Dynamic Spectrum Sensing with Automatic Modulation Classification for a Cognitive Radio Enabled NomadicBTS

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ABSTRACT

An existing Nomadic Base Transceiver Station (NomadicBTS) architecture designed and implemented in the literature was built on software defined radio technology. This technology performs radio functions via software modules. Cognitive radio on the other hand is essentially built on software defined radio technology integrated with artificial intelligence. This research work extends the existing NomadicBTS architecture with cognitive radio capability for the purpose of introducing dynamic (opportunistic) spectrum sensing for efficient spectrum utilization in mobile networks. This is achieved by developing an Automatic Modulation Classification (AMC) model for spectrum sensing based on Multi-Layer Perceptron (MLP) Artificial Neural Network (ANN). A suitable AMC model with optimum accuracy of 92.57% and Mean Square Error (MSE) of 0.0185 was empirically determined and deemed acceptable for incorporation into the NomadicBTS architecture.

Keywords: AMC, Cognitive Radio, Spectrum Sensing, Software Defined Radio (SDR), NomadicBTS.

1.0 Introduction

Cognitive Radio (CR) is a promising technology in the domain of wireless communications, especially with respect to next generation applications. It was proposed by Mitola in 1999 [1] to address the inefficient utilization and apparent lack of spectrum owing to the inherent inefficiencies of the conventional Fixed Spectrum Access (FSA) policy deployed in most countries [2]. In FSA, channels are assigned to specific wireless services and technologies, and only licensed users have permission to communicate via such channels while the other channels are left unused. From analytical studies of spectrum measurement and usage around the world, the FSA policy will not successfully accommodate the continuous growth in mobile traffic and increased demand for high data transmission rate in the near future. It is therefore of paramount importance to realize a more flexible and efficient spectrum access, which supports users of more congested channels making use of sensed less congested channels or opportunities for communication in order to improve quality of service and user experience. This policy is referred to as the Dynamic (or opportunistic) Spectrum Access (DSA).

In CR systems, a transceiver can intelligently detect frequency bands in the spectrum environment and automatically make use of the available channels while bypassing the occupied ones [1]. This optimizes the use of unoccupied radio-frequency spectrum with minimized interference to Primary
Users (PUs) and Secondary (unlicensed) Users (SUs). CR possesses some very important functions that enable a more flexible DSA. These functions are spectrum management, spectrum sharing, spectrum mobility and spectrum sensing. However, spectrum sensing is the most important of these functions and is the very component upon which the whole operation of CR is based [4]. Spectrum sensing involves the periodic monitoring of the status of spectrum bands of interest in order to identify unused portions of the spectrum at a point in time or geographical space. Such portions are regarded as spectrum holes or white spaces [1]. This allows SUs to detect the presence or absence of PU signals in a specific frequency band, and decide whether or not to transmit in that band.

1.1 Related Studies

These are various conventional methods or algorithms applied in achieving spectrum sensing by CR that have been reported in literature and widely deployed in CR based systems. According to [5], they include Energy Detection (ED), Matched Filter Detection (MFD), Cyclostationary Feature Detection (CFD), Covariance Based Detection (CBD), Compressed Sensing (CS) and Multi-Channel Sub-Nyquist Sampling (MCSN). However, each of the methods is found to possess certain inherent drawbacks that contributed to non-optimal detection efficiencies. The comparison among these methods is presented in Table 1.

| Sensing Techniques | Merits | Drawbacks | References |
|--------------------|--------|-----------|------------|
| **Energy detection** | i. Convenient implementation | i. High false alarm rate | [6-9] |
|                    | ii. Does not need any previous information about PU signal characteristics | ii. Low sensing efficiency in environments having low SNRs. | |
|                    | iii. High sensitivity to noise uncertainty | iii. | |
| **Cyclostationary feature Detection** | i. Resistant to noise uncertainty | i. Needs high sensing time to obtain a good detection performance | [6-9] |
|                    | ii. Effectively distinguish between signal and noise | ii. High consumption of energy where there is large number of samples. | |
|                    | iii. Reduced of false alarm probability in low SNR conditions. | | |
Matched Filter based detection
i. Higher detection in low SNR environments
ii. Has optimal sensing

Covariance-based detection
i. Does not need prior knowledge of the PU signal and noise
ii. Involves blind detection

Machine learning based algorithms are major state-of-the-art methods that seek to address are drawbacks associated with the conventional methods and improve the overall performance of the CR system [10]. They are aimed at detecting the availability of frequency channels by applying the concept of classification [11]. A major sub-field of machine learning based spectrum sensing which has attracted the attention of researchers over the past few years is spectrum sensing based on Automatic Modulation Classification (AMC).

AMC is essentially the combination of signal detection and modulation classification. It is the automatic recognition of the modulation properties of a sensed signal [12]. It is based on the principle that any modulation scheme is used by all PUs for transmission over a target frequency channel. Therefore, the detection of any modulation scheme deployed by a PU would be sufficient to verify the presence of the primary user’s signal in the frequency channel. Such channel will be regarded as a busy channel and thus unsafe for transmission by a SU. The absence of any modulation scheme in the channel indicates that the channel is a free channel and thus safe for transmission by a SU [13]. Generally, there are four main stages in modulation classification based spectrum sensing methods: (i) Data Acquisition, (ii) Pre-processing, (iii) Feature extraction and (iv) Classification. In the literature, a large number of AMC methods with respect to spectrum sensing have been developed and are grouped into the following broad categories: (i) Likelihood-based, (ii) Feature-based and (iii) Deep learning-based methods [12]. As seen in [13-21], some studies in the literature, which addressed AMC for spectrum sensing in CR deployed various simulated datasets and feature types such as constellation shapes and higher order statistics. However, in the study at hand, real-time Radio Frequency (RF) dataset were curated and non-complex first order statistical features were employed to develop an AMC model to incorporate CR capability in the NomadicBTS architecture.

2.0 Methodology
An existing Nomadic Base Transceiver Station (NomadicBTS) built essentially on Software Defined Radio (SDR) was proposed by [22] as shown in Figure 1 with its interconnection to the conventional Global System for Mobile Communications (GSM) and the Public Switched Telephone Network (PSTN) architecture. The NomadicBTS architecture comprises the following major sub-modules: (i) Software Defined Radio (SDR) hardware at the front end and (ii) SDR software back-end running on a Personal Computer (PC) or embedded system [22]. However, it does not incorporate dynamic spectrum sensing through CR. For instance, tuning of the station to any desired frequency is only manually achievable. The study at hand is majorly aimed at developing an AMC based intelligent spectrum sensing model that will form part of the SDR software back-end as shown in Figure 1. This is done in order to extend the existing NomadicBTS prototype into a CR based prototype for opportunistic (or dynamic) spectrum access on a femto-cell scale to accommodate selected modulation schemes.

![Figure 1: Block diagram of NomadicBTS architecture with spectrum sensing functionality](image)

In this work, the following modulation schemes were considered: (i) Amplitude Modulation (AM), (ii) Frequency Modulation (FM) and (iii) Gaussian Minimum Shift Key (GMSK) for Airtel, MTN, 9mobile and Glo GSM operators. Airtel, MTN, 9mobile and Glo are licensed GSM operators in Nigeria and these modulation schemes represent output classes in the AMC spectrum sensing model. Also, a No-Modulation class was included to represent opportunities or holes in a real situation. Thus, there were seven modulation classes identified in this study. In practice, when this model is incorporated into the NomadicBTS architecture, it will be able to distinguish between
occupied and available spectrum bands in the spectrum environment. The stages involved in the development of the AMC model in this study are hereafter described.

2.1 Real-time RF Data Acquisition

In this work, raw RF signals were captured at different frequencies corresponding to the aforementioned modulation schemes. This was achieved using the Universal Software Radio Peripheral (USRP B200) device and GNU-Radio Companion (GRC) software installed on Linux-Ubuntu 16.04 LTS operating system. The technical specifications of the USRP B200 are outlined in Table 2, while the GRC interface displaying the flow-graph used for signal capture for each modulation class is shown in Figure 2. A total of 350 samples, i.e. 50 real-time signals for each class were captured.

| Description            | Values          |
|------------------------|-----------------|
| Radio spectrum         | 50MHz – 6GHz    |
| Bandwidth              | 50MHz           |
| Sample rate (ADC/DAC)  | 61.44MS/sec     |
| ADC/DAC Resolution     | 12 bits         |
| Duplex                 | Full            |
| DC Input               | 6V              |
| FPGA type              | Spartan6 XC6SLX75|
| Interface type         | USB 3.0         |
| Interface speed        | 4.8Gbps         |

Figure 2: GRC interface indicating flow-graph for signal capture

2.2 Feature Extraction
For this study, First Order Statistics (FOS) were extracted for each signal sample in MATLAB 2017a environment. FOS were selected based on their (i) ability to identify distinguishing characteristics of signals, (ii) sensitivity to signal modulation types, (iii) insensitivity to Signal to Noise Ratio (SNR) variations and (iv) reduced complexity compared to higher order statistics [23]. The statistical features used were the mean, variance, standard deviation, skewness, kurtosis, root mean square, entropy and median [26].

2.3 AMC Model Development
This involves the development and training of a hybrid AMC model (i.e. with analog and digital modulation schemes as aforementioned). This model was developed using a Multi-Layer Perceptron (MLP) Artificial Neural Network (ANN) with the following selected specifications:

i. **Architecture type**: Feed-forward network with back-propagation consisting was selected to achieve optimum classification accuracy [13]. It consisted of an input layer with eight neurons representing the features, one hidden layer with an empirically varying number of neurons and an output layer of seven neurons representing the seven aforementioned modulation classes.

ii. **Activation functions**: Linear activation function, i.e. Purelin was used in the input layer. Also, the bipolar sigmoidal function, i.e. Tan-Sigmoid function was used in both the hidden layer and output layer to introduce non-linearity to the network [13].

iii. **Learning algorithms**: The Scaled Conjugate Gradient (SCG) and Levenberg-Marquardt (LM) algorithms were used in training the network to experimentally determine the optimum training algorithm for the model. The algorithms were chosen on the bases of training speed, efficiency, stability and high accuracy [13], [24-25,28].

iv. **Performance functions**: The Mean Square Error (MSE) and accuracy were used to test the training performance.

3.0 Results and Discussion
Figures 3 – 6 show the various spectrum plots for some of the acquired raw RF signal samples. These spectrum plots were generated and displayed on the FFT sink in GRC environment as seen in Figure 2.
Figure 4: Spectrum plots for FM signals

Figure 5: Spectrum plots for (Sample 1) GMSK Airtel signal, (Sample 2) GMSK 9mobile signal, (Sample 3) GMSK Glo signal and (Sample 4) GMSK MTN signal respectively
Figures 7 - 9 show the bar charts illustrating the extracted FOS features for each of the classes earlier described. This indicates very high likelihood of classification of signals by the developed AMC model. The indices 1 – 8 on the horizontal axis of each bar chart represent the FOS namely; mean, variance, standard deviation, skewness, kurtosis, root mean square, entropy and median. It can be observed that the patterns for each of the FOS features for each class is unique, which is an essential requirement for classification of the patterns with AMC approach.
The SCG and LM algorithms were deployed to experimentally determine the optimum learning algorithm for the developed AMC model. For each learning algorithm, the number of neurons in the hidden layer was varied to experimentally determine the number of hidden layer neurons that yielded minimal MSE with maximum accuracy.

From the comparative analysis of the results, the least MSE of 0.0185 and maximum accuracy of 92.57% was achieved by the model when it was trained using the LM algorithm with ten (10) neurons in the hidden layer. It was also observed that while training repeatedly with LM for every pre-set number of hidden-layer neurons, the accuracy values obtained were within a close stable range. However for SCG, the accuracy values obtained for each pre-set number of hidden-layer neurons.
neurons fluctuated almost unprecedentedly. Figures 10 and 11 respectively show the confusion matrix and Receiver Operating Characteristic (ROC) curves for the best AMC model in this study. Table 3 shows the specifications of this model while Figure 12 shows its topology.

![Confusion Matrix](image)

**Figure 10:** Confusion Matrix for LM-trained Model with 10 hidden-layer neurons

![ROC curves](image)

**Figure 11:** ROC curves for LM-trained Model with 70 hidden-layer neurons

Given the performance of the AMC model, the NomadicBTS architecture [22, 27] will thus be enhanced with CR capability. The result in this study also demonstrates the possibility of optimum classification of signals with similar modulation scheme but operating at different frequency bands. This provides opportunities for detecting operators with spectrum whole in a particular
geographical location or at a given time, which other operators could opportunistically loan for capacity enhancement as secondary users.

Table 3: Optimum Specifications for Developed AMC model

| Specification                        | Value          |
|--------------------------------------|----------------|
| Number of input layer neurons        | 8              |
| Number of hidden layer neurons       | 10             |
| Number of output layer neurons       | 7              |
| Activation function for the input layer | Purelin       |
| Activation function for the hidden layer | Tan-sigmoid  |
| Activation function for the output layer | Tan-sigmoid  |
| Mean Square Error (MSE)              | 0.0185         |
| Accuracy                             | 92.57%         |
| Learning algorithm                   | Levenberg-Marquardt (LM) |

Figure 12: Topology of the Best AMC Model

4.0 Conclusion

In this paper, we have presented the development of a hybrid AMC based spectrum sensing model towards the incorporation of opportunistic spectrum sensing into the NomadicBTS architecture. Selected analog and second generation (2G) digital modulation schemes were considered and the accuracy of the best model obtained will afford optimal detection of spectrum hole within the considered bands.

5.0 Recommendation

This study can further be extended for a more robust and enhanced NomadicBTS architecture based on CR technology. Interesting areas where such extensions can be realized include: (i) the implementation of CR based NomadicBTS architecture for mobile technologies up to Fifth Generation (5G), (ii) interconnection of multiple NomadicBTS for cooperative spectrum sensing, (iii) incorporation of other CR capabilities such as spectrum management, spectrum mobility and spectrum sharing, and (iv) development of deep learning based AMC models.
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