# FEATURE EXTRACTION METHODS ON A NOVEL MODULATION CLASSIFICATION TECHNIQUE FOR COGNITIVE RADIO APPLICATIONS

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## ABSTRACT

We report here on the framework of a full model for a novel modulation classification technique. This model includes a method for estimating the location of the signal transmitters using angle-of-arrival techniques, performing a full modulation classification process on the signal, and extracting the parameters and the data from the signal. We are investigating angle-of-arrival methods with low computational complexity and based on subspace reduction using multistage Wiener filtering. Comparison is based on accuracy, the length of training sequence, and performance in the presence of a strong interferer and multipath fading. We include a study of Gaussianity tests to find the most efficient method of classifying single-carrier versus multi-carrier signals that is computationally less complex and more resilient to white Gaussian noise. Further implementation and refinement of the novel single-carrier modulation classification technique using the I–Q diagram for modulations is discussed. A model for classification of multi-carrier signals is investigated, including Gaussianity, cyclostationarity, and autocorrelation tests for further extracting Orthogonal Frequency Division Multiplexing (OFDM) signal parameters. Further, their implementation on the Universal Software Radio Peripheral (USRP) platform will be discussed.

## 1. INTRODUCTION

Software-defined radio (SDR), by definition, is a radio consisting of a receiver and/or a transmitter, each with the following properties:

a. The received signal is digitized and then processed using software-programmable digital signal processing techniques (digitization may occur at RF, IF, or baseband);
b. The modulated signal to be transmitted is generated as a digital signal using software-programmable digital signal processing techniques; the digital signal is then converted to an analog signal for transmission (the conversion to analog may occur at baseband, IF, or RF); and
c. Software programmability enables changes of the radio's fundamental characteristics such as modulation type, operating frequency, bandwidth, multiple access scheme(s), source and channel coding/decoding method(s), frequency spreading/despreading technique(s), and encryption/decryption algorithm(s) [1].

According to the FCC, the definition of cognitive radio (CR) is given as a radio that can change its transmitter parameters based on the environment in which it operates [2]. This interaction may involve active negotiations with other spectrum users and/or passive sensing and decision making (i.e., smart radio). CRs will require SDR technologies .Some of the advantages of CR are sensing the RF environment and modifying frequency, power, and/or modulation, allowing for real-time spectrum management and hence, significantly increasing spectrum efficiency.

CRs are currently used in Local Area Network (LAN) devices, Code Division Multiple Access (CDMA) networks, cordless phones, and Unlicensed National Information Infrastructure (U-NII/DFS) (Europe).Some of the possible CR techniques are

- Dynamic frequency selection (DFS),
- Adaptive modulation,
- Transmit power control (TPC),
- Adjustable transmit parameters based on location, and
- Spectrum sharing between a licensee and a third party (including security features for authorized use).

In this context, modulation classification (MC) plays an important role in most CR applications and it comes as an intermediate step between signal detection and demodulation. MC is a challenging problem as there are many parameters involved—such as carrier frequency, symbol timing, number of carriers, etc.—that have to be extracted from the original signal.

The complete model we propose includes a block for estimating the location of the signal transmitters using angle-of-arrival (AoA) techniques, performing a full MC process on the signal and extracting the parameters and the date. The block diagram of the model is shown in Figure 1.

The MC method that we propose uses a hierarchical structure and a series of check points to identify the type of modulation. The proposed structure is shown in Figure 2.

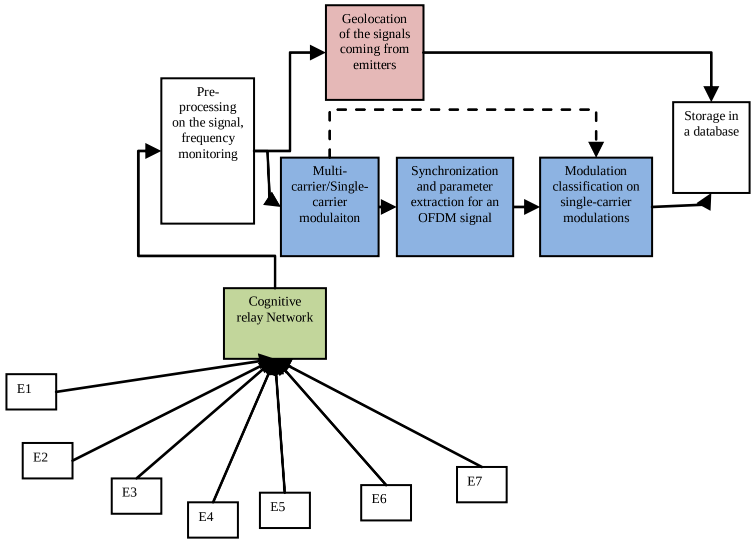

Figure 1. Block diagram of the model as a whole

An overview of the entire system has been discussed in a previous work [3]. Here, we present some more details and results for two main steps in this algorithm.

The first step is to determine whether we have a single-carrier or multi-carrier signal. If multi-carrier, a number of processes are performed to identify the parameters of the OFDM signal. If single-carrier, further classification methods are performed to determine the exact type of modulation.

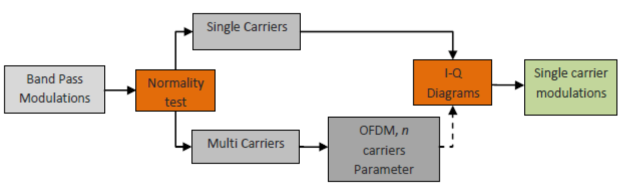

Figure 2. Block diagram of modulation classification process

## 2. METHOD OF AUTOMATIC MODULATION CLASSIFICATION

In OFDM modulation, all orthogonal subcarriers are transmitted simultaneously. That is, the entire allocated channel is occupied with the aggregated sum of the narrow orthogonal sub-bands. Thus, since it is a combination of multiple carriers, the OFDM-modulated signal can be considered to be composed of a great number of independent identically distributed (IID) random variables. Therefore, using the central limit theorem (CLT), we can assert that the amplitude distribution of the sampled signal can be approximated with a normal (Gaussian) distribution. However, this cannot be said for the case of a single-carrier modulated signal. Hence, multi-/single-carrier classification can be made with a simple normality (i.e., Gaussianity) test.

### 2.1. Multi-/Single-Carrier Selection

Normality tests have been discussed in the literature and a few of them have been proposed for this task [6, 7, 8]. Although there are a vast number of tests available, some of them, such as $\chi^2$ (Chi square) test or Epps test, are not well suited for digital modulation due to their high noise sensitivity. The tests that have been recommended for classifying single-carrier versus multi-carrier modulations are modified versions of the aforementioned tests, such as Giannakis–Tsatsanis test. With all the tests available, there has not been a thorough study on the most appropriate test for classifying multicarrier modulations and with this study we seek to fill that gap.

A normal distribution can be expressed as

$$f(x) = \frac{e^{\frac{-(x-\mu)^2}{2\sigma^2}}}{\sigma\sqrt{2\pi}}, \qquad 1$$

where $\mu$ is the mean and $\sigma$ is the standard deviation of the distribution. We use Gaussianity tests as hypothesis testing to determine whether or not signal samples are normally distributed.

Hypothesis testing is a statistical decision-making technique. These techniques rely on using the information in a random sample from the population of interest. If this information is consistent with the hypothesis, then the decision will be that the hypothesis is true. On the other hand, if this information is inconsistent with the hypothesis, then the decision will be that the hypothesis is false. It must be emphasized that the truth or falsity of a particular hypothesis can never be known with certainty. Hypothesis testing can be a two-sided alternative or one-sided hypothesis. In either case, two statements are claimed: $\mathcal{H}_0$

and $\mathcal{H}_1$. The value of $\mathcal{H}_0$ is referred to as the null hypothesis, while $\mathcal{H}_1$ is referred to as the alternative hypothesis. The decision will be either *reject* or *fail to reject* the null hypothesis.

In testing for the normal distribution, the null hypothesis $\mathcal{H}_0$ is that the random variable under consideration is distributed normally. If either $\mu$ or $\sigma$ is not specified completely, then the null hypothesis under consideration is a complete hypothesis. Here, we deal with the complete null hypothesis with both $\mu$ and $\sigma$ unknown [4].

We have to keep in mind that cumulants, which are needed in these tests, involve expectations and cannot be computed in an exact manner from real data. Hence, they must be approximated. Therefore, we replace their true values with their sample averages.

The tests which we have considered in this study are

a. Cramer–von Mises
b. Lilliefors
c. Jarque–Bera
d. Kolmogorov–Smirnov
e. Anderson–Darling
f. D'Agostino–Pearson
g. Shapiro–Wilk
h. Giannakis–Tsatsanis
i. Chi square

Chi square is considered as a measure of comparison for other methods, despite being unsuitable for use in signal detection. Most of these tests have already been implemented in MATLAB. We implemented two different versions of the Giannakis–Tsatsanis test, which are described as follows.

In Giannakis–Tsatsanis, the theoretical cumulant $c_{4x}$ is consistently estimated by the sampled averages

$$\begin{aligned}\hat{c}_{4x}(i_1,i_2,i_3) &= \frac{1}{T}\sum_{i=0}^{T-i_1-1} x(i)x(i+i_1)x(i+i_2)x(i+i_3) \\ &-\left[\frac{1}{T}\sum_{i=0}^{T-i_1-1} x(i)x(i+i_1)\right]\left[\frac{1}{T}\sum_{i=0}^{T-i_2+i_3-1} x(i)x(i+i_2-i_3)\right] \\ &-\left[\frac{1}{T}\sum_{i=0}^{T-i_2-1} x(i)x(i+i_2)\right]\left[\frac{1}{T}\sum_{i=0}^{T-i_3+i_1-1} x(i)x(i+i_3-i_1)\right] \\ &-\left[\frac{1}{T}\sum_{i=0}^{T-i_3-1} x(i)x(i+i_3)\right]\left[\frac{1}{T}\sum_{i=0}^{T-i_1+i_2-1} x(i)x(i+i_1-i_2)\right] \qquad 2\end{aligned}$$

where $\hat{c}_{4x}$ is the estimated 4th order cumulant, $x(i)$ is the signal, and $T$ is the number of samples. Cumulants that are higher than second order are insensitive to additive Gaussian noise of unknown covariance (AGN/UC). Some cumulants give the most relevant features of the modulation [5]. According to proposed test in [10], all the cumulants $c_{4x}(i_1,i_2,i_3)$ with $0 \le i_1 \le i_2 \le i_3 \le M-1 < \infty$ of the received signal must be computed. Generally we take $M \approx T^{0.4}$.

We will now simplify the computations, but first it must be noted that the tested process must be normally stationary, although it is not the case for modulated signals that are cyclostationary. However, the results in [5] justify that the test results remain suitable in our case. The simplified algorithm will be as follows:

Compute $c_{4x}(0,t,t)$, with $0 \le t \le M < \infty$ by using the estimation

$$\hat{c}_{4x}(0,t,t) = -\frac{1}{T}\sum_{i=0}^{T-t-1} x^4(i) + x^2(i)x^2(i+t)\,; \qquad 2$$

or, as a second version with fewer samples involved, we can also use

$$\hat{c}_{4x}(0,t,t) = -\frac{1}{T}\sum_{i=t+1}^{T-t-1} x^4(i) + x^2(i)x(i+t)x(i-t)\,. \qquad 3$$

The next step will be to compute

$$\Sigma_{c_{4x}} = \operatorname{cov}\{c_{4x}(0,t_i,t_i), c_{4x}(0,t_j,t_j)\}\,. \qquad 4$$

Finally, if the inequality

$$d_{G4} = c_{4x}^T \Sigma_c^{-1} c_{4x} < \tau \qquad 5$$

is verified, where $\tau$ is an opportunely set threshold, then the Gaussianity test is passed.

### 2.2. Cyclostationarity Test

A Gaussianity test that is passed indicates Gaussian distribution in the incoming signal. However, plain additive white Gaussian noise (AWGN) can also pass the Gaussianity test. Thus, a cyclostationarity test is needed to distinguish the OFDM signal from AWGN. It has been proven that an OFDM signal is cyclostationary with period $T_s$ [11], which denotes the interval of one OFDM symbol

$$T_s = T_b + T_{cp}, \qquad 6$$

where $T_b$ and $T_{cp}$ are the data and cyclic prefix durations, respectively. If the cyclostationarity test fails and no cyclostationarity is detected, then we can conclude that incoming signal is not OFDM but rather noise.

To define the test here, we first show how a baseband OFDM signal is stated mathematically as

$$x(t) = \sum_{k=0}^{K-1}\sum_{l=-\infty}^{\infty} d(k,l)g(t-lT_s)e^{j2\pi(k-(K-1)/2)\Delta f(t-lT_s)}, \qquad 7$$

where $d(k,l)$ is a complex symbol sequence corresponding to carrier $k$ and symbol number $l$, $K$ is the total number of carriers, $T_s$ is the total symbol duration, $\Delta f$ is the carrier spacing and $g(t)$ is the unit rectangular pulse with duration $T_s$ centered at 0.

The cyclic autocorrelation vector $\hat{\mathbf{r}}_{xx^{(*)}}$ is given by [9]

$$\hat{\mathbf{r}}_{xx^{(*)}} = \begin{bmatrix} \mathrm{Re}\{\hat{R}_{xx(*)}(\alpha,\tau_1)\},\ldots,\mathrm{Re}\{\hat{R}_{xx(*)}(\alpha,\tau_N)\}, \\ \mathrm{Im}\{\hat{R}_{xx(*)}(\alpha,\tau_1)\},\ldots,\mathrm{Im}\{\hat{R}_{xx(*)}(\alpha,\tau_N)\} \end{bmatrix}. \qquad 8$$

An estimate of the cyclic autocorrelation $\hat{R}_{xx^{(*)}}(\alpha,\tau)$ may be obtained using $M$ observations as

$$\begin{aligned} \hat{R}_{xx^{(*)}}(\alpha,\tau) &= \frac{1}{M}\sum_{t=1}^{M} x(t)x^{(*)}(t+\tau)e^{-j2\pi\alpha t} \\ &= R_{xx^{(*)}}(\alpha,\tau) + \boldsymbol{\varepsilon}_{xx}(\alpha,\tau) \end{aligned}, \qquad 9$$

where $x(t)$ denotes the received complex valued signal, $t$ is the discrete time index, (*) denotes an optional complex conjugation, and $\boldsymbol{\varepsilon}_{xx}(\alpha,\tau)$ is the estimation of error. The notation covers both cyclic autocorrelation and conjugate cyclic autocorrelation with only one expression. It is assumed that $x(t)$ has zero mean (in practice the mean can be estimated and subtracted from the signal). In addition, we assume the signal to be sufficiently oversampled. Oversampling at rate $f_s \geq 2KB$, where $K$ is the order of cyclostationarity and $B$ is the monolateral signal bandwidth (i.e., $[-B, B]$), guarantees that there is no aliasing in the cyclic frequency domain.

Similar to the Equation 10, the row vector of the true (asymptotic) value of the cyclic autocorrelation function $R_{xx}(\alpha,\tau)$ is defined by

$$\hat{\mathbf{r}}_{xx^{(*)}}(\alpha,\tau) = \mathbf{r}_{xx^{(*)}}(\alpha,\tau) + \boldsymbol{\varepsilon}_{xx^{(*)}}(\alpha,\tau). \qquad 10$$

Then, the test for the presence of second-order cyclostationarity at any of the cyclic frequencies of interest $\alpha$ simultaneously is formulated as [4]

$$\begin{aligned} &\mathcal{H}_0 : \hat{\mathbf{r}}_{xx^{(*)}}(\alpha,\tau) = \boldsymbol{\varepsilon}_{xx^{(*)}}(\alpha,\tau) && \text{signal not present} \\ &\mathcal{H}_1 : \hat{\mathbf{r}}_{xx^{(*)}}(\alpha,\tau) = \mathbf{r}_{xx^{(*)}}(\alpha,\tau) + \boldsymbol{\varepsilon}_{xx^{(*)}}(\alpha,\tau) && \text{signal present} \end{aligned} \qquad 11$$

### 2.3. Estimation of Number of Subcarriers in OFDM Signals

In [6], we see a detailed approach towards the estimation of the number of subcarriers using several FFT processors in parallel. Each processor that is termed an FFT branch will compute the FFT of the incoming OFDM signal. It is assumed that the number of carriers is a multiple of 2 and that no Gaussianity exists after the OFDM is demodulated. Each branch performs the FFT of the signal to compute $M$, where $M = N'/N$ where $N'$ is the classifier Digital Fourier Transform (DFT) size and $N$ is the transmitter Inverse DFT(IDFT) size.

In [10], the estimation of the number of subcarriers is made simpler by assuming that we know the symbol and the bit duration exactly. The concept of blind estimation is used here, wherein this value is corrected at various predictor–corrector steps and estimated using blind estimation theory. The number of subcarriers is given by a simple ratio of $N = \lfloor T_s / T_b \rfloor$, where the estimate of $T_s$ will be iteratively estimated and can be viewed as a summation of the autocorrelation of the signal.

## 3. GEOLOCATION

Accurate estimation of a signals direction of arrival (DOA) is of particular interest in non cooperative communication applications for cognitive radio such as electronic surveillance, first responders for disaster scenarios, interference identification, and spectrum management [12,13,14].

In this work, we use the multistage Wiener filter–based subspace reduction methods for estimation of signal subspace for 2D MUSIC algorithm application because of its low computational complexity. We evaluated the performance of the proposed algorithm for Circular, Rectangular, L Shaped and 2–L Shaped planar arrays for DQPSK waveforms. Simulation results indicate that 2-L Shaped arrays provide best resolution and highest accuracy when compared against Cramer Rao Bound [15, 16].

We implemented the 2D Music algorithm for angle of arrival estimation for 2–L shaped array using the testbed configuration shown in Figure 4. The results of implementation are shown in Figure 3. The angles to be estimated are [50, −70], [−45, −50] and [45, 60].

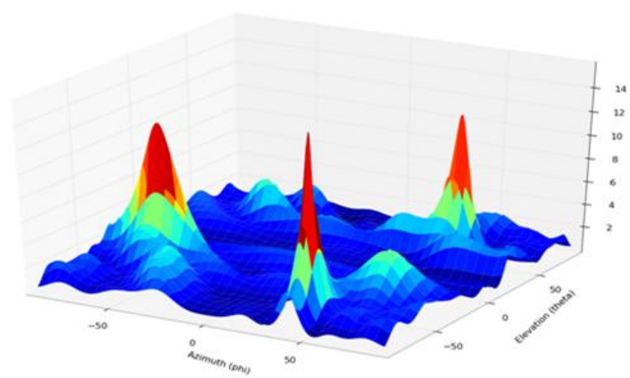

Figure 3. 2-D MUSIC with Multi Stage Wiener Filtering for noise and signal subspace separation

## 4. HARDWARE IMPLEMENTATION

The tests for each algorithm were performed according to the data flow in Figure 4. The USRP was used as a signal sink to record three unique streams of data. This data was then fed into GNU Radio and passed through a DQPSK modulator flow graph, which performed the required symbol mapping, modulation, and up-conversion to RF where white Gaussian noise was added. The three RF signals were then processed to emulate the effects of being received on an $M$-element antenna array. In the 1-D case, the array was a linearly separated $\lambda/2$ configuration, while in the 2-D cases a circular array was used. The $M$ incident signals were then passed through GNU Radio processing blocks to handle the DQPSK signal reception, downconversion, demodulation, and symbol extraction. Before the data are extracted in this receiver chain, the signal with carrier information is stripped off and sent to the various AoA algorithms. The results of each algorithm are then plotted using Python's Matplotlib library. The algorithms of interest for this hardware test were the 1-D ESPRIT and 1-D and 2-D MUSIC methods. All methods utilized multi-stage Wiener filters (MSWF) and were tested both with and without spatial smoothing.

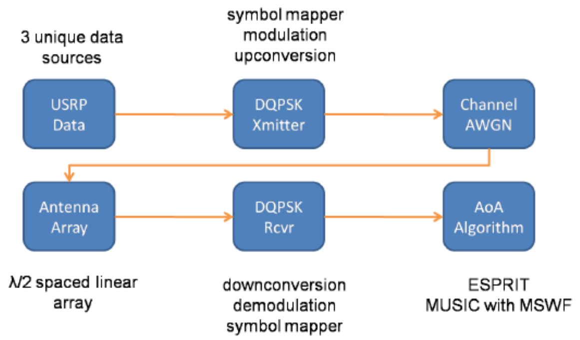


Figure 4. USRP and GNU Radio testbed configuration

Figure 5 shows the time necessary for each test to determine the Gaussianity of a Gaussian noiseless signal. Figure 6 has the same data for tests rejecting the Gaussianity of a noiseless uniformly distributed signal. One of the parameters in these tests is the significance level, which determines the probability of incorrectly rejecting the null hypothesis.

Based on the calculations for error rate, Kolmogorov–Smirnov and Cramer–von Mises did not show any error in distinguishing the Gaussian signal. Figure 7 shows the error

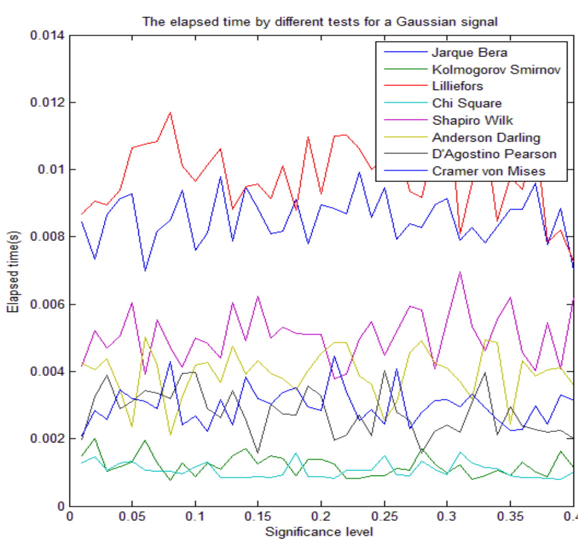


Figure 5. Elapsed time by Gaussianity tests for Gaussian signals

rate for the rest of the tests. Figure 8 corresponds to our single-carrier MC that uses *k*–means and *k*–center algorithms on I–Q diagrams of modulations to determine the modulation type.

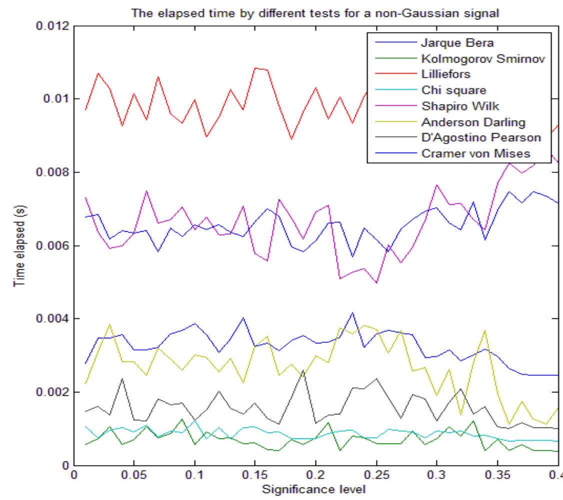


Figure 6. Elapsed time by Gaussianity tests for non-Gaussian signals

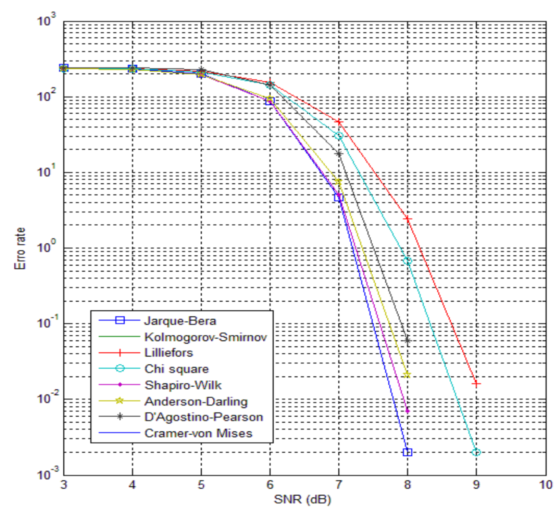


Figure 7. Error rate vs. SNR for Gaussianity tests

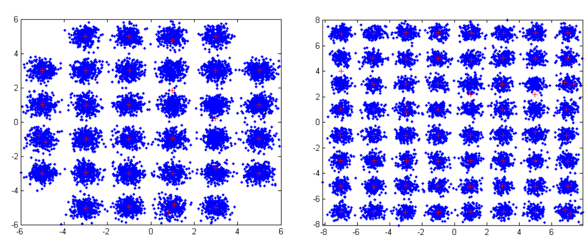

Figure 8.Clustering on 32-QAM and 64-QAM signals. The + sign shows the center of each cluster.

## 5. CONCLUSION AND FUTURE WORK

The goal of this project is to design and implement a comprehensive modulation classification system to be used in a cognitive radio. A hierarchical structure has been proposed and one important part of this algorithm is being able to separate single-carrier signals from multi-carrier signals. We have extensively studied Gaussianity tests to determine the most appropriate test available for this task.

The results show that, although some of the available tests require fewer calculations and, thus, less processing time, their performance degrade significantly when a Gaussian noise is introduced into the signal. Based on the simulations, it seems Kolmogorov–Smirnov test has both a very good processing time and achieves good results when dealing with a noisy signal.

Next steps will be to complete the feature extraction of an OFDM signal. Future work will include recovery of timing, cyclic prefix detection, autocorrelation test, and a bank of FFTs to estimate the number of subcarriers in an OFDM signal. These will combine with a previously developed single-carrier modulation classification to complete our MC algorithm.

To further show the applicability of software-defined radio geolocation methods, a new testbed will be created using multiple time-synchronized USRP boards with two receive antennas each to create an actual linear array to perform live geolocation tests.

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