to execute spectrum measurements and perform the spectrum data acquisition, perform the processing of the spectrum data into the REM construction, and finally used the constructed REM data for various spectrum management purposes. Therefore, a functional REM architecture should consist of at least the following functional entities: Measurement Capable Devices (MCDs), REM data Storage and Acquisition unit (REM SA), REM Manager and a REM User. Figure 7 demonstrates an interconnected architecture of this concept. Any device able to perform spectrum measurements can act as an MCD, i.e. devices such as base stations, terminals, or even dedicated spectrum sensors can be seen as MCDs.

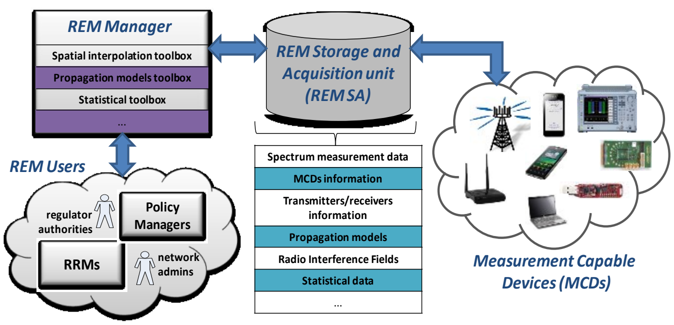

Figure 6 A general functional REM architecture

The MCDs can perform the spectrum measurements, signal detection/classification/recognition etc. The REM SA is the storage point of the REM architecture storing all types of REM information explained above, i.e. can keep the spectrum measurements from the MCDs, the locations/configurations of the transmitters, the propagation characteristics etc. The REM Manager is the functional entity performing the main processing tasks for REM data creation and evaluation. It should be modularly constituted, comprising various toolboxes that serve for localization of transmitters, statistical analyses of the spectrum usage, assessment of the environment propagation characteristics, estimation of RIFs etc. The REM User is the end user of the REM data, it can perform the frequency/power allocation, manage the spectrum access and usage, various cognitive network optimization etc.

Regarding the signal classification and recognition functionalities in the focus of the investigation in this paper, they can be embedded in specific types of MCDs, i.e. the MCDs capable of performing IQ based spectrum measurements. Instead of just performing the raw spectrum measurements and signal detection, this type of MCDs can perform the signal classification and recognition based on the known and/or learned features of the PUs or SUs signals. This type of REM information can be reported to the REM SA by the MCDs, and, as mentioned before, can be crucial for the optimal resource management decisions. Namely, recognizing the PUs and SUs transmissions the cognitive radio/network can perform optimal decision on the spectrum access, sharing and mobility in the wireless environment.

VI. CONCLUSION

This work has shown a simple yet efficient classifier that is able to discriminate between three different radio access technologies in an automated supervised learning manner. A testbed implementation has demonstrated the practicality of the research undertaken. Using such a classifier, secondary users will be able to sense whether a band is occupied by a primary or secondary user through detecting their transmission protocols. The classifier is an enabler for the concept of coexistence between secondaries with different types of radio access technologies. The paper also discusses some other use cases of the research undertaken, namely, to integrate RAT classification into Radio Environmental Maps and make them RAT literate. This research project is currently in progress. A Self-Organizing Map (SOM) classifier is presently under investigation for further enhancement of the classification performance.

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