Signal Classification and Identification for Cognitive Radio

Sanjay Yadav[1], Dr Priyanka Jaiswal[2]

1- Master of Technology, Electronic and Communication Engineering, GITM, Lucknow.
Professor, Electronic and Communication Engineering, GITM, Lucknow.

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Abstract - *SDR (software-defined radio) devices have gotten a lot of interest lately because to their low cost and ease of use when it comes to hands-on testing. In cognitive radio (CR), they may be utilised to create dynamic spectrum allocation (DSA) algorithms. These CRs are currently unable to determine which DSA method is most suited for a given situation, despite much study in both machine learning and signal processing. Machine learning and statistical signal processing approaches may be used to compare the spectrum sensing algorithms for CRs and spectrum observatories in resource restricted contexts. We've decided to take on the issues of detecting multiple transmitters and automatically classifying modulation patterns (AMC). Multiple transmitter identification algorithms using machine learning and statistical signal processing are evaluated side by side. For multi-transmitter identification, the machine learning method has an accuracy of 70 percent and 80 percent for two and five user systems, respectively, while the statistical signal processing technique has an accuracy of 50 percent for two and five user systems, respectively. Machine learning beats the signal processing technique for 1000 test samples in AMC, even if both algorithms have 100% accuracy beyond 10 dB for 100 test samples (64-QAM is an exception). Signal processing techniques in both situations take a fraction of the time needed by machine learning algorithms, according to the time comparison.*

Key Words: Signal, Cognitive, ratio, identification, SDR, DSA.

1. INTRODUCTION

The current state of wireless systems is characterised by a radio function that is always on, a spectrum allocation that is always the same, and very little network coordination between mobile devices. In this day and age, it is common practise to utilise a remote web connection that is given by a portable device as the main method of one-on-one communication. This is because remote web connections are more reliable than traditional dial-up connections. Because of the developments that have been made in the web of things (IoT) based gadgets, for example, reconnaissance frameworks, sensor frameworks, implanted wellbeing observing frameworks, and numerous other similar frameworks, researchers and specialists are attempting to relegate a range band to every one of these gadgets for the purpose of impedance free correspondence [1]. This is a direct result of the limited radio spectrum, which came about as a direct result of the decision made by the administrative commissioners to proactively allocate a significant percentage of the available radio spectrum to a number of different administrations. As a direct result of this decision, there is now a limited amount of radio spectrum. There are a few distinct groups that are responsible for the overwhelming bulk of the congestion, yet the great majority of the available space is underutilised [2].

1.1. Software-Defined Radios

Figure 1-1 illustrates one of the fundamental building blocks that comprise the digital communication system. It is equipped with an RF front end that is connected to the antenna. Amplification of the analogue signal that either has to be broadcast or received is performed by this block. The conversion is carried out via the digital to analogue (DAC) and analogue to digital (ADC) converters respectively. The baseband signals are changed from a stop band into a pass band and back again by the digital up-conversion (DUC) and digital down-conversion (DDC) processes. In baseband processing, each and every processing activity, such as establishing a connection, frequency equalisation, and encoding/decoding, is carried out in its entirety [4]. This kind of technology is referred to as software-defined radio (SDR), and it executes these tasks on software modules that are either operating on field-programmable gate arrays (FPGA) or digital signal processors (DSP), or a mix of the two.

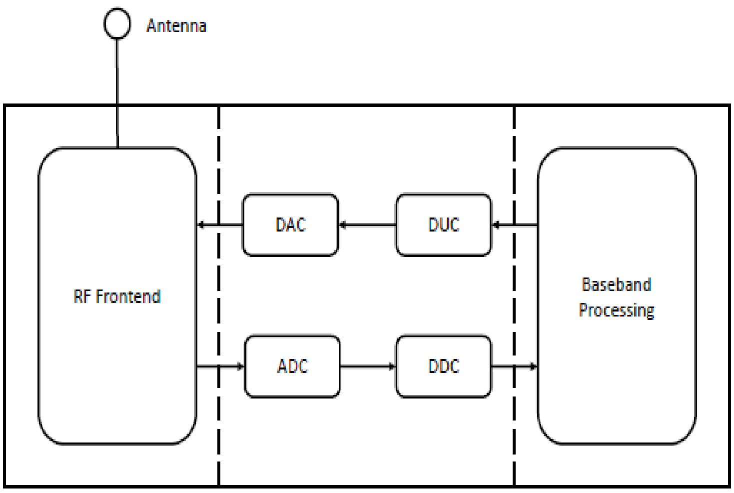

Figure-1: A basic Digital Radio Block.

1.2. COGNITIVE RADIOS

Radios are able to alter their functions and operations because reconfigurable characteristics supplied by SDRs make this possible. However, the SDR is not capable of doing these operations on its own; more specifically, it cannot reconfigure itself into the shape that is going to be the most useful for its user unless that user gives it instructions to do so. A device that is capable of self-reconfiguration in order to improve its performance is known as a cognitive radio (CR) [4]. These days, CRs are becoming more popular as a result of the perceived lack of bandwidth that is generated by the fixed frequency allotment [2]. A CR is able to detect the current status of the channel and adjust itself accordingly in order to get the highest possible throughput. In the beginning, the concept of CR was conceived with the intention of gaining opportunistic access across the digital TV bands in order to facilitate secondary communication inside a wireless regional area network. However, in today's world, CRs are being utilised not only in the business sector but also in the military sector. This is due to the fact that, in comparison to conventional radios, CRs provide the extra benefit of greater flexibility and security.

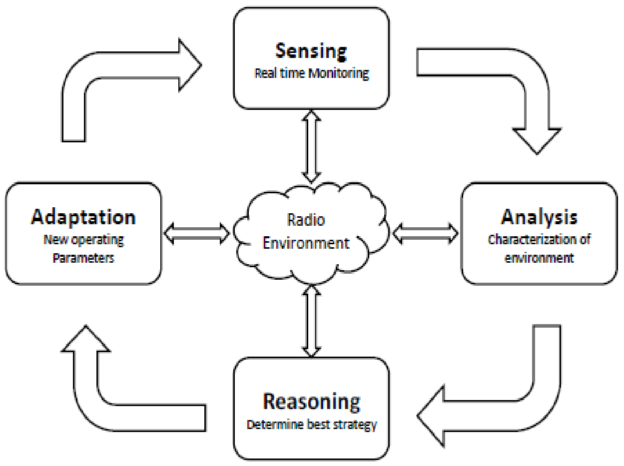

Figure-2: A basic block diagram of CR.

1.3. Dynamic Spectrum Access

Because of the rise in demand for wireless communication in today's world, there is a significant challenge posed by the static spectrum allotment as well as the restricted network coordination among mobile devices [10]. Along these same lines, a significant portion of the radio spectrum is put to use. The vast majority of the range is rather little used, although a few specific groupings are extremely obstructed. The solution to this problem is called dynamic range access (DSA), and it may be found in [11]. The primary goal of the DSA is to re-use recurrence groups with a low level of participant involvement while at the same time causing the genuine authorised customers no obstruction [12].

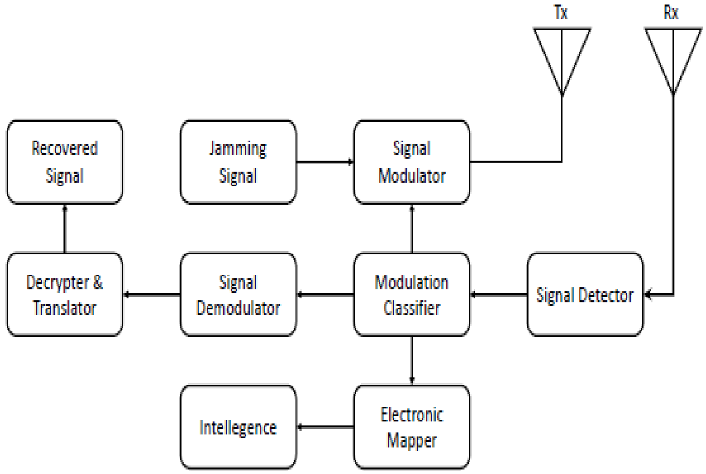

Figure-3: Illustration of AMC in Military applications.

2. DATA PREPARATION AND MULTISCALE

The parameter initialisation is one drawback of the mixed model. The issue is identifying many transmitters without prior knowledge, which cannot be done optimally unless the starting values input into the algorithms are properly chosen. Furthermore, spectral measurements are employed in this technique. As a result, the measured log-spectral values should be linearized. After converting the data to linear form, it is divided into time-frequency bins and categorised. Multiscale is the name for this grouping method.

Table-1: Multiscale and time-frequency bins.

Serial Number	Multiscale Resolution (I_{max})	T-F Bins
1	I_{max} =1.0	4
2	I_{max} =2.0	16
3	I_{max} =3.0	64
4	I_{max} =4.0	128

3. RESULT DATA

The IQ samples with known number of transmitters are required. To accomplish this, a GNU radio toolkit based on Python programming language is used to generate the data. The data is divided into three sets containing 500 files each. Each set has 100 files of IQ samples with 0, 10, 20, 30, 40 dB of additive white Gaussian noise for statistical relevance. Also, each set has one, two, and five transmitters, respectively. The waterfall plot of the data in each set is shown in figure 4 to figure-6.

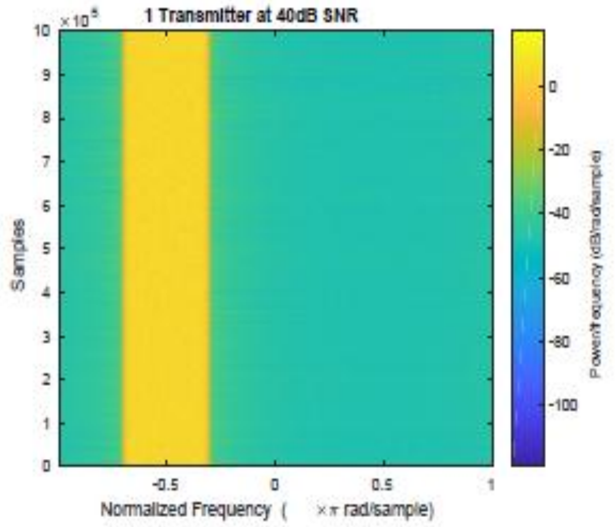

Figure-4: A spectrogram of generated data for 1 transmitter.

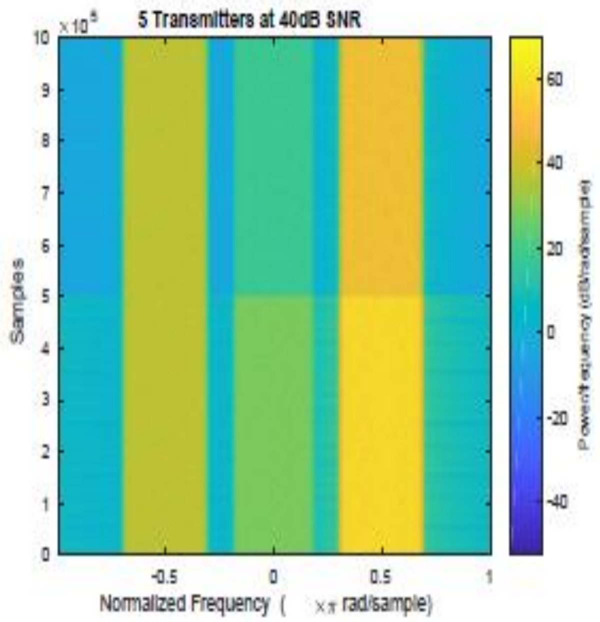

Figure-6: A spectrogram of generated data for 5 transmitters

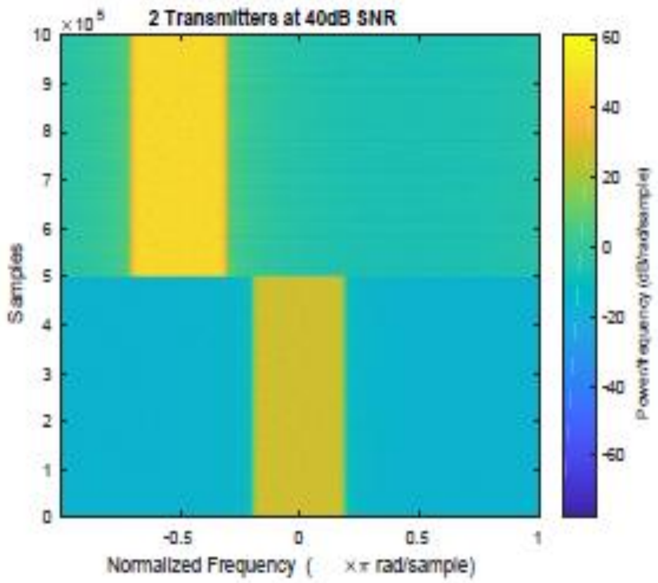

Figure-5: A spectrogram of generated data for 2 transmitters.

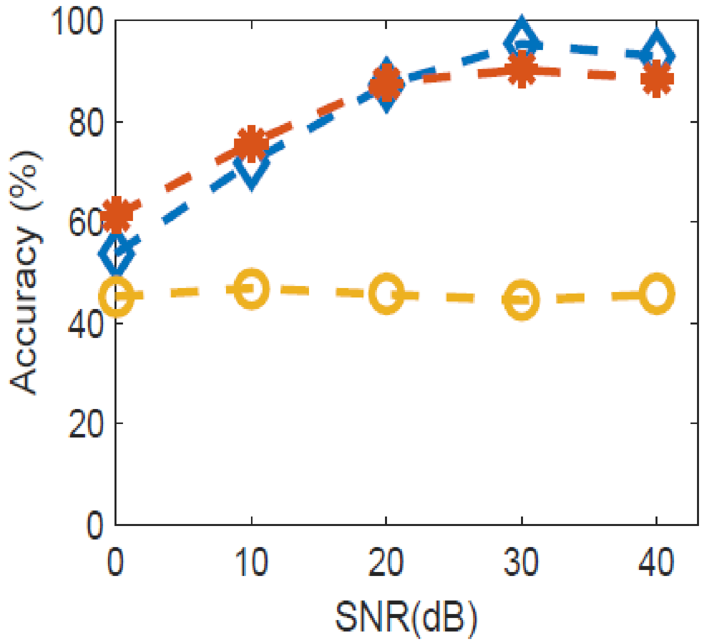

Figure-7: Accuracy comparison of multi-transmitter detection algorithms with time window = 0:5 ms, n-point fft= 2048. multiscale = 3 and No. of Tx's = 5

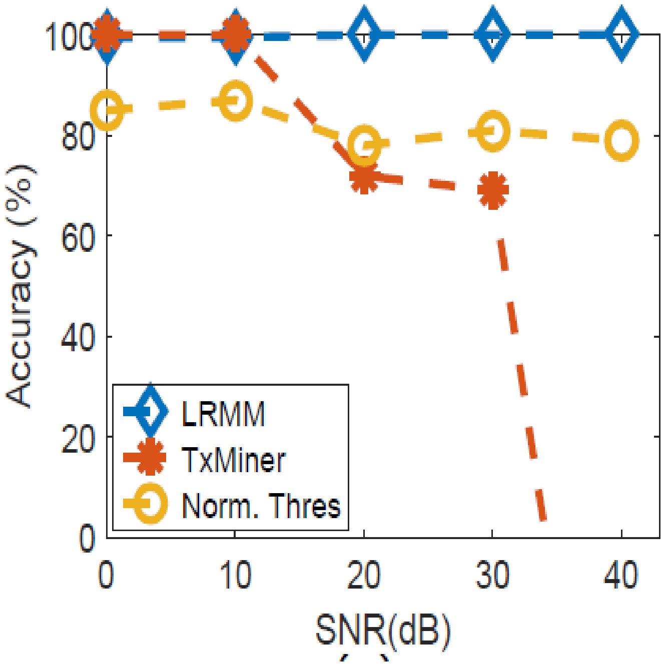

Figure-8: Accuracy comparison of multi-transmitter detection algorithms with time window = 1 ms, n-point fft= 1024.T multiscale = 2 and No. of Tx's = 1.

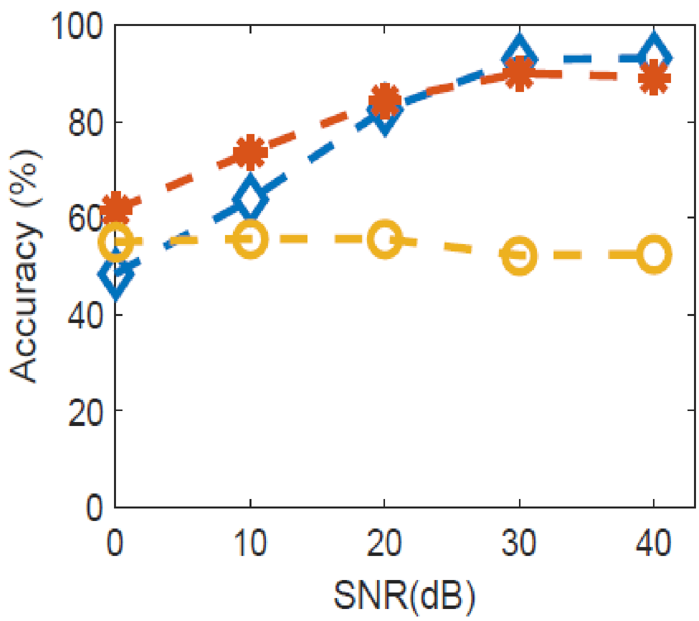

Figure-9: Accuracy comparison of multi-transmitter detection algorithms with time window = 1 ms, n-point fft= 1024, multiscale = 3 and No. of Tx's = 5.

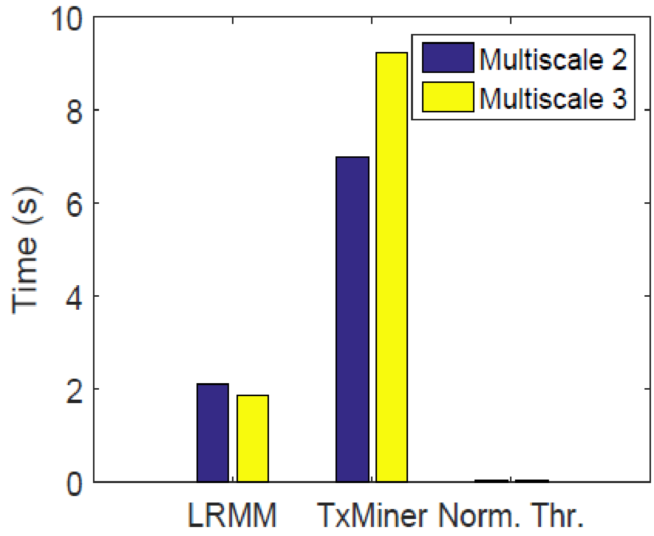

Figure-10: Time comparison of multi-transmitter detection algorithm time window = 0:5 ms, n-point fft= 1024.

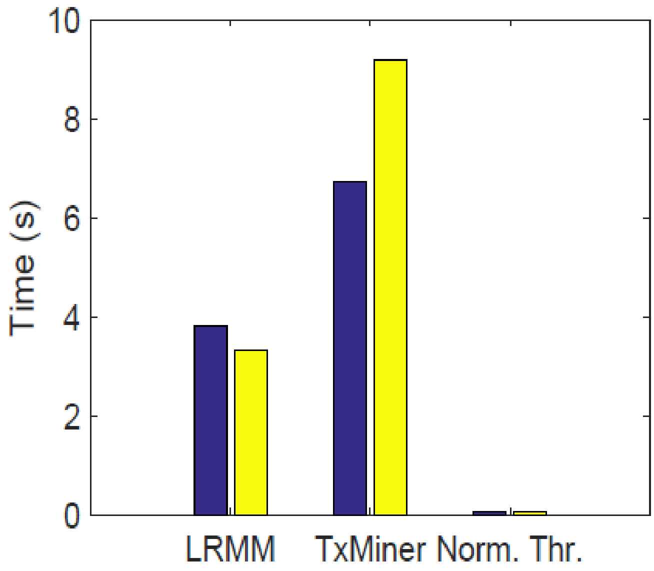

Figure-11: Time comparison of multi-transmitter detection algorithm time window = 1 ms, n-point fft = 2048.

4. CONCLUSION

CRs were the focus of this study, which compared machine learning and statistical signal processing techniques. AMC and multi-transmitter identification were selected as test tasks for this study. For the comparison of two novel methods, log-Rayleigh mixing model and normalised threshold energy sensing technique based multi-transmitter detection algorithm were utilised. The TxMiner algorithm was used as a benchmark for these algorithms. K-next neighbour and greatest likelihood AMC are also evaluated. According to the results of the comparison, machine learning algorithms outperform signal processing techniques. It is possible to boost the accuracy of supervised learning (k-nearest neighbour) by increasing the number of training samples. A large enough number of samples is necessary for unsupervised learning techniques (EM algorithm) in order to ensure that the results are statistically significant. It is also possible to draw the conclusion that the time required to run machine learning algorithms grows significantly as the number of samples for detection/classification processes increases. As a result, it is possible to think of algorithm selection as a trade-off between accuracy and execution time.

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